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Analysis of Influencing Factors of Learning Engagement and Teaching Presence in Online Programming Classes

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Abstract

This study analyzed the influencing factors of learning engagement and teaching presence in online programming practice classes. The subjects of this study were students enrolled in an industrial specialized high school, who practiced creating Arduino circuits and programming using a web-based virtual practice tool called Tinkercad. This research adopted a tool that can measure task value, learning flow, learning engagement, and teaching presence. Based on this analysis, learning flow had a mediating effect between task value and online learning engagement, as well as between task value and teaching presence. Increasing learning engagement in online classes requires sensitizing the learners about task value, using hands-on platforms available online, and expanding interaction with instructors to increase learning flow of students. Furthermore, using virtual hands-on tools in online programming classes is relevant in increasing learning engagement. Future research tasks include: confirming the effectiveness of online learning engagement and teaching presence through pre- and post-tests, and conducting research on various practical subjects.

Index Terms: Arduino, Learning Engagement, Learning Flow, Online Programming Class, Teaching Presence

I. INTRODUCTION

In this era of the Fourth Industrial Revolution, the ability to solve problems based on basic technology knowledge has become vital [1]. Understanding how to solve problems based on computational thinking is essential for everyone [2,3]. Moreover, the structure of industry has been reorganized, centering on programming, and programming classes centered on hands-on practice have become more critical, especially for students in industrial specialized high schools, who want to find a career related to programming.

However, owing to COVID-19 pandemic, students' in-person programming classes have changed to online classes. Accordingly, this has drawn attention to how to practice programming effectively in online classes. Effective student engagement and a concept of teaching presence through active interaction with instructors will be the success factors of online programming classes [4, 5].

Therefore, in this study, task value and learning flow were set as variables that influence online programming classes, and the predictive power was analyzed. Furthermore, in an online programming class using a web-based virtual practice tool, such as Tinkercad, the predictive relationships between the task value of learner and both learning flow and teaching presence were empirically analyzed. This study focuses to help establish the basis for educational direction and environmental design to promote engagement in online programming classes.

The remainder of this paper is structured as follows. Chapter 2 considers various theories about online classes as

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related works, and Chapter 3 describes the research method. Chapter 4 analyzes the research results, and then discussions and conclusions in Chapter 5.

II. RELATED WORKS

A. Online Classes and Programming Practice Learning

Previous studies provided many examples of programming classes conducted as online classes. These examples include: taking online courses through a website, viewing e-books, filling out programming results and reflection logs, and using programming video courses to conduct flipped learning. Among these examples, online classes, e-books viewing, and flipped learning were effective in providing teaching presence and learning achievement. However, most of these studies were limited to block coding tools, such as Scratch, or text programming languages, such as C [6-9].

In this study, the Tinkercad web-based virtual practice tool was used. The existing studies that employ Tinkercad have been primarily related to 3D printing. However, Tinkercad has a menu that can also be used with the Arduino Virtual Programming Tool. In a previous case study of online education that used virtual training for equipment practice, all measured aspects, including teaching presence, educational effect, and learning satisfaction, were highly evaluated [10].

B. Learning Engagement and Teaching Presence in Online Classes

Owing to the COVID-19 pandemic, schools have begun to adopt online classes. Accordingly, it has become important to understand whether learners can learn while accepting the teaching strategy and learning process intended by the instructor in an online classroom environment without distortion. Furthermore, it is challenging to help learners become immersed and actively involved in the learning offered by teachers in an online learning environment. The online learning environment requires active engagement of learners.

Factors that promote willingness to engage and achieve a set goal in online learning include: task value, learning flow, and teaching presence. "Task value" refers to the subjective criterion by which learners perceive the learning content to be valuable to them, and "learning flow" refers to the degree to which learners learn diligently while participating in online classes. "Teaching presence" is the emotion that learners perceive about instruction as teachers design and promote learning activities. According to a study [4] conducted to verify teaching presence, perceived usefulness, and task value for learning flow and intention to continue learning in cyber universities, it was found that learning flow and intention to continue learning were significantly mediated based on task value and perceived usefulness. Furthermore, teaching presence had an indirect effect on learning flow, and became an influential parameter among perceived usefulness, intention to continue learning, and task value [5].

Based on this study, it is suggested that research on teaching presence and intention to participate in online programming classes is necessary.

III. RESEARCH METHOD

A. Research Context

The subjects of this study consisted of 50 first-year students (46 male students and 4 female students) in the robot-related department of an industrial specialized high school. Because of COVID-19 pandemic, they started online school immediately they enrolled in high school. If they had started school normally, the class would have been held in a lab, and each student would have been able to borrow and use an Arduino Uno practice kit. However, owing to the adoption of online classes, each student had to study at home and use Tinkercad to learn Arduino Uno Simulation Programming.

The instructor pre-produced the learning content and uploaded it to the online platform based on the class time, and the students watched the videos and learned using Tinkercad. This study was conducted on online programming practice classes for a period of 17 weeks, 2 h per week. The contents are shown in Table 1.

Table 1. Weekly Arduino Lesson Plan Using Tinkercad

Week	Main Topic	Learning Topic
1	Output Parts & Circuits	Orientation & Arduino's Elements
2		LED Output
3		RGB LED Output
4		Servo Motor Output
5		DC Motor Output
6		Character Output by FND
7		Character Array Output by LCD
8		Piezo Speaker Output
9	Middle Test	
10	Input Parts & Circuits	Output by Button & Switch Input
11		Output by Keypad Input
12		Output by Joystick Input
13		Output by PIR Sensor Input
14		Output by Ultrasonic Sensor Input
15		Output by Temperature Sensor Input
16		Output by Photo Register Input
17	Final Test	

B. Learning Contents

For this study, the learning activities performed each week consisted of a circuit-programming practice exercise and a learning-performance assessment through an online class platform.

1) Make a Circuit

Tinkercad provides a simulator to compose the circuit shown in Fig. 1. Learners can learn while watching the pre-produced Arduino circuit creation video that is uploaded to the online class platform.

2) Programming Practice Learning

Tinkercad provides a virtual integrated development environment (IDE) for programming practice, as shown in Fig. 2. This virtual IDE includes: a compiler, debugger, and serial monitor almost identical to the original Arduino IDE. Thus, students can learn in the same manner as real Arduino programming. Furthermore, students could learn while watching the pre-produced Arduino programming practice video that was uploaded by the instructor to the online class platform.

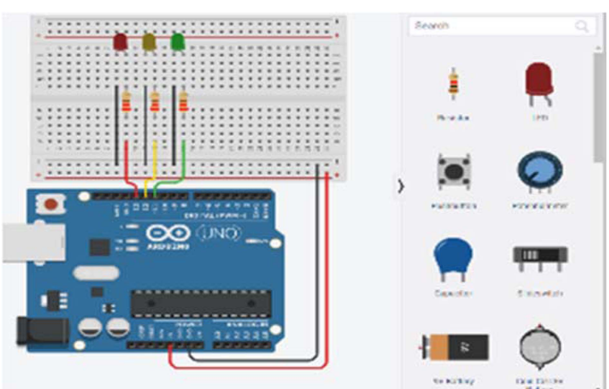

Fig. 1. Tinkercad "Make Arduino" circuits simulator

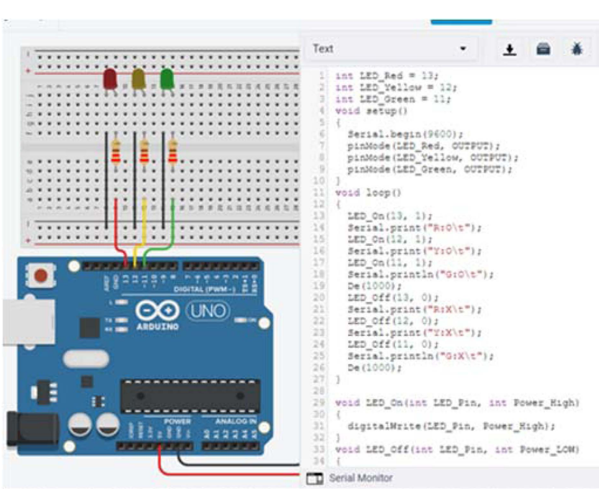

Fig. 2. Tinkercad Arduino programming simulator

3) Performance Assessment

After making a circuit and practicing programming, the students verified the virtual operation of the Arduino circuit in Tinkercad. Subsequently, the instructor presented application problems to the learners, and conducted performance evaluations. After solving the application problems, students submitted their programming results file to the instructor by email for evaluation. Questions by the students, arising during the programming practice process, were solved using social networking service (SNS) chatting tools.

C. Research Tools

1) Task Value

The tools used by Eccles et al. (1985) were modified, and then used to measure the task value of the assignment in the online programming practice classes conducted in this study [11]. This consists of six questions. In this study, the reliability of intra-item consistency was Cronbach's α of .925.

2) Learning Flow

The Jackson and Marsh (1996) Flow State Scale (FSS) was used to measure learning flow of students. This scale consists of nine elements [12]. However, in this study, only two elements were extracted and used. This analysis comprised six questions about focusing on the task at hand and the feeling of control. In this study, the reliability of intra-item consistency was a Cronbach's α of .824.

3) Teaching Presence

Swan (2008) was modified, and then used to measure teaching presence [13]. This analysis comprised 13 questions. In this study, the reliability of intra-item consistency was Cronbach's α of .968.

4) Learning Engagement

Sun and Rueda (2012) were modified, and then used to measure learning engagement [14]. This analysis comprised 15 questions. In this study, the reliability of intra-item consistency was Cronbach's α of .918.

D. Data Analysis Method

The data collected in this study were analyzed as follows. First, Cronbach's α was calculated to verify the reliability of measurement tools for task value, learning flow, teaching presence, and learning engagement. Second, descriptive statistics and correlation analyses were conducted for the collected data. The existence of multicollinearity was confirmed before the regression analysis. Third, predictive variables that influence teaching presence and learning engagement were analyzed. Fourth, the mediating analysis method proposed by Baron and Kenny (1986) was used to verify the mediating effect of learning flow [15, 16]. Finally, the bootstrap method proposed by Hayes (2009) was employed to determine the significance of the mediating effect [17]. The number of re-extracted samples was set to 5000 and verified at a 95% confidence level.

IV. RESEARCH RESULTS

A. Descriptive Statistics

Table 2 presents the descriptive statistics of task value, learning flow, teaching presence, and learning engagement in online software classes using Arduino.

From Table 3, significant correlations, at a significance level of .01, exist between all variables.

Before performing regression analysis, the multicollinearity for variables suspected of multicollinearity owing to high correlation was confirmed based on the tolerance limit and variance inflation factor (VIF). All tolerance limit values were greater than 0.1, and VIF values less than 10. Consequently, there was no problem with multicollinearity, and a regression analysis was conducted.

Table 2. Descriptive statistics (n = 44)

	Min.	Max.	M	SD
Task Value	1.83	5.00	3.96	.74
Learning Flow	2.17	5.00	3.33	.68
Teaching Presence	2.63	5.00	3.83	.73
Learning Engagement	2.13	5.00	3.38	.63

Table 3. Correlation analysis (n = 44)

	Task Value	Learning Flow	Teaching Presence	Learning Engagement
Task Value	-			
Learning Flow	.584*	-		
Teaching Presence	.597*	.694*	-	
Learning Engagement	.632*	.715*	.618*	-

*p < .01

B. Regression Analysis of Learning Engagement

1) Analysis of Predictive Variables

The task value and learning flow were set as predictive variables, and learning engagement was set as the criterion variable. A multiple regression analysis of the input method was then performed. As depicted in Model 2 of Table 5, task value (β = .33, p < .01) and learning flow (β = .49, p < .00) significantly predicted the learning engagement. This result explains the 58% of the total variance of learning engagement (adj.R^2 = .56) when both task value and learning flow were included.

2) Verification of the Mediating Effect of Learning Flow

Based on the multiple regression analysis, in which task value and learning flow significantly predict learning engagement, a mediated analysis was conducted to analyze whether learning flow has a mediating effect between task value and learning engagement.

First, a regression analysis was conducted to confirm whether the task value significantly predicted the learning flow. Consequently, as depicted in Table 4, the task value had significant predictive power (β = .58, p < .01) on learning flow. The explanatory power for the learning flow was 34% (adj.R^2 = .33).

Finally, a hierarchical regression analysis was conducted to determine whether learning immersion significantly predicts participation in an online learning environment when both task value and learning flow are injected into the regression equation under the control of task value.

As shown in Model 1 of Table 5, the explanatory power of learning engagement when only the task value was input was 39% (adj.R^2 = .38). However, when learning flow was added, as in Model 2, the explanatory power increased from approximately 19% to 58% (adj.R^2 = .56).

Therefore, learning flow has a mediating effect between task value and learning engagement. Furthermore, based on bootstrapping to determine whether the mediating effect was statistically significant, the upper and lower limits of the 95%

Table 4. Regression Analysis of Learning Flow (n = 44)

Predictive variable	Criterion variable	B	SE	β	t	p	F	R^2 (adj.R^2)
Task Value	Learning Flow	.54	.12	.58	4.66*	.00	21.76	.34 (.33)

*p < .01

Table 5. Regression Analysis of Learning Engagement (n = 44)

Model	Predictive variable	Criterion variable	B	SE	β	t	p	F	R^2 (adj.R^2)
1	Task Value	Learning Engagement	.54	.10	.63	5.28*	.00	27.91*	.39 (.38)
2	Task Value		.28	.11	.33	2.61*	.01	28.40*	.58 (.56)
	Learning Flow		.49	.12	.53	4.21*	.00		

*p < .01

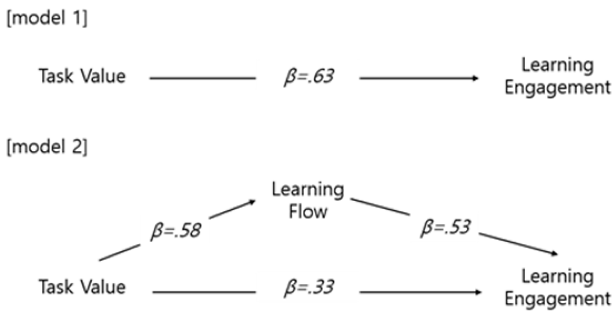

Fig. 3. Mediation Model of Learning Flow in the Relationship Between Task Value and Learning Engagement

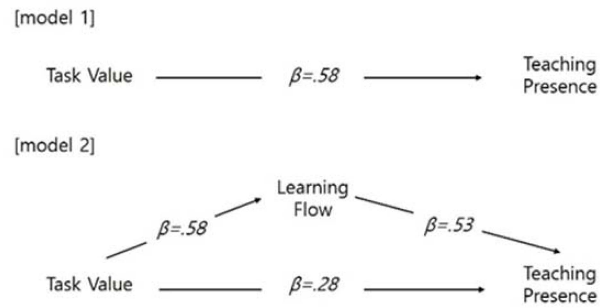

Fig. 4. Mediation Model of Learning Flow in the Relationship Between Task Value and Teaching Presence

confidence level did not contain 0; thus, they were significant.

Fig. 3 illustrates these results visually.

C. Regression Analysis of Teaching Presence

1) Analysis of Predictive Variables

Task value and learning flow were set as predictive variable, while teaching presence as the criterion variable; multiple regression analysis of the input method was performed. Consequently, as shown in Model 2 of Table 6, task value (β = .28, p < .01) and learning flow (β = .53, p < .00) significantly predict the presence of teaching. This result explained 53% of the total variance in teaching presence (adj.R^2 = .51) when both task value and learning flow were included.

2) Verification of the Mediating Effect of Learning Flow

Based on the multiple regression analysis, in which task value and learning flow significantly predicted teaching presence, a mediated analysis was conducted to analyze whether learning flow has a mediating effect between a task value and teaching presence.

From the results of the previous regression analysis, the task value had significant predictive power in the learning flow. The explanatory power for the learning flow was 34% (adj.R^2 = .33).

Finally, a hierarchical regression analysis was conducted to confirm whether learning flow significantly predicted teaching presence when both task value and learning flow were included in the regression equation under the control of task value.

As depicted in Model 1 of Table 6, the explanatory power of teaching presence when only the task value was input is 34% (adj.R^2 = .33). However, when the learning flow was added, as in Model 2, the explanatory power increased from approximately 19% to 53% (adj.R^2 = .51).

Therefore, Learning flow has a mediating effect between task value and teaching presence. Furthermore, based on bootstrapping to determine whether the mediating effect was statistically significant, the upper and lower limits of the 95% confidence level did not contain 0; hence, they were significant.

Fig. 4 depicts these results visually.

V. CONCLUSION AND DISCUSSION

In this study, a regression analysis was conducted on learning engagement and teaching presence in programming-related classes in specialized high schools. The classes were conducted online because of COVID-19 pandemic. Because students had to practice Arduino programming online, they used Tinkercad for circuit making and programming practice. Based on this analysis, learning flow had a mediating effect between task value and online learning engagement, as well as between task value and teaching presence.

Increasing engagement in online learning and the sense of realism in teaching in online programming practice classes require sensitizing the task value of the learner. Moreover, because learning flow has a significant influence as a mediating variable, increasing learning flow in online programming classes is essential.

Therefore, when conducting online classes in a global pandemic situation, such as COVID-19, Arduino virtual training tools, such as Tinkercad (used in this study), can be useful.

Table 6. Regression Analysis of Teaching Presence (n = 44)

Model	Predictive variable	Criterion variable	B	SE	β	t	p	F	R^2 (adj.R^2)
1	Task Value	Teaching Presence	.58	.12	.58	4.69*	.00	22.03	.34 (.33)
2	Task Value		.27	.13	.28	2.09*	.04	28.40*	.53 (.51)
	Learning Flow		.57	.14	.53	4.05*	.00		

*p < .05

Furthermore, it is worth using a single board computer, such as the Raspberry Pi, a microprocessor, such as the Atmel series, or a compatible CPU, such as the ARM Coretex series, as virtual practice tools. Consequently, the development of virtual practice tools for such uses should be promoted.

Finally, the implication of this research is that web-based virtual lab tools, such as Tinkercad, can be used to anticipate the educational effects of programming practices for online classes. For future studies, the effectiveness of online learning engagement and teaching presence through pre- and post-tests should be confirmed, as well as a research on various practical subjects should be conducted.

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