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RESEARCH ARTICLE

Exploring the relationship between computational thinking and learning satisfaction for non-STEM college students

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Abstract

While various studies have focused on the significance of computational thinking (CT) for the future career paths of individuals in science, technology, engineering, and mathematics (STEM), few studies have focused on computational thinking for non-STEM college students. This study explores the relationship between computational thinking and learning satisfaction for non-STEM-major college students. A conceptual model is proposed to examine the structural relationships among computational thinking, self-efficacy, self-exploration, enjoyment and learning satisfaction in an AppInventor-based liberal education course. Collecting data from 190 undergraduate students from Taiwan and analyzing the data by using partial least squares (PLS) methods, the research framework confirms the six proposed hypotheses. These results show that both computational thinking and enjoyment play significant roles in both self-exploration and digital self-efficacy. Moreover, digital self-efficacy and self-exploration also have a significant positive influence on learning satisfaction. These findings have implications for influencing the learning outcomes of non-STEM-major college students, computational thinking course instructors, and computational thinking relevant policies.

Keywords: Computational thinking, Digital self-efficacy, Self-exploration, Enjoyment, Learning satisfaction, Non-STEM college students

Highlights

- This study develops a model for computational thinking and learning satisfaction.
- Computational thinking positively influences on digital self-efficacy and self-exploration.
- Enjoyment positively influences on digital self-efficacy and self-exploration.
- Digital self-efficacy and self-exploration positively influence on learning satisfaction.

Introduction

Computational thinking is regarded as a thinking process that enables the understanding of problems and the formulation of creative solutions to these problems through the iteration of abstraction and algorithmic thinking (Chen et al., 2017a, 2017b; Romero et al., 2017). Computational thinking has been defined as "solving problems, designing systems, and understanding human behavior, by drawing on the concepts fundamental to computer science" (Wing, 2006, p. 33). Computational thinking, an essential part of science, technology, engineering, and mathematics (STEM) education, addresses the essential concepts of STEM and involves the integration of multiple disciplines and cross-domain knowledge during the problem-solving process (Lu et al., 2021). That is, by drawing on principles and practices central to computer science, computational thinking is a capacity and skill set that individuals should possess and acquire at a basic level to solve ambiguous, complex and open-ended problems for the future world in various contexts (ISTE, 2022). It is therefore considered one of the essential twenty-first century skill that not only STEM workers but also everyone from different disciplines should learn (Güven & Gulbahar, 2020; Tekdal, 2021).

Computational thinking has been a trending topic in recent decades in learning research and educational practice. Scholars argue that children as young as 4 to 6 years old can build and program robots and learn computational thinking skills (Bers et al., 2014). Previous studies have also suggested that learning computer science and STEM in early childhood assists students in developing certain competences and thinking archetypes, and the early experiences of children are likely to allow them to substantially develop positive attitudes toward perseverance in future career development (Chen et al., 2017a, 2017b; Israel et al., 2015). However, the majority of these studies have focused on the STEM field with no mention of computational thinking. According to a computational thinking review article from Hsu and her colleagues, the existing computational thinking studies are largely aimed at biology, program coding, computer science, and robot design classes in terms of the subject and at K12 students in terms of age (Hsu et al., 2018; Tikva & Tambouris, 2021). Computational thinking should not be a privilege of STEM-related majors, but rather it is imperative to learn for students in other domains to learn to solve problems relevant to all disciplines (Czerkawski & Lyman, 2015; Wing, 2008). How to foster the learning performance of computational thinking for non-STEM college students remains unknown.

A very recent bibliometric analysis of computational thinking education research identified and selected 321 articles published from 2008 to 2020 in 36 journals in which the authors included the term computational thinking to investigate (Tekdal, 2021). The review indicates that the current computational thinking studies are largely conducted with students from elementary education to high school and focuses on the integration of computational thinking into STEM education. The author also recommended that future studies be expanded to cover higher education.

In a similar vein, Czerkawski and Lyman (2015) called for applying computational thinking methods to address some of the most challenging problems facing society. The purpose of social studies is to promote civic competence to confront large and complex problems and to provide information about diverse disciplines such as geography, history, law, and civics (Güven & Gulbahar, 2020). College students studying social

studies can use the core concepts of computational thinking—abstraction and algorithmic thinking—to reason about and solve complex problems, design systems, and understand human behaviors (Kules, 2016). Other than these few conceptual studies that tout the application of computational thinking to social studies, there is limited empirical research relating this topic to college students in non-STEM disciplines. The gap in this area explicitly indicates that there is a need for critical research on the learning effectiveness of computational thinking in non-STEM disciplines among college students.

The study, consequently, addresses this gap in the educational literature and aims to examine how the learning effectiveness of computational thinking can be enhanced. Specifically, the purpose of this study is to investigate the structural relationships among computational thinking, self-efficacy, self-exploration, enjoyment, and learning satisfaction in an AppInventor-based liberal education class for non-STEM-major college students. The results contribute significant information for non-STEM-major college students that can help to improve their critical thinking skills while encouraging a more innovative and forward-thinking mindset to discover computational solutions (Chong et al., 2018; Kules, 2016). Moreover, the findings also aid computational thinking instructors in designing more accommodating computational thinking courses to reduce the digital divide that results from socioeconomic and cultural backgrounds (Czerkawski & Lyman, 2015).

Conceptual framework and hypothesis development

Computational thinking

The definitions of computational thinking vary by scholar. Wing (2006) introduced the concept of computational thinking and characterized it as a recursive process that uses the skill of abstraction and decomposition to confront a large complex task or design a large complex system. Israel et. al. (2015, p. 246) developed the definition and characterized computational thinking as "students using computers to model their ideas and develop programs that enhance those programs." Barr and Stephenson (2011, p. 115) explained the concept of computational thinking in the K-12 context as "an approach to solving problems in a way that can be implemented with a computer."

Although the definitions of computational thinking vary and a consensus is lacking, the various accounts have several implications. It can be accepted that fostering computational thinking-relevant skills can enhance problem solving and abstract reasoning capability. Computational thinking is a type of analytical thinking for problem solving that comprises the scoping of problems with a suitable expressive format or media, interpreting these topics through abstraction, and finally formulating computerized solutions to the problems (Gong et al., 2020). In addition, some computational thinking involves learning the competencies and know-how required to engage in programming skills. Finally, computational thinking essentially encompasses the concepts of abstraction, problem solving, analysis, decomposition, integration, algorithmic thinking, generalization, coding, and debugging (Yılmaz et al., 2018).

Enjoyment

Enjoyment is defined as a positive affective reaction that mirrors general feelings such as liking, delight, and fun derived from an activity in which an individual is engaged

(Raedeke, 2007). Applying this notion to the learning field, enjoyment can be described as the extent to which a learner gains a sense of pleasure, joy, and fun and as a factor that contributes to a positive, all-inclusive experiences from a class (Moorthy et al., 2019). Enjoyment is an intrinsic motivation with an innate tendency to discover novelty and is experienced when an individual faces challenges in expanding and exercising his or her abilities to learn and explore (Gomez et al., 2010; Teo & Noyes, 2011). A previous study has shown that learners' motivations are positively related to learning performance (Gomez et al., 2010). Students experience psychological pleasure in game-based classes. That is, game-oriented teaching can promote learners' motivations and interests, and learners enjoy these learning activities (Hsu et al., 2018).

Digital self-efficacy

Rooted in social cognitive theory, self-efficacy refers to beliefs about one's capabilities to learn or perform behaviors at designated levels (Bandura, 2006, 2010). The concept postulates that an individual's achievement relies on interactions among one's behaviors, personal factors (e.g., thoughts, beliefs), and environmental conditions (Bandura, 2006; Bandura & Schunk, 1981). Self-efficacy accounts for individual accomplishments and human well-being. Specifically, individuals with a higher sense of self-efficacy believe that they possess greater capabilities to accomplish challenging and difficult tasks. In a digital learning environment, digital self-efficacy, also called computer efficacy or internet efficacy, is usually used to measure individual self-efficacy in the digital domain (Mun & Hwang, 2003; Wei et al., 2020). Venkatesh and Davis defined digital self-efficacy as a self-assessment of one's ability to use information technology (IT) or one's belief that people can use computer or internet-related technologies well (Venkatesh & Davis, 1996). Based on this definition, this study modifies the definition to fit the research setting and defines digital self-efficacy as the learner's assessment of his or her ability to learn in an IT-mediated environment or his or her belief that he or she can use internet-related technologies to learn.

The relationship between computational thinking and digital self-efficacy

Expectancy-value theory posits that individuals' expectations for success and the value of them succeeding are important factors in their motivation to accomplish various tasks (Eccles, 1983). That is, if a learner accepts that a class that he or she takes contributes to his or her capabilities or future career development, then the perceived value will increase and motivate the learner to engage more fully in the class. Applying this rationale to a computational thinking class, a student's motivation to learn may be aroused if the student can learn analytical skills, problem-solving skills, and thinking skills and thus improve his or her capabilities. Therefore, this study proposes the following hypothesis:

H1   Computational thinking has a positive influence on digital self-efficacy.

The relationship between enjoyment and digital self-efficacy

Enjoyment is an intrinsic and affective motivation that can result in behavior changes and active learning (Goh & Yang, 2021). Self-efficacy reflects one's internal motivation

based on ability, while emotional arousal is a critical source of the development of self-efficacy (Bandura, 2006, 2010). When an individual faces threatening situations or difficult tasks, negative emotions, such as anxiety, may emerge and thus restrain one's capabilities to cope. In contrast, when an individual perceives the tasks to be interesting or joyful, he or she might have more confidence in his or her ability to accomplish these tasks. A substantial body of evidence has shown positive associations between aspects of enjoyment and self-efficacy. For example, Chen et. al. (2017a, 2017b) found that enjoyment is an antecedent of self-efficacy in a physical activity environment. Mun and Hwang (2003) also concluded that learners with higher perceived levels of enjoyment exhibit higher digital self-efficacy when using web-based information systems. Based on such findings, this study proposes the following hypothesis:

H2   Enjoyment has a positive influence on digital self-efficacy.

Self-exploration
Self-exploration is an individual's conscious internal or external behavior of analyzing information and pursuing knowledge related to his or her career (Flum & Kaplan, 2006). Furthermore, information analysis results in the formation of self-meaning and has a systemic influence on fostering self-development. Educational psychologists argue that self-exploration is one of the core factors that explains identity formation because it assists individuals in examining their identifications by facing them in terms of their underexamined viewpoints, advancing beliefs about alternatives, and directing them to explore novel and unfamiliar knowledge areas (Kaplan & Madjar, 2017). Self-exploration is integral to career development and vocational choices (Flum & Kaplan, 2006).

The relationship between computational thinking and self-exploration
One goal of education is to cultivate in students the competencies and capabilities to leverage current technologies to solve undiscovered problems (Durak & Saritepeci, 2018). The International Society for Technology in Education (ISTE, 2022) also emphasizes that the purpose of computational thinking is to educate young students as computational thinkers who can solve tomorrow's problems by using today's technologies. Computational thinking is essentially a set of transferable skills that enable people to foster technological literacy for the twenty-first century and to succeed in a wider range of jobs and tasks beyond their own disciplines (Nägele & Stalder, 2017). Since computational thinking is cross-disciplinary, a non-STEM college student who takes a computational thinking class might think about how these skills can be used in his or her major domain and explore the feasibility of applying these skills to his or her future career. When a class is more highly valued, the possibility is higher that the student seeks ideas for his or her own sake and links to his or her innate values and beliefs. Therefore, this study proposes the following hypothesis:

H3   Computational thinking has a positive influence on self-exploration.

The relationship between enjoyment and self-exploration

Enjoyment is an intrinsic affective motivation that drives individuals to do something that they enjoy (Gomez et al., 2010; Moorthy et al., 2019; Raedeke, 2007; Teo & Noyes, 2011). Self-exploration is associated with the framing of an individual's identity in terms of intrinsic cognitive motivation (Kaplan & Madjar, 2017). Similar to enjoyment and self-efficacy, which are both forms of intrinsic motivation and are correlated with one another (Meyer et al., 2019), we assume enjoyment and self-exploration to be positively related. On the basis of self-determination theory, interesting or joyful classes might increase the engagement of students because students are eager to know and make discoveries about these classes' influences and outcomes (Ryan & Deci, 2017). Enjoyment might foster an individual's psychological reflection and self-exploration. Therefore, this study hypothesizes that students with higher perceptions of enjoyment have stronger self-exploration motives.

H4   Enjoyment has a positive influence on self-exploration.

Learning satisfaction

Learning satisfaction and learning achievement are two typical indicators of learning effectiveness, which is an ultimate learning outcome (Hu & Hui, 2012). Learning satisfaction is the overall level of fulfillment of a learner's expectations that pertains to a class experience (Cidral et al., 2018). Because the research setting of the present study involves a technology-based learning environment (i.e., AppInventor) that enjoys the advantages of increased learning opportunities, the satisfaction of students' requirements, the support of blended learning (both online and offline workshops), and exceedingly diversified learning, an assessment of learning performance should consider in the learning environment both the actual effectiveness in learning content and students' attitudes and expectations (Bostrom et al., 1990). Additionally, previous literature on information systems and computer-assisted learning has indicated that learner or user satisfaction is an important measure of learning performance and the effectiveness of online learning system implementation (Ke & Kwak, 2013). Consequently, this study uses learning satisfaction as the dependent variable in the proposed model.

The relationship between digital self-efficacy and learning satisfaction

Higher self-efficacy contributes to higher academic performance and satisfaction (Karadag et al., 2021). Learners with higher efficacy set higher goals and believe that they can achieve these goals, even when facing difficulties (Bandura, 2006, 2010). That is, students with higher self-efficacy may reflect and engage in their learning experiences and reshape their learning behaviors to achieve better learning performance. Self-efficacy has been regarded as one of the critical determinants that accounts for a learner's achievement in an educational setting. Zysberg and Schwabsky (2020), for example, it has been recently confirmed that self-efficacy acts as a mediator that links school climate and academic achievement (i.e., math, English and the relative rank) for middle and high school students. Similarly, Vayre and Vonthron (2019) suggest that both academic

self-efficacy and learning engagement are antecedents that predict successfully passing exams for students enrolled in online university courses. Therefore, this study hypothesizes the following:

H5   Higher digital self-efficacy leads to higher learning satisfaction.

The relationship between self-exploration and learning satisfaction

A university education is an important stage for employment preparation and career development. Before career development, individuals usually engage in self-exploration to understand the relationship between their interests, values, and needs and the external environment through information gathering and processing, experience accumulation, and self-evaluation (Cai et al., 2015). As self-exploration is a factor of career development, it is reasonable to assume that when individuals understand themselves more, their tendency is higher to engage in tasks with the purpose of enhancing their capabilities, namely, to learn, to understand and to develop skills. Therefore, a positive association between self-exploration and learning satisfaction can be expected.

H6   Higher self-exploration leads to higher learning satisfaction.

Drawing on the arguments above, the research model is shown in Fig. 1 for computational thinking, enjoyment, self-efficacy, self-exploration, and learning satisfaction and their hypotheses. The hypotheses are repeated below for ease of reference.

H1   Computational thinking has a positive influence on digital self-efficacy.
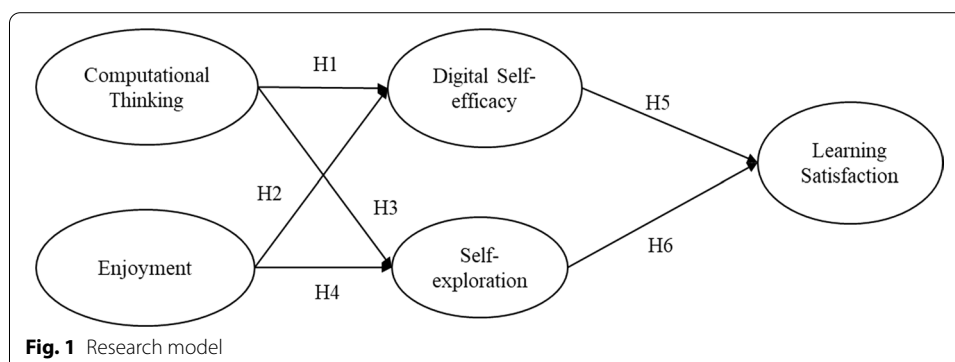
H2   Enjoyment has a positive influence on digital self-efficacy.

H3   Computational thinking has a positive influence on self-exploration.

H4   Enjoyment has a positive influence on self-exploration.

H5   Higher digital self-efficacy leads to higher learning satisfaction.

H6   Higher self-exploration leads to higher learning satisfaction.

Fig. 1 Research model

Method

Measures

The proposed model with five variables and six hypotheses was assessed by using a quantitative survey. All constructs were measured with multiple items, and seven-point Likert-type scales that ranged from "strongly agree" to "strongly disagree" were used. The five variables were adopted from the relevant literature and modified to fit the current research context (Cho et al., 2017). That is, learning satisfaction was measured by using five items adopted from Hu and Hui (2012), computational thinking was measured with five items modified from Durak and Saritepeci (2018), enjoyment (EJ) was measured by using four items from Kong et. al. (2018), digital self-efficacy was measured with four items from Kim and Jang (2015), and self-exploration was measured by using four items from Afzal et. al. (2010). Because the survey participants were Chinese students, the original instruments were translated into Chinese by a professional translator. After the authors ensured that the intended meaning was conveyed by the instruments, a reverse translation was performed to ensure accurate interpretation (Cidral et al., 2018). These items and sources are listed in Appendix 1. The questionnaire is divided into five sections, each of which consists of questions designed to elicit information about one of the constructs, specifically, computational thinking, enjoyment, self-efficacy, self-exploration, or learning satisfaction.

The context, participants, and procedures

Data were collected from a university in northern Taiwan. The university opened a liberal education course worth two credits. The course was a mobile device programming class that was available only to undergraduate students whose major was not STEM. This course aimed to teach students how to solve problems by identifying the problem and understanding the modeling, abstracting, and designing of an algorithm and by teaching basic computer programming concepts to students who were without programming skills. AppInventor (https://www.appinventor.mit.edu/), which was originally invented by Google and transferred to the Massachusetts Institute of Technology (MIT) for operation and management in 2012, served as the main instrument for teaching computational thinking concepts in this course, while other problem-solving techniques, such as flowcharts and case studies, were discussed in the class. To gain hands-on computational thinking experiences and inspire learning interest, students who took the class practiced how to solve daily problems with AppInventor. Specifically, the instructor used online restaurant ordering, body mass index (BMI), and a ninety-nine multiplication table as the course materials to deliver the core concepts of computational thinking. The students could build their own apps after observing the instructor's initial demonstration. Some of the student works are shown in Appendix 2. Moreover, the students were assigned a term project to propose how to leverage their skills and application of computational thinking in their daily life or profession.

At the end of the school term, the instructor communicated the objectives of the survey to all students who took the class and emphasized that there were no definite right or wrong answers or perspectives and that answers to the survey would not impact their class performance. Later, a follow-up email with a link to a GoogleDoc survey was sent

to all students to encourage them to participate. A small amount of extra credit was offered to encourage students to complete the survey (Shapiro et al., 2017). The students voluntarily completed the survey, and they could choose to omit their name if they had any concerns. Of the 276 enrolled students from six classes in five semesters, 190 students participated in the survey for a 71.7% participation rate. The gender distribution was 68.9% female and 31.1% male. Of the sample, 36.8% were 1st-year students, 49.5% were 2nd-year students, 3.7% were 3rd-year students, and 10.0% were 4th-year students.

Results

Because the proposed model contains five constructs, which are also referred to as latent variables, and the purpose of this study is to explore the relationship among these constructs, structural equation modeling (SEM) is suitable for assessing the results (Hair et al., 2017a). SEM is a statistical method that examines and tests causal relationships with a combination of statistical data and theoretical causal assumptions (Sarstedt et al., 2017). There are two types of SEM techniques, namely, covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM). CB-SEM is a parametric statistical method that is primarily used for the confirmation of an established theory. Accordingly, statistical significance is a standard output of this technique; in contrast, PLS-SEM is considered to be more relevant for analyzing complex models and exploratory research (Lee & Jung, 2021).

To assess the proposed model and test the study hypotheses, the present study applied PLS-SEM to examine the relationships among the constructs in complex models. There are several advantages to using this technique. First, PLS-SEM comprises a measurement model and a structural model evaluation, which makes it superior to the one-step evaluations of SEM (Hair et al., 2010; Molinillo et al., 2018). The structural model examines the relationships among constructs in structural models, whereas the measurement model assesses the reliability and validity of the constructs (Hair et al., 2017a, 2017b). Reliability refers to the consistency of the scale items (Hair et al., 2017b). The measurement indicators include individual item reliability and internal consistency. Factor loading is usually used to assess individual item reliability. In contrast, composition reliability (CR) and the Cronbach's alpha are two metrics that test the internal consistency of the latent variable. The recommended threshold value must exceed 0.7 (Hair et al., 2017a, 2017b).

Validity refers to the correctness of the scale items, and the measurement metrics usually include convergent validity and discriminant validity. Convergent validity measures the correlation between items within the same construct. Discriminant validity measures the correlation between items with different constructs. The average variance extraction (AVE) is a suitable indicator to detect discriminant validity, providing the recommended threshold value exceeds 0.5 (Hair et al., 2017a, 2017b). If the square root value of the diagonal AVE is greater than the correlation coefficient value of the horizontal or vertical column, then this represents discriminant validity (Hair et al., 2017b).

Second, PLS-SEM is particularly suitable for research in fields such as education and requires only a limited sample size (Goh & Yang, 2021; Hair et al., 2017a). Otherwise, the data do not follow a normal distribution (Molinillo et al., 2018). Moreover, as in the present research, predicting capability and evaluating the relationships of latent variables

Table 1 Reliability and convergent validity

|	AVE	Composite reliability	Cronbach's alpha
Computational thinking	0.835	0.962	0.950
Enjoyment	0.907	0.975	0.966
Learning satisfaction	0.876	0.972	0.964
Digital self-efficacy	0.790	0.938	0.911
Self-exploration	0.899	0.973	0.962

Table 2 Correlation among the construct scores

	Computational thinking	Enjoyment	Learning satisfaction	Digital self-efficacy	Self-exploration
Computational thinking	**0.914**				
Enjoyment	0.782	**0.952**			
Learning satisfaction	0.788	0.791	**0.936**		
Digital self-efficacy	0.730	0.769	0.800	**0.889**	
Self-exploration	0.793	0.803	0.827	0.823	**0.948**

The boldface figures on the diagonal represent the square root of the AVE figures

(unobservable constructs) enable PLS-SEM to develop exploratory analysis models (Hair et al., 2017a). Unlike traditional statistical techniques such as a t-test and analysis of variance (ANOVA) that examine whether the group means differ from one another or whether one group's mean differs in different times, PLS-SEM enables the education studies to explore the structural relationships among a group of latent variables. Additionally, PLS-SEM is more suitable for exploratory studies to understand the specific path coefficients and variance of the dependent variable as explained by the independent variables in the proposed framework instead of examining the goodness of model fit (Hair et al., 2017a, 2017b; Lee & Jung, 2021).

Assessment of the measurement model

The measurement model estimates construct validity and reliability, including convergent and discriminant validity. The Cronbach's alpha, which represents construct reliability, is used to test the reliability of all constructs in the proposed framework. The Cronbach's alphas fell between 0.911 and 0.966 for all constructs in this research model. These values far exceed the threshold of 0.7 (Nunnally & Bernstein, 1994). In addition, the composite reliability (CR) was beyond 0.938, which far exceeds the cutoff value of 0.5 (Chin & Gopal, 1995). These results confirm the internal reliability of each construct. Moreover, estimated pairwise correlations between factors did not exceed the 0.85 limit (Kline, 2015). The average variance extracted value (AVE) was applied to examine convergent validity. The outcome AVE value fell between 0.790 and 0.907, which exceeded the cutoff value of 0.5 (Hair et al., 2010). Fornell–Larcker criteria are commonly used to test discriminant validity and require that the square root of the AVE be greater than all correlations between each pair of constructs (Fornell & Larcker, 1981). The reliability and convergent validity results of the proposed constructs are summarized in Tables 1

Fig. 2 Results of the research model
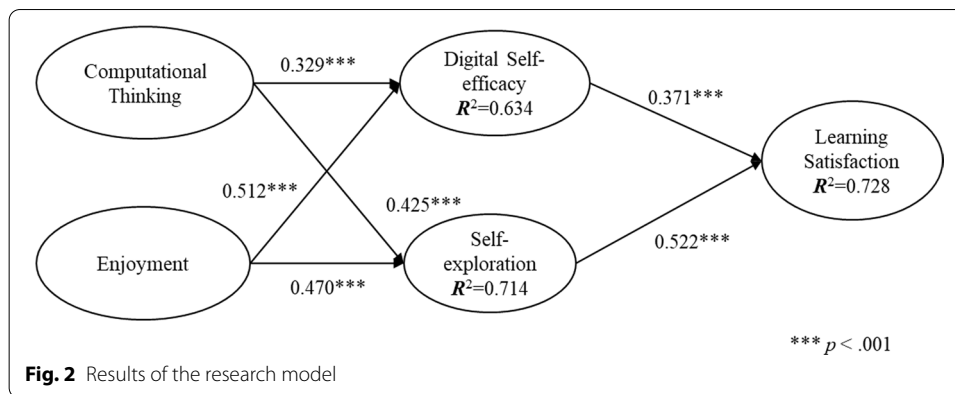
Table 3 Summary of the hypothesis results

	β	*t*-statistic	*p*-value	Result
H1: Computational thinking → digital self-efficacy	0.329	3.976	***	H1 supported
H2: Enjoyment → digital self-efficacy	0.512	6.253	***	H2 supported
H3: Computational thinking → self-exploration	0.425	5.549	***	H3 supported
H4: Enjoyment → self-exploration	0.470	6.586	***	H4 supported
H5: Digital self-efficacy → learning satisfaction	0.371	4.671	***	H5 supported
H6: Self-exploration → learning satisfaction	0.522	6.592	***	H5 supported

and 2. Additionally, the factor loadings of items fell between 0.872 and 0.968, which exceeded the cutoff value of 0.5 (Lee & Jung, 2021), as displayed in Appendix 1.

Assessment of the structural model

PLS uses bootstrapping with a substantial resampling (3000 times in this study) to compute the beta (β), R^2, and respective *t*-statistics of the structure model (Hair et al., 2017a). The beta (β) represents the regression path coefficient. The *t*-statistics test the statistical significance of both the outer and inner models and are also provided with *t*-value ≥ 1.96, *t*-value ≥ 2.58, and *t*-value ≥ 3.29, which denote $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively (Field, 2009). The R^2 value indicates the explained variance of the endogenous latent variables for the structural model. A graphic illustration of the structural model for this study is given in Fig. 2, while a summary of the hypotheses is presented in Table 3.

Based on Fig. 2 and Table 3, all proposed hypotheses in the research model were supported.

- Computational thinking had a statistically significant positive impact on digital self-efficacy ($\beta = 0.329$, *t*-value $= 3.976$, $p < 0.001$), which supports H1.
- Enjoyment had a statistically significant positive impact on digital self-efficacy ($\beta = 0.512$, *t*-value $= 6.253$, $p < 0.001$), which supports H2.
- Computational thinking had a statistically significant positive impact on self-exploration ($\beta = 0.425$, *t*-value $= 5.549$, $p < 0.001$), which supports H3.

- Enjoyment had a statistically significant positive impact on self-exploration ($\beta = 0.470$, *t*-value $= 6.586$, $p < 0.001$), which supports H4.
- Digital self-efficacy had a statistically significant positive impact on learning satisfaction ($\beta = 0.371$, *t*-value $= 4.671$, $p < 0.001$), which supports H5.
- Self-exploration had a statistically significant positive impact on learning satisfaction ($\beta = 0.522$, *t*-value $= 6.592$, $p < 0.001$), which supports H6.

Moreover, the interpretation of variation (R^2) from computational thinking and enjoyment to digital self-efficacy was 0.634. The R^2 from computational thinking and enjoyment to self-exploration was 0.714, and that from digital self-efficacy and self-exploration to learning satisfaction was 0.728.

Discussion

The findings show that computational thinking has a positive impact on both digital self-efficacy ($\beta = 0.329$, $p < 0.001$) and self-exploration ($\beta = 0.425$, $p < 0.001$), and enjoyment also has a positive impact on both digital self-efficacy ($\beta = 0.512$, $p < 0.001$) and self-exploration ($\beta = 0.470$, $p < 0.001$). Furthermore, both digital self-efficacy ($\beta = 0.371$, $p < 0.001$) and self-exploration ($\beta = 0.522$, $p < 0.001$) have a positive impact on learning satisfaction. These findings have several implications. First, computational thinking courses are not proprietary to STEM curricula or precollege students. Empirically confirming a previous study (Czerkawski & Lyman, 2015), this study empirically suggests that non-STEM college students can enjoy the learning benefits of computational thinking and take an interest in computational thinking classes. That is, computational thinking teaches a set of transferable and marketable skills that are appropriate for any domain.

Next, computational thinking fosters digital self-efficacy ($\beta = 0.329$, $p < 0.001$), even in students in non-STEM majors. The results indicate that computational thinking classes can stimulate students to think about how to understand themselves and explore new ideas. This implies that students might think about how to use these skills to solve problems in their majors or related areas.

In addition, this study shows that enjoyment is a factor of digital self-efficacy ($\beta = 0.512$, $p < 0.001$). Previous studies have shown that enjoyment is positively associated with digital self-efficacy (Mun & Hwang, 2003; Wei et al., 2020) and learning satisfaction in online learning settings. This study shows that interesting or game-based classes can promote student digital self-efficacy. Interesting classes can remove or reduce learning barriers and encourage students to challenge themselves and can enhance student growth and development.

Furthermore, this study creates a computational thinking class with a suitable design by adding an interesting element and can promote learners' digital self-efficacy ($\beta = 0.512$, $p < 0.001$) for non-STEM-major students, which further enhances their learning satisfaction.

Finally, this study contributes to the literature on computational thinking learning in that self-exploration is an antecedent of learning satisfaction ($\beta = 0.522$, $p < 0.001$). Self-exploration helps prepare students for career development and vocational choices (Flum & Kaplan, 2006). In this study, students with a higher degree of self-exploration skills

showed greater readiness for career preparation. Accordingly, classes that can increase student confidence in career preparation will lead to higher learning satisfaction.

This study has several implications for computational thinking instructors. AppInventor is an effective instrument for learning computational thinking and for the promotion of computational thinking education. In addition to developing problem-analysis, thinking, and problem-solving skills, computational thinking learning assists students in understanding themselves. Furthermore, instructors can encourage students to use computational thinking to solve problems in their domains or daily lives to enhance their learning satisfaction. Although AppInventor contains entertaining ingredients, an instructor might add more entertaining factors to his or her classes. This study, for example, used restaurant ordering as a lab exercise for learning content. A practical but interesting daily problem might help or persuade a student to overcome challenges and increase learning satisfaction. Correspondingly, this study provides educational policy makers with a venue for computational thinking education for non-STEM college students. Computational thinking educational resource allocation for non-STEM college students will enhance overall social thinking skills. Additionally, as enjoyment can effectively lower the learning barrier, computational thinking educational resource configuration can be linked to joyful or playful learning material.

Limitations

One limitation of this study is that all participants were students at a college located in northern Taiwan. Future studies might investigate the effect of cultural, social, or economic factors on computational thinking learning performance for non-STEM college students.

Another limitation of this study is that AppInventor limits the learning material considered. In addition to AppInventor, other relevant learning tools, such as Turtle Art, Scratch, Code.org, and Scalable Game Design (Hsu et al., 2018), could be considered for similar studies. Future studies should examine the learning outcomes of other tools. It would be interesting to explore the relationships between information and communications technology (ICT) learning tools and non-ICT tools such as flow charts, fishbone diagrams, brain storming, and mind maps. Understanding the role of the relationships between these tools will help learners obtain comprehensive problem-solving skills and transferable knowledge.

Finally, because the course was not mandatory but elective, it might also be a limitation of this study that non-STEM students had the choice of enrolling or not enrolling in this particular course, and those who enrolled already may have had a positive attitude toward technology, programming and computational thinking. Future studies might investigate a comparison of the results of this class property (mandatory vs. elective) or other factors that affect attitudes toward computational thinking.

Conclusion

This study affirms that non-STEM college students can effectively learn computational thinking with the support of proper learning instruments. As society becomes increasingly digitalized, it is virtually certain that non-STEM knowledge workers will be required to interact with information technology professionals in a variety of domains.

Learning computational thinking does not make it possible for a student who does not understand how to program to become a qualified programmer, but it does cultivate the thinking and logic competencies for problem solving and aids the student in interacting across domains.

These findings also emphasize the importance of the computational thinking curriculum in self-exploration and how effective computational thinking learning can be achieved. The findings of this study help make the argument that computational thinking provides benefits across the curriculum. Furthermore, these findings encourage policy makers to allocate resources to expand the use of this beneficial educational tool in the classroom.

Appendix 1. Questionnaire items and sources

Construct	Item	Factor loading	Source
Computational thinking	CT1. I can learn analytical skills	0.874	Durak and Saritepeci (2018)
	CT2. I can learn problem-solving skills	0.926	
	CT3. This class can train my thinking skills	0.920	
	CT4. This class can strengthen my thinking skills	0.901	
	CT5. This class can improve my capabilities	0.945	
Enjoyment	EJ1. Programming is interesting	0.950	Kong et. al. (2018)
	EJ2. I am curious about the content of programming	0.936	
	EJ3. I think the content of programming is fun	0.955	
	EJ4. I am very attracted to computer programming activities	0.968	
Self-efficacy	SE1. Compared with other students in this class, I expect to do well	0.895	Kim and Jang (2015)
	SE2. I am certain I can understand the ideas taught in this course	0.872	
	SE3. I expect to do very well in this class	0.910	
	SE4. Compared with others in this class, I think I am a good student	0.877	
Self-exploration	SX1. I want to understand myself better	0.944	Afzal et. al. (2010)
	SX2. I want to explore new ideas	0.940	
	SX3. I want to challenge myself	0.953	
	SX4. I want to enhance my personal growth and development	0.955	
Learning satisfaction	LS1. I like the idea of learning AppInventor in a lab like this	0.921	Hu and Hui (2012)
	LS2. Learning AppInventor by taking a lab like this is a good idea	0.944	
	LS3. My learning experience in this lab is positive	0.953	
	LS4. Overall, I am satisfied with this lab	0.909	
	LS5. As a whole, the lab is effective for my learning AppInventor	0.952	

Appendix 2. Some student works

(A) Restaurant Ordering App

(B) BMI Calculator

(C) Ninety-nine Multiplication Table

Declarations

Competing interests
The authors declare that they have no competing interests.

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