Influences of depression, self-efficacy, and resource management on learning engagement in blended learning during COVID-19

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A B S T R A C T

This study examined the structural relationships among self-efficacy, resource management, and learning engagement during the COVID-19 era based on self-regulation theory. We also investigated whether the level of depression moderates the structural relationships among the factors by comparing a non-depressed group and a moderate-to-high depressed group. This study confirmed that resource management influenced learning engagement regardless of the depression level. Self-efficacy for learning also influenced resource management. The implications of this study are that self-efficacy is a prerequisite for resource management for learning. However, the direct influences of self-efficacy on learning engagement were observed only in the non-depressed group. Self-efficacy for learning indirectly influenced learning engagement through resource management in the depressed group. The self-regulated behaviors, such as resource management should be encouraged to enhance learning engagement of depressed students. Students' depression should also be monitored on a regular basis to help improve learning engagement during as well as after the COVID-19 era.

1. Introduction

The world has experienced the consequences of the COVID-19 pandemic since early 2020. This unprecedented pandemic has fundamentally changed our lives, including our educational pursuits. Most notably, how we teach and learn has changed from the dominance of face-to face classes to predominantly or fully online learning (i.e., synchronous or asynchronous) or blended learning due to social distancing. Many people have become highly stressed and uneasy due to the radical changes in the educational landscape.

As might be expected, students have encountered high levels of stress in the new learning environments that have emerged. Educators around the world have expressed tremendous concern about students' psychological well-being because they have been restricted from meeting their friends and teachers at school (Birmingham et al., 2021; Lischer, Safi, & Dickson, 2021). As an example, Villani et al. (2021) surveyed 501 Italian university students to examine their psychological well-being during COVID-19. They found that 72.93% of these students were depressed and 35.33% of the participants were anxious.

The likelihood of anxiety increases when students are prohibited

from attending classes and are isolated from their friends. Similarly, Hamaideh, Al-Modallal, Tanash, & Hamdan-Mansour (2022) studied depression, anxiety, and stress of 1380 undergraduate students in Jordan. They also found that Jordanian undergraduate students experienced a moderate to high level of depression, anxiety, and stress during the COVID-19 period. These results remind us of early research findings in the field of distance education indicating that students are lonely or feel isolated when they learn through distance learning (Gunawardena & Zittle, 1997). However, the loneliness and anxiety has grown to a much larger population with COVID-19 restrictions. Hence, it is necessary to examine how students' psychological well-being has influenced learning during COVID-19 pandemic.

Online learning during COVID-19 has allowed (or forced) students to have more autonomy in terms of how to study, and the time and place to learn. That is, students learn synchronously or asynchronously online at a convenient time and place, including at home. However, autonomy without self-efficacy and self-regulated learning may have negative results, such as procrastination. Wäschle, Allgaier, Lachner, Fink, and Nückles (2014) warned that those who have low self-efficacy are likely to procrastinate, which leads to low learning outcomes (Akinsola, Tella,

& Tella, 2007; Michinov, Brunot, Le Bohec, Juhel, & Delaval, 2011).

To respond to the current changes in learning modality and environments, this study aims to examine how students' psychological well-being affects learning from a self-regulated perspective. First, we investigate the influences of self-efficacy and resource management (e. g., time and study environment management and effort regulation) as self-regulated behaviors on learning engagement. Second, we examine the extent to which depression moderates the influences of self-efficacy for learning and resource management on learning engagement. The research questions for this study are as follows:

1. What are the influences of self-efficacy for learning and resource management on learning engagement?
2. Does the depression level of students moderate the influences of self-efficacy for learning and resource management on learning engagement?

2. Literature review

2.1. Psychological factors (depression, self-efficacy) and learning engagement

Students' engagement in learning has become a key indicator of the quality of courses in higher education since the advent of the National Survey of Student Engagement (NSSE) in 2000 (Hsieh, 2014; Schreiner & Louis, 2011). Considering the multifaceted nature of engagement, this study conceptualizes learning engagement based on three interrelated components: cognition, emotion, and behavior. Cognitive engagement incorporates psychological investment and strategy use in learning (Richardson & Newby, 2006; Xu, Chen, & Chen, 2020). It refers to being interested in the learning content and connecting it to previous learning and future benefits. Emotional engagement refers to students' affective reactions in the learning context (Molinillo, Aguilar-Illescas, Anaya-Sánchez, & Vallespín-Arán, 2018; Özhan & Kocadere, 2020), and includes students' positive emotions toward online learning experiences. Behavioral engagement includes actual participation in academic and social activities in school (Fredricks, Blumenfeld, & Paris, 2004; Park & Yun, 2018). It also includes participation in online discussions and asking questions of one's peers and teachers.

Learning engagement can contribute to active involvement and persistence throughout the learning process and thus directly impacts successful learning achievement. Scholars have paid increasing attention to the degree of learning engagement in class and have identified the increased importance of learning engagement in online learning (Jung & Lee, 2018). Identifying factors that influence positive learning engagement must be a priority in providing educators and institutions with meaningful feedback to enhance the quality of online learning (Sun & Rueda, 2012).

Determining the psychological factors influencing college students' learning engagement and outcomes has been a topic of considerable interest in higher education studies for many years (Guo, Yang, Zhang, & Gan, 2021). However, the affective domains in psychology have recently gained greater attention than the cognitive domains (Ben-Eliyahu, 2019). Affective factors including depression, anxiety, and stress can adversely affect learning engagement and academic achievement, and, in turn, impact students' overall mental health and psychological well-being (Pascoe, Hetrick, & Parker, 2020).

Many students in higher education face numerous normative stress factors related to ongoing academic demands and future career development. The COVID-19 pandemic has been another important stressor for students' psychological well-being, particularly since the COVID-19 pandemic has lasted longer than expected (Panchal, Kamal, Cox, & Garfield, 2021). Given that students' psychological well-being is a prerequisite for successful learning outcomes, educators have expressed concern about students' psychological well-being during the COVID-19 era. Several recent studies in numerous countries have investigated students' psychological well-being during the pandemic in terms of the affective domains of psychology mentioned above; namely, depression, anxiety, and stress (Hamaideh et al., 2022; Kwok et al., 2021). Among the affective factors influencing psychological well-being of college students, this study focuses on depression and self-efficacy, both of which are critical factors for understanding engagement in successful learning.

According to the World Health Association (WHO), depression is defined as a common mental health disorder that often results in a downcast mood, loss of interest, feelings of low self-esteem, disturbed sleep or appetite, low energy, and poor concentration (Garvik, Idsoe, & Bru, 2014). In a recent OECD report on the mental health impact of the COVID-19 crisis across countries, South Korea was ranked the highest country in the prevalence of depression (OECD, 2021). Most countries that participated in the survey reported double or more than double depression or anxiety levels in early 2020 compared with previous years. Social distancing, unemployment, and financial insecurity during COVID-19 may have led to the worse depression levels. Students are not excluded from the impact of this unprecedented pandemic. In fact, many studies have reported that depression among college students during the pandemic has affected their learning engagement and academic achievement (Liu, Yao, Li, & Zhang, 2020). These studies have also found that students who are depressed become less engaged in emotional and cognitive processing across various learning contexts (Suldo, Parker, Shaunessy-Dedrick, & O'Brennan, 2019; Varghese, Norman, & Thavaraj, 2015; Wang, Chow, Hofkens, & Salmela-Aro, 2015). Not surprisingly, they show lower school involvement and academic performance (Awadalla, Davies, & Glazebrook, 2020; Chow, Tan, & Buhrmester, 2015; Owens, Stevenson, & Hadwin, 2012).

Self-efficacy related to learning is another psychological factor impacting learning engagement. Self-efficacy is defined as "beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments" (Bandura, 1997, p. 3). Much research has found that self-efficacy is a predictor of learning engagement and learning achievement (Diseth, 2011; Olivier, Archambault, De Clercq, & Galand, 2019; Tsai, Chuang, Liang, & Tsai, 2011). Students with high levels of self-efficacy tend to display increased academic effort and active involvement, while demonstrating stronger persistence when facing difficulties (Zhao, Zheng, Pan, & Zhou, 2021). In particular, self-efficacy for learning is positively related to self-regulated learning.

Lynch and Dembo (2004) found a significant correlation between self-efficacy for learning and utilizing self-regulated learning strategies including time and study environment management, and help seeking in blended learning. In the context of online learning, Lee, Watson, and Watson's (2020) study on massive online open courses (MOOCs) also found that self-efficacy was statistically correlated with adopting self-regulated strategies. According to Liu et al. (2020), students' efficacy belief can boost their intrinsic motivation to learn, promote the use of effective learning strategies, and further enhance their engagement. However, Wu, Li, Zheng, and Guo (2020) reported no significant effects of self-efficacy on academic performance in medical education. Given the lack of research on self-efficacy in online and distance learning (Johnson & Lockee, 2018; Vayre & Vonthron, 2019), and the inconsistent results related to it in blended and face-to-face learning contexts, additional research is needed on the relation between self-efficacy and learning engagement.

2.2. Self-regulated learning and successful online learning

Self-regulated learning is a crucial element for successful learning outcomes (Zimmerman & Schunk, 2001), and, thus, has gained recent attention in research on online study environments (Doo, Bonk, Shin, & Woo, 2021; Handoko, Grosneth, McNeil, Bonk, & Robin, 2019; Ng, 2018). Pintrich (2000) explained that self-regulated learning behaviors include setting goals for learning and then attempting to monitor, regulate, and control one's cognition, motivation, and behavior while

guided and constrained by "the contextual features of the environment" (p. 453). According to Pintrich (2000), self-regulated learning includes four phases in sequence: (1) forethought, planning, and activation, (2) monitoring, (3) control, and (4) reaction and reflection. The four phases explain the self-regulation process in terms of cognition, motivation, behavior/execution, and context. That is, to obtain successful learning outcomes, learners should be able to make plans, monitor their learning progresses, control the resources for learning including the study environment and time for learning, and regulate their efforts for learning.

Given that online study environments often allow students greater autonomy compared to traditional learning, learners need to use appropriate strategies in online courses to self-regulate their learning. Self-regulated learning strategies include four aspects: (1) cognition, (2) metacognition, (3) motivation, and (4) resource management such as behavioral control (Barak, Hussein-Farraj, & Dori, 2016; Wolters, Pintrich, & Karabenick, 2005). Among these strategies, this study focuses on resource management as a critical factor in online learning, including managing and controlling time, effort, and study environment (Biwer et al., 2021; Lee, Choi, & Kim, 2013). Time management involves scheduling, planning, and managing one's study time. Study environment management refers to creating a setting where students can optimize their learning for academic success (Adam, Alzahri, Cik Soh, Abu Bakar, & Mohamad Kamal, 2017; Pintrich, Smith, García, & McKeachie, 1991). Finally, effort management or regulation refers to students controlling their self-effort and attention despite potential distractions (Broadbent, 2017).

Broadbent and Poon (2015) conducted a meta-analysis of eleven self-regulated studies published between 2004 and 2014. They found that resource management strategies, including time management and effort regulation, were statistically correlated with learning achievement. Similarly, Michinov et al. (2011) emphasized the importance of time management as a key success factor of online learning since inefficient time management leads to procrastination which is negatively correlated with performance.

The use of self-regulated learning strategies is a signal of learners' active learning engagement in online and blended learning contexts (Xie, Hensley, Law, & Sun, 2017). Elaboration strategies performed on the learning content combined with critical thinking allows learners to deeply process learning content and to critically evaluate learning outcomes (Li & Lajoie, 2021; Pellas, 2014; Woolley, 2011). Several studies have shown that resource management or regulation including time, study environment, and learning effort in online learning are related to behavioral and emotional engagement in learning (Kassab, Al-Shafei, Salem, & Otoom, 2015; Li, Chen, Su, & Yue, 2021; Park & Yun, 2018). Importantly, as shown by Ketonen et al. (2019) and Kuh (2003), learning engagement is a strong predictor of learning achievement and has been extensively researched because of its high correlation with motivation, learner satisfaction, and learning achievement. Hence, it is expected that learning engagement is influenced by resource management.

2.3. Relationship among variables in this study

Many studies have addressed the reciprocal relationship between students' self-efficacy and self-regulated learning to achieve learning goals in most learning contexts (Bradley, Browne, & Kelley, 2017; Müller & Seufert, 2018). However, this study posits that self-efficacy is a critical factor for students to self-regulate their learning (Schunk & Usher, 2011) because motivational and affective experiences precede the cognitive and behavioral commitment in learning success (Ben-Eliyahu & Linnenbrink-Garcia, 2013).

Self-efficacious students self-regulate their learning more and engage actively in learning processes, and obtain better learning outcomes (Duchatelet & Donche, 2019). Li and Zheng (2018) found a strong association between self-efficacy and students' self-regulated learning in a one-to-one computing environment. In the context of online learning,

Lee et al.'s (2020) study on massive online open courses (MOOCs) also found that self-efficacy was statistically correlated with adopting resource management strategies, including environment structuring, goal setting, time management, help seeking, task strategies, and self-evaluation. According to Liu et al. (2020), students' self-efficacy beliefs can boost their intrinsic motivation to learn, promote the use of effective learning strategies, and further enhance their engagement. Along these same lines, Lynch and Dembo (2004) found a significant correlation between self-efficacy for learning and resource management in blended learning; however, their study also pointed out that only self-efficacy for learning significantly contributed to learning outcomes in this particular study. Wolters and Hussain (2015) also reported a positive correlation between self-efficacy and time and study environment management. Regarding effort regulation, Cho and Shen (2013) showed that academic self-efficacy indirectly affected effort regulation through metacognitive regulation in online learning. Similarly, Sungur and Tekkaya (2006) identified a correlation between self-efficacy and resource management in problem-based learning. Interestingly, Pellas (2014) revealed that computer self-efficacy and metacognitive self-regulation in online courses were not only positively correlated with student's cognitive and emotional engagement factors, but were also negatively correlated with behavioral factors. Based on these previous research findings, we hypothesize that self-efficacy positively influences resource management, including effort regulation and time/study environment management as well as learning engagement (H1, H2, and H3).

Compared to self-efficacy research, few studies have discussed the influence of resource management on learning engagement. Claessens, van Eerde, Rutte, and Roe (2007) conducted a review of the time management literature including academic settings and work situations and found that college grades and study habit scores in academic settings were positively affected by time management. However, a non-significant or modest correlation between time management and job performance was found in work situations. List and Nadasen (2017) also examined the effects of self-regulation including time management on learning achievement. However, in that study, there was no significant correlation between time management and cumulative or semester GPA. Finally, in terms of the role of effort regulation, Shea and Bidjerano (2010) reported the indirect effects of self-efficacy on cognitive presence through effort regulation in online learning. Based on previous research findings related to resource management, we hypothesize that time and study environment management and effort regulation have a positive influence on learning engagement (H4 and H5). Given the lack of research on resource management in online and distance learning (Johnson & Lockee, 2018; Vayre & Vonthron, 2019), and the mixed results related to the relationship between self-efficacy and resource management in blended and face-to-face learning contexts, additional research is critically needed on the relation among self-efficacy, the use of resource management, and learning engagement.

Depression, as another psychological factor in this study, is associated with expectations of learning outcomes and self-efficacy beliefs, which are linked to interest and persistence in a task as well as active performance (Linnenbrink & Pintrich, 2003). While depression as an emotional state is an important source that can influence self-efficacy beliefs, self-efficacy beliefs influence depressive mood and active performance (Maddux & Meier, 1995). Some studies reported the negative relationship between depression and self-efficacy, and the influence of depression on individual performance. Individuals with high levels of depression tend to have low levels of motivation (Xiao et al., 2021) and self-efficacy (King, Wu, & Niranjan, 2014; Melo et al., 2021), less control of their cognition and behaviors (Zhang et al., 2020), and poor performance (Son & Won, 2017). Also, depression contributes to weaken self-regulation, often influencing the ability to organize time and study environment, and to regulate emotion and effort, which may lead to decreases in learning engagement and performance (Hinkson Jr. et al., 2021). Similarly, Xie et al. (2020) reported the negative impact of

depression on time management in nursing management, while Van Nguyen, Laohasiriwong, Saengsuwan, Thinkhamrop, and Wright (2015) found negative relationships between depression and resource management strategies among medical students.

The important role of depression on individuals' cognition and behaviors has also been examined mainly in the fields of psychiatry and mental health. For example, Przepiorka, Blachnio, and Cudo (2019) showed the predictive power of depression in adolescents' Internet addiction. Elhai, Levine, Dvorak, and Hall (2017) found that depressed individuals are less active in social activities and have fewer interactions with others on their smartphones. Similarly, Garvik et al. (2014) emphasized the impact of depression on school engagement as well as academic achievement. They recommended that a higher priority be placed on research that attempts to better understand the link between depression and school engagement given the mixed results on the relationship between depression and learning engagement (e.g., Abe, 2020; Liu et al., 2020). From a clinical perspective, Admon and Pizzagalli (2015) reported dysfunctional reward processing of depressed students. Reward processing includes motivation, reinforcement learning, and reward responsiveness (i.e., hedonic capacity), which are related to how individuals learn. They explained that depressed individuals' reward processing does not work properly, and dysfunctional reward processing is the most common symptom of depression. Similarly, Olino et al. (2012) reported that depression moderates the relationship outcomes and reward anticipation by comparing depressed and non-depressed students. They found that depressed students tended to expect fewer rewards than non-depressed students even when they experienced successful outcomes.

Most previous studies investigated correlation or direct effects of depression on individual cognition and behaviors. There is a need to have more investigation on the effect of depression in learning processes and outcomes from a different angle. Based on these research findings, we hypothesize that depression moderates the relationship among learning processes (H6). Given that researchers have paid less attention to the effects of depression in learning engagement and particularly the influence in the current online learning environment (Aldhahi, Alqahtani, Baattaiah, & Al-Mohammed, 2021; Wang, Yang, Li, & van Aalst, 2021), more studies are needed to examine the influence of depression on learning processes and outcomes. Thus, we first tested the relationships between self-efficacy, resource management (e.g., time and study environment management and effort regulation) and learning engagement in blended learning. Considering the reciprocal relationships between depression and other variables, we also examined whether depression moderates the influence of self-efficacy and resource management on learning engagement.

Based on the literature review, we present the following hypotheses:

H1. Self-efficacy for learning is positively related to effort regulation.

H2. Self-efficacy for learning is positively related to time and study environment management.

H3. Self-efficacy for learning is positively related to learning engagement.

H4. Effort regulation is positively related to learning engagement.

H5. Time and environment management is positively related to learning engagement.

H6. Depression moderates the influences of self-efficacy for learning and resource management on learning engagement.

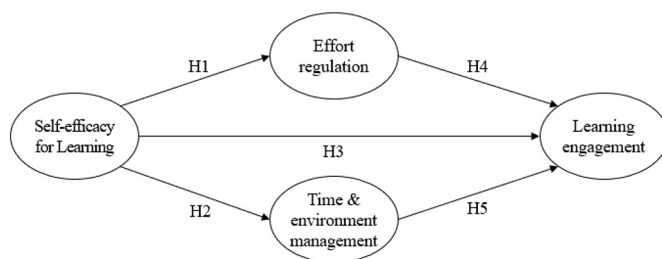Fig. 1 illustrates the research model and the six hypotheses guiding the research questions.

Fig. 1. Research model.

3. Methods

3.1. The context of the study and participants

The context of this study is a 4-year residential university in South Korea (Korea, hereafter). Due to the social distancing policy during COVID-19, this university decided to adopt online learning as well as face-to-face and blended classes based on the class size (e.g., less than 30 students or more than 30 students) and based on the types of classes (e.g., lecture-based, requiring hands-on experience or experiments). The types of classes included: (1) online, (2) face-to-face, or (3) a mix of face-to-face and online classes (or blended learning). Students had different combinations of class types depending on which classes they registered for, which determined how many days per week they went to campus.

The participants of this study were 1435 undergraduates who were enrolled in Spring semester 2021. More female students (897 students, 62.5%) than male students (538 students, 37.5%) participated in this study. The participants were proportionally distributed from freshmen to seniors. Since the survey was conducted across the university, the participants' majors were quite diverse. See Table 1 for detailed demographic information.

The ratio of online courses the participants attended varied: less than 20% of their courses (22.8% of participants), 29–40% (17.9% of participants), 49–60% (21.2% of participants), 69–80% (16.9% of participants), and greater than 81% (21.3% of participants). We also asked how many days per week students went to campus ranging from none (8.9%), one day (10.3%), two days (17.4%), three days (22.4%), four days (23.5%), to every day (five days) (17.5%). These responses indicated that students' learning experiences during the pandemic were widely diverse.

To collect data, an online survey was distributed university-wide using an electronic bulletin board and the learning management system of the university. Students voluntarily participated in the survey and there were no course credits given for completing the survey. Potential participants were informed that there was no penalty or pressure if they did not participate in this study. The online survey was administered in May and June 2021.

3.2. Measurement instruments

The 36-question, Web-based survey included: (1) demographic information (7 items); (2) depression (9 items); (3) self-efficacy for

Table 1
Demographic information of participants.

Years	# of participants	Majors	# of participants
1st year	321 (22.4%)	Engineering	375 (26.1%)
2nd year	369 (25.7%)	Life bioscience	310 (21.6%)
3rd year	361 (25.2%)	Education	230 (16.0%)
4th year and beyond	384 (26.8%)	Liberal arts	230 (16.0%)
		Social science	220 (15.3%)
		Others	70 (4.8%)
Total	1435	Total	1435

learning (8 items); resource management including (4) effort regulation (2 items) and (5) time and study environment management (3 items); and (6) learning engagement (7 items). Demographic information included the class year, gender, major, ratio of online classes, the location for online learning, and number of days they went to campus.

Depression was measured with a self-test for diagnosing depression during COVID-19 developed by Korea Disease Control and Prevention Agency (KDCA). The assessment included nine yes-or-no questions (i.e., symptoms) measuring depression during COVID-19. The scoring guidelines of this assessment included instructions for individuals to consult with an expert if they experienced more than five of the nine symptoms listed on the questionnaire. Example statements of depression include, "Depression for most of the day lasts more than two weeks" and "I feel fatigue and lack of vigor."

Since one of the theoretical frameworks of this study is self-regulated learning, we adopted the Motivated Strategies for Learning Questionnaire (MSLQ) by Pintrich et al. (1991) to measure self-efficacy for learning and resource management including effort regulation and time and study environment management. We chose the MSLQ because many self-regulated learning studies have adopted this instrument (Cho & Shen, 2013; Lee et al., 2020; Shea & Bidjerano, 2010; Xie et al., 2017). According to the systematic review of self-regulated learning measurement by Roth, Ogrin, and Schmitz (2016), the MSLQ is the most popular instrument to assess self-regulated learning and is widely used globally with translations into different languages.

The original scale was translated into Korean and then reviewed by a bilingual university faculty member. A thorough review confirmed that the questions were still appropriate for the survey participants during the COVID-19 pandemic. Sample questions of self-efficacy in learning are, "I'm confident I can do an excellent job on the assignments and tests in this course" and "I'm certain I can master the skills being taught in this class." Time and study environment were measured with three questions including "I usually study in a place where I can concentrate on my course work," "I make good use of my study time for this course," and "I make sure I keep up with the weekly readings and assignments for this course." The two questions measuring effort regulation are "I work hard to do well in this class even if I don't like what we are doing" and "Even when course materials are dull and uninteresting, I manage to keep working until I finish."

Learning engagement was measured with seven items of the Engaged Learning Index.

developed by Schreiner and Louis (2011). The original scale consisted of ten items; however, three of the questions were deleted due to low factor loadings (e.g., below 0.5). To satisfy the factor loading requirement of structural equation modeling (i.e., larger than 0.50), items with low factor loadings were deleted (Hair, Black, Babin, Anderson, & Tatham, 2006). Examples of learning engagement items include "I feel as though I am learning things in my classes that are worthwhile to me as a person" and "I can usually find ways of applying what I'm learning in class to something else in my life."

The measurement scales of this study are presented in Table 2,

Table 2
Research instruments.

Variables	Number of items	Cronbach's alpha	Reference
Depression	9	0.92	Korea Disease Control and Prevention Agency (KDCA)
Self-efficacy for learning	8	0.94	Pintrich et al. (1991)
Effort regulation	2	0.66	Pintrich et al. (1991)
Time and study environment management	3	0.72	Pintrich et al. (1991)
Learning engagement	7	0.84	Schreiner and Louis (2011)

including references, the number of items, and the Cronbach's alphas for the latent variables. The reliability coefficients for the latent variables were acceptable given that Cronbach's alpha for each latent variable was higher than 0.70 except for effort regulation.

3.3. Confirmatory factor analysis

Confirmatory factor analysis (CFA) assessed the convergent validity and discriminant validity of the indicators of the four constructs. The results indicated a good fit to the data ($\chi^2 = 1089.54$; $df = 164$; $\chi^2/df = 6.64$; TLI = 0.929; CFI = 0.939; RMSEA = 0.063; SRMR = 0.037). To estimate the convergent validity, we calculated average variance extracted (AVE) and composite reliability (CR). The CFA results indicated that factor loadings, AVE, and CR values of the data were acceptable (Fornell & Larcker, 1981) (see Table 3).

Discriminant validity for the measurement model was satisfactory because the AVE values for the latent variables were greater than the square root of the correlation, as shown in Table 4.

3.4. Data analysis

To answer Research Question #1, we used descriptive analysis and multiple regression. We conducted structural equation modeling using maximum likelihood estimation to examine our two research questions and test the six hypotheses of this study. Since structural equation modeling is a combination of factor analysis and multiple regression, it allows us to estimate direct effects (i.e., H1, H2, H3, H4, and H5), indirect effects, and total effects of the variables (Schreiber, Nora, Stage, Barlow, & King, 2006; Ullman, 2001). We conducted bootstrap estimation with 500 samples using bias-corrected percentile method reported at the 95% confidence level (Cheung, 2007). To examine Research Question #2, we used multi-group moderation in structural equation modeling using a chi-square difference test to examine the moderation effects of depression (i.e., non-depressed students vs. depressed students) on the influences of self-efficacy for learning and resource management on learning engagement.

Multiple fit indices for analysis were employed to assess any discrepancy between the proposed model and the data: the comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), standardized root mean square residual

Table 3
Results of confirmatory factor analysis.

Latent variable	Measurement variable	Factor loading (> 0.5)	AVE (> 0.5)	CR (>0.7)
Self-efficacy for Learning	SE1	0.77	0.67	0.94
	SE2	0.81		
	SE3	0.80		
	SE4	0.80		
	SE5	0.83		
	SE6	0.85		
	SE7	0.77		
	SE8	0.83		
Time and Study Environment Management	Resource Mgmt 1	0.58	0.60	0.81
	Resource Mgmt 2	0.72		
	Resource Mgmt 3	0.56		
Effort Regulation	Efforts 1	0.68	0.64	0.78
	Efforts 2	0.83		
Learning Engagement	Engagement 1	0.56	0.66	0.93
	Engagement 2	0.70		
	Engagement 3	0.74		
	Engagement 4	0.67		
	Engagement 5	0.59		
	Engagement 6	0.67		
	Engagement 7	0.71		

Table 4
Discriminant validity for the measurement model.

Measures	1	2	3	4	AVE	CR
Self-efficacy for learning ($\rho2$)		0.65 (0.42)	0.57 (0.33)	0.65 (0.42)	0.67	0.94
Time/Environment management ($\rho2$)		–	0.66 (0.43)	0.69 (0.48)	0.60	0.88
Effort regulation ($\rho2$)			–	0.65 (0.43)	0.61	0.86
Learning Engagement ($\rho2$)				–	0.66	0.85

(SRMR), and a chi-square test. CFI and TLI values larger than 0.90 were deemed to be a good fit between the proposed model and the data. RMSEA, a value of 0.05 indicates a close fit, 0.08 is a fair fit, and 0.10 is a marginal fit. A value lower than 0.05 is a good fit for SRMR (Browne & Cudeck, 1993). The statistical software SPSS (version 21.0) and Amos (version 23.0) were used for data analysis.

4. Results

4.1. Descriptive analysis

Descriptive analysis indicated that the participants scored above neutral (i.e., above 3 points) on a 5-point Likert scale for self-efficacy for learning ($M = 3.55$, $SD = 0.80$), effort regulation ($M = 3.46$, $SD = 0.71$), time and environment management ($M = 3.72$, $SD = 0.59$), and learning engagement ($M = 3.53$, $SD = 0.65$). The range of skewness and kurtosis was between −1 and 1, indicating that the four major variables were normally distributed. The correlations between variables ranged from 0.33 to 0.66 and they were statically significant at $p < .001$ (see Table 5).

To estimate the influences of three independent variables (i.e., self-efficacy, time and study environment management, and effort regulation) on learning engagement, multiple regression analysis was performed. The results indicated that self-efficacy ($\beta = 0.38$, $t = 16.81$ $p < .001$), effort regulation ($\beta = 0.25$, $t = 9.60$, $p < .001$), and time and study environment management ($\beta = 0.20$, $t = 7.98$, $p < .001$) significantly predicted learning engagement. The three variables predicted about 49.3% of learning engagement, $R^2 = 0.49$, $F (3, 1431) = 463.46$, $p < .001$.

Depression was treated as a categorical variable (i.e., non-depressed and depressed group) following the guidelines provided by Korea Disease Control and Prevention Agency (KDCA). The guidelines recommend getting help from experts if individuals experience more than five of the nine symptoms listed in the depression scale. Thus, we divided the participants into two groups: (1) those who experienced less than five symptoms ($N = 1225$) (i.e., non-depressed group) and (2) those who had five symptoms or more ($N = 210$) (i.e., depressed group). Accordingly, we compared the two groups for self-efficacy, time and study environment management, effort regulation, and learning engagement. The results are detailed in Table 6.

The difference between the depressed group and non-depressed group was statistically significant: Self-efficacy ($F (1, 1433) = 77.27$,

Table 5
Correlations among the variables.

Measures	1	2	3	4	5
Depression	–	−0.38**	−0.36**	−0.38**	−0.33**
Self-efficacy for learning		–	0.53**	0.47**	0.61**
Effort regulation			–	0.66**	0.59**
Time and study environment management				–	0.55**
Learning engagement					–
Means	2.23	3.55	3.46	3.72	3.54
SD	0.94	0.80	0.71	0.59	0.65

** $p < .001$.

Table 6
Non-depressed group vs. depressed group.

	Non-depressed group ($N = 1225$)		Depressed group ($N = 210$)	
	M	SD	M	SD
Self-efficacy	3.62	0.77	3.12	0.82
Time and study environment management	3.78	0.56	3.38	0.59
Effort regulation	3.53	0.68	3.08	0.71
Learning engagement	3.59	0.64	3.20	0.63

$p < .001$), time and learning engagement management ($F (1, 1433) = 89.50$, $p < .001$), effort regulation ($F (1, 1433) = 76.19$, $p < .001$), and learning engagement ($F (1, 1433) = 68.28$, $p < .001$).

4.2. Hypothesis testing

The statistical significance of the path coefficients among the latent variables were assessed. As Table 7 presents, the hypothesized model indicated a good fit to the data ($\chi^2 = 1599.69$; $df = 368$; $\chi^2/df = 4.35$; $TLI = 0.907$; $CFI = 0.908$; $RMSEA = 0.048$; $SRMR = 0.043$).

We compared the results for the first five hypotheses of the two groups, non-depressed students ($N = 1225$) and depressed students ($N = 210$). As for the non-depressed students, the research findings indicated that all hypotheses were accepted ($t > 3.30$, $p < .001$). Self-efficacy had a significant influence on effort regulation ($\beta = 0.55$, $t = 13.48$), time and environment management ($\beta = 0.65$, $t = 14.47$), and learning engagement ($\beta = 0.25$, $t = 5.38$); consequently, H1, H2, and H3 were supported. Effort regulation ($\beta = 0.35$, $t = 8.81$) and time and environment management ($\beta = 0.34$ $t = 6.87$) had a positive influence on learning engagement; thus, H4 and H5 were supported (See Table 8 and Fig. 2).

The hypothesis testing results indicated differences between the depressed and non-depressed student groups. Whereas all the hypotheses were accepted with non-depressed students at $p < .001$, only four hypotheses were accepted with depressed students at $p < .001$ and $p < .05$: Self-efficacy had a significant influence on effort regulation ($\beta = 0.69$, $t = 6.60$) and time and environment management ($\beta = 0.52$, $t = 4.28$) at $p < .001$; therefore, H1 and H2 were supported. However, the influence of self-efficacy on learning engagement was not found ($\beta = 0.18$, $t = 1.409$, ns); as a result, H3 was not supported. Effort regulation ($\beta = 0.35$, $t = 2.76$) and time and environment management ($\beta = 0.36$, $t = 3.17$) had a positive influence on learning engagement at $p < .05$: thus, H4 and H5 were supported (See Table 9 and Fig. 3).

We compared the direct and indirect effects of each variable in the two groups (See Table 10). Direct effects of self-efficacy on learning engagement were not found in the depressed group in the hypothesis testing. However, the indirect effect of self-efficacy on learning engagement through time and study environment management and effort regulation were statistically significant at $p < .05$.

4.3. Model comparison

To test the moderating effects of depression on the influences of self-efficacy and resource management on learning engagement with the two groups (i.e., non-depressed students and depressed students), we conducted multi-group moderation using a chi-square difference test. The results indicated that the two groups are not invariant; (i.e., differ at the model level) as shown in Table 11; hence, the influences of self-efficacy and resource management on learning engagement were moderated by students' depression level. Thus, H6 (i.e., Depression moderates the influences of self-efficacy for learning and resource management on learning engagement.) was supported.

Table 7

Results of the fitness examination of the hypothesized model ($n = 1435$).

	χ^2	p	df	TLI	CFI	SRMR	RMSEA (90% Confidence Interval)
Structural model	1599.69	0.000	368	0.907	0.918	0.043	0.048 (0.046– 0.051)
Fit criteria	–		–	> 0.90	> 0.90	< 0.08	< 0.08

Table 8

Hypothesis testing results of non-depressed students ($N = 1225$).

Hypothesis	B	Standard Path Coefficient β	SE	t-value
H1: SE → Effort regulation	0.42	0.55	0.027	13.48[***]
H2: SE → Time and environment management	0.40	0.65	0.027	14.47[***]
H3: SE → Learning engagement	0.20	0.25	0.037	5.38[***]
H4: Effort regulation → Learning engagement	0.36	0.35	0.041	8.81[***]
H5: Time and environment management → Learning engagement	0.45	0.34	0.065	6.87[***]

[***] $p < .001$.

Fig. 3. Hypothesis testing results: depressed students ($N = 210$). [***]$p < .001$, [**]$p < .01$, [*]$p < .05$.

Table 10

Comparisons of direct and indirect effects of the variables.

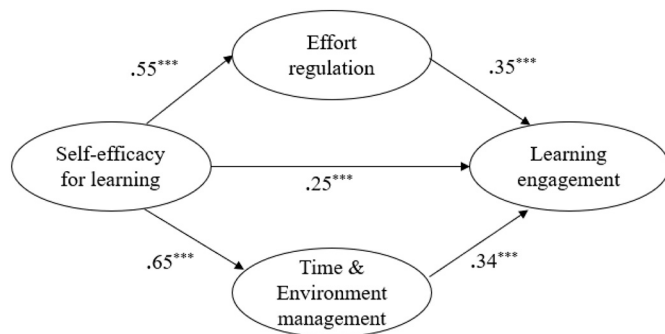| Hypothesis	Non-depressed Group			Depressed Group		
	Total effects	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects
H1: SE → Effort regulation	0.55[*]	0.55[*]		0.69[*]	0.69[*]	
H2: SE → Time and environment management	0.65[*]	0.65[*]		0.52[*]	0.52[*]	
H3: SE → Learning engagement	0.66[*]	0.25[*]	0.32[*]	0.60[*]	0.17	0.43[*]
H4: Effort regulation → Learning engagement	0.35[*]	0.35[*]		0.35[*]	0.35[*]	
H5: Time and environment management → Learning engagement	0.34[*]	0.34[*]		0.36[*]	0.36[*]	

[*] $p < .05$.

Fig. 2. Hypothesis testing results: non-depressed students ($N = 1225$). [***]$p < .001$, [**]$p < .01$, [*]$p < .05$.

Table 9

Hypothesis testing results of depressed students ($N = 210$).

Hypothesis	B	Standard Path Coefficient β	SE	t-value
H1: SE → Effort regulation	0.62	0.69	0.09	6.60[***]
H2: SE → Time and environment management	0.30	0.52	0.07	4.28[***]
H3: SE → Learning engagement	0.19	0.17	0.13	1.41
H4: Effort regulation → Learning engagement	0.41	0.35	0.15	2.76[*]
H5: Time and environment management → Learning engagement	0.66	0.36	0.21	3.17[*]

[***] $p < .001$.
[*] $p < .05$.

Table 11

Results of Chi-square difference tests.

Model	χ^2	df	p	RMSEA	CMIN	$\Delta\chi^2$
Unconstrained	1449.98	330	0.000	0.049	4.39	159.38 [***]
Constrained	1609.36	335	0.000	0.048	4.35	($df = 5$)

[***] $p < .001$.

5. Discussion

Given that the COVID-19 pandemic has lasted longer than expected, educators and scholars have expressed concern about students' psychological well-being and the negative impact on learning outcomes. This study examined the influences of self-efficacy and resource management on learning engagement from a self-regulated perspective. We also investigated whether this relationship was moderated by students' depression during the COVID-19 era by comparing a non-depressed student group ($N = 1225$) and a depressed student group ($N = 210$).

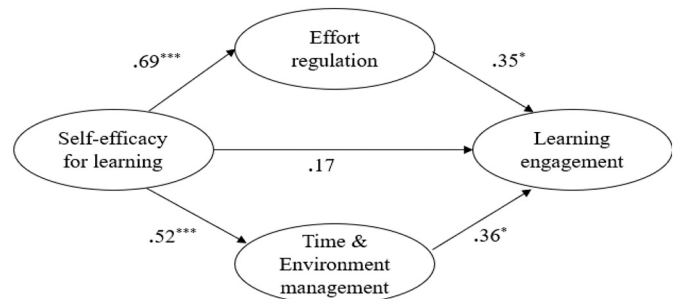The findings indicate that self-efficacy positively influenced resource management including time and study environment management as well as effort regulation in both groups.

This result supports previous research findings about the influence of self-efficacy on time and study environment management (Klassen, Krawchuk, & Rajani, 2008; Lee et al., 2020; Li & Zheng, 2018; Lynch & Dembo, 2004; Schunk & Usher, 2011; Wäschle et al., 2014; Wolters & Hussain, 2015). In addition, our research finding about the influences of self-efficacy on effort regulation supports Cho and Shen (2013) and Sungur and Tekkaya (2006). Taken together, this study confirmed that self-efficacy influences resource management as self-regulated behaviors.

Another major finding is that self-efficacy directly and indirectly influences learning engagement in the non-depressed group. This result supports the research findings of Tsai et al. (2011) and Olivier et al. (2019). As shown in the present study, self-efficacy for learning by itself is only related to learning engagement in non-depressed students. By extrapolation, then, when learners have a high level of self-efficacy, they can be more confident and self-assured that the learning tasks and problems can be adequately mastered. However, direct influences of self-efficacy on learning engagement were not found in the depressed group. Instead, in the depressed group, self-efficacy indirectly influenced learning engagement through resource management. To compensate for some learners' lower levels of self-efficacy, there should be further support to help students become more competent in self-regulated learning and effectively allocate personal resources when faced with challenging learning situations.

In terms of resource management, influences of time and study environment management on learning engagement were also found in both groups. This result confirms the findings of Broadbent and Poon (2015), Michinov et al. (2011), and Akinsola et al. (2007), mentioned earlier. However, it does not support List and Nadasen's (2017) findings, which reported no correlation between time management and GPA. This result may be explained by the difference between learning engagement and actual learning achievement. In addition, this study identified indirect effects of self-efficacy on learning engagement through resource management including time and study environment management and effort regulation. This finding supports Shea and Bidjerano's (2010) results that self-efficacy indirectly influenced cognitive presence through effort regulation in online learning environments. As Claessens et al. (2007) mentioned, time management training as resource management is more effective in academic settings than work situations. It is necessary, therefore, to provide workshops or manuals to enhance time and study environment management for successful learning. However, we found a difference between the non-depressed and depressed groups in terms of the influences of time and student environment management on learning engagement. Specifically, the influences of time and study environment management on learning engagement in the depressed group were larger than in the non-depressed group. These findings imply that instructors need to pay more attention to students with a moderate-to-higher level of depression to strengthen their time and study environment management to enhance their learning engagement. Last, we examined whether students' depression level moderates the influences of self-efficacy for learning and resource management on learning engagement using multi-group analysis. There were statistical differences between the non-depressed group and the depressed group. Importantly, such results support the research findings of Admon and Pizzagalli (2015) and Olino et al. (2012). Such findings indicate that variables, such as self-efficacy for learning, effort regulation, or time and study environment management, influence learning engagement, and the influence may be different based on the learners' depression levels. In other words, we need to apply different instructional strategies and provide distinct support for depressed students.

This result demonstrates a need to consider students' depression level in explaining or predicting student learning from a self-regulated perspective during the COVID-19 pandemic. Villani et al. (2021), Hamaideh et al. (2022), and Kwok et al. (2021) examined students' anxiety, depression, and stress in different countries during the global crisis, and concluded that it is necessary to look at learning from a more integrated perspective, including students' psychological well-being. They also highlighted that students' psychological well-being is a highly prominent issue around the world. Simply put, instructors across every educational sector and grade level need to be in tune with their students' mental state as it plays a huge role in the entire learning process. It would be prudent for educational researchers to further explore this area and begin to close the gaps between those who are depressed and those who are not. For example, psychological capital (PsyCap) by Luthans, Avolio, Avey, and Norman (2007), the composite

construct characterized by self-efficacy, optimism, hope, and resilience, would be a valuable theoretical framework to explore and expand the scope of this research.

This unprecedented pandemic has had a substantial impact on students. Many studies have reported that depression among college students during the pandemic has affected their learning engagement and academic achievement (Liu et al., 2020). Studies have also found that students who become depressed are less engaged in emotional and cognitive processing across various learning contexts (Suldo et al., 2019; Varghese et al., 2015; Wang et al., 2015). Not surprisingly, such individuals have lower involvement in school and lower academic performance (Awadalla et al., 2020; Chow et al., 2015; Owens et al., 2012).

The current COVID-19 pandemic has heightened the awareness and criticality of this issue. Given the crucial nature of self-efficacy for learning to task engagement and ultimate performance, instructors should be vigilant about detecting signs of unrest or anxiousness among their students. In addition, colleges and universities as well as programs and departments might want to sponsor seminars and certificates on this topic as well as discussion forums and effective information dissemination related to learner affective and emotional needs.

Some instructors may want to employ or fashion surveys on student well-being at the beginning of a semester to flag potential issues and concerns related to high levels of stress and anxiety and individual students' potential for depression. They might go one step further and conduct action research in their own face-to-face, blended, and online courses. In these fast-changing and highly stressful times, instructors might review course policies in the syllabi of colleagues known for their effective classroom climate and engaging pedagogy and compare them to their own practices. Humanistic psychologist, Rogers (1983) argued for study environments that are psychologically healthy and comfortable where the instructor is a facilitator or guide to learning and is open to students' suggestions and exploration. This type of welcoming learning environment ethos can be critical for students battling depression and other illnesses.

6. Limitations and suggestions for future research

This study has several limitations, which provide opportunities for future researchers who are eager to extend this research. First, this study administered a survey to students at a single university in Korea. Hence, caution should be taken in generalizing the research findings to students in different countries and cultures. Future scholars are encouraged to collect data from diverse population groups in other countries and regions of the world. Second, this study adopted a cross-sectional research design approach (i.e., survey methods). Since the variables of this study were measured in a concurrent manner, we were unable to speculate on causal relationships (i.e., cause and effects) using an experimental design. Third, we used the self-reported checklist of depression developed by Korea Disease Control and Prevention Agency (KDCA) to measure students' psychological well-being during the COVID-19 pandemic. Although the reliability of this measurement is outstanding (i.e., 0.92), researchers should be cautious in applying this measurement to non-Korean participants without validating the instrument prior to implementation.

Despite these limitations, the results of this study add insights on this vital topic. Still, we need to know more about the emotional and cognitive factors that impact learning engagement in proliferating online and blended study environments. Educational organizations and institutions spanning the entire globe have come to grips with the fact that online learning not only can play a role in learning across age groups and educational sectors but will play an increasingly more vital role throughout the lifespan due to an assortment of social, economic, political, and cultural factors in modern society. The current pandemic is just one factor. Hundreds of millions of people were forced to learn online or in a blended learning environment during the past two years (Miks & McIlwaine, 2020; Theirworld., 2020; United Nations, 2020). As

a result, students around the world have struggled in online learning environments with emotional acclimation, resource management skills, and the competencies needed to succeed and maintain sufficient academic self-confidence as they adjust to the challenges and barriers in this new environment.

Future studies could explore the impact of stress and anxiety as well as depression on learning in highly complex blended or HyFlex (Beatty, 2019) study environments where students often must interact with peers via collaborative technology as well as face-to-face. Whatever the targeted age level, education sector, or region, we know that research in this area has the potential to be impactful. As such, we hope to entice others to join in and push for a deeper focus on the emotional well-being of our students. Additionally, we look forward to more extensive research efforts in this area and the new programs that are designed and disseminated to address the problems and concerns that are uncovered in the coming years. Educators and researchers should not wait for another pandemic before pushing further into this critical area.

Funding

Availability of data and material

The data used and/or analyzed in the current study are available from the author upon request.

Conflicts of interest

There were no conflicts of interest in this research.

Data availability

Data will be made available on request.

Acknowledgement

Appendix A. Measurement items used in this research

Depression (9 items)

1. Depression for most of the day lasts more than two weeks.
2. Interests or pleasure about anything radically decreases.
3. There was weight gain or loss for no special reasons.
4. There was unexplained weight gain or loss.
5. I feel extreme anxiety or no feeling (or lethargic).
6. I feel fatigue and lack of vigor.
7. I feel guilty or worthless.
8. Decreases in concentration and indecisiveness continues.
9. I repeatedly think of death or suicide.

Note: If you experience more than five symptoms above, consult with an expert.
** Adapted from "A self-test for diagnosing depression during COVID-19" by Korea Disease Control and Prevention Agency (KDCA) (2020).

Self-efficacy for learning (8 items)

1. I believe I will receive an excellent grade in this class.
2. I'm certain I can understand the most difficult material presented in the readings for this in course.
3. I'm confident I can understand the basic concepts taught in this course.
4. I'm confident I can understand the most complex material presented by the instructor in this course.
5. I'm confident I can do an excellent job on the assignments and tests in this course.
6. I expect to do well in this class.
7. I'm certain I can master the skills being taught in this class.
8. Considering the difficulty of this course, the teacher, and my skills, I think I will do well in this class.

Time and Study Environment Management (3 items)

1. I usually study in a place where I can concentrate on my course work.
2. I make good use of my study time for this course.
3. I make sure I keep up with the weekly readings and assignments for this course.

Effort Regulation (2 items)

1. I work hard to do well in this class even if I don't like what we are doing.
2. Even when course materials are dull and uninteresting, I manage to keep working until I

finish.
** Measurement items for Self-efficacy, Time and Study Environment, and Effort Regulation were adapted from "Motivated Strategies for Learning Questionnaire (MSLQ)" by Pintrich et al. (1991).

Learning engagement (7 items)

1. I often discuss with my friends what I'm learning in class.
2. I regularly participate in class discussions in most of my classes.
3. I feel as though I am learning things in my classes that are worthwhile to me as a person.
4. I can usually find ways of applying what I'm learning in class to something else in my life.
5. I ask my professors questions during class if I do not understand.
6. I find myself thinking about what I'm learning in class even when I'm not in class.
7. I feel energized by the ideas that I am learning in most of my classes.

** Adapted from "The Engaged Learning Index" by Schreiner and Louis (2011).

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