IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received November 4, 2021, accepted January 5, 2022, date of publication January 26, 2022, date of current version February 2, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3146128

The Impact of Achievement Goal Orientation, Learning Strategies, and Digital Skill on Engineering Skill Self-Efficacy in Thailand

DISSAKOON CHONSALASIN[1] AND BURATIN KHAMPIRAT[2]
[1]Institute of Engineering, Suranaree University of Technology, Nakhon Ratchasima 30000, Thailand
[2]Institute of Social Technology, Suranaree University of Technology, Nakhon Ratchasima 30000, Thailand

Corresponding author: Buratin Khampirat (buratink@sut.ac.th)

This work was supported in part by the National Research Council of Thailand (NRCT) and Suranaree University of Technology (SUT) under Grant NRCT5-RSA63009-02, in part by the National Science, Research and Innovation Fund (NSRF) via the Program Management Unit for Human Resources and Institutional Development, Research, and Innovation under Grant B05F640220, in part by SUT Research and Development Fund under Grant IRD2-202-64-12-12, and in part by the Thailand Science Research and Innovation (TSRI).

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Human Researches Ethics Committee of the Suranaree University of Technology, under Application No. EC-64-119, and performed in line with the Declaration of Helzinki, The Belmont Report, CIOMS guideline, International Conference on Harmonization in Good Clinical Practice (ICH-GCP) and 45CFR 46.101(b).

ABSTRACT Rapid technological changes in industry and institutions of higher education required that their continuous learning and teaching methods conform to the needs of the labor market in the digital era. Building the engineering skill self-efficacy of students should be a key goal for educational institutions as they develop necessary skills for future engineers. This work investigated structural factors influencing engineering skill self-efficacy by conducting a questionnaire survey among 1,316 engineering students in Thailand. Structural equation modeling was used to validate the proposed model. The research results indicated that engineering skill self-efficacy was contributed to digital skills, learning strategies, and achievement goal orientation. Learning strategies were predicted by achievement goal orientation, and they positively associated with digital skills. These empirical findings reflect a sustainable educational development structure for engineering education. The results may benefit educators by specifying methods of educational development and learning activity design and promoting pedagogical system to develop learners' characteristics to enhance their engineering skill self-efficacy. Students can then be prepared with digital skills to apply to their further work, which will affect capacity building and the overall image of a country's development.

INDEX TERMS Achievement goal orientation, learning strategies, digital skills, engineering skill self-efficacy.

I. INTRODUCTION

The current global labor market demands high skilled engineers with advanced technological knowledge and capabilities to promote innovative industries in the present digital technology disruptive era. However, employers have been facing an oversupply of low skilled engineering graduates [1]. Manufacturing companies and enterprises are also experiencing a shortage of manufacturing-related engineering skills, such as core skills-related engineering discipline, use of advanced technology, and programming skills [2]–[4]. Because in the present wave of technology and digital economy, knowledge engineering has changed rapidly, the employment of new engineering graduates is linked to their advanced technological skills and capabilities to improve advanced technology business. A study in Malaysia by Azmi, *et al.* [5] reported that due to the development of digitalization and robotics, only qualified and highly skilled fresh engineering graduates, who are able to control these technologies, will be employed by industries. In the United States, McGunagle and Zizka [6] indicated that there is a gap in employability between science, technology, engineering and math (STEM) students and the needs of manufacturing. Therefore, it is necessary for preparing students to be the best candidate for future workplace. In UK, Lewis [7] showed that innovative industries prefer skilled technicians

The associate editor coordinating the review of this manuscript and approving it for publication was Daniela Momete.

to work with new technologies, but there is still a shortage of technicians and graduates who are able to do such work effectively. Although educational institutions produce a large number of engineering graduates, there is still a shortage of workforce with high-level STEM skills, especially in digital and engineering fields [1, 8]. As a result, new engineering graduates face high competition in the job market and high unemployment rate for low skilled graduates seems to be a problem all over the world [9]. This might result from a mismatch between manpower production and entrepreneurs' demand in various production sectors, including candidates who have nonessential qualifications or specific techniques relevant to work [10]. As Thailand approaches the technological and communication era, it faces major changes domestically and internationally that occur quickly. These changes are complicated by the recent labor context, whose challenges include new technologies, digitization, and automation, as well as continuous changes in working conditions. Thus, most jobs increasingly require professional knowledge and skills, along with an advanced level of technical and managerial experience [11]. In addition, the change in population structure, with its continuously decreasing number of young people [12], affects the number of learners at the basic education level and might result in a lack of labor in the future. In addition, the COVID-19 epidemic affects economic activities due to the disruption and limitation of movement, and economic recovery is expected to take a reasonable period after the epidemic. Therefore, it is necessary to place importance on applying the benefits of information and communication technology (ICT) to preserve the continuous work operation of each organization. This may create opportunities and risks in a country's development in the face of such different forms of change. Therefore, it is important for students to be prepared to develop and increase their professional skills so they can graduate with the ability to work effectively, in accordance with the marketing demand of the digital era, and to promote economic competition and sustainable social development, including the well-being of newly graduated engineers.

In the digital economy era, in addition to engineering efficacy and knowledge, one important skill for economic and social development and employability is digital literacy [3], [11], which is essential and in demand in the labor market. Previous studies in the relevant context of science, technology, engineering, and mathematics (STEM) prioritized digital skills as a support tool for students' self-learning and development [13], to obtain good job opportunities and career growth. Researchers in the education field have used technology to teach students at higher education levels [14], [15]. Some research has focused on the use of technological application in learning platform [16]. Other research has investigated structures affecting students' digital literacy [17], [18]. Previous studies have indicated factors predicting digital literacy/digital competence in learning, such as self-regulated learning strategies [19], mastery orientation [20], [21], and academic aspirations [20]. Moreover, digital skills (domain-specific IT skills) also are associated with creative self-efficacy [22].

Nevertheless, in reference to the literature review, few studies have investigated the relationship between learning strategies, digital skills, and engineering skill self-efficacy (ENSE). Bandura [23] indicated the importance of self-efficacy as a key to support that could be used to understand students' confidence and beliefs about their ability to perform specific tasks or activities. Having high self-efficacy can significantly increase the chances of success [24]. Furthermore, students' ENSE is an important aspect that entrepreneurs worldwide expect in employment. ENSE plays a key role in effective work and conformance to entrepreneurs' demands in different production sectors, and it is highly desired by the business sector [25]. Therefore, it is necessary to conduct empirical research to improve the understanding of factors predicting ENSE.

This study proposed a model to investigate the causal relation between achievement goal orientation, learning strategies, digital skills, and ENSE of engineering students. The results provide better understanding of the importance of structural factors such as achievement goal orientation, learning strategies, and digital skills to explain the ENSE of students at higher education levels. The obtained information can benefit educational institutions, students, policy makers, and employers in designing learning activities, which helps support the ENSE of students, increase opportunities for employment, and promote career prosperity [26].

II. LITERATURE REVIEW AND HYPOTHESES

In recent days, the world has changed rapidly due to digitalization and technological innovations. Digital skills are considered an important tool of support in learning and working. In particular, when students know how to use specialized tools and new technology, they tend to be wanted by the labor market, whereas digital literacy supports learning and development [27]. In addition, students' ENSE is regarded as the main skill that entrepreneurs seek and consider for employment. The higher a student's ENSE, the greater their opportunity to benefit entrepreneurs. However, to create ENSE among students, first, it is essential to understand factors affecting ENSE as a method to specify the role of administrative planning in building ENSE accurately. We applied four factors in total as follows.

A. ACHIEVEMENT GOAL ORIENTATION SCALE

Achievement goal orientation refers to one's inspiration to engage in activities geared toward achieving goals that will lead him or her to develop behaviors or mindsets [28], [29] or focusing on motivation toward qualitatively different abilities relevant to outcomes and chance of learning [30]–[33]. Therefore, it is used as a tool to specify criteria for target behavior and as a feedback mechanism to improve the target behavior and engage in self-monitoring [23]. Achievement goal orientation also encourages individuals to specify criteria for working behavior and put in the effort to perform better to achieve performance goals. Those who have achievement goal orientation will be more successful in work than others who do not [26]. The concept of achievement goal orientation also divides the characteristics of goal orientation into various kinds. However, one's behavior depends on identifying achievement goal orientation, confidence, and different abilities [34], [35]. Elliot and Church [36] developed achievement goal orientation and divided it into three kinds: mastery goals, performance approach goals, and performance avoidance goals. Dweck and Leggett [29] indicated that motivation for achievement is specified by mastery goals and performance goals. An empirical study found that those who have mastery goals focus on gaining skills, seek learning opportunities, acquire new knowledge, and enjoy a self-growth process. In general, those who have applied the goal orientation method want to be above others in terms of skill and efficacy, and they pay attention to competition and comparison with others [29], [37].

Previous research has shown that achievement goal orientation is linked to learning strategies. For example, Diseth [38], Fenollar, *et al.* [39], Liem, *et al.* [40], Phan [41], Khampirat [26], and Guo and Leung [42] found that deep processing strategies are predicted by mastery goals. Lim and Lim [43] found that mastery goal orientation positively predicts self-regulation in collaborative learning. Hatlevik and Christophersen [20], and Hatlevik [44] found that mastery orientation is positively correlated with digital competence. Khampirat [26] found that achievement goal orientation is positively connected to learning outcomes (knowledge and skills in engineering). Du, *et al.* [45] found that mastery goals and performance approaches are positively associated with creative self-efficacy, and Turner, *et al.* [46] found that performance approach goals have a positive influence on speaking self-efficacy. Moreover, some studies have found that deep learning strategies are a mediator between mastery goals and academic performance [47], [48]. For the reasons mentioned above, we offer the following research hypotheses.

Hypotheses on direct contributions:

Hypothesis 1 (H1): Achievement goal orientation has a direct contribution to learning strategies.

Hypothesis 2 (H2): Achievement goal orientation has a direct contribution to digital skills.

Hypothesis 3 (H3): Achievement goal orientation has a direct contribution to ENSE.

Hypotheses on indirect contributions:

Hypothesis 3a (H7): Achievement goal orientation has an indirect contribution to digital skills through learning strategies.

Hypothesis 3b (H8): Achievement goal orientation has an indirect contribution to ENSE through learning strategies.

B. LEARNING STRATEGIES

Learning strategies have been defined as learning methods in which learners prefer to learn in a more efficient way in responding or interacting with learning circumstances [49] to achieving learning-related goals [50]. Using effective learning strategies is essential for positive long-term academic performance [51], helping students to be more productive in nature, and increase their levels of self-efficacy [52]. In the last century, the meaning of learning strategies is identified in many different ways, from behaviorism to cognitive learning theories [53]. Most studies describe learning strategies related to learner success [54]. In the modern learning era, various learning-teaching forms play an important role in providing support to increase education efficacy by focusing on learners in researching and creating knowledge by themselves and among their peers. This article presents the concept and integration of collaborative learning and attempts to regulate self-effort by taking the dominant characteristics of both learning methods to integrate into the learning process, which is a useful form for teachers and learners. Collaborative learning is a study form that focuses on collaboration attempts between students and teachers to support collaborative operations and their information and skill sharing to pursue group collaborative learning [49]. Self-effort regulation is the goal orientation process relevant to the *"purposive use of specific processes, strategies, or responses"* [55]. Self-regulation is students' basis to follow their goals, in order to control thoughts, feelings, and other factors affecting learning, including system arrangement in the control of external factors affecting students [56]. Previous research in educational contexts have found that self-regulated learning strategies positively predicted digital literacy in a significant way [19]. According to the impact of learning strategies on self-efficacy, previous research has indicated that learning strategies are important to increase information literacy self-efficacy level in a significant way [57], and self-regulated learning strategies are cause a positive increase in self-efficacy among students [58], [59]. According to these concepts, we can create hypotheses 4 and 5 as follows.

Hypothesis 4 (H4): Learning strategies have a direct contribution to digital skills.

Hypothesis 5 (H5): Learning strategies have a direct contribution to ENSE.

C. DIGITAL SKILL

Digital skill is a concept encompassing skill and specific techniques that are necessary for the use of effective digital technology [60]. In the last few years, several studies have used various terms to explain skills and the ability to use digital technology in learning activities—e.g., digital skills [61], [62], technology skills [63], [64], digital literacy [65], [66], digital competence [67], [68], digital tools [69], 21st century skills [70]–[74], ICT literacy [75]–[77], and ICT skills [78]. Regarding the latest competence areas relevant to digital literacy skills, UNESCO [79] suggested a concept frame of operation in seven major dimensions: devices and software operations, information and data literacy, communication and collaboration, digital content creation, safety, problem solving, and career-related competencies. In this research, digital skills relate to having knowledge and skills in using advanced computers and ICTs and professional tools in engineering practice in different work situations.

Research has found that increasing the technological skills of teachers could also lead to higher confidence as an efficient teacher with ICT [80], [81]. Yang and Cheng [22] found a positive relationship between students' ability relevant to IT skills and creative self-efficacy. Moreover, a higher level of digital skill could predict a higher level of actual performance [82], [83]. Given these concepts, we can make the following hypothesis.

Hypothesis 6 (H6): Digital skill has a direct contribution to ENSE.

D. ENGINEERING SKILL SELF-EFFICACY

Bandura [84] defined self-efficacy as *"the belief in one's capabilities to organize and execute the courses of action required to manage prospective situations."* Therefore, self-efficacy is correlated with the belief that one's capabilities will lead to success [23]. In this study, we are interested in investigating the importance of ENSE. Mamaril, *et al.* [85] indicated that ENSE is students' belief in self-efficacy on engineering skills related to design, experimental, and tinkering skills. Processes relevant to ENSE are regarded as the basic composition that leads engineers to success; for example, student self-efficacy has been found to be a good predictor of outstanding academic success [86]–[89]. As mentioned above, we can see that self-efficacy is a key variable that can express one's behavior leading to one's desired result. Therefore, it is important to prove which structures are key variables to predict ENSE.

III. MATERIALS AND METHODS

A. SAMPLE AND DATA COLLECTION

The target population of this study was all the 222,129 undergraduate engineering students of higher educational institutions in Thailand in the 2018 academic year. The participants were mainly junior and senior students from eleven universities, distributed into four geological regions of the country and various curricula of engineering fields. There were 1,316 samples, which was an appropriate sample size for multivariate analysis [90] and according to Cochran's recommendation [91]. This research designed a cross-sectional survey by taking a student questionnaire as a tool with multiprocess sampling. The survey was conducted in regular classrooms and meeting rooms. There were thirteen staff members on the survey team, consisting of researchers, research assistants and university staff. Permission to collect data was obtained before distributing each questionnaire. All students received a memorandum of agreement to clarify and be thankful for responding to questionnaires. They were also informed that participation was voluntary and that they could quit at any time. It was also ensured that their responses to the questionnaire were kept confidential and anonymized. The questionnaire took 15 minutes. Most participants were male

TABLE 1. Demographic data of the participants.

Demographic	Category	Frequency	%
Gender	Male	805	61.17
	Female	508	38.60
	N/A	3	0.23
Age (years old)	18 – 22	970	73.71
	23 – 27	335	25.46
	28 – 34	4	0.30
	N/A	7	0.53
Year of Study	1st	25	1.90
	2nd	63	4.79
	3rd	491	37.31
	4th	664	50.45
	5th	51	3.88
	6th	14	1.06
	7th	3	0.23
	N/A	5	0.38
GPA	< 2.00	22	1.67
	2.00 – 2.50	467	35.49
	2.51 – 3.00	464	35.26
	3.01 – 3.50	263	19.98
	> 3.50	68	5.17
	N/A	32	2.43
University Type	Private University	250	19.00
	Public University	947	71.96
	Vocational University	103	7.83
	Open University	16	1.21

(61.17%, $N = 805$), 38.60% ($N = 508$) were female, and 0.23% ($N = 3$) provided no gender. Most participants were 18–22 years old (73.71%, $N = 970$), and 25.46% ($N = 335$) were 23–27 years old. More than half of the participants were senior students (50.45%, $N = 664$), and 37.31% ($N = 491$) were junior students. In terms of university type, 71.96% ($N = 947$) studied at public universities, 19.00% ($N = 250$) were from private universities, 7.83% ($N = 103$) were studying at vocational universities, and 1.21% ($N = 16$) were studying at open universities. Demographic data are presented in Table 1.

B. MEASURES

The indicator construct used in the study was applied and developed from previous studies to make it reliable and accurate. However, some items were partly adjusted to suit the study characteristics of Thailand's context. In addition, there was a pilot test to check the understanding of the questionnaire, and the researcher adjusted the questionnaire along with additional suggestions from respondents until we received the completed questionnaire. This research was certified by the Human Research Ethics Office, Suranaree University of Technology. Indicator lists are shown in Table 2, including 4 dimensions of the factoring structure.

Achievement goal orientation: The scale was applied from Mamaril [92]. It consisted of 8 items for measuring

2 subscales: performance avoidance goals (4 items) and performance approach goals (4 items). A 5-point Likert scale was used to evaluate each item's score ranging from 1 (not at all true) to 5 (strongly agree).

Learning strategies: The scale was applied by Pintrich, *et al.* [93], Ribera, *et al.* [94], and Terenzini, *et al.* [95] to assess 2 subscales: collaborative learning (9 items) and self-effort regulation (2 items). It included 11 items measured on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree).

Digital skills: This scale was developed by the researcher based on previous research, the ABET framework, and measurements of engineering students' learning outcomes. It included 8 self-reported items scored on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree).

Engineering skill self-efficacy: The scale was developed by Mamaril's scale [92] to assess 3 subscales: engineering design self-efficacy (4 items), experimental skills self-efficacy (5 items), and tinkering skills self-efficacy (5 items). It included 14 items measured on a 5-point rating scale (1 = strongly disagree, 5 = strongly agree).

C. DATA ANALYSIS

SPSS 18 software was used to record data on participants' characteristics and to analyze descriptive statistics. Pearson correlation was used to explain relations between indicators. The internal consistency or reliability between several items was evaluated by Cronbach's alpha reliability coefficient. Analysis of structural equation modeling (SEM) was performed using Mplus 8.3 and estimated with the maximum likelihood method. Confirmatory factor analysis (CFA) was used to test the relation between observed variables and their latent variables. SEM is a tool used in multicausal testing at a given time in a theoretical structure, including manifest (observed variables) and latent variables (constructs). Moreover, it not only ensured model suitability in the overall image, but also could evaluate both direct and indirect impacts on the causal model [90].

The goodness-of-fit index of the model was specified according to the following criteria: the proportion of chi-square and degrees of freedom (χ^2/df), which should be less than 3 [96]; root mean square error of approximation (RMSEA), which should be less than 0.07 [97]; standardized root mean square residual (SRMR), which should be ≤ 0.08; Tucker–Lewis index (TLI), which should be > 0.95; and comparative fit index (CFI), which should be > 0.95 [98].

IV. RESULTS

A. DESCRIPTIVE ANALYSIS

The mean (M) and standard deviation (SD) for the indicators used for dimensions or subscales in the measurement models are shown in Table 2. Item P1 (It's important to me that I don't look stupid in my engineering class) of the performance avoidance goal subscale had the highest mean score ($M = 3.609$, $SD = 0.814$). The highest means of items for other subscales was as follows: for the performance approach goal subscale, P6 (I want to do well in this class to show my ability to my family, friends, advisors, or others – $M = 3.708$, $SD = 0.834$); for the collaborative learning subscale, L1 (I try to work on assigned subjects with my peers to finish assignments – $M = 4.036$, $SD = 0.702$); for the self-effort regulation subscale, L11 (Even though textbooks are not enjoyable and not interesting, I still read or learn to the end – $M = 3.708$, $SD = 0.673$); for the engineering design self-efficacy subscale, E4 (I firmly believe that I can recognize changes needed for an engineering design solution to work – $M = 3.723$, $SD = 0.720$); for the experimental skill self-efficacy subscale, E7 (I firmly believe that I can communicate the experimental results by speech – $M = 3.597$, $SD = 0.714$); for the tinkering skills self-efficacy subscale, E10 (I firmly believe that I can work with the machines – $M = 3.720$, $SD = 0.745$); for the digital skills subscale, DS8 (Have enthusiasm and desire to research and learn in advanced ICT to move forward to be the engineering professional that I specialize in – $M = 3.811$, $SD = 0.691$).

Investigation of the multivariate normal distribution of data, which is a key criterion for parameter estimation via the maximum likelihood method, can be considered in terms of skewness (SK), which must not exceed 3, and kurtosis (KU), which must not exceed 10 [96]. The results shown in Table 2 reveal that skewness was between −0.535 and 0.138, and kurtosis was between −0.326 and 0.869. This signified that all indicators were in the acceptable range. Brown [99] suggested that these kinds of data are normally distributed, so they are suitable for further analysis.

This study investigated the problem of multicollinearity with Pearson correlation analysis. The correlation matrix between 33 items in Table 2 had coefficients between items at −0.001 to 0.778. All indicators had coefficients less than 0.80, which meant that their relation was not high enough to have multicollinearity [90]. Therefore, all indicators were suitable for further analysis.

B. RELIABILITY AND VALIDITY OF THE MEASURES

Cronbach's alpha (α) of each subscale and construct are presented in Tables 2. Their values were between 0.506 – 0.923, which exceeded 0.50 according to the advice of Streiner and Norman [100], signifying that there was internal consistency of a tool to measure the convergent validity of the measurement model. This was confirmed by construct reliability (CR), where all construct values were between 0.843 – 0.949 (Table 3), whereas the general standard of CR should exceed 0.6 [90]. Such a construct tended to approach the standard, confirming the reliability of the tools in this study. Referring to the average variance extracted (AVE), which should exceed 0.5 [101], the AVE values were between 0.625 and 0.754 (Table 3), showing that the used tools have adequate construct validity. As mentioned above, CR was in accordance with all conditions. In conclusion, the data were accurate and suitable.

C. RESULTS OF CONFIRMATORY FACTOR ANALYSIS (CFA)

Tables 3 shows goodness of fit statistics for the four measurement models applied in this study. The results of CFA showed that the four tested constructs had a good fit to empirical data compared to information in the data analysis sub-section, implying that the observed variables (and 33 indicators) were reliable in their four latent constructs: achievement goal orientation, learning strategies, digital skills, and ENSE. The values of standardized loading of the 33 indicators were between 0.329 and 0.850, and all indicators had statistical significance ($p < 0.001$) (Table 2).

The results on the standardized factor loading of each model in Table 2 can be summarized as follows:

(1) achievement goal orientation, the scale comprises two subscales, namely performance avoidance goals and performance approach goals. The highest standardized loading for performance avoidance goals was P4 ($\lambda = 0.819$, $t = 61.280$), while the lowest factor loading was P1 ($\lambda = 0.660$, $t = 31.044$). For performance approach goals subscale, the highest loading was P5 ($\lambda = 0.765$, $t = 45.819$), while P6 had the lowest loading ($\lambda = 0.609$, $t = 28.551$). These results indicated that the item with the strongest association to the underlying achievement goal orientation latent construct was P4.

(2) learning strategies, the scale comprises two subscales, namely collaborative learning and self-effort regulation. The highest standardized loading for collaborative learning was L4 ($\lambda = 0.778$, $t = 48.000$), the lowest was L9 ($\lambda = 0.588$, $t = 26.520$). For self-effort regulation, the highest loading was L10 ($\lambda = 0.627$, $t = 17.335$), the lowest was L11 ($\lambda = 0.524$, $t = 15.597$). This means that the item with the strongest association to the underlying learning strategies latent construct was L4.

(3) digital skills, it was measured as unidimensional construct. The highest standardized loading was DS3 ($\lambda = 0.827$, t = 61.507), the lowest was DS8 ($\lambda = 0.329$, $t = 12.372$). This means that the item with the strongest association to the underlying digital skills latent construct was DS3.

(4) ENSE, the scale consists of three subscales, namely engineering design self-efficacy, experimental skill self-efficacy, and tinkering skills self-efficacy. The highest standardized loading for engineering design self-efficacy was E1 ($\lambda = 0.842$, $t = 70.446$), the lowest was E4 ($\lambda = 0.691$, $t = 31.615$). For experimental skill self-efficacy, E6 had the highest loading ($\lambda = 0.751$, $t = 44.480$), whereas E5 had the lowest ($\lambda = 0.697$, $t = 34.597$). For tinkering skills self-efficacy, the highest loading was E13 ($\lambda = 0.850$, $t = 74.898$), the lowest was E10 ($\lambda = 0.678$, $t = 38.643$). This means that the item with the strongest association to the underlying ENSE latent construct was E13.

As mentioned above and in Table 3, all items or measured variables could confirm and define the factor structure of each latent construct. Therefore, there was statistical evidence to gain specific confidence in such constructs.

D. HYPOTHESIS TESTING

The goodness-of-fit index for SEM of higher education students' ENSE was $\chi^2 = 182.910$, $df = 66$, $p < 0.001$, $\chi^2/df = 2.771$, RMSEA = 0.037, CFI = 0.986, TLI = 0.978, SRMR = 0.027 (see Fig. 1). These goodness-of-fit indicators signified that the results were suitable compared with the suggested statistics in the data analysis sub-section. These three predictor variables in the model explained 77.8% of the variance in ENSE ($R^2 = 0.778$). Therefore, it can be concluded that the SEM of higher education students' ENSE as a theoretical structure was a good fit to empirical data.

Achievement goal orientation was positively correlated with learning strategies, and ENSE had a statistically significant level at 0.001 ($\beta = 0.565$, $t = 15.815$, and $\beta = 0.188$, $t = 4.692$, respectively), supporting H1 and H3. Learning strategies positively contributed to digital skill and ENSE with a statistically significant level of 0.001 ($\beta = 0.621$, $t = 12.432$, and $\beta = 0.406$, $t = 6.853$, respectively), showing that H4 and H5 were supported. Similarly, ENSE was directly predicted by digital skill ($\beta = 0.444$, $t = 10.527$, $p < 0.001$), supporting H6. However, achievement goal orientation was positively correlated with digital skill with no significance ($\beta = 0.035$, $t = 0.070$), so it did not support H2. Achievement goal orientation was indirectly correlated with digital skills, and ENSE was statistically significant at the 0.001 level ($\beta = 0.351$, $t = 8.567$, and $\beta = 0.229$, $t = 5.800$, respectively), supporting H7 and H8.

E. MEASUREMENT MODEL IN SEM

Table 4 shows the results of four measurement models in SEM: the achievement goal orientation model, the learning strategies model, the digital skill model, and the ENSE model. These models comprised 15 indicators in total, where all indicators could confirm the factoring of each measurement model with statistical significance ($p < 0.001$); that is, the measurement model was valid and reliable. The standardized factor loading of each list was as follows:

Achievement goal orientation: The performance avoidance goals (ACH1) had the highest standardized factor loading ($\lambda = 0.779$, $t = 34.347$), whereas performance approach goals (ACH2) were 0.772 ($t = 34.073$).

Learning strategies: Collaborative learning (LS1) had the highest standardized CFA loading ($\lambda = 0.639$, $t = 24.473$), whereas self-effort regulation (LS2) was 0.612 ($t = 23.947$).

Digital skill: The value of each standardized factor loading was between 0.380 and 0.771. DS1, "Can design the working system, components, or engineering process according to the needs and requirements of the job," had the highest standardized factor loading ($\lambda = 0.771$, $t = 48.511$), followed by DS2, "Have the skills, knowledge, and competence in using modern techniques and tools in ICT for engineering practice" ($\lambda = 0.727$, $t = 43.970$); DS3, "Have skills in using the advanced computer and information technology to produce, design and develop engineering work" ($\lambda = 0.670$, $t = 35.594$); DS4, "Can interact with cutting-edge software

TABLE 2. Descriptive statistics and results of CFA for measurement models.

Constructs	Subscales and Items	Source	*M*	*SD*	*SK*	*KU*	Standardized Loading (λ)	*t*-value	R^2
Achievement goal orientation (α = 0.873)									
	Performance avoidance goals (ACH1, α = 0.842)								
	P1 It's important to me that I don't look stupid in my engineering class.	Mamaril [81]	3.609	0.814	-0.535	0.869	0.660	31.044**	0.435
	P2 One of my goals in my engineering class is to avoid looking like I have trouble doing the work.	Mamaril [81]	3.369	0.905	-0.441	0.266	0.739	46.882**	0.547
	P3 It's important to me that my instructor doesn't think that I know less than other students in my engineering class.	Mamaril [81]	3.397	0.861	-0.382	0.398	0.814	61.880**	0.663
	P4 One of my goals is to keep other engineering students from thinking I'm not smart in class.	Mamaril [81]	3.278	0.895	-0.403	0.261	0.819	61.280**	0.670
	Performance approach goals (ACH2, α = 0.817)								
	P5 My goal in this engineering class is to get a better grade than most of the other students.	Mamaril [81]	3.198	1.000	-0.291	-0.293	0.765	45.819**	0.585
	P6 I want to do well in this class to show my ability to my family, friends, advisors, or others.	Mamaril [81]	3.708	0.834	-0.451	0.493	0.609	28.551**	0.371
	P7 Getting a good grade in this class is the most important thing for me right now.	Mamaril [81]	3.387	0.948	-0.399	0.029	0.755	42.803**	0.571
	P8 My main concern in this class is getting a good grade.	Mamaril [81]	3.261	1.006	-0.378	-0.123	0.756	38.631**	0.571
Learning strategies (α = 0.880)									
	Collaborative learning (LS1, α = 0.891)								
	L1 I try to work on assigned subject with my peers to finish assignment.	Pintrich, et al. [82]	4.036	0.702	-0.433	0.436	0.601	29.627**	0.362
	L2 I have exchanged opinions with other peers regarding the studied subjects.	Ribera, et al. [83]	3.935	0.668	-0.262	0.207	0.638	33.526**	0.407
	L3 Teachers of the subject guide for learning method, and knowledge research rather than lecturing.	Terenzini, et al. [84]	3.910	0.679	-0.237	0.184	0.690	37.496**	0.476
	L4 Teachers of the subjects encourage students to listen to, evaluate, and exchange ideas with other students.	Terenzini, et al. [84]	3.899	0.677	-0.139	-0.204	0.778	48.000**	0.605
	L5 Learning-teaching of the subjects focuses on questioning and corresponding among student-student and/or student-teacher.	Ribera, et al. [83]	3.797	0.728	-0.201	0.002	0.736	45.779**	0.542
	L6 In classrooms, I am encouraged to express the concept of applying problem solving into each situation.	Terenzini, et al. [84]	3.688	0.726	-0.094	-0.069	0.681	33.267**	0.464
	L7 Whereas studying, I have chance to continuously practice essential and important skills in the major subjects.	Terenzini, et al. [84]	3.755	0.732	-0.316	0.357	0.676	34.086**	0.457
	L8 Teachers give details and information reflecting my study and performance results.	Terenzini, et al. [84]	3.776	0.709	-0.265	0.131	0.683	35.439**	0.466
	L9 I try to find classmates who I can ask for help on studying where necessary.	Pintrich, et al. [82]	3.847	0.721	-0.286	0.154	0.588	26.520**	0.346
	Self-effort regulation (LS2, α = 0.506)								
	L10 I work hard whereas studying in this field in order to get the best result.	Pintrich, et al. [82]	3.702	0.705	-0.003	-0.326	0.627	17.335**	0.393
	L11 Even though textbooks are not enjoying and not interesting, I still read or study to the end.	Pintrich, et al. [82]	3.708	0.673	0.051	-0.248	0.524	15.597**	0.275
Digital skills (DS, α = 0.852)									
	DS1 Can design the working system, components, or engineering process according to the needs and requirements of the job.	Researchers	3.503	0.697	-.004	-.078	0.697	41.523**	0.485
	DS2 Have the skills, knowledge, and competence in using modern techniques and tools in ICT for engineering practice.	Researchers	3.640	0.706	.107	-.370	0.762	52.452**	0.580
	DS3 Have skills in using the advanced computer and information technology to produce, design and develop engineering work.	Researchers	3.625	0.744	.033	-.202	0.827	61.507**	0.683
	DS4 Can interact with cutting-edge software interfaces such as human-machine interfaces, human-robot interaction, etc.	Researchers	3.390	0.763	.138	.008	0.721	39.417**	0.520
	DS5 Have the skills in applying digital technology (such as computers, PDAs, media players, GPS, etc.) to communicate and create professional engineering network properly.	Researchers	3.508	0.773	.051	-.183	0.731	44.028**	0.534
	DS6 Have knowledge and competence in using necessary and modern information technology media variously for targeted communication such as project/ report presentation, opinion expression, and motivation creation.	Researchers	3.658	0.699	.061	-.261	0.507	22.047**	0.257
	DS7 Can further the knowledge to enhance your skills and knowledge in ICT to create more opportunities to be more professional.	Researchers	3.752	0.683	-.027	-.288	0.427	17.310**	0.182
	DS8 Have enthusiasm and desire to research and learn in advanced ICT to move forward to be the engineering professional that I specialize in.	Researchers	3.811	0.691	-.161	-.052	0.329	12.372**	0.109
Engineering skill self-efficacy (α = 0.923)									
	Engineering Design Self-Efficacy (ENSE1, α = 0.877)								
	E1 I firmly believe that I can identify an engineering design need.	Mamaril [81]	3.371	0.809	-0.134	0.223	0.842	70.446**	0.710
	E2 I firmly believe that I can develop engineering design solutions.	Mamaril [81]	3.511	0.738	-0.218	0.450	0.777	54.477**	0.604
	E3 I firmly believe that I can evaluate an engineering design.	Mamaril [81]	3.510	0.738	-0.250	0.512	0.772	53.271**	0.595
	E4 I firmly believe that I can recognize changes needed for an engineering design solution to work.	Mamaril [81]	3.723	0.720	-0.277	0.364	0.691	31.615**	0.477
	Experimental Skills Self-Efficacy (ENSE2, α = 0.813)								
	E5 I firmly believe that I can perform experiments independently.	Mamaril [81]	3.237	0.877	-0.236	0.000	0.697	34.597**	0.485
	E6 I firmly believe that I can analyze data resulting from experiments.	Mamaril [81]	3.594	0.718	-0.370	0.534	0.751	44.480**	0.564
	E7 I firmly believe that I can communicate the experimental results by speech.	Mamaril [81]	3.597	0.714	-0.489	0.836	0.671	31.097**	0.450
	E8 I firmly believe I can communicate results of experiments in written form.	Mamaril [81]	3.587	0.685	-0.225	0.214	0.712	39.379**	0.506
	E9 I firmly believe that I can solve problems of engineering experiment by using computer.	Mamaril [81]	3.571	0.756	-0.119	-0.091	0.725	34.159**	0.525
	Tinkering Skills Self-Efficacy (ENSE3, α = 0.873)								
	E10 I firmly believe that I can work with the machines.	Mamaril [81]	3.720	0.745	-0.350	0.258	0.678	38.643**	0.460
	E11 I firmly believe that I can build the machines.	Mamaril [81]	3.252	0.901	-0.249	-0.024	0.794	68.310**	0.630
	E12 I firmly believe that I can manipulate engineering components and devices.	Mamaril [81]	3.517	0.767	-0.350	0.509	0.816	68.930**	0.665
	E13 I firmly believe that I can assemble advanced engineering equipment or things.	Mamaril [81]	3.297	0.875	-0.219	0.111	0.850	74.898**	0.723
	E14 I firmly believe that I can disassemble advanced engineering equipment or things.	Mamaril [81]	3.316	0.902	-0.254	-0.028	0.773	60.274**	0.598

Note: *M* = Mean, *SD* = Standard deviation, and ** significant at $p < 0.001$.

TABLE 3. Summary of psychometric properties and goodness-of-fit indices for the measurement models.

Constructs	Construct Reliability (CR)	Average Variance Extracted (AVE)	χ^2	*df*	χ^2/df	SRMR	RMSEA	*CFI*	TLI
Achievement goal orientation	0.907	0.740	27.685	13	2.130	0.010	0.029	0.997	0.993
Learning strategies	0.894	0.657	75.076	27	2.781	0.019	0.037	0.992	0.983
Digital skills	0.843	0.625	34.239	13	2.634	0.017	0.035	0.995	0.989
Engineering skill self-efficacy	0.949	0.754	154.982	53	2.924	0.024	0.038	0.990	0.983

TABLE 4. Para meter estimation of measurement model in SEM.

Constructs and Indicators	Standardized Loading (λ)	*t*-value	R^2
Achievement Goal Orientation			
ACH1	0.779	34.347**	0.606
ACH2	0.772	34.073**	0.596
Learning Strategies			
LS1	0.639	24.473**	0.408
LS2	0.612	23.947**	0.375
Digital skills			
DS1	0.771	48.511**	0.595
DS2	0.727	43.970**	0.529
DS3	0.670	35.594**	0.448
DS4	0.661	35.563**	0.436
DS5	0.657	34.402**	0.432
DS6	0.557	23.496**	0.310
DS7	0.484	19.940**	0.235
DS8	0.380	14.237**	0.145
Engineering skill self-efficacy			
ENSE1	0.779	49.317**	0.607
ENSE2	0.777	51.483**	0.604
ENSE3	0.774	48.027**	0.600

Note: ** significant at $p < 0.001$.

interfaces such as human-machine interfaces, human-robot interaction, etc.'' (λ = 0.661, *t* = 35.563); DS5, ''Have the skills in applying digital technology (such as computers, PDAs, media players, GPS, etc.) to communicate and create professional engineering network properly'' (λ = 0.657, *t* = 34.402); DS6, ''Have knowledge and competence in using necessary and modern information technology media variously for targeted communication such as project/report presentation, opinion expression, and motivation creation'' (λ = 0.557, *t* = 23.496); DS7, ''Can further the knowledge to enhance your skills and knowledge in ICT to create more opportunities to be more professional'' (λ = 0.484, *t* = 19.940); and DS8, ''Have enthusiasm and desire to research and learn in advanced ICT to move forward to be the engineering professional that I specialize in'' (λ = 0.380, *t* = 14.237).

ENSE: Engineering design self-efficacy (ENSE1) had the highest standardized factor loading (λ = 0.779, *t* = 49.317), followed by experimental skill self-efficacy (ENSE2) with a standardized factor loading of 0.777 (*t* = 51.483). The lowest was tinkering skills self-efficacy (ENSE3) (λ = 0.774, *t* = 48.027).

V. DISCUSSION

This research focused on creating ENSE among engineering students and considering factors affecting the development of digital skills and learning strategies. The research results found that all factors of this study (achievement goal orientation, learning strategies, and digital skill) are important to the behavioral building of ENSE for engineering students at higher education levels.

This finding indicated that ENSE depends on digital skill, learning strategies, and achievement goal orientation, which is rarely regarded in previous studies. The results of digital skill show that it is the most important variable, which means that the ENSE of engineering students is most reflected by digital skill. This often occurs when students have the knowledge and skills to apply advanced computers and ICTs and professional tools in engineering practice to different work situations. Digital skill is regarded as a supporting tool to provide learners with self-learning and development to obtain good chances of work and professional growth (learning and growth). This result is similar to that of Yang and Cheng [22], who found that students' IT skills predicted creative self-efficacy. Learning strategies play a key role in the development of ENSE for students. It is assumed that if we manage learning by integrating collaborative learning and self-effort regulation, learners will develop their self-ability to support more perceived self-efficacy and self-confidence, which is in accordance with the Ebru [57], Fernandez-Rio, *et al.* [102], and Tavakolizadeh and Ebrahimi-Qavam [103]. Another factor positively correlated with ENSE is when students have achievement goal orientation in the context of performance approach goals and performance avoidance goals, which affect behavioral control. Du, *et al.* [45] and Turner, *et al.* [46] found that achievement goals affect creative self-efficacy and speaking self-efficacy. Therefore, to develop students' ENSE, educational institutions or policy makers must plan for learning activity design to provide students with digital skills for further work operations. Students must have the knowledge, skills and ability to use specialized tools and ICT to produce and design working systems and to use digital technology (such as computers, PDAs, media players, GPS, etc.) for communication and creation of suitable engineering professional networks. We must also consider learning strategies that prepare learners for collaborative learning by specifying students' learning management, focusing on attempts to collaborate between students and teachers and to promote collaboration, information and skill sharing to pursue a group's

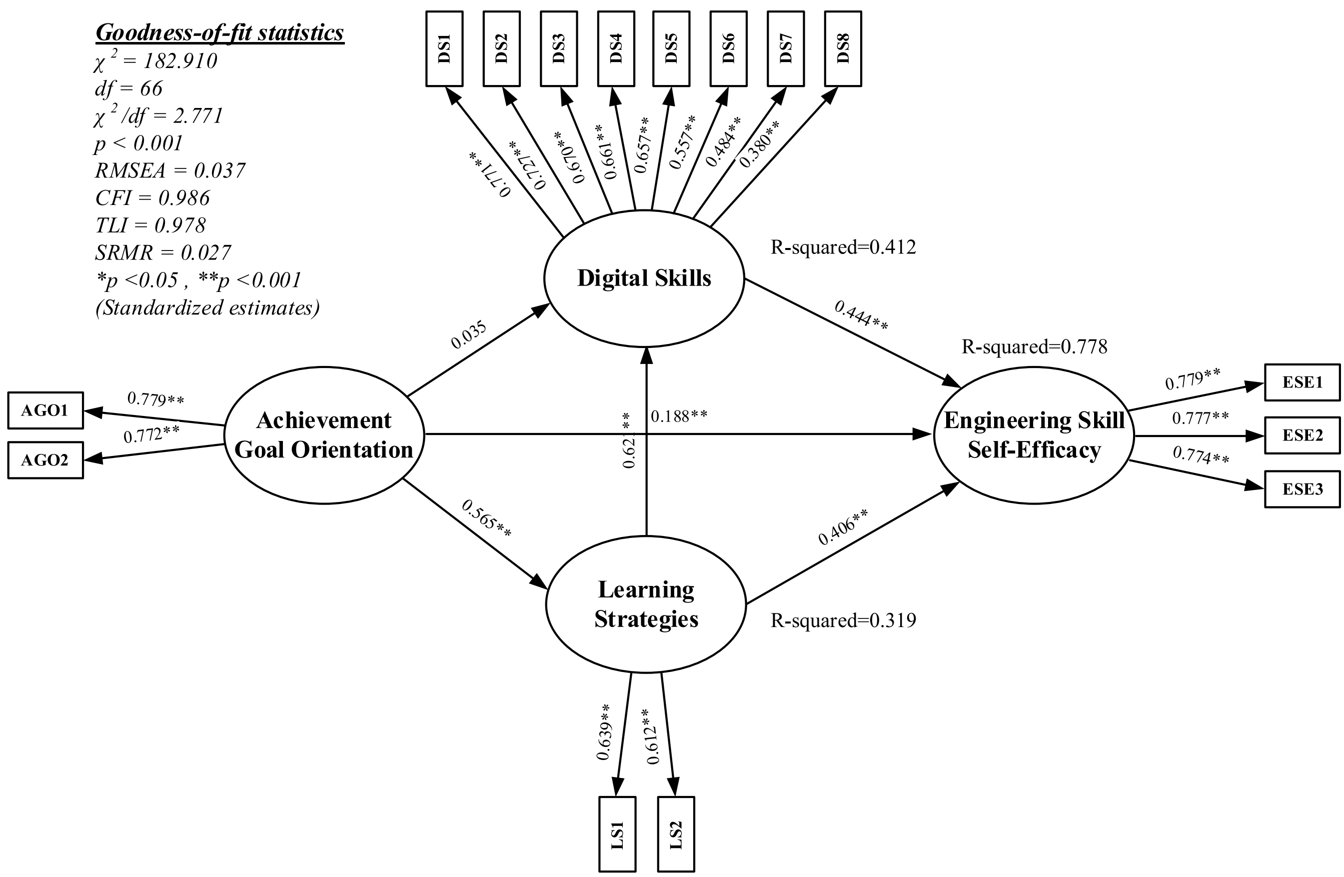

FIGURE 1. Results of SEM for testing the hypothetical mode.

TABLE 5. The results of structural model.

Hypothesis path	Standardized Estimate (β)	Standard error	*t*-value	Result
Direct Contribution				
H1: Achievement goal orientation → Learning strategies	0.565	0.036	15.815**	Supported
H2: Achievement goal orientation → Digital skills	0.035	0.050	0.707	Not Supported
H3: Achievement goal orientation → Engineering skill self-efficacy	0.188	0.040	4.692**	Supported
H4: Learning strategies → Digital skills	0.621	0.050	12.432**	Supported
H5: Learning strategies → Engineering skill self-efficacy	0.406	0.059	6.853**	Supported
H6: Digital skills → Engineering skill self-efficacy	0.444	0.042	10.527**	Supported
Indirect Contribution				
H7: Achievement goal orientation → Digital skills	0.351	0.041	8.567**	Supported
H8: Achievement goal orientation → Engineering skill self-efficacy	0.229	0.040	5.800**	Supported

Note: → = regression on, ** significant at $p < 0.001$.

learning goals. Students' self-effort regulation is the learning process in which students actively participate in self-learning management. Therefore, lecturers should apply a strategy of self-effort regulation by considering indicators of this study; e.g., train learners to have self-effort regulation in studying hard in this field to achieve the best result, and train learners to have self-effort regulation in completing tasks and educational goals even though the textbooks are not enjoyable and not interesting. Along achievement goal orientation, education institutions or teachers may organize class activities to create learners' goal orientation; i.e., according to this study context, achievement goal orientation is measured by indicators of performance avoidance goals and performance approach goals, whereas teachers can consider the priority of the factor with the highest factor loading. This study found that the factor of performance approach goals had the highest factor loading. Teachers must particularly prioritize this factor by organizing activities to create performance approach goals by considering indicators of CFA results (see Table 2). Thus, it is beneficial to learners' self-efficacy development to create learning and understanding based on what they have learned to achieve the goal orientation.

According to the SEM model, learning strategies were positively correlated with digital skills. This finding explains the structure relevant to the learning strategies factor, including collaborative learning and self-effort regulation, which are important techniques to develop digital skills in engineering students. Learning strategies are like a goal orientation tool that helps learners achieve more effective self-learning in accordance with Anthonysamy, *et al.* [19], who confirmed that self-regulated learning strategies can promote digital literacy of university students. Therefore, educators or policy-makers should plan to integrate students' learning management by focusing on collaborative learning and self-effort regulation to gain knowledge, skills and ability to use techniques and tools to develop engineering works. If we integrate both learning methods, it will provide learners with higher-quality education. Therefore, we can apply indicators of both factors (collaborative learning, self-effort regulation) from the CFA results (see Table 2).

The model results showed that learning strategies were predicted by achievement goal orientation, measured from performance approach goals and performance avoidance goals. Achievement goal orientation is a key variable for learners' learning strategies, leading to a higher level of success. Therefore, if students have an achievement goal orientation, they will seek learning methods and develop achievements or try to avoid failure to achieve goals, in accordance with previous results of Diseth [38], Fenollar, *et al.* [39], Liem, *et al.* [40], Phan [104], Barrera Verdugo [105], and Ramos, *et al.* [106]. Therefore, the method or operation of classrooms and educational institutions should offer performance approach goals and performance avoidance goals, which will help learners perceive that their classroom prioritizes the comparison of behavior or self-efficacy with others to further develop learners' efficacy.

This study also found that achievement goal orientation indirectly affected digital skill and ENSE through learning strategies as a mediator, which was consistent with Fenollar, *et al.* [39], Sins, *et al.* [47], Hampton, *et al.* [61], and Honicke, *et al.* [107]. This study indicates the key role of collaborative learning and self-effort regulation in higher education students' learning context as components of learning strategies. This study helps promote the capacity of achievement goal orientation toward support for students' digital skills and ENSE. The indirect positive contributions of achievement goal orientation are evidence for further research investigating the mediating mechanisms of learning strategies.

However, the study also found that achievement goal orientation cannot confirm a direct statistically significant correlation with digital skill. This may be because the participants of this study were mostly junior and senior students who were about to graduate and prepare for job training, and they might have been mainly focused on school record goals, achieving a good grade as presenting self-efficacy, etc.

VI. CONCLUSION

The nonstop technological changes caused by globalization and digital transformation, along with the current state of institutions of higher education, necessitate the continuous development of learning-teaching in accordance with the labor market of the digital era and force educational institutions to adjust to prepare students for the working world in response to such situations. Developing ENSE to promote work operations has become a key point in academia. Therefore, this study aims to investigate the correlation among the achievement goal orientation, learning strategies, digital skills, and ENSE of engineering students in the Thai universities. This study generates support and an in-depth understanding of the educational structure, emphasizing the development of ENSE among university students to achieve educational sustainability during this era of disruption. Statistical results revealed that ENSE was positively predicted by digital skill, learning strategies, and achievement goal orientation. The greatest direct contribution was between learning strategies and digital skills, followed by achievement goal orientation and learning strategies; digital skill and ENSE; learning strategies and ENSE; and achievement goal orientation and ENSE, respectively. The research results also found that achievement goal orientation indirectly predicted digital skill and ENSE through a mediator of learning strategies.

The research outcomes might benefit educators toward developing specifications on learning activity design to promote students' ENSE, including preparing students to be part of the digital future, possess the digital skills to apply for further work operations, and know how to integrate digital technology knowledge to benefit lifetime education.

VII. LIMITATIONS AND FUTURE RESEARCH

This study investigates the correlation among different factors and the concept of ENSE. However, we have considered only a research sample of engineering students, which is regarded as a limitation of this study. To further develop the model, we should consider a sample of students in fields other than engineering. We may also test a sample of business sectors by conducting in-depth study or focus groups among education institutions, students, and business entrepreneurs to seek a method to develop educational institutions' learning-teaching.

DISCLOSURE STATEMENT

The author declares no potential conflicts of interest with respect to the publication of this paper.

REFERENCES

[1] S.-N. Theerasak and B. Khampirat, "Comparing employability skills of technical and vocational education students of Thailand and Malaysia: A case study of international industrial work-integrated learning," *J. Tech. Educ. Training*, vol. 11, no. 3, pp. 94–110, Sep. 2019, doi: 10.30880/jtet.2019.11.03.012.

[2] J. R. Bryson, R. A. Mulhall, N. Lowe, and J. Stern, ''Engineering and the skills crisis in the U.K. and USA: A comparative analysis of employer-engaged education,'' in *Value Creation Through Engineering Excellence*, Z. Y. and G. M. Eds. Cham, Switzerland: Palgrave Macmillan, 2018, pp. 327–349.

[3] B. Khampirat, C. Pop, and S. Bandaranaike, ''The effectiveness of work-integrated learning in developing student work skills: A case study of Thailand,'' *Int. J. Work-Integr. Learn.*, vol. 20, no. 2, pp. 127–146, 2019.

[4] O. Doherty and S. Stephens, ''The skill needs of the manufacturing industry: Can higher education keep up?'' *Educ. Training*, vol. 63, no. 4, pp. 632–646, May 2021, doi: 10.1108/ET-05-2020-0134.

[5] A. N. Azmi, Y. Kamin, M. K. Noordin, and A. N. M. Nasir, ''Towards industrial revolution 4.0: Employers' expectations on fresh engineering graduates,'' *Int. J. Eng. Technol.*, vol. 7, pp. 267–272, 2018, doi: 10.14419/ijet.v7i4.28.22593.

[6] D. McGunagle and L. Zizka, ''Employability skills for 21st-century STEM students: The employers' perspective,'' *Higher Educ., Skills Work-Based Learn.*, vol. 10, no. 3, pp. 591–606, Apr. 2020, doi: 10.1108/HESWBL-10-2019-0148.

[7] P. Lewis, ''Developing technician skills for innovative industries: Theory, evidence from the U.K. Life sciences industry, and policy implications,'' *Brit. J. Ind. Relations*, vol. 58, no. 3, pp. 617–643, Sep. 2020, doi: 10.1111/bjir.12532.

[8] A. Padwick, C. Davenport, R. Strachan, J. Shimwell, and M. Horan, ''Tackling the digital and engineering skills shortage: Understanding young people and their career aspirations,'' in *Proc. IEEE Frontiers Educ. Conf. (FIE)*, Oct. 2020, pp. 1–8, doi: 10.1109/FIE44824.2020.9274242.

[9] (2020). NESDC. *Social Situation and Outlook 2020*. Office of the National Economic and Social Development Council. Bangkok, Thailand. [Online]. Available: https://www.nesdc.go.th/ewt_news.php?nid=10291

[10] M. Curtarelli, V. Gualtieri, M. S. Jannati, and V. Donlevy. (2016). *ICT for Work: Digital Skills in the Workplace*. European Commission. Luxembourg, Belgium. [Online]. Available: https://digital-strategy.ec.europa.eu/en/library/ict-work-digital-skills-workplace

[11] P. Bejaković and Ž. Mrnjavac, ''The importance of digital literacy on the labour market,'' *Employee Relations, Int. J.*, vol. 42, no. 4, pp. 921–932, Apr. 2020, doi: 10.1108/ER-07-2019-0274.

[12] NESDC. (2019). *Report of the Population Projections for Thailand 2010–2040*. Office of the National Economic and Social Development Council. Bangkok. [Online]. Available: https://social.nesdc.go.th/social/Default.aspx?tabid=70

[13] V. López Simó, D. Couso Lagarón, and C. Simarro Rodríguez, ''Educación STEM en y para el mundo digital: STEM education in and for the digital world,'' (in Spanish), *Revista Educación Distancia*, vol. 20, no. 62, p. 29, Mar. 2020, doi: 10.6018/red.410011.

[14] F. D. Guillén-Gámez, M. J. Mayorga-Fernández, and J. A. Contreras-Rosado, ''Incidence of gender in the digital competence of higher education teachers in research work: Analysis with descriptive and comparative methods,'' *Educ. Sci.*, vol. 11, no. 3, p. 98, Mar. 2021, doi: 10.3390/educsci11030098.

[15] M. Henderson, N. Selwyn, and R. Aston, ''What works and why? Student perceptions of 'useful' digital technology in university teaching and learning,'' *Stud. Higher Educ.*, vol. 42, no. 8, pp. 1567–1579, Aug. 2017, doi: 10.1080/03075079.2015.1007946.

[16] I. Arpaci, ''A hybrid modeling approach for predicting the educational use of mobile cloud computing services in higher education,'' *Comput. Hum. Behav.*, vol. 90, pp. 181–187, Jan. 2019, doi: 10.1016/j.chb.2018.09.005.

[17] H. Kim, A. Hong, and H.-D. Song, ''The relationships of family, perceived digital competence and attitude, and learning agility in sustainable Student engagement in higher education,'' *Sustainability*, vol. 10, no. 12, p. 4635, Dec. 2018, doi: 10.3390/su10124635.

[18] K. Tuamsuk and M. Subramaniam, ''The current state and influential factors in the development of digital literacy in Thailand's higher education,'' *Inf. Learn. Sci.*, vol. 118, no. 5/6, pp. 235–251, May 2017, doi: 10.1108/ILS-11-2016-0076.

[19] L. Anthonysamy, A. C. Koo, and S. H. Hew, ''Self-regulated learning strategies in higher education: Fostering digital literacy for sustainable lifelong learning,'' *Educ. Inf. Technol.*, vol. 25, no. 4, pp. 2393–2414, Jul. 2020, doi: 10.1007/s10639-020-10201-8.

[20] O. E. Hatlevik and K.-A. Christophersen, ''Digital competence at the beginning of upper secondary school: Identifying factors explaining digital inclusion,'' *Comput. Educ.*, vol. 63, pp. 240–247, Apr. 2013, doi: 10.1016/j.compedu.2012.11.015.

[21] O. E. Hatlevik, G. B. Guòmundsdóttir, and M. Loi, ''Examining factors predicting Students' digital competence,'' *J. Inf. Technol. Educ. Res.*, vol. 14, pp. 123–137, 2015.

[22] H.-L. Yang and H.-H. Cheng, ''Creative self-efficacy and its factors: An empirical study of information system analysts and programmers,'' *Comput. Hum. Behav.*, vol. 25, no. 2, pp. 429–438, Mar. 2009, doi: 10.1016/j.chb.2008.10.005.

[23] A. Bandura, *Social Foundations of Thought and Action: A Social Cognitive Theory*. Englewood Cliffs, NJ, USA: Prentice-Hall, 1986, p. 617.

[24] A. Bandura, *Self-Efficacy: The Exercise of Control*. New York, NY, USA: W.H. Freeman, 1997, p. 606.

[25] A. Audibert, D. A. Vieira, A. L. De Andrade, and M. Z. de Oliveira, ''Transversal and professional skills self-efficacy scale: Cultural adaptation and evidence of validity,'' *Trends Psychol.*, vol. 28, no. 3, pp. 368–380, Sep. 2020, doi: 10.1007/s43076-020-00030-6.

[26] B. Khampirat, ''The impact of work-integrated learning and learning strategies on engineering Students' learning outcomes in thailand: A multiple mediation model of learning experiences and psychological factors,'' *IEEE Access*, vol. 9, pp. 111390–111406, 2021, doi: 10.1109/ACCESS.2021.3055620.

[27] S. C. Ukwoma, N. E. Iwundu, and I. E. Iwundu, ''Digital literacy skills possessed by students of UNN, implications for effective learning and performance,'' *New Library World*, vol. 117, no. 11/12, pp. 702–720, Nov. 2016, doi: 10.1108/NLW-08-2016-0061.

[28] C. Ames, ''Classrooms: Goals, structures, and student motivation,'' *J. Educ. Psychol.*, vol. 84, no. 3, pp. 261–271, 1992, doi: 10.1037/0022-0663.84.3.261.

[29] C. S. Dweck and E. L. Leggett, ''A social-cognitive approach to motivation and personality,'' *Psychol. Rev.*, vol. 95, no. 2, pp. 256–273, 1988, doi: 10.1037/0033-295X.95.2.256.

[30] J. Kunchai, D. Chonsalasin, and B. Khampirat, ''Psychometric properties and a multiple indicators multiple cause model of the career aspiration scale with college students of rural Thailand,'' *Sustainability*, vol. 13, no. 18, p. 10377, Sep. 2021, doi: 10.3390/su131810377.

[31] A. J. Elliot, ''Approach and avoidance motivation and achievement goals,'' *Educ. Psychol.*, vol. 34, no. 3, pp. 169–189, Jun. 1999, doi: 10.1207/s15326985ep3403_3.

[32] A. J. Elliot, ''A conceptual history of the achievement goal construct,'' in *Handbook of Competence and Motivation*, A. J. Elliot and C. S. Dweck, Eds. New York, NY, USA: The Guilford Press, 2005, pp. 52–72.

[33] J. G. Nicholls, ''Achievement motivation: Conceptions of ability, subjective experience, task choice, and performance,'' *Psychol. Rev.*, vol. 91, no. 3, pp. 328–346, 1984, doi: 10.1037/0033-295X.91.3.328.

[34] S. Hwang, M. Machida, and Y. Choi, ''The effect of peer interaction on sport confidence and achievement goal orientation in youth sport,'' *Social Behav. Personality, Int. J.*, vol. 45, no. 6, pp. 1007–1018, Jul. 2017, doi: 10.2224/sbp.6149.

[35] A. L. Miller, K. T. Fassett, and D. L. Palmer, ''Achievement goal orientation: A predictor of Student engagement in higher education,'' *Motivat. Emotion*, vol. 45, no. 3, pp. 327–344, Jun. 2021, doi: 10.1007/s11031-021-09881-7.

[36] A. J. Elliot and M. A. Church, ''A hierarchical model of approach and avoidance achievement motivation,'' *J. Personality Social Psychol.*, vol. 72, no. 1, pp. 218–232, 1997.

[37] M. Crouzevialle and F. Butera, ''Performance-approach goals deplete working memory and impair cognitive performance,'' *J. Experim. Psychol., Gen.*, vol. 142, no. 3, pp. 666–678, 2013, doi: 10.1037/a0029632.

[38] Å. Diseth, ''Self-efficacy, goal orientations and learning strategies as mediators between preceding and subsequent academic achievement,'' *Learn. Individual Differences*, vol. 21, no. 2, pp. 191–195, Apr. 2011, doi: 10.1016/j.lindif.2011.01.003.

[39] P. Fenollar, S. Román, and P. J. Cuestas, ''University students' academic performance: An integrative conceptual framework and empirical analysis,'' *Brit. J. Educ. Psychol.*, vol. 77, no. 4, pp. 873–891, Dec. 2007, doi: 10.1348/000709907x189118.

[40] A. D. Liem, S. Lau, and Y. Nie, ''The role of self-efficacy, task value, and achievement goals in predicting learning strategies, task disengagement, peer relationship, and achievement outcome,'' *Contemp. Educ. Psychol.*, vol. 33, no. 4, pp. 486–512, Oct. 2008, doi: 10.1016/j.cedpsych.2007.08.001.

[41] H. P. Phan, ''Unifying different theories of learning: Theoretical framework and empirical evidence,'' *Educ. Psychol.*, vol. 28, no. 3, pp. 325–340, May 2008, doi: 10.1080/01443410701591392.

[42] M. Guo and F. K. S. Leung, "Achievement goal orientations, learning strategies, and mathematics achievement: A comparison of Chinese miao and han students," *Psychol. Schools*, vol. 58, no. 1, pp. 107–123, Jan. 2021, doi: 10.1002/pits.22424.

[43] J. Y. Lim and K. Y. Lim, "Co-regulation in collaborative learning: Grounded in achievement goal theory," *Int. J. Educ. Res.*, vol. 103, 2020, Art. no. 101621, doi: 10.1016/j.ijer.2020.101621.

[44] O. E. Hatlevik, "Examining 'digital divide' in upper secondary school: A multilevel analysis of factors with an influence on digital competence," *Int. J. Technol., Knowl., Soc.*, vol. 6, no. 3, pp. 151–164, 2010.

[45] K. Du, Y. Wang, X. Ma, Z. Luo, L. Wang, and B. Shi, "Achievement goals and creativity: The mediating role of creative self-efficacy," *Educ. Psychol.*, vol. 40, no. 10, pp. 1249–1269, Nov. 2020, doi: 10.1080/01443410.2020.1806210.

[46] J. E. Turner, B. Li, and M. Wei, "Exploring effects of culture on students' achievement motives and goals, self-efficacy, and willingness for public performances: The case of Chinese students' speaking English in class," *Learn. Individual Differences*, vol. 85, Jan. 2021, Art. no. 101943, doi: 10.1016/j.lindif.2020.101943.

[47] P. H. M. Sins, W. R. van Joolingen, E. R. Savelsbergh, and B. van Hout-Wolters, "Motivation and performance within a collaborative computer-based modeling task: Relations between students' achievement goal orientation, self-efficacy, cognitive processing, and achievement," *Contemp. Educ. Psychol.*, vol. 33, no. 1, pp. 58–77, Jan. 2008, doi: 10.1016/j.cedpsych.2006.12.004.

[48] M. Leenknecht, P. Hompus, and M. van der Schaaf, "Feedback seeking behaviour in higher education: The association with students' goal orientation and deep learning approach," *Assessment Eval. Higher Educ.*, vol. 44, no. 7, pp. 1069–1078, Oct. 2019, doi: 10.1080/02602938.2019.1571161.

[49] W. M. Alenazy, W. M. Al-Rahmi, and M. S. Khan, "Validation of TAM model on social media use for collaborative learning to enhance collaborative authoring," *IEEE Access*, vol. 7, pp. 71550–71562, 2019, doi: 10.1109/ACCESS.2019.2920242.

[50] J. A. C. Hattie and G. M. Donoghue, "Learning strategies: A synthesis and conceptual model," *npj Sci. Learn.*, vol. 1, no. 1, p. 16013, Dec. 2016, doi: 10.1038/npjscilearn.2016.13.

[51] F. Biwer, M. G. A. O. Egbrink, P. Aalten, and A. B. H. de Bruin, "Fostering effective learning strategies in higher education—A mixed-methods study," *J. Appl. Res. Memory Cognition*, vol. 9, no. 2, pp. 186–203, Jun. 2020, doi: 10.1016/j.jarmac.2020.03.004.

[52] M. G. Baltaoglu and M. Güven, "Relationship between self-efficacy, learning strategies, and learning styles of teacher candidates (Anadolu university example)," *South Afr. J. Educ.*, vol. 39, no. 2, pp. 1–11, May 2019, doi: 10.15700/saje.v39n2a1579.

[53] B. L. McCombs, "Historical review of learning strategies research: Strategies for the whole learner—A tribute to claire ellen weinstein and early researchers of this topic," (in English), *Frontiers Educ.*, vol. 2, p. 6, Apr. 2017, doi: 10.3389/feduc.2017.00006.

[54] A. A. Hardan, "Language learning strategies: A general overview," *Proc. Social Behav. Sci.*, vol. 106, pp. 1712–1726, Dec. 2013.

[55] B. J. Zimmerman, "Theories of self-regulated learning and academic achievement: An overview and analysis," in *Self-Regulated Learning and Academic Achievement: Theoretical Perspectives*, B. J. Zimmerman and D. H. Schunk, Eds., New York, NY, USA: Routledge, 2001, pp. 1–38.

[56] J. T. Nigg, "Annual research review: On the relations among self-regulation, self-control, executive functioning, effortful control, cognitive control, impulsivity, risk-taking, and inhibition for developmental psychopathology," *J. Child Psychol. Psychiatry*, vol. 58, no. 4, pp. 361–383, Apr. 2017, doi: 10.1111/jcpp.12675.

[57] E. Kiliç-Çakmak, "Learning strategies and motivational factors predicting information literacy self-efficacy of e-learners," *Australas. J. Educ. Technol.*, vol. 26, no. 2, pp. 192–208, Apr. 2010, doi: 10.14742/ajet.1090.

[58] H. N. J. Ho, J.-C. Liang, and C.-C. Tsai, "The interrelationship among high school students' conceptions of learning science, self-regulated learning science, and science learning self-efficacy," *Int. J. Sci. Math. Educ.*, Aug. 2021, doi: 10.1007/s10763-021-10205-x.

[59] J. Roick and T. Ringeisen, "Students' math performance in higher education: Examining the role of self-regulated learning and self-efficacy," *Learn. Individual Differences*, vol. 65, pp. 148–158, Jul. 2018, doi: 10.1016/j.lindif.2018.05.018.

[60] E. van Laar, A. J. A. M. van Deursen, J. A. G. M. van Dijk, and J. de Haan, "Determinants of 21st-century digital skills: A large-scale survey among working professionals," *Comput. Hum. Behav.*, vol. 100, pp. 93–104, Nov. 2019, doi: 10.1016/j.chb.2019.06.017.

[61] K. N. Hampton, C. T. Robertson, L. Fernandez, I. Shin, and J. M. Bauer, "How variation in internet access, digital skills, and media use are related to rural Student outcomes: GPA, SAT, and educational aspirations," *Telematics Informat.*, vol. 63, Oct. 2021, Art. no. 101666, doi: 10.1016/j.tele.2021.101666.

[62] X. Li and R. Hu, "Developing and validating the digital skills scale for school children (DSS-SC)," *Inf., Commun. Soc.*, pp. 1–18, Dec. 2020, doi: 10.1080/1369118X.2020.1864002.

[63] R. Hartshorne, G. Miller, and J. Gretes, "Examining student perceptions of technology skills before and after an introductory educational technology course: A three-year case study," *Int. J. Technol. Learn.*, vol. 5, no. 1, pp. 37–48, 2009.

[64] H. King, C. L. Miller, and J. Bayerl, "Building technology competency: An evidence-based approach to improving Student technology skills," *J. Formative Design Learn.*, vol. 1, no. 1, pp. 45–55, Jun. 2017, doi: 10.1007/s41686-017-0001-5.

[65] A. Monteiro and C. Leite, "Digital literacies in higher education: Skills, uses, opportunities and obstacles to digital transformation," *Revista de Educación a Distancia (RED)*, vol. 21, no. 65, Jan. 2021, doi: 10.6018/red.438721.

[66] Ş. M. Pala and A. Başıbüyük, "The predictive effect of digital literacy, self-control and motivation on the academic achievement in the science, technology and society learning area," *Technol., Knowl. Learn.*, Jun. 2021, doi: 10.1007/s10758-021-09538-x.

[67] O. E. Hatlevik, G. B. Guòmundsdóttir, and M. Loi, "Digital diversity among upper secondary students: A multilevel analysis of the relationship between cultural capital, self-efficacy, strategic use of information and digital competence," *Comput. Educ.*, vol. 81, pp. 345–353, Feb. 2015, doi: 10.1016/j.compedu.2014.10.019.

[68] F. Pettersson, "On the issues of digital competence in educational contexts—A review of literature," *Educ. Inf. Technol.*, vol. 23, no. 3, pp. 1005–1021, May 2018, doi: 10.1007/s10639-017-9649-3.

[69] G. Greefrath, C. Hertleif, and H.-S. Siller, "Mathematical modelling with digital tools—A quantitative study on mathematising with dynamic geometry software," *ZDM*, vol. 50, nos. 1–2, pp. 233–244, Apr. 2018, doi: 10.1007/s11858-018-0924-6.

[70] J. C. González-Salamanca, O. L. Agudelo, and J. Salinas, "Key competences, education for sustainable development and strategies for the development of 21st century Skills. A systematic literature review," *Sustainability*, vol. 12, no. 24, p. 10366, Dec. 2020, doi: 10.3390/su122410366.

[71] E. van Laar, A. J. A. M. van Deursen, J. A. G. M. van Dijk, and J. de Haan, "Determinants of 21st-century skills and 21st-century digital skills for workers: A systematic literature review," *SAGE Open*, vol. 10, no. 1, Jan. 2020, Art. no. 215824401990017, doi: 10.1177/2158244019900176.

[72] V. Silber-Varod, Y. Eshet-Alkalai, and N. Geri, "Tracing research trends of 21st century learning skills," *Brit. J. Educ. Technol.*, vol. 50, no. 6, pp. 3099–3118, Nov. 2019, doi: 10.1111/bjet.12753.

[73] F. Karakoyun and O. J. Lindberg, "Preservice teachers' views about the twenty-first century skills: A qualitative survey study in Turkey and Sweden," *Educ. Inf. Technol.*, vol. 25, no. 4, pp. 2353–2369, Jul. 2020, doi: 10.1007/s10639-020-10148-w.

[74] S. M. Stehle and E. E. Peters-Burton, "Developing Student 21st century skills in selected exemplary inclusive STEM high schools," *Int. J. STEM Educ.*, vol. 6, no. 1, p. 39, Nov. 2019, doi: 10.1186/s40594-019-0192-1.

[75] F. Siddiq, O. E. Hatlevik, R. V. Olsen, I. Throndsen, and R. Scherer, "Taking a future perspective by learning from the past—A systematic review of assessment instruments that aim to measure primary and secondary school students' ICT literacy," *Educ. Res. Rev.*, vol. 19, pp. 58–84, Nov. 2016, doi: 10.1016/j.edurev.2016.05.002.

[76] H. S. Kim, S. H. Ahn, and C. M. Kim, "A new ICT literacy test for elementary and middle school students in republic of Korea," *Asia–Pacific Educ. Researcher*, vol. 28, no. 3, pp. 203–212, Jun. 2019, doi: 10.1007/s40299-018-0428-8.

[77] H. Lei, Y. Xiong, M. M. Chiu, J. Zhang, and Z. Cai, "The relationship between ICT literacy and academic achievement among students: A meta-analysis," *Children Youth Services Rev.*, vol. 127, Aug. 2021, Art. no. 106123, doi: 10.1016/j.childyouth.2021.106123.

[78] M.-T. Kaarakainen, O. Kivinen, and T. Vainio, "Performance-based testing for ICT skills assessing: A case study of students and teachers' ICT skills in Finnish schools," *Universal Access Inf. Soc.*, vol. 17, no. 2, pp. 349–360, Jun. 2018, doi: 10.1007/s10209-017-0553-9.
[79] UNESCO. (2018). *A Global Framework of Reference on Digital Literacy Skills for Indicator 4.4.2*. UNESCO Institute for Statistics. Montreal, QC, Canada. [Online]. Available: http://uis.unesco.org/sites/default/files/documents/ip51-global-framework-reference-digital-literacy-skills-2018-en.pdf
[80] G. Falloon, "From digital literacy to digital competence: The teacher digital competency (TDC) framework," *Educ. Technol. Res. Develop.*, vol. 68, no. 5, pp. 2449–2472, Oct. 2020, doi: 10.1007/s11423-020-09767-4.
[81] F. Fanni, I. Rega, and L. Cantoni, "Using self-efficacy to measure primary school teachers' perception of ICT: Results from two studies," *Int. J. Educ. Dev. Using Inf. Commun. Technol.*, vol. 9, no. 1, pp. 100–111, 2013.
[82] A. Rohatgi, R. Scherer, and O. E. Hatlevik, "The role of ICT self-efficacy for students' ICT use and their achievement in a computer and information literacy test," *Comput. Educ.*, vol. 102, pp. 103–116, Nov. 2016, doi: 10.1016/j.compedu.2016.08.001.
[83] G. Argentin, M. Gui, L. Pagani, and L. Stanca, "The impact of digital skills on educational outcomes: Evidence from performance tests," *Educ. Stud.*, vol. 42, pp. 1–26, Mar. 2016, doi: 10.1080/03055698.2016.1148588.
[84] A. Bandura, *Self-Efficacy in Changing Societies*. Cambridge, U.K.: Cambridge Univ. Press, 1995.
[85] N. A. Mamaril, E. L. Usher, C. R. Li, D. R. Economy, and M. S. Kennedy, "Measuring undergraduate students' engineering self-efficacy: A validation study," *J. Eng. Educ.*, vol. 105, no. 2, pp. 366–395, Apr. 2016, doi: 10.1002/jee.20121.
[86] T. Honicke and J. Broadbent, "The influence of academic self-efficacy on academic performance: A systematic review," *Educ. Res. Rev.*, vol. 17, pp. 63–84, Feb. 2016, doi: 10.1016/j.edurev.2015.11.002.
[87] J. G. Martinez and A. R. Medina, "Approaches to learning self-regulation and self-efficacy and their influence on academic performance in university students," *Eur. J. Investig. Health Psychol. Educ.*, vol. 9, no. 2, pp. 95–107, 2019, doi: 10.30552/ejihpe.v9i2.323.
[88] M. Schneider and F. Preckel, "Variables associated with achievement in higher education: A systematic review of meta-analyses," *Psychol. Bull.*, vol. 143, no. 6, pp. 565–600, 2017, doi: 10.1037/bul0000098.
[89] M. C. W. Yip, "The linkage among academic performance, learning strategies and self-efficacy of Japanese university students: A mixed-method approach," *Stud. High. Educ.*, vol. 46, no. 8, pp. 1–13, 2019, doi: 10.1080/03075079.2019.1695111.
[90] J. F. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, *Multivariate Data Analysis: A Global Perspective*, 7th ed. Upper Saddle River, NJ, USA: Pearson, 2014.
[91] W. G. Cochran, *Sampling Techniques*, 3rd ed. New York, NY, USA: Wiley, 1977.
[92] N. J. A. Mamaril, "Measuring undergraduate students' engineering self-efficacy: A scale validation study," Ph.D. dissertation, Dept. Educ., School, Counseling Psychol., Univ. Ky., Lexington, KY, USA, 2014.
[93] P. R. Pintrich, D. A. F. Smith, T. Garcia, and W. J. McKeachie, "A manual for the use of the motivated strategies for learning questionnaire (MSLQ)," Nation Center Res. Improve Postsecondary Teaching Learn., Ann Arbor, MI, USA, Tech. Rep. NCRIPTAL-91-B-004, 1991.
[94] T. Ribera, A. K. Ribera, A. BrckaLorenz, and T. N. Laird, "Faculty fostering collaborative learning and personal and social responsibility," presented at the Assoc. Inst. Res. Annu. Forum, New Orleans, LA, USA, Jun. 2012.
[95] P. T. Terenzini, A. F. Cabrera, C. L. Colbeck, J. M. Parente, and S. A. Bjorklund, "Collaborative learning vs. lecture/discussion: Students' reported learning gains," *J. Eng. Educ.*, vol. 90, no. 1, pp. 123–130, Jan. 2001.
[96] R. B. Kline, *Principles and Practice of Structural Equation Modeling*, 3rd ed. New York, NY, USA: The Guilford Press, 2011.
[97] J. H. Steiger, "Understanding the limitations of global fit assessment in structural equation modeling," *Personality Individual Differences*, vol. 42, no. 5, pp. 893–898, May 2007, doi: 10.1016/j.paid.2006.09.017.
[98] L. T. Hu and P. M. Bentler, "Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives," *Struct. Equ. Model.*, vol. 6, no. 1, pp. 1–55, 1999, doi: 10.1080/10705519909540118.
[99] T. A. Brown, *Confirmatory Factor Analysis for Applied Research*. New York, NY, USA: The Guilford Press, 2006.
[100] D. L. Streiner and G. R. Norman, *Health Measurement Scales: A Practical Guide to Their Development and Use*, 3rd ed. Oxford, U.K.: Oxford Univ. Press, 2003.
[101] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *J. Marketing Res.*, vol. 18, no. 1, pp. 39–50, Feb. 1981, doi: 10.1177/002224378101800104.
[102] J. Fernandez-Rio, J. A. Cecchini, A. Méndez-Gimenez, D. Mendez-Alonso, and J. A. Prieto, "Self-regulation, cooperative learning, and academic self-efficacy: Interactions to prevent school failure," *Frontiers Psychol.*, vol. 8, Jan. 2017, doi: 10.3389/fpsyg.2017.00022.
[103] J. Tavakolizadeh and S. Ebrahimi-Qavam, "Effect of teaching of self-regulated learning strategies on self-efficacy in students," *Proc. Social Behav. Sci.*, vol. 29, pp. 1096–1104, Jan. 2011, doi: 10.1016/j.sbspro.2011.11.343.
[104] H. P. Phan, "Relations between goals, self-efficacy, critical thinking and deep processing strategies: A path analysis," *Educ. Psychol.*, vol. 29, no. 7, pp. 777–799, Dec. 2009, doi: 10.1080/01443410903289423.
[105] G. B. Verdugo, "Relationship between innovation and sustainability in latin American countries: Differences by perceptual characteristics of early-stage entrepreneurs," *Cogent Bus. Manage.*, vol. 7, no. 1, Jan. 2020, Art. no. 1831766, doi: 10.1080/23311975.2020.1831766.
[106] A. Ramos, B. De Fraine, and K. Verschueren, "Learning goal orientation in high-ability and average-ability students: Developmental trajectories, contextual predictors, and long-term educational outcomes," *J. Educ. Psychol.*, vol. 113, no. 2, pp. 370–389, Feb. 2021, doi: 10.1037/edu0000476.
[107] T. Honicke, J. Broadbent, and M. Fuller-Tyszkiewicz, "Learner self-efficacy, goal orientation, and academic achievement: Exploring mediating and moderating relationships," *Higher Educ. Res. Develop.*, vol. 39, no. 4, pp. 689–703, Jun. 2020, doi: 10.1080/07294360.2019.1685941.

DISSAKOON CHONSALASIN received the B.E. and M.E. degrees in transportation engineering, in 2013 and 2015, respectively, and the Ph.D. degree in civil, transportation and geo-resources engineering from the Suranaree University of Technology, Nakhon Ratchasima, Thailand, in 2020. He is currently a Researcher with the Institute of Research and Development, Suranaree University of Technology. His research interests include public transport (air, rail, and bus transportation), safety research, and career and student development.

BURATIN KHAMPIRAT received the B.Ed., M.Ed., and Ph.D. degrees from Chulalongkorn University, Thailand. She was a Visiting Professor with the Universidad Nacional de Educación a Distancia (UNED), in 2019. She is currently an Associate Professor in educational research with the Suranaree University of Technology, Thailand. Her research interests include the assessment of efficiency and effectiveness in HEIs, employability, career and student development, and assessment of competencies using SEM and multilevel modeling. She received a number of national and international awards/honors, most notably the best refereed research paper award from WACE, in 2017 and 2018. She is also a Co-Convenor of the European Educational Research Association (EERA) in Network 11-Educational Effectiveness and Quality Assurance.