Effects of Self-Efficacy and Online Learning Mind States on Learning Ineffectiveness during the COVID-19 Lockdown

Jon-Chao Hong[1], Xiaohong Liu[2], Wei Cao[2], Kai-Hsin Tai[1] and Li Zhao[2*]
[1]Department of Industrial Education, National Taiwan Normal University, Taiwan // [2]School of Education Science, Nanjing Normal University, Nanjing, China // tcdahong@gmail.com // xiaohongliu1211@gmail.com // 2576901707@qq.com // star99xin@gmail.com // li.zhao@njnu.edu.cn
[*]Corresponding author

ABSTRACT: With the outbreak of COVID-19, more online learning has been adopted for distance learning. However, the effectiveness of online learning for those students engaged in it for the first time has not been discussed. This study aims to investigate perceived ineffectiveness of online learning and its antecedents related to cognitive and affective factors. Internet self-efficacy (ISE) and Self-efficacy of interacting with learning content (SEILC) were hypothesized to have a correlation with perceived ineffectiveness of online learning (PIOL) mediated by participants' Internet cognitive fatigue (ICF) and mind-unwandered, while ICF was hypothesized to have a correlation with mind-unwandered. Data of 251 students collected from high schools in China during the lockdown period of COVID-19 were subjected to confirmatory factor analysis via AMOS. Results indicated that participants' ISE and SEILC were positively related to mind-unwandered, but negatively related to ICF during online learning, while ICF was positively associated with PIOL. On the other hand, mind-unwandered was negatively associated with PIOL. Furthermore, students' ISE and SEILC indirectly affected their PIOL mediated by ICF. Findings suggest that an enhancement of learners' ISE and SEILC could have reduced the level of PIOL the first time that online learners experienced under the COVID-19 lockdown to promote their learning effectiveness. This understanding will be useful in case of another pandemic outbreak.

Keywords: E-learning, High school students, Internet cognitive fatigue, Mind-unwandered, Online learning

1. Introduction

More than 130 countries affected by the coronavirus outbreak have temporarily closed down offline educational facilities to contain the diffusion of COVID-19. To mitigate the immediate impact of school closures, the United Nations Educational, Scientific and Cultural Organization (UNESCO) has launched distance learning solutions (UNESCO, 2020). Most online courses are synchronous online lectures via Zoom or Tencent Meeting.

With COVID-19 disrupting our learning and lives without warning, students had some difficulties with this urgent online distance learning (Zainuddin et al., 2020). Particularly, many teachers or students had no previous experience of online teaching or learning due to the main form of education still being face-to face learning. Therefore, this large-scale online learning phenomenon was undoubtedly a new challenge for the vast majority of teachers and students. For example, some students were not able to use any internet-enabled devices to participate in their study at home or to connect to a mobile network. Differences in the speed of Internet access and the type of learning device may also cause fatigue for some learners (Carter Jr et al., 2020). Whether in face-to-face or online classes, the key to a student's academic success is engagement (Buelow et al., 2018). In the traumatic environment of the COVID-19 epidemic, many learners may not be in a suitable emotional state to focus on learning (Carter Jr et al., 2020). How to maximize academic achievement or learning outcomes of online learning has been the focus of educators and researchers (Yokoyama, 2019), with most studies comparing the overall effect of online learning with traditional learning, or exploring the correlation between learning outcomes and behavior in online learning (e.g., number of attendance and discussions) (Koç, 2017; Zheng et al., 2020). Considering that the ineffectiveness of online learning has not been extensively studied in the context of online learning during the COVID-19 lockdown, this study explores the correlates of learning ineffectiveness in the online learning context. In particular, the learning ineffectiveness mentioned in this study refers to the negative evaluation of learning effectiveness by students who experienced online learning during the COVID-19 lockdown (Hong et al., 2021).

The cognitive theory of multimedia learning (CTML) attempts to explain how multimedia instructional design can affect learners' cognitive processing and learning performance (Mayer, 2005). In the learning process, individuals' cognition is limited in the face of multimedia information, and they can only process a certain amount of information within a given time (Liu et al., 2018). CTML provides a foundation for understanding factors that both promote and inhibit the input attention of learners in online learning. For example, students' attention levels influence their learning effectiveness within a MOOC learning environment (Chang et al., 2019). Moreover, students' attention plays a mediating role between their self-efficacy and achievement (Sun & Yeh, 2017). Extending the CTML to online learning environments, this study evaluates studies on attention level related to Internet cognitive fatigue (Hong et al., 2015) (i.e., being considered as cognitive fatigue in online learning) and mind-unwandered (Siegel, 2016) during online learning predicted by self-efficacy and reflecting learning ineffectiveness.

Individual nursing students' perceptions of self-efficacy were found to play a key role in their adoption of behaviors and maintenance of better performance (Karabacak et al., 2019). However, adolescents seldom express positive values of others' actions, and are likely to be biased in their response tendencies (Soto et al., 2008; van Herk et al., 2004). For example, an acquiescent "worth to myself" response is a tendency to respond negatively to survey items which are related to others or systems (Daniel & Benish-Weisman, 2019). For example, participants usually face some difficulties that prevent them from feeling satisfied with participating in online courses (Rabin et al., 2020). Considering this, by adopting the opposite self-rating, learning ineffectiveness replaced learning effectiveness for high-school-student participants to self-evaluate their perceptions of their online learning performance. This study aimed to explore the correlates between those students' different types of self-efficacy, Internet cognitive fatigue and mind-unwandered during online learning, and to determine whether those factors had a strong association with the high school students' perceptions of online learning ineffectiveness during the COVID-19 lockdown.

2. Theoretical background

Drive theory can be used to explain various individual difference measures, including motivation, attitudes, and psychological interests (Bouchard Jr., 2016). According to drive theory, there are two noteworthy ways to involve individuals in activities to achieve certain goals: 1) competence and confidence, and 2) cognition and emotion (Hrtoňová et al., 2015). Considering this, this study included participants' self-efficacy and attentional factors related to reflecting meaningfully on the ineffectiveness of online learning.

2.1. Internet self-efficacy and interacting with learning content self-efficacy in the context of online learning

According to Bandura's (1977) concept of self-efficacy, which is an individual's belief in his/her ability to succeed, individuals will try to do what they believe they can do, will choose to perform activities according to their efficacy beliefs, and will put efforts into activities and persist when faced with obstacles based on estimates of their efficacy. Considering the concept of interaction between the environments, the structure, and the individuals, the most prominent framework of interaction in distance education includes learner-environment interaction and learner–content interaction (Moore, 2013). Self-efficacy can affect performance (Morfoot & Stanley, 2018). When relating self-efficacy to online learning, researchers have proposed various types of self-efficacy from different angles (Hodges, 2008). For example, Chu and Tsai (2009) highlighted a two-dimensional category and classified ISE into general Internet self-efficacy (GISE) and communication Internet self-efficacy (CISE). GISE showed the confidence in overcoming the fundamental challenges associated with the operation of the Internet, whereas CISE is related to the confidence in communicating and interacting with others through the Internet (Chu, 2010; Chu & Tsai, 2009). Considering this, learners' interacting ability and confidence in online learning, considered as two types of self-efficacy: Internet self-efficacy (ISE) (i.e., learner-online system interaction) and self-efficacy of interacting with learning content (SEILC) (i.e., learner-content interaction), were taken into account in this study.

Internet self-efficacy (ISE) refers to users' self-efficacy when interacting with a website, the system itself, and interactive content designed for users. ISE has been defined as an individual's belief in his/her ability to successfully use the Internet, and is considered as an important antecedent of the effects of e-learning (Eastin & LaRose, 2000; Jokisch et al., 2020). Additionally, with respect to interactive actions, content should have a strong relationship to information searching that has effects on learning self-efficacy (Jokisch et al., 2020). Regarding the interactive content in online learning systems, self-efficacy can achieve the confidence of information transfer between humans and computers (Hong et al., 2011). Accordingly, the two types of online learning self-efficacy: ISE and Self-efficacy of interacting with learning content (SEILC), were examined to understand how they affect participants' online learning, as mentioned above. Considering online learning during the COVID-19 lockdown in which students had to interact with transactional media and transactional content, this study explored how their ISE and SEILC interacted during their online learning was explored in this study.

2.2. Attention factors: Internet cognitive fatigue and mind-unwandered in the context of online learning

As a key factor in cognitive processing and human perception, attention can arouse individual's perception of events and lead to the cognitive processing needed for meaningful learning (Baars, 1997). Humans cannot respond to or process all of the environmental stimuli they encounter due to their limited attention capacities (Pashler, 1998). In online learning environments, learners obtain the information that meets their respective aims by performing online searches, which requires them to pay attention to the learning tasks (Wu & Xie, 2018). Therefore, within the online search paradigm, focused attention on tasks related to active cognitive control is related to current information processing.

Attention is usually treated as a dichotomy: inattention is considered as mind-wandering as a result of losing attention when performing a task, while the other option is full attention, which is postulated as mind-unwandered when attention is focused on a task. At different hierarchical levels of cognitive processing, mind-unwandered can keep attention focused on the external input and sustain cognitive processing (Schad et al., 2012). In addition, mind-unwandered refers to paying attention to one's thoughts and emotions, which make one's experiences on a moment-to-moment basis during the cognitive process (Siegel, 2016). Mind-unwandered therefore pertains to task-related thought which can probe on-task thoughts in online education contexts.

As for cognitive processing, attention failure can be assessed by comparing participants' response errors with the distractions that they experience when performing tasks, which results in cognitive fatigue (Geva et al., 2013). Cognitive fatigue is defined by DeLuca as "time-related deterioration in the ability to perform certain mental tasks" (2005, p. 38). Accordingly, Hong et al. (2015) extended this type of cognitive disability to the Internet world, as Internet cognitive fatigue (ICF), with the aim of exploring the effect of ICF on vocabulary memorization to support the argument that ICF represents a correlation or expression of a reduction in a learner's online performance. Cognitive fatigue undermines task performance, because participants will reduce their attention and its allocation to stimuli that are unrelated to the task (Was et al., 2019).

When attention shifts from a task due to distractions in the environment, or due to internal thoughts, attention failures will occur, leading to failures in intended actions (Unsworth et al., 2012). On the other hand, during activities that are demanding and which require concentration, if an individual has a high level of mind-unwandered, it often leads to better performance and accuracy (Hollis & Was, 2016). The idea here is that online learning is likely a common need in the COVID-19 lockdown for students who are engaging in an online course and are hence interacting with an online learning system and trying to stay on task. Accordingly, the inhibitor or promoter for maintaining attention in online courses will influence students' performance. This study therefore aimed to evaluate individual differences in Internet cognitive fatigue and mind-unwandered, while participants had lessons in an online learning system, and it analyzed how various factors influenced their learning performance.

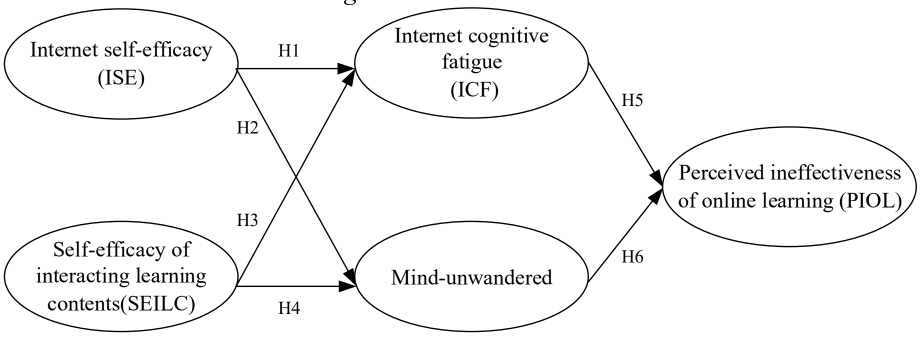
2.3. Research model and hypotheses

Gray (1982) conceptualized only two behavioral systems, the behavioral approach system (BAS) and the behavioral inhibition system (BIS). Oguchi and Takahashi (2019) suggested that the activated BIS predicts inattention and avoids the pursuit of desired goals; on the other hand, BAS drives more attention to the persistent pursuit of desired goals. Considering the learning potential effectiveness influenced by the behavioral system, BAS is activated by positive factor stimuli, while BIS is activated by negative factor stimuli; both stimuli affect learning performance (Chan & Tse, 2018). Accordingly, the present study focused on the attention level related to the deactivating factor: Internet cognitive fatigue as a BIS factor, and the activating factor, mind-unwandered, as a BAS factor, predicted by the positive psychological trait, self-efficacy, that reflects learning ineffectiveness in an online learning context. Thus, to explore the correlates between those factors, the present study referred to drive theory to develop a conceptual model, shown as follows (see Figure 1).

Working memory capacity is generally considered to be capable of processing information and of retaining it (van Merriënboer & Ayres, 2005). Cognitive ability affects the working memory capacity of the learners, who will then invest mental effort in maintaining attention to attain the learning that will enhance their performance outcomes (Kirschner et al., 2006). An individual with greater self-efficacy will experience a lower burden on working memory resources than an individual with less self-efficacy (Mayer et al., 2001). That is, self-efficacy enables learners to manage attention during practice in on-demand situations (Maertz Jr. et al., 2005). For example, Hong et al. (2016) posited that high levels of self-efficacy are related to low levels of Internet cognitive disability. In that sense, how ISE and SEILC affect Internet cognitive fatigue and mind-unwandered during online learning was hypothesized as follows:

H1: ISE is negatively related to students' ICF.
H2: ISE is positively related to students' mind-unwandered.
H3: SEILC is negatively related to students' ICF.
H4: SEILC is positively related to students' mind-unwandered.

Figure 1. Research model



Executive attention refers to the system that controls interference and resolves conflicts between possible reactions (Fan et al., 2002). According to Fougnie (2008), attention is mostly concerned with the manipulation of information during the learning process. Several studies have confirmed that the control of attention is strongly related to performance scope (Shipstead et al., 2016). For example, Musso et al. (2019) partially demonstrated the differential levels of cognitive processes that affect the prediction of mathematics performance. In addition, self-evaluation affects academic performance, both directly and indirectly mediated by cognitive ability (Demetriou et al., 2020), providing a foundation to further explore cognitive performance. Accordingly, the interaction effects between different types of attention: Internet cognitive fatigue and mind-unwandered on performance tasks, were hypothesized as follows:

H5: ICF is positively related to students' PIOL.
H6: Mind-unwandered is negatively related to students' PIOL.

In an online learning environment, students' self-efficacy is critical to improve learning performance. Students in online learning environments have a higher dropout rate (Bawa, 2016), and this dropout rate is related to students' low self-efficacy (Lee & Choi, 2011). In online learning, because students are required to mentally combine redundant information or integrate different sources of information, unnecessary working memory will be increased (Schmeck et al., 2015; Sweller et al., 2019). For example, in the context of online learning, if students waste too much time searching for information, then de-motivation tends to occur (Simunich et al., 2015). Therefore, the present study considered that the two types of self-efficacy (ISE and SEILC) would indirectly affect students' PIOL by affecting their Internet cognitive fatigue and mind-unwandered,. The following hypotheses were thus proposed:

H7a: The two types of self-efficacy are negatively related to PIOL mediated by ICF.
H7b: The two types of self-efficacy are negatively related to PIOL mediated by mind-unwandered.

3. Method

3.1. Data collection and participants

In this study, random sampling was adopted and data were collected using online questionnaires which were administered during the COVID-19 lockdown period of April 20-30, 2020. The data were collected through a web-based survey of 279 students from high schools in Jiangsu province, China. Participants took part in the online survey voluntarily and anonymously. However, 28 questionnaires were removed due to missing values or because the response time was too short. The remaining 251 data from the questionnaire were analyzed.

The participants consisted of 95 boys (37.8%) and 156 girls (62.2%). The students were aged between 15 and 18 years (M = 16.87, SD = .95); 39 (15.5%) reported that they spent less than 2h/day on online courses, 125 (49.8%) reported that they spent 2h-4h, 61 (24.3%) spent 4h-6h, while the remaining 26 (10.4%) reported spending more than 6h. As for the number of online courses the participants had attended in the current semester, 30 (12.0%) had attended less than 3, 203 (80.9%) had attended 4-6, 14 (5.5%) had attended 7-9, and the remaining four

(1.6%) participants had attended 10-12 online courses. Most of the participants (Frequency = 67, 26.7%) took courses online between 71% and 80% of the time in the current semester.

3.2. Instruments

The items of five constructs were adapted from previous studies and were created by having the original items professionally translated into Chinese. Face validity was conducted by research experts. Finally, a 5-point Likert scale was employed (i.e., ranging from 1 indicating *strongly disagree* to 5 indicating *strongly agree*), and the reliability of the constructs was subsequently tested. After omitting the items with low factor loadings or which were highly correlated with other items in the research model, final constructs showed good composite reliability, internal consistency reliability, and convergent validity (as shown in Table 1).

3.2.1. Internet self-efficacy measurement

This Internet self-efficacy scale was originally developed by Eastin and LaRose (2000), to assess the undergraduate students' Internet self-efficacy. In the context of ISE, consistency in appearance, control, and function of the website is important to the user (Cheng & Tsai, 2011). Accordingly, six items were designed in this study; exemplary items include: "I am confident in successfully dealing with the emergent problems of human-computer interaction in online learning" and "If I come across any trouble while using a website to learn, I have confidence in overcoming it."

3.2.2. Self-efficacy of interacting with learning content measurement

This study integrated Kuo's (2010) and Kao and Tsai's (2009) scales to develop the Self-Efficacy of Interacting with Learning Content measurement. All items were reviewed by two experts in online learning. Thus, six items were designed for this study; two example items are: "I have the confidence to understand new content on an e-learning platform" and "If I come across difficult content in e-learning, I have confidence in my ability to learn it well."

3.2.3. Internet cognitive fatigue measurement

This scale was adapted from Hong et al. (2015). It was originally developed to measure cognitive fatigue from time-on-task in terms of concentration, attention, memory, perception and motor control, and to evaluate the task-specific mistakes as time-related degradation in ability. Thus, five items were designed in this study; exemplary items include: "I lose concentration very quickly during online learning" and "I reach attention deficit very quickly during online learning."

3.2.4. Mind-unwandered measurement

The mind-unwandered scale was originally developed by Brown and Ryan (2003), to measure participants' general tendency to pay attention to assessing natural propensity and to focus on the current moment. Accordingly, the state of mind-unwandered as being fully attentive to present internal and external stimuli was considered when designing the questionnaire items. Thus, eight items were designed for this study, all of which were reviewed by two experts in online learning. Exemplary items include: "When studying online, I can follow the teacher's teaching steps even if I am away from the teacher" and "When I'm learning online, I don't leave the learning interface to do things that aren't related to what I'm learning in class."

3.2.5. Perceived ineffectiveness of online learning measurement

The Perceived Ineffectiveness of Online Learning scale was originally developed by Hong et al. (2021) to measure college students' perceived learning ineffectiveness. Six items were designed for this study; exemplary items are: "Since learning online, my learning efficiency has decreased" and "Since learning online, the quality of my homework has gotten worse."

3.3. Reliability and validity analysis

First, items with factor loading values less than 0.5 in each construct were deleted in each construct. After conducting CFA, items with the highest residual value in each construct were deleted until those CFA values reached the threshold suggested by Hair et al. (2019). The measurement model exhibited a good fit, with χ^2 = 132.276, df = 109, p < .001, χ^2/df = 1.214, GFI = .944, NFI = .952, CFI = .991, and RMSEA = .029. Hence, 22 remaining items were kept for further analysis, including three items each for ISE, SEILC, and ICF, and four each for mind-unwandered and PIOL.

Second, the internal and composite reliabilities of the questionnaire were analyzed. George and Mallery (2003) stated that if the Cronbach's alpha coefficient is greater than 0.7, it means that internal consistency is high, and reliability is high. The composite reliability (CR) over 0.70 indicates good external reliability (Hair et al., 2019). Table 1 displays that CR and Cronbach's alpha were both above 0.7, with CR ranging from .765 to .943 and Cronbach's alpha ranging from .764 to .942, indicating that the Cronbach's alpha and CR values of all the constructs met the threshold.

Third, convergent validity is determined by the factor load (FL) and average variable extraction (AVE) of each observed variable. The FL and AVE for each observed variable should be higher than 0.5 based on George and Mallery (2003) and Hair et al. (2019). Table 1 shows that the AVE of each construct was more than .50 (ranging from .522 to .805), and the FL of each construct was greater than .50 (ranging from .721 to .896). In sum, the convergent validity of each construct was acceptable.

Table 1. Reliability and validity analysis

Variables	*M*	*SD*	Cronbach's α	CR	AVE	FL
Threshold	--	--	> 0.7	> 0.7	> 0.5	> 0.5
Internet self-efficacy	2.426	0.783	0.786	0.789	0.557	0.743
Self-efficacy of interacting with the learning content	3.988	0.720	0.729	0.800	0.573	0.755
Internet cognitive fatigue	3.714	0.623	0.764	0.765	0.522	0.721
Mind-unwandered	3.836	0.637	0.898	0.901	0.695	0.831
Perceived ineffectiveness of online learning	2.675	1.054	0.942	0.943	0.805	0.896

3.4. Data analysis

Descriptive statistics of participants' information and the reliability and validity of the questionnaire were obtained in the current study by using SPSS (version 20.0). Moreover, we used first-order confirmatory factor analysis (CFA) to confirm the item suitability of the measuring questionnaire. Afterward, model-fit indexes of the measurement items were used to verify the measurement model. Structural equation modeling (SEM) was then conducted to assess the hypothetical structural model via AMOS (version 22.0).

4. Results

4.1. Model fit analysis

The model fit and statistical significance of the hypothesized path among the five potential variables were examined to test the structural model. The standardized regression weight, item communalities, and model-fit indexes of the measurement items were applied to identify the structural validity of the measurement model. Various measures were conducted to assess the fit of the models, such as the root mean square error of approximation (RMSEA), the goodness of fit index (GFI), the normed fit index (NFI), the comparative fit index (CFI), and chi-square normalized by degree of freedom (Chi-square/df).

The χ^2 of this study is 274.378 and the degree of freedom (df) is 113, which makes χ^2/df equal to 2.428 The resulting ratio is less than 3, which is regarded as being indicative of a good fit (Kline, 2010). The RMSEA value below .08 is considered to be a good fit. On the other hand, a GFI value below .08 means a good model fit (Hair et al., 2019). Moreover, Kline (2010) suggested that the AGFI value has to surpass the threshold value of .80. In the present study, RMSEA was .076, GFI was .901, and AGFI was .875, all meeting the threshold values. Additionally, the Normed Fit Index (NFI) was .901, the Non-Normed Fit Index (NNFI) was .926, the Comparative Fit Index (CFI) was .939, and the Incremental Fit Index (IFI) was .939; therefore, the present model fits were all above .90, indicating a good fit (Kline, 2010). Moreover, PNFI and Parsimonious Goodness of Fit

Index (PGFI) were .749 and .665, which passed the suggested threshold value of .5 (Hair et al., 2019). These indicators show that the hypothesis model proposed in this study has good fitness.

4.2. Path analysis

To test the six hypotheses, AMOS was used to calculate the correlation coefficient among the five latent constructs and the research model's explanatory power. The standardized path coefficients of the hypothesized model are shown in Table 2 and Figure 2. The results indicate that Hypotheses 1, 2, 3, 4, 5 and 6 were all supported. The ISE was positively related to SEILC and mind-unwandered (β = 0.567, t = 7.133***; β = 0.326, t = 4.980**). The ISE and SEILC were negatively related to ICF (β = -0.374, t = -4.402***; β = -0.423, t = -4.954***). Moreover, ICF was positively related to PIOL (β = 0.350, t = 4.287***), and mind-unwandered was negatively associated with PIOL (β = -0.211, t = -3.041**).

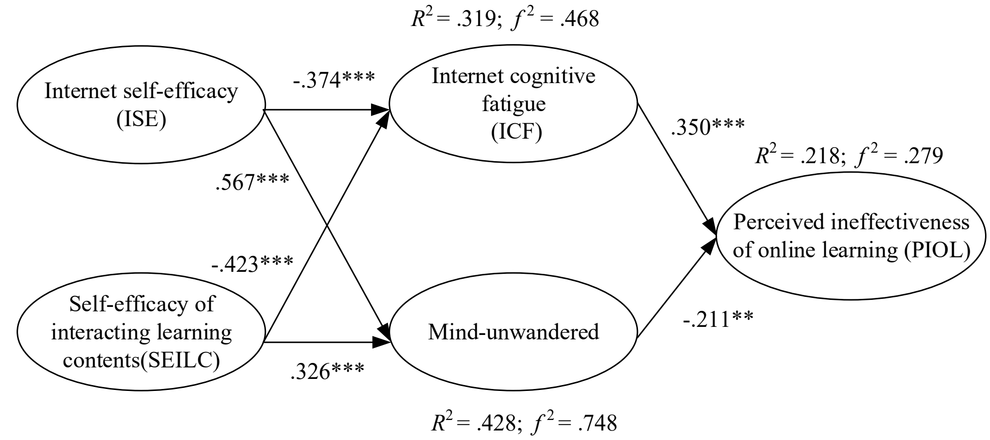
The coefficient of determination (R^2) represents the overall impact of the exogenous variable on the endogenous variable. R^2 values higher than 0.6 are considered to have a high impact effect, 0.3-0.6 are considered medium, and less than 0.3 is considered as having a low impact effect (Sanchez, 2013). Those R^2 values in Figure 2 indicate that ISE and SEILC had a medium impact on ICF and mind-unwandered, and the effect of ICF and mind-unwandered on PIOL was low. In addition, effect size (Cohen's f^2) was proposed by Cohen (1988), where f^2 values greater than 0.8, between 0.2 and 0.8, and less than 0.2 can be considered as large, medium and small, respectively. As shown in Figure 2, the explanatory power of ISE and SEILC on ICF was 31.9% (f^2 =.468), and on mind-unwandered it was 42.8% (f^2 =.748). The explanatory variance of ICF and mind-unwandered on PIOL was 21.8% (f^2 =.279). Hence, the six variables in this study have good predictive power (Hair et al., 2019).

Table 2. Coefficients of the hypothesized model

Hypothesis	Path	Standardized coefficient (β)	*S.E.*	*t*	Supported?
H1	ISE→ ICF	-0.374	0.103	-4.402***	Yes
H2	ISE→ Mind-unwandered	0.567	0.116	7.133***	Yes
H3	SEILC→ ICF	-0.423	0.099	-4.954***	Yes
H4	SEILC→ Mind-unwandered	0.326	0.091	4.98***	Yes
H5	ICF→PIOL	0.35	0.137	4.287***	Yes
H6	M→PIOL	-0.211	0.097	-3.041**	Yes

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

Figure 2. Verification of the research model



4.3. Indirect effects of SEILC and ISE on PIOL mediated by two types of attention

To provide additional evidence to explore whether the indirect effects contained in the research model are significant, 1,000 resample bootstrappings were performed in this study. The bootstrapping results are shown in Table 3, which provides the un-standardized coefficient and upper and lower bound of 95% confidence intervals. It can be observed that the bootstrapping confidence intervals of indirect effects did not comprise zero in the two paths, including ISE→ICF→PIOL (95% CI= [-.398, -0.044]) and SEILC→ICF→PIOL (95%CI = [-0.408, -0.046]). Therefore, ISE and SEILC were negatively related to PIOL mediated by ICF, revealing that H7a was supported. Mind-unwandered did not mediate the effect from ISE and SEILC to PIOL, due to the bootstrapping confidence interval of indirect effects which contained zero, indicating that H7b was unsupported.

Table 3. Bootstrapping results

Model paths	Un-standardized coefficient	95% CI	
		Lower bound	Upper bound
Indirect effect			
ISE→ ICF→ PIOL	-.268	-0.398	-0.044
ISE→ Mind-unwandered→ PIOL	-.244	-0.359	0.077
SEILC→ ICF→ PIOL	-.288	-0.408	-0.046
SEILC→ Mind-unwandered→ PIOL	-.133	-0.205	0.038

5. Discussion

Considering the potential learning effectiveness influenced by the behavioral system, BAS was activated by positive factor stimuli, and BIS was activated by negative factor stimuli, with both stimuli affecting learning performance (Chan & Tse, 2018). Accordingly, the present study is focused on the attention level related to the BIS factor: Internet cognitive fatigue, and the BAS factor: mind-unwandered, predicted by the positive psychological trait: self-efficacy, that reflects the perception of learning ineffectiveness in an online learning context. Basically, this behavioral system provided a multidimensional model for understanding online learning with an emphasis on student focus factors (i.e., Mind-unwandered and ICF) and self-efficacy (i.e., ISE and SEILC). The results of this study help us to understand the students' perceived ineffectiveness of online learning during the COVID-19 lockdown.

Working memory capacity is generally considered to be capable of processing information and of retaining it (van Merriënboer & Ayres, 2005). With high working memory capacity, an individual will have greater self-efficacy; on the other hand, an individual with less self-efficacy will experience a lower burden on working memory resources (Mayer et al., 2001). Self-efficacy of interacting with learning content is another predictor of students' participation in online learning, due to its being able to build trust in the interaction between the user and the computer (Hong et al., 2011). In addition, ISE is an important predictor of students' participation in the online learning environment (Kuo et al., 2014). The present study further confirms this point, and the results suggest that ISE and SEILC show positive effects on students' mind-unwandered and negative effects on their ICF. H1 and H3 were hence negatively supported, and H2 and H4 were positively supported.

As cognitive ability affects the working memory capacity of the learners, they will then invest mental efforts in paying attention to attaining the learning that will enhance their performance outcomes (Kirschner et al., 2006). For example, cognitive fatigue is usually accompanied by loss of concentration (Was et al., 2019), and this relationship still exists in Internet cognitive fatigue (Hong et al., 2015). The results of the present study verified that ICF can positively predict perceived learning ineffectiveness, revealing that H5 was positively supported.

In an online learning environment, mind-unwandered is an important prerequisite for students to participate in learning activities. However, mind-unwandered is easily interfered with by environmental and personal concerns, especially when learners need to focus on multitasking (Miller et al., 2020; Sana et al., 2013). The results of the current study showed that the negative effect of mind-unwandered on the students' perceived ineffectiveness of online learning was significant. This finding supports Was's et al. (2019) view that mind-wandering is detrimental to learners' learning of course content, and potentially damaging to their learning performance in an online learning environment, showing that H6 was negatively supported.

Perceived ineffectiveness of online learning, as the cognition of students in online learning, is also a factor that should be captured as part of learners' learning outcomes (Ruhland & Brewer, 2001). In summary, ISE and SEILC have an indirect relationship with students' perceived ineffectiveness of online learning, mediated by Internet cognitive fatigue. Therefore, this result was supported by several researchers' views that there is a correlation between self-efficacy and students' learning performance (e.g., Huang & Mayer, 2018; Pellas, 2014). Thus, H7a was supported. In addition, the two types of self-efficacy are positively correlated with attention, and attention is negatively correlated with learning effect. However, mind-unwandered does not play a mediator role in the indirect effect from the two types of self-efficacy to PIOL (and so H7b was not supported).

6. Conclusions

How to promote the effectiveness of online learning is important in the period of the pandemic lockdown. To understand how high school students perceive their efficacy of interacting with an online learning system and content, and their attentional states when interacting with online learning, which is then reflected in their perception of learning ineffectiveness, this study distinguished two types of self-efficacy (Internet self-efficacy and self-efficacy of interacting with learning content) in the context of students' online learning, while exploring how these two types of self-efficacy affect the students' perceived ineffectiveness of online learning as mediated by Internet cognitive fatigue and mind-unwandered. The results provided evidence to show that high school students' perceived ineffectiveness of online learning can be reduced when their mind-unwandered is improved upon and when their cognitive fatigue is reduced. In addition, students' PIOL was indirectly affected by their ISE and SEILC, mediated by ICF.

6.1. Implications

The theoretical contribution of this study is to prove that Internet self-efficacy and self-efficacy in interacting with learning content do extend to the online learning environment, and it was validated that these two kinds of self-efficacy will indirectly influence the students' perceived ineffectiveness of online learning.

The practical contribution of this research is that the findings can provide some guidance to instructors in order to improve their online learning classes. For example, teachers should provide guidance for those students with low Internet self-efficacy and self-efficacy of interacting with learning content. They can provide reminders when students' minds start wandering, and increase learners' interaction within the teaching tool to prolong their mind-unwandered (Ha & Im, 2020; Sun & Yeh, 2017). In addition, teachers can also design their own methods to strengthen the interactivity and collaboration of online learning activities (Liu et al., 2021), helping to reduce isolation and lack of interaction between students in distance online learning, thus improving students' attention.

Finally, it would also be beneficial for teachers to improve the students' ISE and SEILC in order to save online learning time. Enhancing students' mind-unwandered and reducing their ICF will in turn increase their online learning effectiveness.

6.2. Limitations and future study

Although the present study provides some important contributions to the literature, there are several limitations which should be recognized. First, the causal relationship among the observed variables cannot be determined because of the cross-sectional survey. Second, the data of this study were collected in one province of China by random sampling, which did not cover high schools of different levels and therefore cannot represent all Chinese high school students. More and larger representative samples will be needed in the future to assess the extent to which the findings are applicable to other population groups and other countries to confirm the hypotheses of the present study.

Another limitation is that the participants had to receive online learning to avoid the spread of the COVID-19 outbreak. It is unclear whether students' features would produce the same findings in different settings or stages.

In addition, other factors not covered in this study may also affect students' perceived ineffectiveness of online learning, such as self-regulated learning, learning motivation, learning satisfaction, online interaction quality, and academic procrastination. Future studies might consider adding other factors to future studies that may have effects on perceived ineffectiveness of online learning.

The present study proposed a research model to explore the indirect effect between ISE/SEILC, and PIOL mediated by ICF and mind-unwandered, and there were negative predictions. However, we did not test the direct effect between ISE/SEILC and PIOL; future studies may focus on examining their correlation.

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