International **R**eview of **R**esearch in **O**pen and **D**istributed **L**earning
Volume 23, Number 2

May – 2022

Effects of Online Self-Regulated Learning on Learning Ineffectiveness in the Context of COVID-19

Wei He[1], Li Zhao[1], and Yu-Sheng Su[2*]
[1]School of Education Science, Nanjing Normal University, China, [2]Department of Computer Science and Engineering, National Taiwan Ocean University, Keelung, Taiwan
[*]The corresponding author is Yu-Sheng Su.

Abstract

Within the COVID-19 pandemic and the new normal period, online learning has become one of the main options for learning. Previous studies on self-regulated learning have shown that it was a better predictor of online learning effectiveness. However, this discussion has not been extended to the situation of the COVID-19 pandemic. To address this gap, this study aims to explore the relationship between the three stages of self-regulated learning (SRL) and learning ineffectiveness (LI). Data of 370 high school students were collected during the period of COVID-19. Structural equation modeling was used to perform confirmatory factor analysis on the data. Findings show that the preparatory stage was positively related to the stages of performance and appraisal, and the performance stage was positively related to the appraisal stage; on the other hand, the stages of performance and appraisal were negatively related to learning ineffectiveness. In addition, the preparatory stage had no direct relation to learning ineffectiveness, but the preparatory stage was correlated with learning ineffectiveness, mediated by the stages of performance and appraisal. These results suggest that better performance in the three stages of self-regulated learning decrease learners' perceived online learning ineffectiveness. This understanding can have implications for global education.

Keywords: online learning, self-regulated learning, learning ineffectiveness, COVID-19

Introduction

COVID-19 has had a destructive impact on the field of society, culture, religion, economy and education all over the world (Mustajab et al., 2020). Offline teaching activities in schools have been suspended and replaced with online education (Zhang et al., 2020). Compared with traditional school-based education, online learning is based on open and distributed learning, without the limitations of place, time, and physical materials. Open and distributed learning gives learners more autonomy in their online self-regulated learning (SRL). Samruayruen et al. (2013) have shown that in an open and distributed education environment, learners' SRL was more successful. SRL is a process that is initiated by learners to control their learning (Tuti et al., 2021). However, online learners seldom interact with or receive guidance and supervision from instructors (Broadbent & Poon, 2015; Su & Wu, 2021), which might result in learners struggling to regulate their learning processes (Jansen et al., 2019). It is therefore important to study learners' online SRL during the period of COVID-19 (Zhu et al., 2020).

Hong et al. (2021) has divided SRL into 6 sub-constructs: task strategy, mood adjustment, self-evaluation, environmental structure, time management, and help-seeking. There are several models of SRL with similar components and processes (Chen & Bonner, 2020). Adam et al. (2017), in their review, conclude that previous SRL models comprised the three stages: preparatory, performance, and appraisal. Many researchers have discussed the effects of multiple components of SRL or a single stage on other factors. For instance, the relationships between learning environments, students' beliefs, and multiple dimensions of SRL were explored by Maison and Syamsurizal (2019). Cosnefroy et al. (2018) analyzed the correlation between the forethought stage of SRL and self-regulation failure. Nevertheless, Zeidner and Stoeger (2019) indicate that few studies have considered all stages of SRL simultaneously. However, Liu et al. (2021) discussed the gender difference in each of the three stages of online SRL. The results found that in each of the three stages of SRL female students performed better than male students. Hong et al. (2021) examined the impact of academic procrastination on each of the six sub-constructs of SRL, and each of the six sub-constructs of SRL on learning ineffectiveness (LI). Thus, this study aims to explore the impact of the three stages of SRL: preparatory, performance, and appraisal, not the six sub-constructs of SRL, on LI. According to the effects of the three stages of SRL on learning effectiveness or ineffectiveness, instructors can provide targeted and efficient support for students.

Benefiting from the openness and distribution of online learning, students' online learning effectiveness has been improved accordingly. For example, Zhao, Liu, and Su (2021) have shown students to demonstrate better learning performance in open and distributed education than in face-to-face learning. Students with better ability to self-regulate their online learning were found to have significantly higher levels of perceived effectiveness than those with less ability in this area (Charo et al., 2020). When engaged in online learning, if students lack SRL skills, they may not be able to complete the learning tasks they are assigned in their online courses (Barnard et al., 2009). The abovementioned studies show that students' SRL reduces their learning ineffectiveness (LI) level. However, in the context of COVID-19, all the offline learning suddenly changed to 100% online learning. This study is to explore whether students' SRL was effective and how the different SRL stages affected students' learning effectiveness during this transformation. When students study online, it is necessary and significant to grasp their perceptions of online learning effectiveness or ineffectiveness (Hong et al., 2021). In this study, LI was adopted for high school students to self-rate their perceived learning performance. Therefore, this study explores how the three stages of SRL were related to

LI while high school students were learning online. The findings of the relationships between online SRL and online LI can provide new insights into distance education and provide relevant references for coping with the future online learning research on the normalization of the epidemic.

Literature Review

Online Self-Regulated Learning

Before COVID-19, most students studied face to face in classrooms and did not experience 100% online learning. Prior studies on SRL were conducted in online or offline learning contexts, but little research has been looked at during COVID-19. Students were suddenly faced with the extremely difficult task of self-regulating their learning activities at home amid the influence of the COVID-19 pandemic (Zhang et al., 2021). The shift from offline to online learning during COVID-19 has caused students to lack instructors' guidance, requiring them to have a greater ability to regulate themselves in their learning (Lee et al., 2020). During the specific time of COVID-19, many factors might have multiple negative effects on learners' SRL processes (Cai et al., 2020). SRL is an important capability to actively participate in constructing and interpreting knowledge in a student-centered learning environment (Alsancak Sirakaya & Ozdemir, 2018). "SRL is an active and constructive process in which learners set their own learning goals and then attempt to regulate, plan and control their motivation, cognition, and behavior" (Pintrich, 2000, p.453). During this process, they are both guided and limited by their goals and the environmental background characteristics (Pintrich, 2000.p.453). Learning tasks must have clear beginnings, middles, and ends (Cleary et al., 2012). In online learning courses, there is a clear learning process for before, during, and after lessons.

Several SRL models presenting different stages and subprocesses have been proposed. For example, based on social cognitive theory, Zimmerman (2000) described an SRL model as comprising the forethought, performance, and self-reflection stages. Hadwin et al. (2018) has developed a self-regulation model and divided it into the three components of negotiation and awareness of the task, strategic task engagement, and adaptation. Adam et al. (2017) proposed SRL comprises the stages of preparatory, performance, and appraisal. Thus, the present study selected the three stages which correspond to behaviors of before, during, and after online lessons, as the cyclic processes during the COVID-19 pandemic. During each stage, students use different strategies to monitor and control their learning (Zimmerman, 2000).

In the preparatory stage, the learning environment (e.g., stable Internet connection) and individual characteristics (e.g., mood) have been highlighted as essential components by Hong et al. (2021). Thus, this study specified the preparatory behaviors before engaging in online lessons focusing on mood adjustment and structuring environments. In addition, Adam et al. (2017) stated that the performance stage of SRL is when the actual task is accomplished while monitoring and controlling the progress of performance. In the performance stage, learners use cognitive and certain strategies (e.g., task strategies) and meta-cognitive monitoring processes (e.g., time management) to accomplish tasks (Ridgley et al., 2020; Zhang et al., 2021). Thus, this study specified the performance behaviors during online lessons, from two aspects of time management and the task strategy, When learners completed the learning tasks, they enter the appraisal stage, during which they monitor their learning progress, design help-seeking plan (Zimmerman, 2000), evaluate learning effectiveness (Cleary et al., 2012; Zimmerman, 1990). Considering this, this study specified the appraisal behaviors after engaging in online lessons, from two aspects of help seeking and self-evaluation.

Many studies of online learning have shown a relationship between learning achievement and the subscales of SRL, such as help seeking (Won et al., 2021), and learning environments (Maison & Syamsurizal, 2019). However, most studies did not use all stages of the SRL model (Zeidner & Stoeger, 2019). To improve learners' learning and SRL skills, differential effects of SRL in models and theories should be applied by scholars and teachers (Ernesto, 2017). Therefore, this study focuses on three stages of SRL during the COVID-19 pandemic.

Learning Ineffectiveness (LI) in the Context of COVID-19

With the help of distance education and technology support, students have easy and convenient access to online learning. Online learning effectiveness can be reflected by learners' evaluation of the performance in the cognitive, affective, and psychomotor domains of online learning (Zhao, He, & Su, 2021). The online learning carried out during the COVID-19 pandemic has been effective (Bahasoan et al., 2020). Although learners can learn and benefit from online learning, the learning effectiveness of online learning compared with traditional learning is still considered a debatable issue. For example, Zhao, Liu, and Su (2021) show that compared with traditional learning, flipping classroom learning supported by MOOCs results in better learning achievement; however, Carrol and Burke (2010) support that traditional learning was better than online learning. To ensure effective online learning, teachers and course designers must understand learners' perceptions of online learning effectiveness or ineffectiveness (Hong et al., 2021).

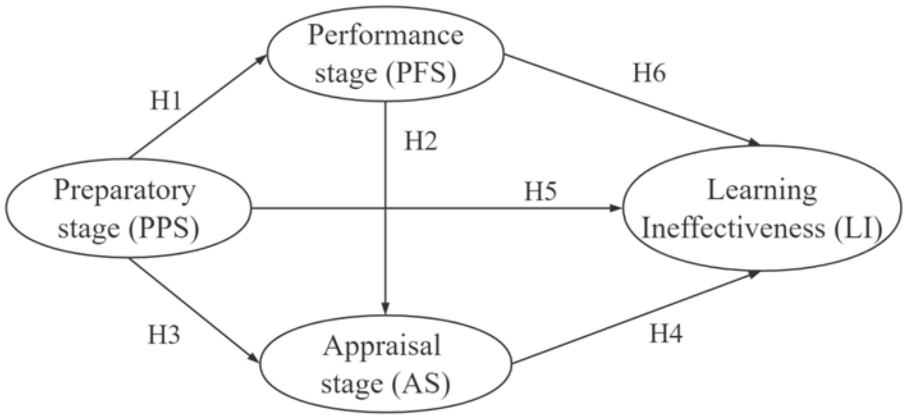
Adolescents are likely to be biased in their tendency to react (van Herk et al., 2004). For example, facing difficulties, learners may feel dissatisfied with engaging in online courses (Rabin et al., 2020). Ruhland and Brewer (2001) argue that students' perceived ineffectiveness of online learning is also a factor that should be captured as part of learning outcomes. Therefore, a good measurement of learning effectiveness requires a considerable understanding of how to best link the course to online learning and how to make online learning meaningful for students' needs and experiences. Hong et al. (2021) originally proposed LI, defined as learners self-evaluating how they feel about their online learning performance. However, limited research exists on LI related to learners' online learning. Thus, this study aimed to investigate students' perceptions of LI during the COVID-19 pandemic.

Research Hypotheses

Extensive research has been done on the impact of SRL on learners' learning and academic achievement (Jansen et al., 2019). Previous studies have found that SRL was a good predictor of academic achievement (e.g., Moghadari-Koosha et al., 2020). Six SRL sub-constructs influenced perceived LI (Hong et al., 2021). In online learning courses, there is a clear learning process of before, during, and after lessons. These three steps in the learning process correspond to the three stages of the SRL process model (Adam et al., 2017). This study furthers the previous study to explore the relationship between the stages of SRL and LI in the context of online learning. Therefore, based on Adam et al.'s (2017) proposed SRL model, we developed the conceptual model shown in Figure 1 for this study. This model reveals the relationship between learners' SRL behaviors at various stages of SRL and their respective influences on their LI.

Figure 1

Research Model



According to Zimmerman (2015), SRL is a cyclical process whereby learners are engaged in three distinct stages. Boom et al. (2004) revealed the self-regulated learning competence map, showing that the learning process includes beginning, performing, and finishing. The beginning stage is directed to the performing stage, and the performing stage is directed to the finishing stage. The emotion regulation strategy is associated with adaptive strategies, such as reappraisal (Aldao et al., 2010). Mood adjustment is considered as an essential component of the preparatory stage. Thus, the following hypotheses were proposed:

H1: The preparatory stage (PPS) is positively correlated with the performance stage (PFS) in online learning.

H2: PFS is positively correlated with the appraisal stage (AS) in online learning.

H3: PPS is positively correlated with AS in online learning.

Academic achievement has significant relationships with the behaviors of the preparatory (e.g., Lehmann et al., 2014), performance (e.g., Alghamdi et al., 2020), and appraisal stages (e.g., Colthorpe et al., 2019). According to Adam et al.'s (2017) SRL process model, this study divided the six constructs of Hong et al.'s (2021) SRL into the preparatory, performance, and appraisal stages. Hong et al. (2021) found all of the six sub-constructs of SRL were negatively correlated with LI. Thus, the interaction effects between the three stages of SRL and LI were hypothesized as follows:

H4: AS is negatively correlated with students' LI in online learning.

H5: PPS is negatively correlated with students' LI in online learning.

H6: PFS is negatively correlated with students' LI in online learning.

Methodology

Participants and Procedure

High school students have to face the college entrance examination, which is a concern for students all around the world, and especially in China. Compared with other levels of education, high school is more intense, and the online learning of high school students has received substantial attention from society during the COVID-19 pandemic. Therefore, we selected high school students at various grade levels in Jiangsu Province, China, as participants for this study. Adapting purposive sampling, teachers who gave online courses were invited to distribute the questionnaire to their students between April 10 and April 20, 2020. All participants were informed that the online questionnaire would be used only for this study and that their privacy would be protected. A total of 395 students from the high schools voluntarily and anonymously completed the online survey. If the questionnaires have missing values needed for the data analysis, they would be removed, leaving 370 samples for analysis.

The participants from grades 1 to 3 (M = 2.14, SD = 1.140) included 75 males (20.3%) and 295 females (79.7%), whose ages were from 15 to 21 years (M = 16.85, SD = 1.156). In addition, all participants had taken part in online lessons. Of all participants, the average study hours per day was 2.40 (SD = 0.847), and that semester's online courses number was between two and nine (M = 4.72, SD = 1.190). Of all participants, 96% studied online courses for 50% of the time during that semester.

Instruments

The questionnaire items were adapted from prior studies and were translated into Chinese by experts. Three high school students were invited to check the whole questionnaire and give comments to all the items to ensure the readability of the measurement items. Each of the items was scored by a 5-point Likert scale, from 1 for strongly disagree to 5 for strongly agree, with 3 representing neutral. Finally, the reliability of the constructs was subsequently tested.

Online SRL of Measurement

According to the SRL instrument of Hong et al. (2021), we designed the scale of the instrument with 22 items consisting of six sub-constructs with good reliability and validity, covering the three stages. The preparatory stage includes mood management, and environment structuring; the performance stage includes adapting time management and task strategies; and the appraisal stage includes help seeking and self-evaluation. The preparatory stage contains 8 items, such as, "Before I study online, I am used to finishing the coursework to avoid distractions in the online class." The performance stage contains 7 items, such as "During learning online, I will adjust my learning style according to the actual learning." The appraisal stage contains 7 items, for example, "After learning online, I test and summarize what I have learned."

Learning Ineffectiveness of Online Learning Measurement

A good learning effectiveness measurement must capture changes in learners' cognitive and affective development as a result of their learning experiences. Previous studies took ineffectiveness instead of effectiveness to assess learners' online learning performance. For example, the scale of learning ineffectiveness in the online learning context was developed to measure college students' LI in the context of COVID-19 (Hong et al., 2021). Therefore, eight items were designed in this study to measure the online learning ineffectiveness of high school students, for example, "Since learning online, my learning confidence has decreased."

Data Analysis

According to Thompson's (2000) recommendation, the number of samples should be between 10:1 and 15:1 for the number of observed variables. This ratio of sample size (N = 370) to observed variables (30 items) is reasonable. IBM SPSS Statistics was used to analyze data from all 370 high school students. Next, descriptive statistics of population information and correlation analysis were obtained using SPSS 24. Then confirmatory factor analysis (CFA) was performed to further test whether the questionnaire satisfied the reliability and validity via Amos (version 22.0). Finally, we conducted structural equation modeling (SEM) to evaluate the hypothetical structural model.

Results

Reliability and Validity Analysis

First, items with a value of factor loadings lower than .50 were deleted in each construct (Hair et al., 2011). During this process, three items in PPS, one item in PFS, and two in AS with factor loadings lower than .50 were deleted. After conducting CFA, items with the highest residual value in each construct were deleted (Hair et al., 2019). During this process, two items in PPS and two in PFS with the highest residual values were deleted. To meet the criteria, some items in each construct needed to be removed: one item in AS and three in LI were removed. The measurement model finally exhibited a good fit, with chi-square divided by the degrees of freedom ($\chi 2/df$) = 2.482, goodness of fit index (GFI) = .925, Bentler–Bonett normed fit index (NFI) = .959, comparative fit index (CFI) = .975, and root mean square error of approximation (RMSEA) = .063. The remaining 16 items—which contained three PPS items, four PFS items, four AS items, and five LI items—were reserved for further analysis.

Second, composite reliability (CR) and Cronbach's alpha (α) were considered together to assess the internal model's consistency. Hair et al. (2019) suggest that the CR should exceed .70. DeVellis (2012) recommends that an acceptable α value should be above .70. Thus, a construct is considered to have achieved internal consistency when both the CR and α exceed .70. Table 1 shows that the CR of all constructs ranged from .862 to .939, and α ranged from .721 to .900. Therefore, the results suggest that each construct measurement variable in the questionnaire had acceptable reliability and internal consistency.

Third, we calculated the construct's average variance extracted (AVE) and the variable measurement condition factor to ascertain the convergent validity. When the convergent effectiveness of construct is sufficient, the value of AVE should exceed .50 (Fornell & Larcker, 1981). Additionally, the convergent validity requirement is satisfied if the variable's measurement factor is greater than .50 (Hair et al., 2019). Table 1 indicates that the AVE of all constructs exceeded .50 (ranging from .677 to .756), and each item's standardized factor loading also exceeded .50 (ranging from .696 to .937). Therefore, the questionnaire had acceptable convergent validity.

Table 1

Reliability and Validity Analysis

Latent variable	Measure item	Standardized factor loading	CR	AVE	Cronbach's α
Preparatory stage (PPS)	PPS1	.748	.862	.677	.721
	PPS2	.888			
	PPS3	.826			
Performance stage (PFS)	PFS1	.897	.921	.747	.819
	PFS2	.921			
	PFS3	.922			
	PFS4	.696			
Appraisal stage (AS)	AS1	.781	.913	.725	.839
	AS2	.803			
	AS3	.907			
	AS4	.906			
Learning ineffectiveness (LI)	LI1	.743	.939	.756	.900
	LI2	.903			
	LI3	.921			
	LI4	.937			
	LI5	.828			

Note. CR = composite reliability; AVE = average variance extracted.

Model Fit Analysis

The model fit and statistical significance of the hypothesized paths between the four potential variables were examined to test the structural model. Kline (2011) suggests that GFI, NFI, and CFI values exceeding .90, a $\chi 2/df$ value less than 3, and an RMSEA value less than .08 can generally be regarded as representing acceptable goodness of fit. The results show that the data ($\chi 2/df$ = 2.466, GFI = .902, NFI = .904, CFI = .940, RMSEA = .077) had an acceptable fit of the hypothesized model. It indicated that the hypothesis model proposed in this study has good fitness.

Path Analysis

The standardized path coefficients (β) of the model of the study are represented in Figure 2 and Table 2. The results indicate that hypotheses 1, 2, 3, 4, and 6 were supported. PPS was positively related to PFS and AS (β = .808, t = 15.695; and β = .325, t = 5.357, respectively). PFS was positively related to AS (β = .636, t = 9.936). Moreover, PFS and AS were negatively related to LI (β = −.453, t = −4.865; and β = −.365, t = −3.495, respectively). However, PPS was not significantly related to LI (β = −.077, t = −1.062). These results indicate that H5 was not supported.

Table 2

Coefficients of the Hypothesized Model

Hypothesis	Path	β	*SE*	*t*	Supported
H1	PPS→PFS	.808	.060	15.695*	Yes
H2	PFS→AS	.636	.062	9.936*	Yes
H3	PPS→AS	.325	.068	5.357*	Yes
H4	AS→LI	−.365	.096	−3.495*	Yes
H5	PPS→LI	−.077	.075	-1.062	No
H6	PFS→LI	−.453	.082	−4.865*	Yes

Note. β = standardized coefficient; H = hypothesis; PPS = preparatory stage; PFS = performance stage; AS = appraisal stage; LI = learning ineffectiveness.

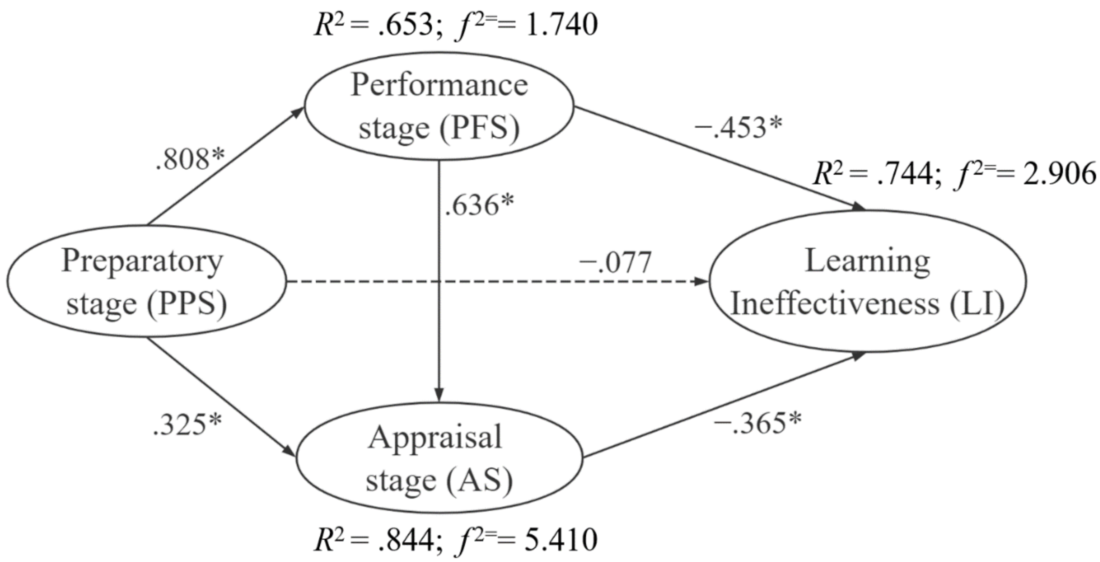
* $p < .001$.

The coefficient of determination (R^2) represents the predictive ability of the model (Fornell & Larcker, 1981), and R^2 values higher than .6 are considered to indicate a high impact effect (Sanchez, 2013). The explanatory power of PPS to PFS was 65.3%, the explanatory power of PPS and PFS to AS was 84.4%, and the explanatory power of PFS and AS to LI was 74.4%. Therefore, all variables had good predictive capacity (Hair et al., 2012).

In addition, f^2 values greater than .8 are considered to have a high effect size, between .2 and .8 are considered medium, and less than .2, small (Cohen, 1988). As shown in Figure 2, the f^2 ranged from 1.740 to 5.410, indicating that the effect size was good. Therefore, the paths between the variables in this study were well verified (Hair et al., 2019).

Figure 2

The Structural Model with Standardized Coefficients



Note. * p < .001.

Finally, 5,000 resample bootstrappings were performed to provide additional evidence related to the significance of the indirect effects. The bootstrapping 95% confidence interval (CI) of the lower and upper bounds of indirect effects did not include zero, indicating that the paths were significant (Preacher et al., 2007). It was significant for the mediated effect of the study model (β = −.672) with 95% CI from −.798 to −.565, indicating that PFS and AS of SRL did have a full mediating effect on the negative correlation between PPS and online LI.

Discussion

The COVID-19 outbreak has caused a growing number of students to adopt online learning, but the effectiveness of online learning is a controversial issue. Research on SRL has been largely from a macro perspective, for example, learning behavior, learning ability, and academic performance. However, there is still a lack of micro perspectives on the interaction mechanism among the various stages of SRL, and it is not clear which stage of behavior has the strongest effect on learning effectiveness. Adopting a micro perspective, this study focused on exploring how stages of learners' SRL behavior affected their perceptions of learning ineffectiveness. The results show that SRL behaviors in the stage of preparatory had a positive effect on the stages of performance and appraisal, and the performance stage had a positive influence on the appraisal stage. We also found that the preparatory stage of SRL affects learning ineffectiveness by mediating the effect of the performance and appraisal stages.

Previous studies indicate that each process in the preparatory stage initiates actions that the learner engages in when performing the task (Ridgley et al., 2020). For example, mood actively activates pre-reflection in

SRL (Lehmann et al., 2014), which initiates actions of the performance stage. In this study, the behaviors in the preparatory stage had a direct positive impact on the performance stage, indicating that if the preparation during the preparatory stage is sufficient, the performance stage process will be easier. Thus, H1 was positively supported.

The use of strategy and meta-cognitive monitoring in the performance stage subsequently influence the appraisal stage, reflect on and evaluate their progress and goal attainment (Ridgley et al., 2020). For example, time management is related to evaluation, reflection, and reaction (Wolters & Brady, 2020). The results show that behaviors in the performance stage had a positive effect on the appraisal stage, indicating that learners would perform better in the appraisal stage according to the adopted task strategies and actively monitor the length of time in the performance stage, positively supporting H2.

Learners need to manage environmental factors such as computer access at home before studying (Cai et al., 2020). Emotion regulation strategies were correlated with reappraisal (Aldao et al., 2010). Pekrun et al. (2011) have proposed that positive emotions may be beneficial in most cases. This could indicate that learners will perform better in the appraisal stage according to their mood adjustment and environment structuring during the preparatory stage. The results of the present research verify that the preparatory stage is positively related to the appraisal stage, supporting H3.

Tzeng and Nieh (2015) state that in the appraisal stage, self-evaluations and self-reactions led learners to feel that their learning was effective and motivated them to continue to work diligently because they believed they could make further progress. Moreover, Zhu et al. (2011) found that learners who were developing help-seeking schemes, such as searching for help on the Internet, were more likely to have good academic performance. By investing more energy in self-evaluation and help seeking after online courses, learners increase their learning effectiveness. The results of the present research verify that the appraisal stage can negatively predict perceived learning ineffectiveness, negatively supporting H4.

Cosnefroy et al. (2018), constructing a self-regulated learning failure model, shows that forethought processes affect academic performance by affecting the performance stage. The actual situation (e.g., noise) and individual characteristics (e.g., mood) influence learning outcomes (Lehmann et al., 2014). Based on the studies mentioned, this research considered that higher SRL when regulating mood and preparing the environment for distance learning can promote learners' behavior within the performance and appraisal stages and reduce learning ineffectiveness. Although the preparatory stage did not show a direct influence on learning ineffectiveness in this study, the preparatory stage was correlated with learners' learning ineffectiveness by mediating the effect of the other two stages. Therefore, H5 was not supported.

The results show that the performance stage of SRL has a high indirect effect on learning ineffectiveness. If they consider a variety of factors such as task strategy and time management during online courses, learners can reduce their learning ineffectiveness; some previous studies (e.g., Alghamdi et al., 2020; Wolters & Brady, 2020) report similar results. Their research shows that task strategy and time management can have positive impacts on academic performance and achievement, respectively. Thus, H6 was negatively supported.

Conclusions

During the outbreak of COVID-19, online learning was comprehensively applied in education. Ways to promote online learning effectiveness in the context of COVID-19 is an important issue. The online learning environment demands learner-centeredness and self-regulation. Self-regulated learning plays a crucial role in online learning. This study divided SRL into three stages and explored the relationship of high school students' SRL from the three stages and learning ineffectiveness. Results indicate that SRL has a predictive effect on learning effectiveness, and high SRL levels can reduce the ineffectiveness of online learning.

Implications

The COVID-19 pandemic has led to the closure of schools around the world, and offline learning has been replaced with distance learning. This study has some implications for online learning in distance education. Epidemic prevention and treatment are moving the world toward normalization. Learning in the post-pandemic era must integrate online and offline learning and maximize students' learning (Mei, 2020), highlighting the importance of online learning and SRL. The exploration of students' online SRL is conducive to understanding the current situation of students' online SRL and points to further improving it. This study has certain reference value for coping with future online learning to deal with such emergencies, which may occur anywhere in the world.

The theoretical significance of the present research is to clarify the impacts of SRL on learning ineffectiveness during COVID-19. This study is also to provide a practical contribution, which is the results show that the preparatory stage of SRL through the performance and appraisal stages affects learners' online learning ineffectiveness. SRL interventions effectively improved learners' SRL, performance, and academic achievement (e.g., Jansen et al., 2019). The results of this study can be applied by high school teachers to enhance students' adaptability in SRL situations by implementing different interventions before, during, and after lessons.

Limitations and Future Study

Several limitations should be acknowledged in this study. First, the sample size was small, and all participants were from the Jiangsu Province, so it is hard to make sure that the sample represents high school education institutions at all levels. Thus, the sample cannot represent all Chinese high school students. Future studies need to collect more and larger representative samples to enhance the conclusions of the study.

Second, the population of the present study was almost 80% female, which may have led to the distribution bias of the results. Gender difference is a potentially important factor affecting SRL and learning performance (Bezzina, 2010). Future studies may explore the role of gender, the three stages of SRL, and learning ineffectiveness.

Moreover, it is increasingly important to explore predictors of online learning success as online courses are becoming more flexible and accessible (Broadbent & Poon, 2015; Su, Ding, & Chen, 2021). Other factors not examined in this study, such as self-efficacy, self-direction, learning motivation, and learning satisfaction, may also affect students' perceived ineffectiveness of online learning. Researchers might consider including other factors that may affect the perceived ineffectiveness of online learning in future studies.

Acknowledgements

This study was supported in part by a grant from National Social Science Foundation (No. BCA200093) and the Priority Academic Program Development of Jiangsu Higher Education Institutions in China. Moreover, this study was supported by the Ministry of Science and Technology, Taiwan, under grant MOST 109-2511-H-019-004-MY2 and MOST 109-2511-H-019-001.

References

Adam, N. L., Alzahri, F. B., Soh, S. C., Bakar, N. A., & Kamal, N. (2017). Self-regulated learning and online learning: A systematic review. In H. Badioze Zaman, P. Robinson, A. F. Smeaton, T. K. Shih, S. Velastin, T. Terutoshi, A. Jaafar, & N. Mohamad Ali (Eds.), *Advances in visual informatics: 5th International Visual Informatics Conference, IVIC 2017, Bangi, Malaysia, November 28–30, 2017, Proceedings* (pp. 143–154). https://doi.org/10.1007/978-3-319-70010-6_14

Aldao, A., Nolen-Hoeksema, S., & Schweizer, S. (2010). Emotion-regulation strategies across psychopathology: A meta-analytic review-science direct. *Clinical Psychology Review*, *30*(2), 217–237. https://doi.org/10.1016/j.cpr.2009.11.004

Alghamdi, A., Karpinski, A. C., Lepp, A., & Barkley, J. (2020). Online and face-to-face classroom multitasking and academic performance: Moderated mediation with self-efficacy for self-regulated learning and gender. *Computers in Human Behavior*, *102*, 214–222. https://doi.org/10.1016/j.chb.2019.08.018

Alsancak Sirakaya, D., & Ozdemir, S. (2018). The effect of a flipped classroom model on academic achievement, self-directed learning readiness, motivation and retention. *Malaysian Online Journal of Educational Technology*, *6*(1), 76–91. https://files.eric.ed.gov/fulltext/EJ1165484.pdf

Bahasoan, A. N., Ayuandiani, W., Mukhram, M., & Rahmat, A. (2020). Effectiveness of online learning in pandemic COVID-19. *International Journal of Science, Technology & Management*, *1*(2), 100–106. https://doi.org/10.46729/ijstm.v1i2.30

Barnard, L., Lan, W. Y., To, Y. M., Paton, V. O., & Lai, S. L. (2009). Measuring self-regulation in online and blended learning environments. *The Internet & Higher Education*, *12*(1), 1–6. https://doi.org/10.1016/j.iheduc.2008.10.005

Bezzina, F. H. (2010). Investigating gender differences in mathematics performance and in self-regulated learning: An empirical study from Malta. *Equality, Diversity and Inclusion*, *29*(7), 669–693. https://doi.org/10.1108/02610151011074407

Boom, G., Paas, F., Merrieenboer, J. J. G. V., & Gog, T. V. (2004). Reflection prompts and tutor feedback in a Web-based learning environment: Effects on students' self-regulated learning competence. *Computers in Human Behavior*, *20*(4), 551–567. https://doi.org/10.1016/j.chb.2003.10.001

Broadbent, J., & Poon, W. L. (2015). Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. *The Internet and Higher Education*, *27*, 1–13. http://doi.org/10.1016/j.iheduc.2015.04.007

Cai, R., Wang, Q., Xu, J. & Zhou, L. (2020). Effectiveness of students' self-regulated learning during the COVID-19 pandemic. *Social Science Electronic Publishing*, *34*(1), 175–182. https://ssrn.com/abstract=3622569

Carrol, N., & Burke, M. (2010). Learning effectiveness using different teaching modalities. *Journal of Business & Economics Research*, *3*(12), 65–72. http://doi.org/10.19030/ajbe.v3i12.966

Charo, R., Maite, A. S., & Guillermo, M. (2020). Self-regulation of learning and MOOC retention. *Computers in Human Behavior, 111*, Article 106423. https://doi.org/10.1016/j.chb.2020.106423

Chen, P., & Bonner, S. (2020). A framework for classroom assessment, learning, and self-regulation. *Assessment in Education Principles Policy and Practice*, *27*(4), 373–393. https://doi.org/10.1080/0969594X.2019.1619515

Cleary, T. J., Callan, G. L., & Zimmerman, B. J. (2012). Assessing self-regulation as a cyclical, context-specific phenomenon: An overview and analysis of SRL microanalysis protocols. *Education Research International*, *2012*, 1–19. https://doi.org/10.1155/2012/428639

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates. http://www.utstat.toronto.edu/~brunner/oldclass/378f16/readings/CohenPower.pdf

Colthorpe, K., Ogiji, J., Ainscough, L., Zimbardi, K., & Anderson, S. (2019). Effect of metacognitive prompts on undergraduate pharmacy students' self-regulated learning behavior. *American Journal of Pharmaceutical Education*, *83*, Article 6646. https://doi.org/10.5688/ajpe6646

Cosnefroy, L., Fe Nouillet, F., Corinne Mazé, & Bonnefoy, B. (2018). On the relationship between the forethought phase of self-regulated learning and self-regulation failure. *Issues in Educational Research*, *28*(2), 329–348. http://www.iier.org.au/iier28/cosnefroy.pdf

DeVellis, R. F., (2012). *Scale development: Theory and applications* (3rd ed.). Sage Publications.

Ernesto, P. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology*, *8*, Article 422. https://doi.org/10.3389/fpsyg.2017.00422

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Hadwin, A. F., Järvelä, S., and Miller, M. (2018). Self-regulation, co-regulation and shared regulation in collaborative learning environments. In D. H. Schunk & J. A. Greene (Eds.), *Handbook of self-regulation of learning and performance* (pp. 83–106). Routledge. https://www.taylorfrancis.com/chapters/edit/10.4324/9781315697048-6/self-regulation-co-regulation-shared-regulation-collaborative-learning-environments-allyson-hadwin-sanna-j%C3%A4rvel%C3%A4-mariel-miller

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage. https://www.cengage.co.uk/books/9781473756540/

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science*, *40*(3), 414–433. https://doi.org/10.1007/s11747-011-0261-6

Hong, J. C., Lee, Y. F., & Ye, J. H. (2021). Procrastination predicts online self-regulated learning and online learning ineffectiveness during the coronavirus lockdown. *Personality and Individual Differences*, *174*(7), Article 110673. https://doi.org/10.1016/j.paid.2021.110673

Jansen, R. S., van Leeuwen, A., Janssen, J., Conijn, R., & Kester, L. (2019). Supporting learners' self-regulated learning in massive open online courses. *Computers & Education*, *146*, Article 103771. https://doi.org/10.1016/j.compedu.2019.103771

Kline, R. B. (2011). *Principles and practice of structural equation modeling*. The Guilford Press. https://www.guilford.com/books/Principles-and-Practice-of-Structural-Equation-Modeling/Rex-Kline/9781462523344

Lee, D., Watson, S. L., & Watson, W. R. (2020). The relationships between self-efficacy, task value, and self-regulated learning strategies in massive open online courses. *International Review of Research in Open and Distance Learning*, *21*(1), 23–39. https://doi.org/10.19173/irrodl.v20i5.4389

Lehmann, T., Haehnlein, I., & Ifenthaler, D. (2014). Cognitive, metacognitive and motivational perspectives on preflection in self-regulated online learning. *Computers in Human Behavior*, *32*, 313–323. https://doi.org/10.1016/j.chb.2013.07.051

Liu, X., He, W., Zhao, L., & Hong, J. C. (2021). Gender differences in self-regulated online learning during the COVID-19 lockdown. *Frontiers in Psychology*, *12*, Article 752131. https://doi.org/10.3389/fpsyg.2021.752131

Maison, S., & Syamsurizal, T. (2019). Learning environment, students' beliefs, and self-regulation in learning physics: Structural equation modeling. *Journal of Baltic Science Education*, *18*(3), 389–403. https://doi.org/10.33225/jbse/19.18.389

Mei, D. (2020, January). Research on multi-integrated online and offline teaching model in the post-epidemic era: Taking numerical analysis course as an example. In *Proceedings of the 2020 5th International Conference on Modern Management and Education Technology (MMET 2020)* (pp. 356–359). Atlantis Press. https://doi.org/10.2991/assehr.k.201023.072

Moghadari-Koosha, M., Moghadasi-Amiri, M., Cheraghi, F., Mozafari, H., & Zandieh, M. (2020). Self-efficacy, self-regulated learning, and motivation as factors influencing academic achievement among paramedical students: A correlation study. *Journal of Allied Health*, *49*(3), e145–e152. https://pubmed.ncbi.nlm.nih.gov/32877483/

Mustajab, M., Baharun, H. & Fawa'Iedah, Z. (2020). Adapting to teaching and learning during COVID-19: A case of Islamic school's initiative of self-regulated learning. *Nadwa*, *14*(2), 241–264. https://doi.org/10.21580/nw.2020.14.2.6515

Pekrun, R., Goetz, T., Frenzel, A. C., Barchfeld, P., & Perry, R. P. (2011). Measuring emotions in students' learning and performance: The achievement emotions questionnaire (AEQ). *Contemporary Educational Psychology*, *36*(1), 36–48. https://doi.org/10.1016/j.cedpsych.2010.10.002

Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation: Theory, research, and applications* (pp. 451–502). Academic Press. https://doi.org/10.1016/B978-012109890-2/50043-3

Preacher, K. J., Rucker, D. D., & Hayes, A. F. (2007). Addressing moderated mediation hypotheses: Theory, methods, and prescriptions. *Multivariate Behavioral Research*, *42*(1), 185–227. https://doi.org/10.1080/00273170701341316

Rabin, E., Henderikx, M., Kalman, Y. M., & Kalz, M. (2020). What are the barriers to learners' satisfaction in MOOCs and what predicts them? The role of age, intention, self-regulation, self-efficacy and motivation. *Australasian Journal of Educational Technology*, *36*(3), 119–131. https://doi.org/10.14742/ajet.5919

Ridgley, L. M., Rubenstein, D., & Callan, G. L. (2020). Gifted underachievement within a self-regulated learning framework: Proposing a task-dependent model to guide early identification and intervention. *Psychology in the Schools*, *57*(3), 1365–1384. https://doi.org/10.1002/pits.22408

Ruhland, S. K., & Brewer, J. A. (2001). Implementing an assessment plan to document student learning in a two-year technical college. *Journal of Vocational Education Research*, *26*, 141–171. https://doi.org/10.5328/JVER26.2.141

Samruayruen, B., Enriquez, J., Natakuatoong, O., & Samruayruen, K. (2013). Self-regulated learning: A key of a successful learner in online learning environments in Thailand. *Journal of Educational Computing Research*, *48*(1), 45–69. https://doi.org/10.2190/EC.48.1.c

Sanchez, G.. (2013). *PLS path modeling with R*. Trowchez Editions. https://www.gastonsanchez.com/PLS_Path_Modeling_with_R.pdf

Su, Y. S., Ding, T. J., & Chen, M. Y. (2021). Deep learning methods in internet of medical things for valvular heart disease screening system. *IEEE Internet of Things Journal, 8*(23), 16921-16932. https://doi.org/ 10.1109/JIOT.2021.3053420

Su, Y. S., & Wu, S. Y. (2021). Applying data mining techniques to explore users behaviors and viewing video patterns in converged it environments. *Journal of Ambient Intelligence and Humanized Computing*. https://doi.org/10.1007/s12652-020-02712-6

Thompson, B. (2000). Ten commandments of structural equation modeling. In L. G. Grimm & P. R. Yarnold (Eds.), *Reading and understanding more multivariate statistics* (pp. 261–283). American Psychological Association.

Tuti, T., Paton, C., & Winters, N. (2021). The counterintuitive self-regulated learning behaviours of healthcare providers from low-income settings. *Computers & Education*, *166*(1), Article 104136. https://doi.org/10.1016/j.compedu.2021.104136

Tzeng, S., & Nieh, H. (2015, September). How self-concept, self-efficacy and self-evaluation relate to relate to achievement outcomes: New technology-based learning models for science and technology universities students. In *Proceedings of 2015 International Conference on Interactive Collaborative Learning (ICL), 20–24 September 2015, Firenze, Italy* (pp. 863–870). https://doi.org/10.1109/ICL.2015.7318141

van Herk, H., Poortinga, Y. H., & Verhallen, T. M. M. (2004). Response styles in rating scales: Evidence of method bias in data from six EU countries. *Journal of Cross-Cultural Psychology*, *35*, 346–360. https://doi.org/10.1177/0022022104264126

Wolters, C. A., & Brady, A. C. (2020). College students' time management: A self-regulated learning perspective. *Educational Psychology Review*. Advance online publication. https://doi.org/10.1007/s10648-020-09519-z

Won, S., Hensley, L. C., & Wolters, C. A. (2021). Brief research report: Sense of belonging and academic help-seeking as self-regulated learning. *The Journal of Experimental Education, 89*(1), 1–13. https://doi.org/10.1080/00220973.2019.1703095

Zeidner, M., & Stoeger, H. (2019). Self-regulated learning (SRL): A guide for the perplexed. *High Ability Studies*, *30*(1–2), 9–51. https://doi.org/10.1080/13598139.2019.1589369

Zhang, T., Taub, M., & Chen, Z. (2021, April). Measuring the impact of COVID-19 induced campus closure on student self-regulated learning in physics online learning modules. In *LAK21: 11th International Learning Analytics and Knowledge Conference* (pp. 110–120). Association for Computing Machinery. https://doi.org/10.1145/3448139.3448150

Zhang, W., Wang, Y., Yang, L., & Wang, C. (2020). Suspending classes without stopping learning: China's education emergency management policy in the COVID-19 outbreak. *Journal of Risk and Financial Management*, *13*(3), Article 55. https://doi.org/10.3390/jrfm13030055

Zhao, L., He, W., & Su, Y. S. (2021). Innovative pedagogy and design-based research on flipped learning in higher education. *Frontiers in Psychology*, *12*, Article 230. https://doi.org/10.3389/fpsyg.2021.577002.

Zhao, L., Liu, X., & Su, Y. S. (2021). The differentiate effect of self-efficacy, motivation, and satisfaction on pre-service teacher students' learning achievement in a flipped classroom: A case of a modern educational technology course. *Sustainability*, *13*, Article 2888. https://doi.org/10.3390/su13052888

Zhu, Y. Q., Chen, L. Y., Chen, H. G., Chern, C. C. (2011). How does Internet information seeking help academic performance? The moderating and mediating roles of academic self-efficacy. *Computers & Education*, *57*(4), 2476–2484. https://doi.org/10.1016/j.compedu.2011.07.006

Zhu, Y., Zhang, J. H., Au, W., & Yates, G. (2020). University students' online learning attitudes and continuous intention to undertake online courses: A self-regulated learning perspective. *Educational Technology Research and Development*, *68*, 1485–1519. https://doi.org/10.1007/s11423-020-09753-w

Zimmerman, B. J. (1990). Self-regulated learning and academic achievement: An overview. *Educational Psychologist*, *25*(1), 3–17. https://doi.org/10.1207/s15326985ep2501_2

Zimmerman, B. J. (2000). Attaining self-regulation: a social cognitive perspective. In M. Boekaerts, P. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13–39). Academic Press. https://doi.org/10.1016/B978-012109890-2/50031-7

Zimmerman, B. J. (2015). Self-regulated learning: Theories, measures, and outcomes. In J. D. Wright (Ed.), *International encyclopedia of the social & behavioral sciences* (2nd ed, pp. 541–546). https://doi.org/10.1016/B978-0-08-097086-8.26060-1