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Gender Differences in Programming Among Primary School Students in Japan

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Abstract

This study aimed to examine gender differences in primary school students' motivation and social factors in learning programming in Japan. The expectancy-value model was used to survey 6th-grade primary school students at the end of the school year. The results revealed that expectancy (self-efficacy) and intrinsic value were significantly lower for girls than for boys. In addition, the psychological cost was significantly higher for girls than boys. This means that girls have lower self-efficacy for programming, less interest in programming, and higher fear of programming failure than boys. This study supports gender differences in motivation and social factors related to programming already at the primary school level. These differences may affect future education trajectories and career choices.
Keywords: gender gap, programming, primary school students, expectancy-value model

1 Introduction

In a society dependent on information technology, computer science has a considerable effect on diverse industry fields [1] and people's lives. Therefore, an increasing number of countries worldwide, including those in Europe, Oceania, and Asia, have introduced computer science at the primary level [2], recognizing the importance of cultivating computer science literacy from K–12 education. Similarly, Japan introduced computer science education at the primary level in 2020.

The Japanese school system includes six years of primary school, three years of middle school, and three years of high school. The nine years of primary and middle school are compulsory, but most students (95.5%) go on to high school even though it is not compulsory [3]. In the revised national curriculum, the programming activities have been exemplified in fifth-grade mathematics, sixth-grade science, and integrated study at the primary level without separate computer science subject. In middle school, computer science education was incorporated into the Technology of Information Processing unit of the Technology and Home Economics subject. The high school informatics subject includes Information I, a mandatory subject based on rigorous computer science, and Information II, an elective subject including data science and designing an information system.

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1.1 Problem and Purpose

In this regard, Japan has recognized the importance of nurturing computer science competencies to prepare students for an increasingly fast-changing, complex, and unpredictable era due to rapid technological development. Despite increasing demand for competencies in computer science, higher education in this field is still gender biased in Japan. For example, OECD [4] demonstrated that among students entering higher education, women accounted for 52% of the OCED but only 27% of Japanese students, the lowest among OECD countries, in the STEM fields of natural sciences, mathematics, and statistics. Furthermore, the share of women graduating in STEM fields (science, technology, engineering, and mathematics) is 17% in Japan, the lowest among OECD countries, compared to the OECD average of 32% [5].

In response to this situation, the Cabinet Office's Council for Science, Technology, and Innovation proposed a policy package that would close the gender gap in STEM fields. The package includes research on why women do not choose STEM fields for academic and career options [6], highlighting that the evidence to address the gender gap in these fields in Japan is lacking. Although empirical and theoretical studies on the gender gap in STEM fields in Japan in K–12 education have accumulated, most of them focused on science or mathematics [7], and only a few studies addressed the gender gap in computer science education in Japan.

Therefore, the purpose of this research was to examine gender differences in motivation toward computer science that lead to educational and career choices in K–12 education before entering higher education in Japan. As part of this research, this study investigated gender differences in motivation to study computer science among primary school students. In particular, this study was guided by a research question of whether gender differences in learning programming can be observed at the primary school level.

1.2 Literature Review

Werner et al. [8] suggested that three factors influence gender differences in students' educational trajectories: individual, relational, and structural. Individual factors include motivation; relational factors entail expectations from family members, peers, and school personnel; and structural factors contain gender role stereotypes [8]. This study focused on individual factors, allowing us to conduct empirical research in the future.

One of the theoretical bases for the individual factors is Eccles et al.'s Expectancy-Value Model. According to this model, the most immediate or direct predictors of achievement performance and choice are individual expectations of success and value beliefs, which are affected by an array of psychological, social, and cultural aspects [9]. This model was initially developed to help explain gender differences in mathematics course choice, such as why females are less likely than males to choose mathematics courses in high school and college [10]. Since then, the author and her colleagues have studied this model in education and occupational choice to identify the motivational and social factors underlying achievement-related decisions by males and females [11].

Eccles et al. [11] defined the expectation of success not as children's evaluation of their current abilities but as children's belief of how well they will do on the next task [9]. In the expectancy-value model, value relates to the qualities of different tasks and their effects on an individual's desire to perform the task; therefore, it includes task value [9].

Eccles [10] suggested the four components of the subjective task value: attainment value, intrinsic value, utility value, and perceived cost [9][11][12][13]. Attainment value is the subjective importance of completing given tasks. This value is based on the assumption that tasks have subjective attainment values when they are associated with personal and social identities [9][10] [13]. Intrinsic value is defined as the enjoyment obtained from working on a task [9]. When there is intrinsic value, children are more likely to become deeply involved in the activity and continue it for a longer period [13]. Utility value describes how a task fits into an individual's current and future goals and plans [13]. In this regard, the utility value is also linked to personal goals and self-perception [9]. Eccles [10] believed that cost also affects the value of a task in terms of the cost/benefit ratio. In other words, if the cost is too big, people do not perform the task [13]. She proposed that the three variables that affect the cost are "(1) the amount of effort needed to succeed, (2) the loss of time that could be used to engage in other valued activities, and (3) the psychological meaning of failure" [10, p. 94]. Therefore, this study adopted Eccles et al.'s Expectancy-Value Model, including the expectations for success and four components of subjective task value.

2 Method

2.1 Participants

The participants were 29 sixth-grade students (15 girls, 14 boys) in Japan. Each student had access to one laptop computer in class and could take a laptop computer home with them. The students could decide whether to use the laptop computers outside of class. During the sixth grade, every student utilized a laptop computer in each subject in every class. Sixth grade students learned about programming concepts unplugged in science class only for one hour. However, students were free to use Scratch installed on their laptop computers during recess and after class.

2.2 Measures

We surveyed children at the end of February 2023, the end of the school year in Japan, using demographic questionnaires and questionnaires based on the expectancy-value model. The demographic questionnaire included questions on gender, frequency of programming experience inside and outside of school, frequency of computer use at home, and frequency of smartphone use at home. Since students use laptop computers for every class during sixth grade, this study examined their frequency of computer and smartphone use outside of class to identify their affinity for these devices. The expectancy-value items (Appendixes 1−3) asked about students' expectations for success and value beliefs in programming, both unplugged and coding. The study did not specify the context in which programming learning took place (e.g., in class or out of class, unplugged or coding), as the purpose of this study was to examine the relationship between each student's general programming notions and gender bias, rather than to target a specific programming activity. However, when asked about programming learning in the questionnaire, we added supplemental information that programming learning includes both using and not using a computer since some students may not consider unplugged activities as learning programming. Although the computer science concepts and practices cover a broader area, computer science education in Japanese primary schools focuses on programming experience; therefore, programming was targeted in the questionnaire.

Eccles's [10] Expectancy-Value Model consists of expectations for success and value beliefs. This study employed scales based on Eccles's Expectancy-Value Model, which has strong theoretical foundations. Furthermore, all components pertaining to the expectations and value beliefs outlined by Eccles's Expectancy-Value Model were measured using these scales. By incorporating these two conditions, this study ensured the validity of the scales. Each scale is presented below.

Expectancy: To measure expectations, Harada et al. [14] developed a self-efficacy scale to identify middle school students' motivation to observe and experiment in science (six items). Since self-efficacy has been used as a measure of expectations in several studies [15], this study used Harada et al.'s [14] 6-item self-efficacy scale to measure expectancies on a 6-point Likert scale (6−very applicable, 1−not applicable at all). In the questionnaire, "science observation and experiment" was replaced with "learning programming." Higher scores on this scale indicate higher self-efficacy for programming.

Task Value: Eccles [10] demonstrated that attainment value, intrinsic value, utility value, and perceived cost are the four components of the subjective task value. Kera & Nakaya [16] conducted an exploratory factor analysis of a survey of middle school students in science using a task value scale based on Eccles's [10] four task value components, practical utility value (3 items), institutional utility value (3 items), intrinsic value (4 items), and attainment value (3 items), to examine the influence of task value on learning activities. This study utilized Kera & Nakaya's [16] task value scale comprising 13 items measured on a 5 Likert scale (5−very applicable, 1−not applicable at all). In the questionnaire, "science contents" was replaced with "learning about programming." Higher scores on this scale indicate higher attainment value, intrinsic value, and utility value of programming.

Although Eccles [10] included the perceived cost of the task value, Kera & Nakaya 's [16] scale does not include the cost component. Kera & Nakaya [17] developed a scale to measure cost perception in college students based on three variables affecting perceived cost proposed by Eccles [10]. This scale includes opportunity cost (4 items), effort cost (4 items), and psychological cost (3 items) sub-scales [17]. This study utilized Kera & Nakaya 's [17] cost perception scale containing 11 items measured on a 7-point Likert scale (7−very applicable, 1−not applicable at all), and in the questionnaire, "psychology learning content" was replaced with "learning about programming." Higher scores on this scale infer higher perceived costs of programming, which means that higher scores hinder motivation to engage in certain things (programming).

3 Results

3.1 Participants' Characteristics

Table 1 summarizes programming experience at school, indicating that 20.0% of the girls were involved in programming more than two to three times a month, compared to 57.1% of the boys. Since sixth grade students had only one hour of learning programming, the results reflect their spontaneous programming outside of classroom. Regarding programming experience outside of school, six students (three girls and three boys) had programming experience outside of school, and all had done a little programming at home. In this case, finding gender differences in the number or the nature of the experience was difficult.

Table 1: Programming Experience at School

	Girls		Boys	
	Count	%	Count	%
At least once a week	2	13.3%	4	28.6%
About 2 or 3 times a month	1	6.7%	4	28.6%
About once every few months	3	20.0%	1	7.1%
Less than the above	4	26.7%	2	14.3%
I don't know	1	6.7%	3	21.4%
No, I don't know.	4	26.7%	0	0.0%
Total	15	100.0%	14	100.0%

Table 2 shows the use of computers by students at home, and Table 3 shows the use of cell phones and smartphones by students at home, revealing that 90% of girls and 60% of boys used computers and smartphones almost every day or sometimes.

Table 2: Use of Computers by Students at Home

	Girls		Boys	
	Count	%	Count	%
Almost every day	3	20.0%	4	28.6%
Sometimes	11	73.3%	5	35.7%
Rarely	1	6.7%	5	35.7%
Never	0	0.0%	0	0.0%
Total	15	100.0%	14	100.0%

Table 3: Use of Cell Phones and Smart Phones by Students at Home

	Girls		Boys	
	Count	%	Count	%
Almost every day	12	80.0%	5	35.7%
Sometimes	2	13.3%	3	21.4%
Rarely	0	0.0%	2	14.3%
Never	1	6.7%	4	28.6%
Total	15	100.0%	14	100.0%

3.2 Expectancy

The means of the total scale scores of expectations for girls (M = 3.611, SD = 0.968) and boys (M = 4.262, SD = 1.007) are shown in Figure 1. The means of each expectancy item by gender are listed in Appendix 1. A t-test was conducted to examine whether the expectancy scale differed by gender. The results indicated a significant difference between boys and girls (t (172) = 4.345, $p < .001$) in the expectancy scale.

3.3 Task Value (Practical Utility Value, Institutional Utility Value, Intrinsic Value, Attainment Value)

The means of the total scale scores of practical utility value, institutional utility value, intrinsic value, and attainment value for girls and boys are shown in Figure 2 (practical utility value: M = 3.711, SD = 0.991 for girls, M = 4.048, SD = 0.936 for boys; institutional utility value: M = 4.156, SD = 0.767 for girls, M = 4.262, SD = 0.912 for boys; intrinsic value: M = 3.550, SD = 1.156 for girls, M = 4.268, SD = 1.000 for boys; attainment value: M = 3.600, SD = 0.863 for girls, M = 3.786, SD = 0.951 for boys). Boys scored slightly higher on each value. The means of each item of practical utility value, institutional utility value, intrinsic value, and attainment value by gender are shown in Appendix 2.

A t-test was conducted to examine whether the expectancy scale differed by gender. The results showed no significant difference between boys and girls in the practical utility value scale (t (85) = 1.625, p = 0.108), the institutional utility value scale (t (85) = 0.590, p = 0.557), and the attainment value scale (t (85) = 0.955, p = 0.342). However, a significant difference was found between boys and girls in the intrinsic value scale (t (114) = 3.566, p = 0.001).

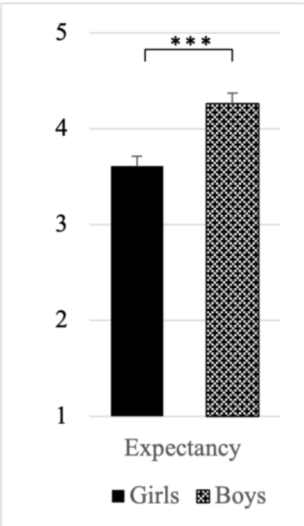

Figure 1: Expectancy

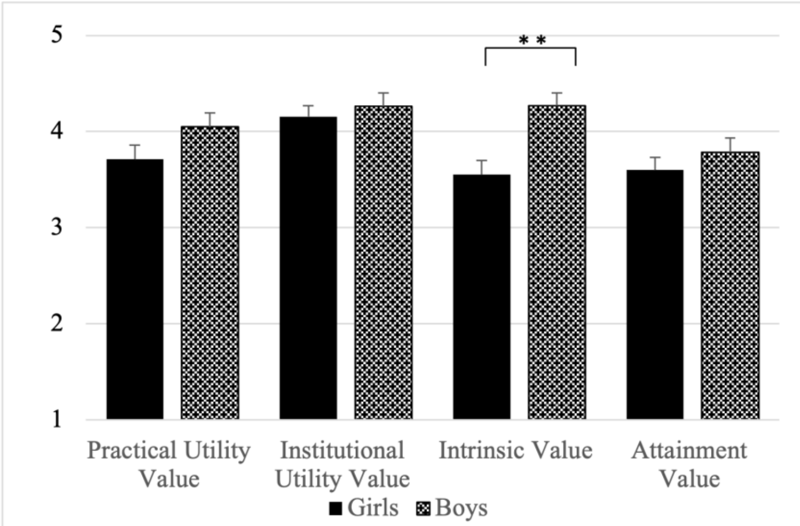

Figure 2: Practical Utility Value, Institutional Utility Value, Intrinsic Value, and Attainment Value

3.3 Task Value (Perceived Cost)

The means of the total scale scores of opportunity cost, effort cost, and psychological cost for girls and boys are shown in Figure 3 (opportunity cost: M = 3.117, SD = 1.530 for girls, M = 3.268, SD = 1.635 for boys; effort cost: M = 4.400, SD = 1.475 for girls, M = 4.196, SD = 1.752 for boys; psychological cost: M = 2.956, SD = 1.623 for girls, M = 2.214, SD = 1.423 for boys). Girls had higher means on effort and psychological cost but lower mean on opportunity cost. The means of each opportunity, effort, and psychological cost items by gender are shown in Appendix 3.

A t-test was conducted to examine whether the expectancy scale differed by gender. The results demonstrated no significant differences between boys and girls in the opportunity cost scale (t (114) = 0.514, p = 0.608) and effort cost scale (t (114) = -0.679, p = 0.499). However, the difference between boys and girls in the psychological cost scale was significant (t (85) = -2.258, p = 0.026).

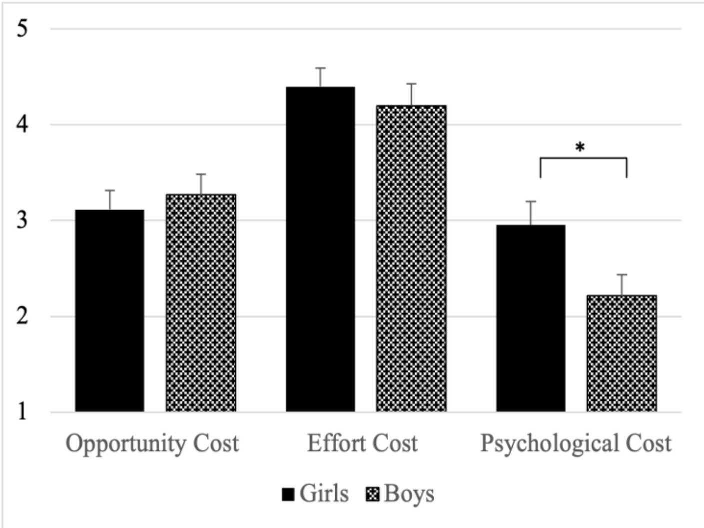

Figure 3: Opportunity Cost, Effort Cost, and Psychological Cost

4 Discussion

This study showed that expectancy and intrinsic value were significantly higher for boys than for girls, and psychological costs were significantly higher for girls than boys. This result provides further evidence that girls have lower self-efficacy and lower intrinsic motivation for learning programming and are more concerned about failure when learning programming compared to boys. This result is consistent with the finding that boys use programming tools more frequently than girls at school (Table 1).

According to Taylor and Betz [18], self-efficacy significantly predicts career indecision. In other words, students who lack confidence in performing a task tend to be indecisive in their career choice. They suggested that individual differences in self-efficacy expectations are the primary mediators of individual differences in behaviors necessary to make career decisions [18]. Thus, it can be said that expectancies (self-efficacy) and psychological costs are related to future career choices. Several studies have supported gender differences in expectancy and psychological cost in programming. Finlayson [19] illustrated that female students performed better than male students but had significantly lower self-esteem compared to male students. Similarly, Hunt et al. [20] reported that female students' self-assessments were significantly lower than those of male students despite achieving similar grades in a college introductory computer science course. Whereas these results were based on data collected from higher education students, the present study found gender differences in self-efficacy and psychological trends among sixth-grade students.

Furthermore, we found that girls had lower scores on intrinsic value than boys. Wigfield and Cambria [21] illustrated that children's values and academic interests tend to decrease as they progress through the school years, and as interest wanes, so does their motivation to learn. Relatedly, studies on changes in attitudes and motivation toward certain subjects at different school stages have been conducted so far in Japan in science and mathematics [22] [23]. However, studies in computer science are lacking. Since there is considerable evidence that subject interest is positively related to school achievement [21], interventions are needed to address the gender gap in intrinsic value at the primary school level, as revealed in this study.

5 Conclusion

This study investigated gender differences in primary school students' motivation to learn computer science in Japan. A survey based on the expectancy-value model was administered to sixth-grade primary school students. The results showed significant differences between girls and boys in expectancy (self-efficacy), intrinsic value, and psychological cost, which means girls have less belief in their ability to program, less interest in learning programming, and more fear of failure in programming. These findings were observed among sixth-grade primary school students. Further studies are needed to investigate the factors contributing to gender differences in self-esteem, interest, and psychological fears in primary school.

A limitation of this study is that it was conducted in only one class in a primary school, which may have biased the results and limited the generalizability of the findings to the general population of children, thereby affecting reliability. Further research should (1) include more primary schools and conduct similar studies in lower primary grades, middle schools, and high schools; (2) investigate the factors that have affected the findings in this study through interviews; and (3) conduct empirical research to test these factors.

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Appendix

Appendix 1: Means of Each Expectancy Item by Gender

Items		Girls		Boys	
		Mean	*SD*	*Mean*	*SD*
Expectancy	I am able to focus when it comes to learning programming.	3.800	0.941	4.571	1.016
	I am able to work very hard in learning programming once I decide to do it.	3.533	1.125	4.357	1.008
	I am willing to learn programming, even if I find it difficult.	3.667	0.900	4.214	1.051
	I am able to work on learning programming without giving up, even if I fail.	3.867	0.743	4.357	1.008

	I am able to tackle difficult problems without making mistakes in learning programming.	3.333	0.900	4.000	1.109
	I am able to keep working until I succeed in learning programming.	3.467	1.187	4.071	0.917

Appendix 2: Means of Each Practical Utility Value, Institutional Utility Value, Intrinsic Value, and Attainment Value Item by Gender

Items		Girls		Boys	
		Mean	*SD*	*Mean*	*SD*
Practical Utility Value	I think learning programming is useful in my daily life.	4.000	1.000	4.071	1.072
	I think that learning programming helps me to understand how things and phenomena around me work.	3.533	0.990	3.929	0.730
	I think that knowing programming can help me in my daily life.	3.600	0.986	4.143	1.027
Institutional Utility Value	I think learning programming is important for my future work.	4.133	0.743	4.214	0.975
	I think learning programming will be useful when I grow up.	4.467	0.640	4.357	0.929
	I think learning programming is important for middle school and high school.	3.867	0.834	4.214	0.893
Intrinsic Value	I think learning programming is interesting.	3.667	1.175	4.286	1.139
	I think learning programming is fun.	3.600	1.183	4.357	1.008
	I think learning programming is boring*.	3.733	1.100	4.214	0.975
	I am interested in learning programming.	3.200	1.207	4.214	0.975
Attainment Value	I think I can grow by understanding and learning about programming.	3.933	0.799	4.000	0.961
	I think that learning about programming will bring me closer to my ideal self, the person I want to become.	3.400	0.737	3.429	0.852
	I think that people who know more about programming are smart.	3.467	0.990	3.929	0.997

*reversed item; the values have been reversed.

Appendix 3: Means of Each Opportunity Cost, Effort Cost, Psychological Cost Item by Gender

Items		Girls		Boys	
		Mean	*SD*	*Mean*	*SD*
Opportunity Cost	I think that learning programming will leave less time for my hobbies.	3.333	1.759	3.286	1.729
	I think that learning programming leaves less time for other things I want to do.	3.400	1.549	3.429	1.950
	I think that to better understand learning programming, I need to spend less time doing other things that I want to do.	3.067	1.438	3.000	1.359

	I think that to better understand learning programming, I need to study programming while giving up activities that I like to do.	2.667	1.397	3.357	1.598
Effort Cost	I think I have to study very hard to better understand learning programming.	4.533	1.506	4.429	1.651
	I think I have to put in a lot of effort to better understand learning programming.	4.867	1.246	4.286	1.684
	I think I have to spend a lot of time to better understand programming.	4.400	1.639	4.643	1.646
	I think I have to spend more time studying than in other subjects to better understand learning programming.	3.800	1.424	3.429	1.950
Psychological Cost	If I don't understand what I'm learning in programming, I feel miserable.	3.067	1.486	2.429	1.555
	I would feel embarrassed if I didn't understand learning programming well.	2.933	1.792	2.071	1.385
	I would feel anxious if I couldn't understand learning programming well.	2.867	1.685	2.143	1.406