Jang, Y., Choi, S., Kim, S., & Kim, H. (2023). The SNS-based E-mentoring and Development of Computational Thinking for Undergraduate Students in an Online Course. *Educational Technology & Society, 26*(2), 147-164. https://doi.org/10.30191/ETS.202304_26(2).0011

The SNS-based E-mentoring and Development of Computational Thinking for Undergraduate Students in an Online Course

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ABSTRACT: Given the importance of digital technology in daily life, computational thinking (CT) has become a necessary skill for everyone, not just for computer scientists. For CT development, students need to receive appropriate social learning support. However, instructors find it difficult to provide such support to many students in online courses. This study aimed to examine the effectiveness of e-mentoring via social network services (SNS) in developing students' CT during large-scale online courses. A total of 327 undergraduate students volunteered to participate in this study, which included 16 weeks of lectures aimed at developing CT. The effects of SNS-based e-mentoring on CT development, the influences of each e-mentoring activity on CT development, and gender differences were analyzed using data on participants' CT assistance scores and their utilization of e-mentoring activities. The findings indicated that SNS-based e-mentoring was effective in developing the CT of undergraduate students' engagement in a large-scale online course. The most influential e-mentoring activities for students' CT development were informational and technical support in a group and informational support in a private environment. Female students benefited more from SNS-based e-mentoring than male students, and they also engaged in more types of e-mentoring activities than male students. Participation in SNS-based e-mentoring was found to lower the gap in CT between students with and without prior learning experience. Our study findings can be used by educational institutions and instructors when designing courses for students' CT development in large-scale online courses or when developing strategies to close the gender gap in CT ability.

Keywords: Computational thinking, e-Mentoring, Social Network Service (SNS), Gender difference, Computational thinking and prior learning experience

1. Introduction

Ever since its mention by Wing (2006), the interest in "computer thinking (CT)" has been growing steadily. Wing (2006) described CT as a "fundamental skill for everyone, not just for computer scientists" (p. 33). People now live in a world where digital technologies are used in various fields such as health care and education (Jung et al., 2022; Jang et al., 2022b; Choi et al., 2022). In a world where digital technology is critical for performing essential daily tasks, individuals must have the skills necessary to both understand critically the technological systems they use and solve problems when things go wrong (Czerkawski, 2015). Consequently, numerous studies on CT education have been conducted across a range of subjects, from K–12 (Angeli et al., 2016; Li et al., 2022) to higher education (Lyon & Magana, 2020; Jocius et al., 2021).

In CT development, problem-based or project-based learning strategies have been primarily used (Hsu et al., 2018), and instructor–student interaction is crucial for the learning process (Kwame Boateng, 2020). Through interactions with students, instructors can positively influence students' CT development by providing just-in-time instructions, role modeling, and other social learning support (Gong et al., 2020; Lye & Koh, 2014).

However, developing students' CT through active interactions between instructors and students is more difficult in large online than in small face-to-face classes. It is difficult for instructors and students to interact actively online (Drange et al., 2015), but it is even more difficult for instructors to interact with multiple students when there are many students to manage.

E-mentoring can be a solution to this problem. E-mentoring refers to a pairwise relationship between a more experienced individual (mentor) and a less experienced individual (mentee), primarily through electronic communication. E-mentoring can provide mentees with informational, psychosocial, and instrumental benefits (Single & Single, 2005), as well as alleviate the problem of lack of interaction between instructors and learners online (Dahalan et al., 2012). For e-mentoring to be effective, users should be comfortable using the mentoring tool (Sánchez et al., 2014). Additionally, when synchronous tools capable of real-time dialogue are used, the effect of e-mentoring is enhanced by making communication more comfortable (Jacobs et al., 2015; Tanis & Barker, 2017). Therefore, it is important to select an appropriate e-mentoring tool to maximize its effect (Chong et al., 2020).

In this study, Social Networking Sites (SNS) were used to help students develop CT through e-mentoring in large-scale online classes. As SNS has become more common in daily life, attempts to use SNS for education have emerged (Lee & Kim, 2016; Rutten et al., 2016; Son et al., 2016). The advantage of using SNS for education is that users are already familiar with it, can readily share various data, and can interact in real time (Sánchez et al., 2014).

Several previous studies have tried to develop students' CT using e-mentoring or SNS. However, there are some research gaps with regard to how e-mentoring using SNS in large online courses affects CT. First, there are studies on how e-mentoring improves CT (Dlab et al., 2019); however, studies on how e-mentoring activities affect CT enhancement are lacking. In addition, there is a limitation that the e-mentoring process proceeded asynchronously as e-mail was used as a tool for mentoring. Therefore, it is necessary to conduct additional research on the effects of real-time e-mentoring via SNS on CT development. Second, a study that developed CT using SNS (Tsutsui & Takada, 2018) was conducted in an offline class with a small number of students. Consequently, the impact of using SNS for e-mentoring in large online courses needs to be investigated further. Third, one study used SNS for e-mentoring (Lee & Mehta, 2015), but it is unclear whether this helps students develop CT in large online courses. Finally, to the best of our knowledge, no research has been conducted to determine whether the effect of SNS-based e-mentoring on CT development differs depending on the gender or prior learning experience of students. Gender gaps in CT education are frequently mentioned (Angeli & Giannakos, 2020; Bati, 2022). Analyzing gender differences in the method or effect of using SNS-based e-mentoring in courses for CT development can provide insight into how to reduce the gender gap when designing CT education classes in the future. However, it is well known that when programming practice is included in a CT development course, students' prior learning experiences have a significant impact on their learning success (Bergersen & Gustafsson, 2011; Lau & Yuen, 2011; Jegede, 2009). Therefore, analyzing whether there is a difference in the effect of CT development through SNS-based e-mentoring based on prior learning experiences can be used as a reference when designing an e-mentoring program in the future while taking students' educational backgrounds into account. Consequently, we designed and conducted research on the following questions.

- RQ 1: Is SNS-based e-mentoring useful for college students' CT development?
- RQ 2: Which e-mentoring activities influence CT development?
- RQ 3: Is there a gender difference in the effects of SNS-based e-mentoring and e-mentoring activities?
- RQ 4: Is there a difference in the CT enhancement effect of SNS-based e-mentoring considering prior learning experience? Is there an interaction effect between prior learning experience and SNS-based e-mentoring?

To answer the research questions and accomplish our research goals, we investigated the effect of SNS-based e-mentoring on the CT development of college students in this study. An informatics course was conducted for 16 weeks with the goal of developing CT for students, and SNS-based e-mentoring was also conducted during this period. Data on students' CT abilities and their utilization of e-mentoring were collected during this process. Through data analysis, the effect of SNS-based e-mentoring on CT development, the effect of e-mentoring activities on CT development, and gender differences were investigated.

2. Literature review

2.1. Computational thinking

Although numerous attempts have been made to integrate CT into various fields of education, there are various opinions on its definition. Wing (2006) described CT as "solving problems, designing systems, and understanding human behavior, by drawing on the concepts fundamental to computer science" (p. 33). Following that, she clarified CT as "the thought processes involved in formulating problems and their solutions so that the solutions are represented in a form that can be effectively carried out by an information-processing agent" (Wing, 2011, p. 20).

Aho (2012) defined CT as "the thought processes involved in formulating problems so their solutions can be represented as computational steps and algorithms" (p. 832) The Royal Society (2012) described CT as "the process of recognizing aspects of computation in the world that surrounds us and applying tools and techniques from Computer Science to understand and reason about both natural and artificial systems and processes" (p. 29). Meanwhile, CT has been also defined as "reformulating a seemingly difficult problem into one we know how to solve, perhaps by reducing, embedding, transforming, or simulating" (Wing, 2006, p. 33).

Although there is currently no universally accepted definition of CT, researchers have come to accept that it is a thought process that incorporates elements of abstraction, generalization, decomposition, algorithmic thinking, and debugging (Angeli et al., 2016). Abstraction is the ability to strip away features or attributes from an object or entity to reduce it to a set of fundamental characteristics (Wing, 2011). While abstraction reduces complexity by concealing unessential details, generalization reduces complexity by substituting a single construct for multiple entities that perform similar functions (Thalheim, 2000). Abstraction and generalization are frequently used in combination, with abstracts generalized via parameterization to increase utility. Decomposition is the ability to reduce complex problems to their simplest components (National Research Council, 2010). Algorithmic thinking is a problem-solving skill that entails formulating a problem solution step-by-step (Selby, 2014). Debugging is the ability to identify when actions do not correspond to instructions and correct errors (Selby, 2014).

Table 1 shows the elements of CT as these have been discussed and defined in this section. This conceptual framework was referenced by Angeli et al. (2016). Accordingly, this conceptual framework was adopted for designing an informatics curriculum for undergraduate students to develop CT.

Table 1. The elements of CT

Element	Definition
Abstraction (AB)	The ability to determine which data about an entity/object to retain and which to discard (Wing, 2011).
Generalization (GN)	The ability to formulate a solution in generic terms for it to be applicable to a variety of problems (Selby, 2014).
Decomposition (DC)	The ability to decompose a complex problem into smaller, more manageable components (National Research Council, 2010; Wing, 2011).
Algorithms (AL)	The ability to create a step-by-step sequence of operations/actions for resolving a problem (Selby, 2014).
Debugging (DB)	The ability to identify, eliminate, and correct errors (Selby, 2014).

2.2. E-mentoring

With the advancement of technology, especially the improvement of electronic communication, the concept of mentoring has been developed without face-to-face elements (Risquez, 2008; Single & Single, 2005). Single and Muller (2001) defined e-mentoring as a relationship or pairwise relationship that occurs naturally within the program, established between a more experienced individual (the mentor) and a less experienced individual (the mentee), mainly using electronic communication. Methods such as e-mail, threaded discussions through learning management systems (LMSs) and SNSs can be used for e-mentoring (Rowland, 2012).

According to Single and Single (2005), e-mentoring has informational, psychosocial, and instrumental benefits. Informational benefits refer to the exchange of knowledge and subject matter beneficial to a newcomer. Psychosocial benefits refer to mentees gaining self-esteem, confidence, and encouragement to take risks as a result of effective mentoring relationships. Instrumental benefits refer to relationships that provide mentees with opportunities for increased visibility and advancement. Instrumental benefit can also be defined in terms of behaviors targeted toward facilitating the mentee's goal attainment (Eby et al., 2013), or practical contributions (Gafni-Lachter et al., 2021). A previous study reported that students felt confused, anxious, and frustrated because of the lack of prompt feedback from instructors and vague instructions on websites (Hara & Kling, 2001). E-mentoring can alleviate this problem because students (mentees) and their mentors can interact regardless of location through email, chat rooms, bulletin boards, forums, and discussions (Dahalan et al., 2012). Several studies have shown that e-mentoring can help improve student performance (de Janasz & Godshalk, 2013; Jacobs et al., 2015).

E-mentoring has also been applied to the development of CT in students. For example, Kahraman and Abdullah (2016) used an online forum and e-mail-based communication tool to conduct e-mentoring, which facilitated the CT development of undergraduate students. In addition, Dlab et al. (2019) demonstrated that the CT of primary school students was developed as a result of e-mentoring using an LMS.

2.3. Social network service

Social network services (SNS) are a collection of web technologies that enable users to create, share, communicate, and interact with one another. SNS users can interact with "friends" or other users or members on and offsite who are invited to connect to their profile. Other connected users, referred to as "friends," "contacts," or "followers," can be anyone who is granted access to the user's profile (to view and share information), and friends can range from close family members to complete strangers (Weber, 2012).

As the use of social media continues to grow, attempts to use it for educational purposes have emerged. The use of SNS in learning involves the advantage of real-time, information sharing, simple posting, and reliable feedback from friends (Du et al., 2013; Popescu, 2014). SNS is effective for writing education (Lee & Kim, 2016) and can help adolescents develop their online career skills (Rutten et al., 2016). In addition, Son et al. (2016) proposed an LMS that enables real-time and reliable feedback for incorrect answers by incorporating an SNS. Tsutsui and Takada (2018) created an SNS platform for programming education and used it in a class for the CT development of students.

Considering the benefits of integrating SNS into education, this study incorporated SNS into the e-mentoring process. KakaoTalk used in this study was released in 2010 and is used by more than 93% of smartphone owners in South Korea (Lee & Kim, 2016).

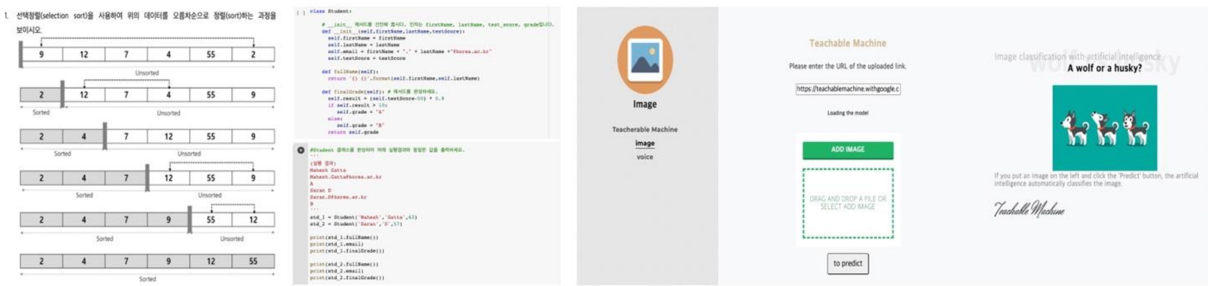
3. Methods

3.1. The course implementation for developing undergraduate students' CT

The researchers in this study developed a CT program for undergraduate students through a 16-week online course. The course was implemented for students at Korea University in the Republic of Korea. Since 2014, the course has been open annually, and it was a relatively large course, with an average of 400 students enrolling each year. Due to the coronavirus (COVID-19) outbreak, the course was conducted entirely online and twice weekly for 90 min each. The course curriculum for 14 weeks is shown in Table 2, excluding the 2 weeks for the midterm/final exams. Each session included a problem-solving activity for CT development based on basic informatics concepts.

The course included lectures on the fundamental concepts of informatics as well as lectures on programming. All classes were conducted via video conferencing in real time (Zoom). At the beginning of the course, the students' programming experience was investigated. According to the survey, 48.0% (N = 157) of the students had programming experience (including block-based programming), but only 17.8% (N = 58) had text-based programming experience. Therefore, a cloud-based programming environment (Google Colaboratory) that does not require complicated environment settings was selected for the programming lectures. In addition, Python was chosen as the programming language because it is simple for beginners to learn. Programming assignments were given after each lecture. A lecture on training a machine learning model using Google Teachable Machine was held for a week. Additionally, by creating a webpage, students could check the results of the trained model directly. Figure 1 illustrates examples of students' primary activity outputs and a researcher-created web page.

Figure 1. Screenshots of students' activity results and a researcher-created web page



(a) Examples of main activities

(b) A website designed to visualize machine learning modeling results.

Table 2. Curriculum of the implemented online course for CT development

Week	Topic	Main concept/contents	Main activity	Related CT elements
1	Computing machine	• Data, information, and knowledge • Automation of information processing process • Automation • Problem solving with machines: abstraction, decomposition, algorithm • History of computing tools	• Distinguish between data and information • Designing an automated machine that recognizes handwriting	AB, DC, AL
2-3	Data representation	• Representation of information using code • Information theory, entropy • Data encoding: number, text, image, sound	• Create code to communicate using five fingers • Calculating entropy • Encoding characters, numbers, images, and sounds	AB, GN, DC, AL
4	Problem solving	•Problem solving: IPO (input–process–output), problem representation, problem decomposition •Data modeling: decision table, entity-relation diagram (ERD), state machine, data flow diagram	• Expressing a problem as a decision table, ERD, etc.	AB, GN, DC, AL, DB
5	Algorithmic thinking	•Algorithm: flowchart, pseudo-code, sequence, flow control •Algorithm and program	• Solve problems by expressing them as flowcharts and pseudo-code	AB, GN, DC, AL, DB
6-7	Algorithm	•Data structure •Sorting: selection, bubble, insertion, quick •Searching: sequential, binary	• Display your favorite soccer teams as an array • Solving sorting problems • Solving searching problems	AB, GN, DC, AL
8	Functional world	•Function, recursive function	• Representing a problem as a function	AB, GN, DC, AL
9-11	Programming	•Python programming	• Creating basic programs in Python	AB, GN, DC, AL, DB
12-13	Alternative computing	•Greedy algorithm •Intelligent model: knowledge based, data based •Evolutionary computing, genetic algorithm •Game theory	• Solve the problem by expressing it with a greedy algorithm • Representing and solving problems with genetic algorithms	AB, GN, DC, AL
14	Machine learning	•Training classification models	• Create image classification and sound classification models using teachable machine	AB, GN, DC, AL, DB

3.2. Participants

Participants in this study were undergraduate students from Korea University in South Korea with 50 different majors (e.g., computer science, philosophy, architecture) enrolled in the same informatics course. Participants were recruited using a voluntary response sampling method (Murairwa, 2015; Tiit, 2021; Jang et al., 2022a) that targeted the students who took this course. At the beginning of the course, the researchers investigated whether students desired e-mentoring and consented to participate in the research. Participation in e-mentoring was optional, but participants were required to write a mentoring report at the end of the course. A total of 380 students attended the course and 327 volunteered to participate in the study. Among the participants, 189 students engaged in e-mentoring and 138 did not.

We categorized the participants into two groups (control and group), depending on whether they engaged in e-mentoring. Therefore, students who did not participate in e-mentoring were assigned to the control group, whereas those who did were assigned to the treatment group.

Table 3 presents the demographics of the participants (mentees). Among the participants, 167 (51.1%) were male and 160 (48.9%) were female. Most of the participants were freshmen (*N* = 131; 40.1%), followed by seniors (*N* = 88; 26.9%) and sophomores (*N* = 78; 23.9%), with the least number of participants being juniors (*N* = 30; 9.1%). The total number of participants' majors was 43, with the largest number of participants majoring in computer science (*N* = 33), followed by mechanical engineering (*N* = 28) and new materials engineering (*N* = 24). In contrast, sociology (*N* = 3), architecture (*N* = 5), and psychology (*N* = 8) were the three majors with the fewest participants. Table 3 shows the characteristics of the participants by group according to their engagement in e-mentoring.

Table 3. Participant demographics by group according to the engagement in e-mentoring

		Engaged in e-mentoring	Not engaged in e-mentoring
Gender	Male	*N* = 82; 49.1%	*N* = 85; 50.9%
	Female	*N* = 107; 66.9%	*N* = 53; 33.1%
The top three majors the most students have		Business (*N* = 18) Biology (*N* = 15) Electronic engineering (*N* = 14)	Computer science (*N* = 22) Mechanical engineering (*N* = 16) Mathematics (*N* = 13)

3.3. E-mentoring process

3.3.1. Recruitment

Mentors and mentees were recruited concurrently during the first week of the course. First, students enrolled in the course were invited to apply for e-mentoring via Google Forms. E-mentors were recruited from among the students who took this course in the prior semester through an e-mail to students who received A0 or A+ grades. Out of a total of 127 students, 19 hoped to participate as mentors. Twelve mentors were selected through online interviews. Of the mentors, seven were male and five were female. Mentors mainly majored in computer science (*N* = 5), and pre-medical (*N* = 3). The remaining mentor majors were electronic engineering, industrial management engineering, economics, and psychology (each *N* = 1). A total of 189 mentees (the treatment group) were assigned to the mentors, with each mentor assigned 15–16 mentees. All mentors agreed to participate in the study.

3.3.2. SNS-based e-mentoring environment

All e-mentoring processes were conducted online through an SNS platform. Figure 2 shows an SNS-based e-mentoring environment. The mentors were included in three chat rooms. The first was a private chat room with individual mentees, the second was a group chat room with matched mentees, and the third was a group chat room with instructors and other mentors. In the chat rooms, both mentors and mentees had to use an account with their real name and could not join anonymously. Figure 3 shows screenshots of the mentor–mentee group chat and private chat conducted in this study.

Figure 2. The SNS-based e-mentoring environments

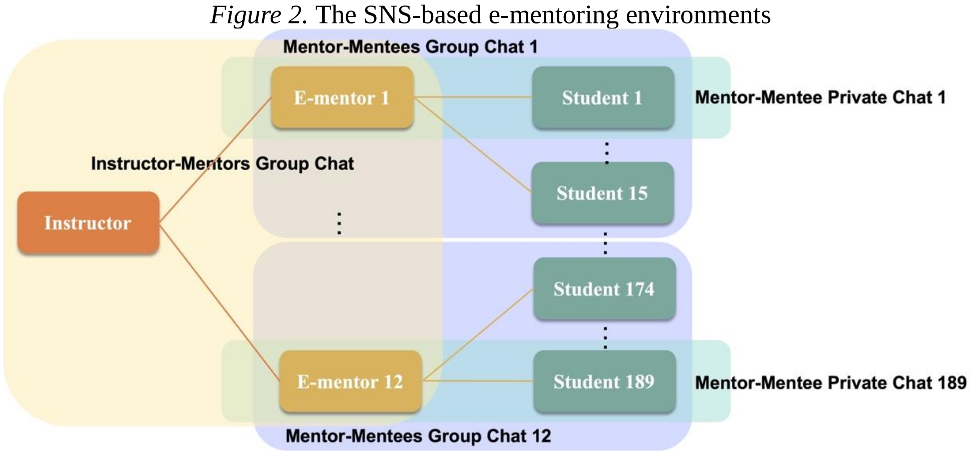
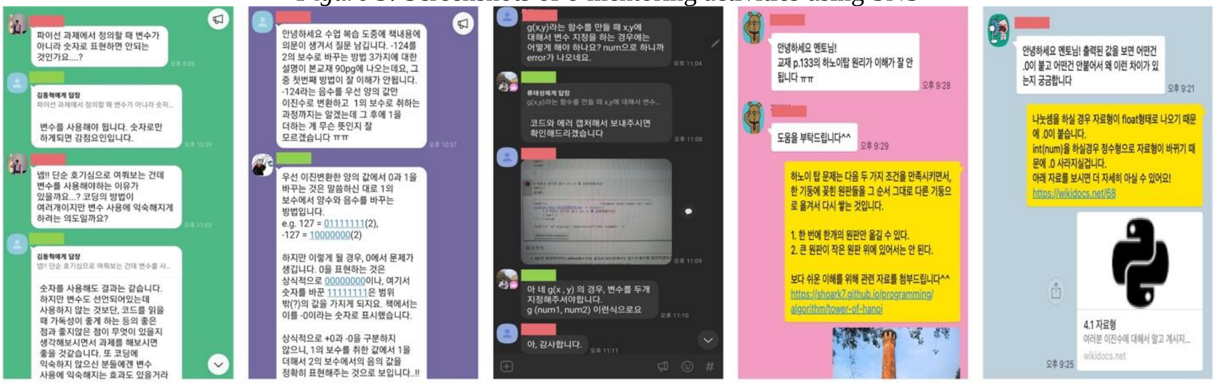


Figure 3. Screenshots of e-mentoring activities using SNS



Screenshots of mentor-mentees group chat

Screenshots of mentor-mentee private chat

3.3.3. E-mentoring activities

E-mentoring can provide informational, psychosocial, and instrumental support to mentees (Single & Single, 2005). In this study, practical benefits provided by instrumental support were limited to “technical benefits.” The curriculum in this study was designed to use various web tools when conducting programming tasks. Consequently, it was planned that e-mentors could assist students with any problems they might encounter while using these tools.

Accordingly, mentors provide informational, psychosocial, and technical support to their mentees. Table 4 shows the e-mentoring activities used in this study. To begin with, with regard to informational activities, e-mentors provided knowledgeable assistance in responding to mentees’ inquiries about their comprehension of class content. Mentors were not allowed to directly answer the assignment questions. Instead, when students encountered difficulties completing assignments, hints or supplementary materials to assist with problem solving were provided via SNS. In addition, e-mentors responded to questions seeking general information about course attendance (e.g., assignment submission form). Second, mentors performed psychosocial activities. When mentees felt frustrated while taking a course or wanted to give up, mentors provided emotional support. For example, they said words that encouraged students, inspired confidence, and shared the difficulties and overcoming processes they had experienced while taking the course. Third, mentors carried out the technical activities. When mentees asked for assistance with using Google Colaboratory, Teachable Machine, and other tools, mentors suggested appropriate solutions.

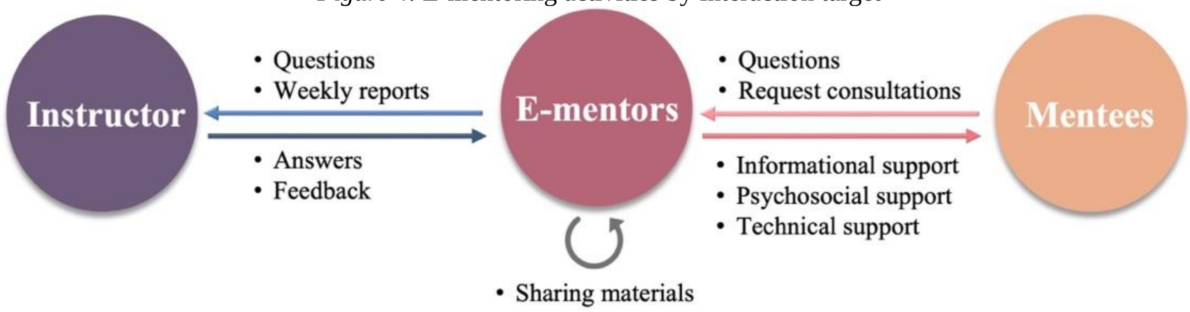
Students who participated in SNS-based e-mentoring (treatment group) received informational, psychosocial, and technical support through an e-mentor, either in a group or privately. In contrast, students who did not participate in e-mentoring (control group) contacted the instructor directly via e-mail when informational, psychosocial, and technical assistance were required.

Table 4. E-mentoring activities

Interaction target	Category of e-mentoring activity	Details of activity
Mentee	Informational activity (IA)	Provide hints or supplementary materials for problem solving
		Answer questions about class content
	Psychosocial activity (PA)	Encouragement, role modeling
	Technical activity (TA)	Help with the skills or tools mentees need on an assignment

Mentors also interacted with other mentors. Figure 4 shows the overall activity of the e-mentors according to the interaction target. To begin, mentors shared useful materials that would aid mentees in their learning. Mentors also interacted with the instructor, and mentors sought answers from the instructor to mentees’ difficult-to-answer questions. In addition, they were responsible for submitting a weekly report to the instructor detailing their interactions with the mentee.

Figure 4. E-mentoring activities by interaction target



3.4. Data collection and data analysis

3.4.1. Assessment of CT

For the CT assessment, course assignments, quizzes, and midterm/final exam scores were used. After converting homework, quizzes, and midterm/final exam scores into a scale of 10, the average value of the total score was used. The purpose of the course was to develop CT for undergraduate students by incorporating the fundamental concepts of informatics. Therefore, all assignments, quizzes, and exams were designed to assist students in developing CT through the resolution of problems related to the lecture's topic. The assignment included nine problem-solving tasks involving informatics and seven programming tasks. The quiz was conducted a total of three times using the quiz function of LMS. The midterm/final exam is not just a test of students' knowledge of fundamental informatics concepts; it is designed to assess their overall CT ability. Table 5 shows examples of the data used for the CT ability measurement.

Table 5. Examples of resources used for CT assessment

	Content	Related CT elements
Assignment	-Create code to communicate using five fingers	AB, GN, DC, AL
	-Proposing a structure to efficiently organize photos in a smartphone photo album	AB, GN, DC
	-Sorting: Select, Insert, Bubble, Quick Sort	AB, GN, DC, AL
	-Python programming: find the cause of the error and fix it correctly	AL, DB
	-Python programming: Creating a fractal pattern using the turtle module and nested loops	AB, GN, DC, AL, DB
	-Creating Image and Sound Classification Models with Teachable Machines	AB, GN, DC, AL, DB
Quiz	-Data representation, problem solving	AB, GN, DC, AL
	-Algorithmic thinking, algorithm	AB, GN, DC, AL, DB
	-Alternative computing	AB, GN, DC, AL
Midterm Exam	- Imagine making a swing hanging on a tree, and explain step-by-step how to make a wooden swing so that someone else can make a swing exactly the way you imagined it. - Using "nodes" and "links" to represent the operational form of this course, which is being taught in a non-face-to-face format because of the coronavirus disease. - Expressing the algorithm for finding the same mate in a pile of socks in pseudocode	AB, GN, DC, AL, DB
Final Exam	- Expressing the Fibonacci sequence in the form of a recursive function in pseudo-code - Structuring and expressing how a valet parking agent stores customers' cars and quickly finds and delivers the right car when the customer wants it -Expressing the whole process of K-means clustering with given data	AB, GN, DC, AL, DB

3.4.2. Utilization of e-mentoring

The frequency of use of each mentee's e-mentoring activity was measured using the weekly activity report submitted by e-mentors. Screenshots of all conversations each mentor had with the mentors via group chat or private chat for a week were attached to the weekly activity report submitted by e-mentors. The conversation between e-mentors and e-mentees included questions and answers about incomprehensible parts of the class, questions and answers about the format of the assignment, questions and answers about error handling during python programming, questions and answers about Blackboard LMS access errors, and how to overcome programming as a non-major. The researchers classified and labeled the activities depicted in the report into three types of e-mentoring activities (IA, PA, and TA), noting their frequency. Content analysis was used for labeling (Clark et al., 2018). First, using weekly activity reports, two researchers independently classified each mentee's conversations with e-mentors on SNS as IA, PA, or TA and recorded the frequency. Afterward, they discussed their classification results to reach a consensus on all e-mentoring activities.

3.4.3. Demographics

Researchers collected demographic data, which included 10-digit students' IDs, gender, grades/year, and majors.

3.4.4. Students' educational background

In this study, we focused on whether students had programming experience (including block or text-based) in their educational backgrounds. An online survey was conducted at the start of the course using Google Forms to determine whether students had programming experience.

The following is why, among the students' educational backgrounds, we focused on programming experience rather than major. First, programming is known to be difficult for many undergraduate students (Ambrósio et al., 2011; Askar & Davenport, 2011; Hawi, 2010), and previous programming experience plays an important role in programming success (Bergersen & Gustafsson, 2011; Lau & Yuen, 2011; Jegede, 2009). Second, based on the demographics of the students, only approximately 10% (*N* = 33) majored in computer science, with the majority of students not majoring in computer science. Furthermore, approximately 40% (*N* = 131) of the students were freshmen who had just started college. Therefore, we determined that prior programming experience was the most important educational background factor given the nature of the course in which this study was conducted.

3.4.5. Data analysis

To determine the effect of SNS-based e-mentoring on CT, the CT assessment scores of those in the mentoring group and those in the comparison group (not engaged in e-mentoring) were compared using an independent sample t-test. Additionally, multiple linear regression analysis was used to determine the influence of each e-mentoring activity conducted in a group and private environment on CT. Finally, we examined whether the effect of SNS-based e-mentoring on CT differed by gender. Two-way analysis of variance (ANOVA) and two multiple linear regression analyses were conducted for this purpose. Data were statistically analyzed using SPSS 26.0, and the alpha level was set at 0.05.

4. Results

4.1. Effects of SNS-based e-mentoring on CT development

RQ1 was to explore potential differences between groups of students who have attended SNS-based e-mentoring and those who have not. As described in Table 6, descriptive statistics showed that the group of students who participated in e-mentoring acquired a mean CT score of 8.475 with 0.531 *SD*, while their counterparts acquired a mean value of 7.186 with 0.637 *SD*.

An independent *t*-test was conducted to identify whether the differences were significant. First, we examined the normality of the data distribution with skewness and kurtosis. As a multivariate normal distribution, all items satisfied the absolute values of skewness (< 3) and kurtosis (< 8) (Kline, 2005). The independent sample *t*-test showed a significant difference in CT scores between the two groups of students. Levene's test did not assume homogeneity of variance ($F = 4.689$, $p = .031$); the t-value was 19.32, and the p-value was < .001.

Table 6. Means and standard deviations for the students' CT score

	N	Mean	*SD*
Engaged in E-mentoring	189	8.475	0.531
Not engaged in E-mentoring	138	7.186	0.637

4.2. Influences on CT by e-mentoring activity

RQ2 was to investigate how each e-mentoring activity affects students' CT. First, each e-mentoring activity was categorized based on the environment in which the interaction took place (group chat or private chat). Thus, six independent variables were considered. As depicted in Table 7, GI was found to be the most utilized activity among participants ($M = 5.047$, $SD = 3.826$), followed by PI ($M = 3.968$, $SD = 4.034$) and GT ($M = 3.074$, $SD = 2.508$). In contrast, psychosocial activity showed relatively less utilization compared to other activities with GP ($M = 0.021$, $SD = 0.144$) and PP ($M = 0.238$, $SD = 0.506$).

Then, multiple linear regression was conducted to analyze the influence of each activity. Tolerance and VIF were assessed to exclude multicollinearity, and the values of all constructs were acceptable (Hair et al., 2010). The values of Durbin–Watson have an upper limit of four and a lower limit of zero (Niresh & Thirunavukkarasu, 2014). In addition, the data were found to be normally distributed (Kline, 2005).

As Table 8 shows, the result of multiple linear regression analysis, all variables were found to be statistically positive with the model explaining 50.7% of the variance in the CT. In addition, the model acquired an acceptable Durbin–Watson value (1.098), indicating that there were no independent errors caused by the residuals (Field, 2013). The three most influential determinants were GI ($\beta = 0.540$), PI ($\beta = 0.436$), and GT ($\beta = 0.244$). In contrast, PP ($\beta = 0.119$), GP ($\beta = 0.127$), and PT ($\beta = 0.132$) were the three least influential determinants.

Table 7. Means and standard deviations for the utilization of e-mentoring activities

E-mentoring activity	*N*	Mean	*SD*
Group-Informational activity (GI)	189	5.047	3.826
Group-Psychosocial activity (GP)	189	0.021	0.144
Group-Technical activity (GT)	189	3.074	2.508
Private-Informational activity (PI)	189	3.968	4.034
Private-Psychosocial activity (PP)	189	0.238	0.506
Private-Technical activity (PT)	189	2.153	1.523

Table 8. Results of multiple linear regression

Dependent variable	Independent variable	B	*SE*	*β*	*t*	Tolerance	VIF
CT	(Constant)	7.57	0.075		100.364^{***}		
	GI	0.075	0.008	0.540	9.056^{***}	0.739	1.353
	GP	0.469	0.193	0.127	2.427^{*}	0.955	1.047
	GT	0.052	0.013	0.244	4.139^{***}	0.755	1.324
	PI	0.058	0.008	0.436	7.281^{***}	0.731	1.368
	PP	0.125	0.057	0.119	2.203^{*}	0.901	1.11
	PT	0.046	0.019	0.132	2.48^{*}	0.923	1.084
$R(.723)$, $R^2(.522)$, adjusted $R^2(.507)$, $F(33.159)$, $p < .001$							

Note. $^{***}p < .001$, $^{*}p < .05$.

4.3. Gender differences regarding the effect of e-mentoring using SNS on CT

RQ3 aimed to determine whether the effect of SNS-based e-mentoring on CT differs by gender. The researchers used a two-way ANOVA and two multiple linear regression analyses. First, participants in this study were classified into four groups according to their gender and whether they engaged in e-mentoring. Descriptive statistics showed that e-mentoring engaged males achieved the highest score on CT assessment ($M = 8.545$, $SD = 0.535$), followed by e-mentoring engaged females ($M = 8.421$, $SD = 0.524$), not engaged males ($M = 7.335$, $SD =$

0.598), and not engaged females (*M* = 6.948, *SD* = 0.632). The two groups with the highest CT scores were those who engaged in e-mentoring. Table 9 describes the results of the descriptive statistics.

Table 9. Means and standard deviations for each group

Gender	E-mentoring	*N*	Mean	*SD*
Male	Engaged	82	8.545	0.535
	Not engaged	85	7.335	0.598
Female	Engaged	107	8.421	0.524
	Not engaged	53	6.948	0.632
	Total	327	7.931	0.572

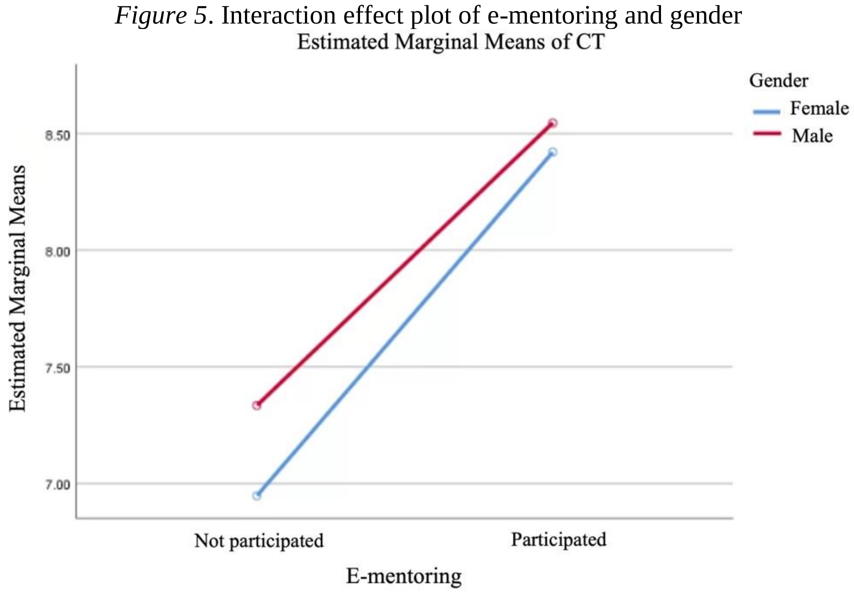
Because there were two independent variables, a two-way ANOVA was performed to investigate the main and interaction effects on the dependent variables. The data were normally distributed according to Kline (2005). As demonstrated in Table 10, both participation in e-mentoring ($p < .001$) and gender $p < .001$) had a significant effect on students' CT. As depicted in Figure 5, an interaction effect was also observed between gender and participation in e-mentoring ($p < .05$).

Table 10. Result of two-way ANOVA

Source	Type III sum of squares	*df*	Mean square	*F*	Partial eta squared
Corrected model	137.997	3	45.999	143.789**	0.572
Intercept	18717.22	1	18717.22	58508.462**	0.995
E-mentoring	137.96	1	137.96	431.252**	0.572
Gender	5.031	1	5.031	15.728**	0.046
E-mentoring * Gender	1.316	1	1.316	4.113*	0.013
Error	103.33	323	0.32		
Total	20810.875	327			
Corrected total	241.327	326			

Note. $R^2 = .572$ (adjusted $R^2 = .568$). $^{**}p < .001$, $^{*}p < .05$.

Figure 5. Interaction effect plot of e-mentoring and gender



Two multiple linear regression analyses were conducted to determine whether the effect of each e-mentoring activity on CT differed by gender. First, we investigated whether the two sets of data were suitable for regression analysis. First, based on the Durbin–Watson value, both models showed no multicollinearity problems (Niresh & Thirunavukkarasu, 2014). Second, according to Kline (2005), the data were normally distributed.

Descriptive statistics showed that male students utilized informational activity through group chat the most (*M* = 7.817, *SD* = 3.916), followed by technological activity through group chat (*M* = 4.512, *SD* = 2.911). In contrast, female students mostly used informational activity through private chat (*M* = 6.514, *SD* = 3.673), followed by informational activity through group chat (*M* = 2.925, *SD* = 2.894). Table 11 demonstrates the results of the descriptive statistics.

As Table 12 indicates, the result of multiple linear regression analysis for male students, three variables were statistically positive with the model explaining 50.9% of the variance in the CT. The three influential determinants were GI (β = 0.395), PI (β = 0.370), and GT (β = 0.180). In the case of female students, the results of multiple linear regression analysis showed that all variables were statistically positive, except for GP. The model explained 56.9% of the variance in CT. The most influential determinant was PI (β = 0.356), followed by GI (β = 0.339), GT (β = 0.272), PP (β = 0.189), and PT (β = 0.173).

Table 11. Means and standard deviations for e-mentoring activity utilization of both genders

Gender	E-mentoring activity	*N*	Mean	*SD*
Male	GI	82	7.817	3.916
	GP	82	0.024	0.155
	GT	82	4.512	2.911
	PI	82	0.646	0.616
	PP	82	0.122	0.329
	PT	82	1.682	1.142
Female	GI	107	2.925	1.941
	GP	107	0.018	0.136
	GT	107	1.972	1.362
	PI	107	6.514	3.673
	PP	107	0.327	0.595
	PT	107	2.514	1.678

Table 12. Results of multiple linear regression

Dependent variable	Gender	Independent variable	B	SE	β	t	Tolerance	VIF
CT	Male	(Constant)	7.754	0.118		65.472^{***}		
		GI	0.054	0.012	0.395	4.401^{***}	0.754	1.326
		GP	0.336	0.284	0.097	1.181	0.895	1.117
		GT	0.033	0.015	0.180	2.153^{*}	0.872	1.147
		PI	0.321	0.078	0.370	4.095^{***}	0.745	1.342
		PP	-0.043	0.13	-0.026	-0.33	0.956	1.046
		PT	0.006	0.037	0.012	0.159	0.994	1.006
	R(.738), R^2(.545), adjusted R^2(.509), F(14.968), p < .001, Durbin–Watson = 1.042							
	Female	(Constant)	7.417	0.094		78.747^{***}		
		GI	0.092	0.018	0.339	5.006^{***}	0.885	1.13
		GP	0.334	0.253	0.087	1.321	0.945	1.058
		GT	0.105	0.026	0.272	4.046^{***}	0.899	1.113
		PI	0.051	0.01	0.356	5.063^{***}	0.823	1.215
		PP	0.167	0.059	0.189	2.849^{**}	0.921	1.085
		PT	0.054	0.021	0.173	2.625^{*}	0.933	1.071
	R(.770), R^2(.593), adjusted R^2(.569), F(24.289), p < .001, Durbin–Watson = 1.375							

Note. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$.

4.4. Differences in the effect of e-mentoring via SNS on CT based on previous learning experience

RQ4 was to determine whether the effect of SNS-based e-mentoring on CT differed according to previous programming experience. The researchers used two-way ANOVA. First, participants were classified into four groups according to their previous programming experience and whether they engaged in e-mentoring. Descriptive statistics showed that e-mentoring engaged students with programming experience achieved the highest score on CT assessment (M = 8.789, SD = 0.435), followed by e-mentoring engaged students with no programming experience (M = 8.259, SD = 0.484), not engaged students with programming experience (M = 7.634, SD = 0.347), and not engaged students with no programming experience (M = 6.569, SD = 0.612). The two groups with the highest CT scores were those who engaged in e-mentoring. Table 13 lists the results of the descriptive statistics.

Because there were two independent variables, a two-way ANOVA was performed to investigate the main and interaction effects on the dependent variables. The data were normally distributed according to Kline (2005). As shown in Table 14, both participation in e-mentoring (p < .001) and programming experience (p < .001) were found to have a significant effect on students' CT. An interaction effect was also observed between programming experience and participation in e-mentoring ($p < .05$). Figure 6 shows the interaction effect plot of e-mentoring and programming experience.

Table 13. Means and standard deviations for each group

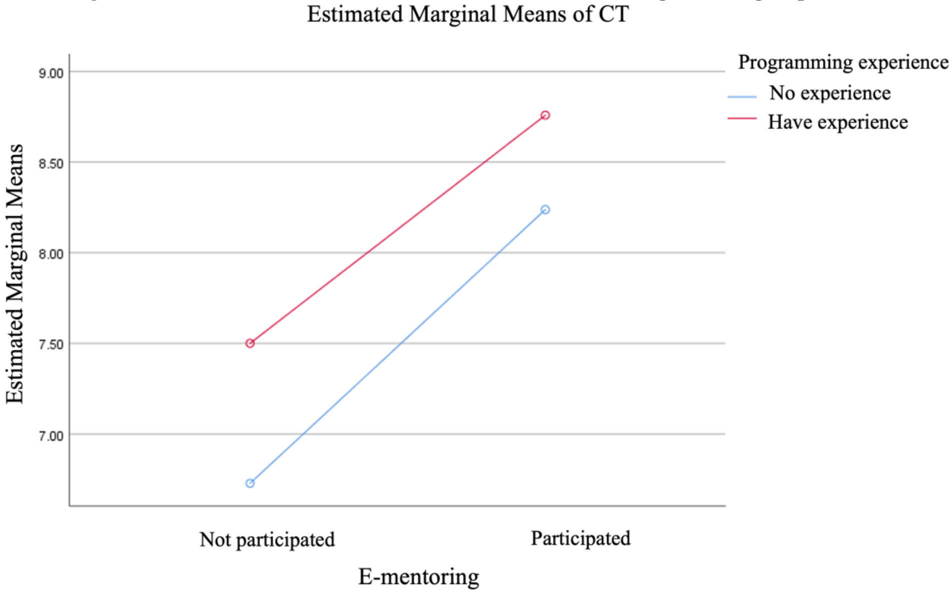
Previous Learning Experience	E-mentoring	*N*	Mean	*SD*
Have programming experience	Engaged	77	8.789	0.435
	Not engaged	80	7.634	0.347
No programming experience	Engaged	112	8.259	0.484
	Not engaged	58	6.569	0.612
	Total	327	7.931	0.572

Table 14. Result of Two-way ANOVA

Source	Type III sum of squares	*df*	Mean square	*F*	Partial eta squared
Corrected model	164.939a	3	54.98	198.113**	0.648
Intercept	18972.083	1	18972.083	68363.756**	0.995
Programming experience	32.542	1	32.542	117.262**	0.266
E-mentoring	149.193	1	149.193	537.599**	0.625
E-mentoring * Programming experience	1.231	1	1.231	4.434*	0.014
Error	89.638	323	0.278		
Total	20824.125	327			
Corrected total	254.577	326			

Note. R^2 = .648 (adjusted R^2 = .645). $^{**}p < .001$, $^{*}p < .05$.

Figure 6. Interaction effect plot of e-mentoring and programming experience



5. Discussion

The independent sample *t*-test revealed a significant difference in students' CT scores depending on whether they participated in SNS-based e-mentoring. This result demonstrates the possibility of SNS-based e-mentoring. This result is consistent with the findings of previous studies. For example, Dlab et al. (2019) showed that utilizing an LMS as an e-mentoring environment is an efficient way of fostering participants' CT. However, an LMS cannot provide real-time interaction. As Grant et al. (2020) stressed, e-mentoring could be advantageous when mentor-mentee interaction occurs anytime and anyplace. In addition, Tsutsui and Takada (2018) applied a real-time SNS platform and showed that it is an effective interaction tool to develop CT for K–12 students, but the study was restricted only to small classes with five to seven students.

In this study, the e-mentoring method was used to assist students in developing CT during large online courses, and an SNS tool was introduced to facilitate quick interaction with them. Additionally, by concurrently facilitating group and individual interactions between mentors and mentees, students can utilize mentoring at their convenience and inclination. It was found that SNS-based e-mentoring was helpful for students' CT development.

Mentees primarily engaged in informational activities, and this e-mentoring activity was most frequently used in both group and private environments. Informational activities also had the greatest influence on CT development. This result is in line with previous studies. In a study using e-mentoring in education, mentees required the most informational support (Cassiani, 2017). Additionally, as a result of analyzing the textual data from the discussion forums of the mentoring group, the only activity identified was informational (Cassiani et al., 2020).

Mentees' psychosocial activity utilization was low in both group interactions and the private environment. In this regard, Kaufman (2017) asserted that e-mentoring necessitates the ability to disclose and share emotions online, and psychosocial activity is difficult to achieve without these abilities. Psychosocial activity benefits role modeling, self-esteem, and learning motivation and has a positive effect on CT development (Lye & Koh, 2014; Gong et al., 2020). Therefore, it was determined that an e-mentoring program should be designed with this point in mind. To facilitate active psychosocial activity in e-mentoring, it is helpful to engage in a personal acquaintance process that includes introductions and searching for mutual interest (Shpigelman et al., 2009).

Gender gaps in CT education are an issue that has consistently been addressed (Angeli & Giannakos, 2020; Bati, 2022). Previous research has produced conflicting findings regarding whether there is a gender difference in CT ability. According to some research, males demonstrated greater CT ability than females, or females required more time to achieve the same level of CT ability (Atmatzidou & Demetriadis, 2016; Jenson & Droumeva, 2016). However, some studies assert that there is no gender difference in CT ability and that females demonstrate superior ability in certain elements of CT (Lee et al., 2017; Wu & Su, 2021). In this study, we found an interaction effect between gender and e-mentoring on students' CT. The mean difference in CT scores between males and females was greater in the group that did not engage in e-mentoring (mean values of male students = 7.335, mean values of female students = 6.948). However, as illustrated in Figure 5, the effect of SNS-based e-mentoring on female students' CT development was greater. This finding implies that SNS-based e-mentoring can contribute to closing the gap in CT abilities between male and female students.

Female students appeared to benefit more from SNS-based e-mentoring because they engaged in various e-mentoring activities more frequently than male students. In particular, female students utilized the psychosocial activity of e-mentoring better than male students, which was consistent with previous research findings (Elliott et al., 2010) And this result is significant because psychosocial activities such as role modeling also contribute to the development of CT (Gong et al., 2020; Lye & Koh, 2014).

Among the various educational activities for developing CT, it is well known that students' prior programming experience has a significant impact on their learning success (Bergersen & Gustafsson, 2011; Jegede, 2009; Lau & Yuen, 2011). Similar to previous studies' findings, there was a statistically significant difference in students' CT scores based on prior learning experience (i.e., programming experience) in this study. It seems that programming is an activity that requires all of the CT elements (AB, GN, DC, AL, DB), and thus, students with programming experience encountered more CT elements.

This study discovered that students' prior learning experience and SNS-based e-mentoring had an interaction effect on their CT. In other words, the difference in CT based on prior learning experience narrowed when students participated in SNS-based e-mentoring. Based on this finding, it is suggested that introducing SNS-based e-mentoring can bridge the gap between students' prior learning experiences when running courses for students from various educational backgrounds, with the goal of developing CT.

6. Conclusion and implication

As CT has become an essential basic skill, several studies have been conducted on its development. The interaction between the instructor and the student is critical in the development of CT. Through interaction with the instructor, students can receive a variety of support, including explicit instruction and role modeling. However, instructors find it difficult to actively interact with individual students in large-scale online courses. Consequently, this study examined the effect of e-mentoring in a large-scale online course aimed at developing students' CT through the use of SNS, which is capable of real-time interaction.

An independent sample *t*-test and multiple linear regression analysis were performed based on the participants' CT assessment scores and the utilization data of e-mentoring activities. The analysis determined that SNS-based e-mentoring is effective in assisting undergraduate students' CT development during a large-scale online course. The most beneficial e-mentoring activities for students' CT development were informational and technical support in the group environment, as well as informational support in the private environment.

To investigate whether there were any gender differences regarding the effect of SNS-based e-mentoring on CT development, a two-way ANOVA analysis, and two multiple linear regression analyses were performed. It was found that the effect of SNS-based e-mentoring was higher for female students than for male students. Additionally, female students engaged in more types of e-mentoring activities than male students.

A two-way ANOVA was used to determine whether the effect of SNS-based e-mentoring on CT development differed depending on students' prior learning experiences. The analysis revealed that participation in SNS-based e-mentoring could narrow the CT gap based on prior learning experience.

Our findings have practical implications for higher education institutions and instructors. First, when planning a course for students' CT development in a large-scale online course, a method of utilizing SNS-based e-mentoring can be considered. Second, the method used in this study can be applied when developing strategies to close the gender gap or the gap in students' prior learning experiences in CT ability.

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