Open Access

OBM Neurobiology

Original Research

Challenges and Problems on Self-directed Learning Readiness in Non–face-to-face Educational Settings During COVID-19

JeongChul HEO [1], Sumi HAN [2, *]

1. Dept. of Liberal Arts, Chodang University, 380, Muanro, Muaneup, Muangun, Jeollanamdo, 58530, South Korea; E-Mail: stronghap@yahoo.com
2. Dept. of Counseling Psychology, Seoul Cyber University, Solmaero 49gil 60, Gang-Buk Gu, 01133, Seoul, South Korea; E-Mail: hsumi@hanmail.net

* **Correspondence:** Sumi HAN; E-Mail: hsumi@hanmail.net

Academic Editor: Raul Valverde

Special Issue: Neuroscience and Information Technology

OBM Neurobiology
2022, volume 6, issue 4
doi:10.21926/obm.neurobiol.2204141

Received: June 6, 2022
Accepted: September 22, 2022
Published: October 08, 2022

Abstract

This study aimed to verify whether self-directed learning readiness (SDLR) level can be significantly predicted by the literacy of learning management system (LLMS), motivation, and feedback interaction (FI) in non–face-to-face educational settings. We performed Pearson's correlation analysis and multiple regression analysis. A total of 206 online college students responded to this web survey using simple random sampling. Results showed that three variables (LLMS, motivation, and FI) were positively associated with SDLR. Moreover, motivation and LLMS affected the SDLR level, and FI did not. Moreover, it is necessary for online educators to understand the problems that learners may face, such as low LLMS, low motivation, and lack of interaction in a non–face-to-face educational circumstances. In addition, this study suggested that they can encourage their students to increase LLMS and motivation for improving self-directed learning of online students during COVID-19 pandemic. Lastly, limitations and suggestions were discussed for future studies.

Keywords
Literacy of learning management system (LLMS); motivation; feedback interaction (FI); self-directed learning readiness (SDLR); online learning

1. Introduction

Despite the expansion and continuous development of information and communication technology (ICT), artificial intelligence, and big data, only 1% of Internet-based higher education courses and 99% of face-to-face (f2f) courses took place in Korea [1]. However, after the outbreak of COVID-19 around the end of 2019, our educational environment has changed considerably, and recovery to normal educational conditions has still been interrupted [1]. The traditional f2f environment in education has been changed into a non-f2f educational setting. Therefore, in Korea, online and blended classes are becoming the best alternative to f2f education from elementary to higher education. In particular, according to Higher Education Disclosure [2], the total number of online classes in Korea's 4-year universities (223 universities) increased from 12,224 in 2019 to 346,053 in 2020. In addition, in 2020, 104,370 hybrid courses were frequently used and developed to reduce the risk for f2f classes.

In addition, students have faced various challenges and problems. For example, the rapid shift from f2f classes to online classes and web-based learning to reduce the risk of COVID-19 in schools has raised several serious educational issues for students. Therefore, several researchers have been interested in the challenges and problems of e-learning experienced by online students with regard to the COVID-19 pandemic and been looking for methods to improve online learning to overcome non-f2f learning [3-6]. Several studies have shown that online learners have to face several challenges, such as connecting to the Internet, downloading class materials, understanding the instructor's assessment and interactions with other students, managing time, and coping with technophobia [5, 6].

In particular, the biggest challenges and problems of online education environments during the COVID-19 pandemic are low level of literacy in learning management system (LMS) and ICT, low motivation, the lack of feedback interaction between students and instructors or among students, and so on [3, 4]. Moreover, it is difficult for online educators to test students' effective learning factors and problems when online students use learning systems or platforms in a situation where the educational environment changes rapidly from f2f to non-f2f learning [7]. Therefore, it is necessary to continuously study the effects of problems faced by online learners and instructors on self-directed learning (SDL) in non-f2f learning environments.

Therefore, this study aimed to determine whether the low level of literacy of LMS (LLMS), lack of feedback interaction (FI), and low motivation that learners may face in online or non-f2f learning may have a significant effect on SDL readiness (SDLR) level.

1.1 Low Level of Literacy in Learning Management System

As the importance of teaching and learning processes spreads in higher education in Korea, LMSs have attracted the attention of several colleges and universities to support and manage teaching and learning [8]. LMS efficiently supports and manages teaching and learning through the web-based LMS-integrated tools and functions (e.g., providing lecture materials, announcements, evaluation, bulletin board, discussion, online lecture delivery, etc.). It is a comprehensive system or web-based platform that supports and tracks results [8, 9].

In other words, LMS allows online students to launch e-learning and helps manage the interaction between the learner and the other related resources in e-learning. In addition, LMS can be accessed through either an extranet (a private network) or the Internet (an interconnected network) and uses Internet technologies to manage the interaction between users and learning resources [9].

In addition, the use of LMS will affect self-directed learning in both f2f and non-f2f education [8]. Therefore, using LMS or LLMS is very necessary in on/offline education during the COVID-19 pandemic, which indicates how well students use the various tools and functions of the LMS.

Online teaching using information technology and LMS transcends time and space [10]. In addition, Saiyad and his colleagues [10] described that various asynchronous online tools and/or platforms (e.g., Blackboard, Moodle, Google classroom, and Schoology) and synchronous ones (e.g., Google suite, Go Webex, Zoom, and Skype) could encourage students to develop their SDL in online learning. Moreover, LMS can be classified into commercial LMS (e.g., WebCT, Blackboard, and Saka) and customized or in-house developed LMS (e.g., Minerva school's LMS, Seoul Cyber University's LMS). However, Anwar and his colleagues [3] found that students faced low technology and computer literacy rates while using their LLMS during the COVID-19 pandemic.

1.2 Low Motivation

In addition, Anwar and his colleagues [3] revealed that students faced challenges and problems of low motivation in their non-f2f learning during COVID-19. Low motivation in students can reduce SDL skills and the quality of online learning [11]. Although motivation is influenced by student characteristics and tends to vary across various educational settings, it plays a significant role in f2f and non-f2f learning [11-13]. Huebner and Wiener [14] suggested that the success of online learning depends on students' motivation and application of technology. In addition, Hargraves [12] emphasized the importance of motivation in successful learning.

1.3 Lack of Feedback Interaction

One of the challenges faced in the expansion of online learning has been the lack of interaction and communication between students and instructors or among students [15, 16]. For decades, FI has been used as a crucial educational tool or method to influence student learning in both online and offline education [17, 18]. Interactions in online learning include questions, responses, and feedback. In addition, Brown, Harris, and Harnett [19] classified the feedback according to the instructors' goals to improve learning, report and comply, or motivate students. Therefore, FI is provided throughout the learning process, and online students use it to evaluate and adjust their learning process to enhance their learning [20, 21].

There are various synchronous/asynchronous interaction and communication tools that support online learning. For instance, online instructors may use asynchronous (e.g., discussion board, quizzes, polls, email, social blog, recorded audio or video, recorded slides with narration, etc.) and synchronous interaction tools (e.g., virtual classroom, live presentation, live text chat, live audio or video chat, videoconference, etc.) to facilitate online learning. The advantage of asynchronous interactive tools in online learning is the flexibility that allows learners to work at different times and places at their own pace. The downside, on the other hand, is the isolation, wherein communication at different times (or communication latency) can delay support, clarity, and feedback [22-24]. Moreover, synchronous interaction tools benefit from social interaction that provides support, communication, discussion, and insight in real-time, along with limitations such as inflexibility (i.e., real-time live scheduling) [22, 24].

1.4 Importance of Self-directed Learning Readiness in Non–face-to-face Education

One of the biggest challenges experienced in education in the post-COVID era will be the transition from f2f to non-f2f education, where interaction and evaluation occur in a virtual learning space. Therefore, students must promote SDL skills that can play crucial roles in online educational environments. For instance, SDLR can strongly predict academic achievement and outcomes such as skills, knowledge, and abilities in distance education and lifelong education [25-28]. Moreover, the SDLR skills of students have the potential to upgrade the quality of learning outcomes in online and offline education [28, 29]. Thus, self-directed students have a positive motivation to learn at their own pace by being independent and autonomous and by successfully completing courses in both online and offline learning [30-32].

Even after the COVID-19 pandemic, SDLR skills of students should be increasingly required as younger generations become more accustomed to online (or non-f2f) education. Furthermore, instructors must understand how the challenges and problems in non-f2f learning (e.g., low level of LLMS, low motivation, and lack of FI) have an effect on SDLR. Therefore, it is crucial to investigate whether LLMS, motivation, and FI have a significant effect on SDLR level prediction to improve the online learning of students.

2. Research Question

The research questions of this study are as follows:

First, is there a significant correlation between LLMS and SDLR?

Second, is there a significant correlation between motivation and SDLR?

Third, is there a significant correlation between FI and SDLR?

Fourth, of the possible three predictor variables (LLMS, motivation, and FI), which one has the greatest effect on predicting SDLR level?

3. Participants

A total of 216 online students from Seoul Cyber University volunteered to participate in this study. A sample of 216 out of total 15,600 online students was selected by using a simple random sampling technique. A web survey was administered to collect data and respond to questionnaires with the consent of all 216 students. We then excluded 10 students who did not complete all of the web questionnaires and denied the consent paper for this study.

Thus, this study included 206 students, 150 (72.4%) females and 56 (27.6%) males. In terms of expectations for online learning, 130 students (63.1%) had mid-expectations, and 70 (34.0%) had high expectations (see Table 1).

Table 1 Participants.

Characteristics Variable	Category	*N*	*%*
Gender	Female	150	72.4
	Male	56	27.6
School year	Freshman	56	27.2
	Sophomore	7	3.4
	Junior	115	55.8
	Senior	28	13.6
Age	First-career adults (21–35)	51	24.8
	Middle career adults (36–45)	77	37.4
	Late career adults (46–60)	78	37.9
Expectation on Online Learning	Very low expectation	1	0.5
	Low expectation	5	2.4
	Mid expectation	130	63.1
	High expectation	70	34.0
Total		206	100

4. Measurements

4.1 Literacy of Learning Management System

Lee and his colleagues [33] developed the SDL scale (SDLS) consisting of eight subscales (learning motivation, goal setting, resources for learning, time management, selection of learning strategies, learning duration, effort attribution evaluation, and self-reflection). Jeon and his colleagues [8] modified SDLS and performed the factor analysis to test the concept validity of modified SDL competency (SDLC). The SDLC consists of six subscales (learning motivation, goal setting, time management, learning duration, effort attribution evaluation, and self-reflection) and two subscales (use of LMS and satisfaction of class with LMS) with a total of 37 items of a five-point Likert type scale. Cronbach's alpha for eight subscales of SDLC ranged from 0.63 to 0.94 [8].

In this study, LLMS was used out of eight subscales of SDLC to measure how well online students use the LMS for their interaction, communication, learning, and management. In addition, it had a high-reliability coefficient (Cronbach's alpha = 0.88).

4.2 Motivation

This study used a short version of the Instructional Materials Motivation Survey (IMMS) [34]. It was adopted in Keller's IMMS, containing 36 items scale with 4 subscales (i.e., attention, relevance, confidence, and satisfaction) [35]. The IMMS short version includes 20 items of a 5-point Likert-type scale ranging from 1 (not true) to 5 (very true). In addition, it consists of five subscales (e.g., attention, relevance, confidence, satisfaction, and external motivation) [34]. It has been translated into Korean with a maximum score of 20 and a minimum of 5 points. The IMMS short version yielded a reliability coefficient of Cronbach's alpha = 0.92 [34]. Cronbach's alpha in this study was as high as 0.94.

4.3 Feedback Interaction

The Self-Evaluation Online Teaching Effectiveness (SEOTE) [36] tends to evaluate online teaching practices with seven subscales on a six-point Likert-type scale. Content validity was evaluated on seven subscales (e.g., student faculty contact, cooperation among students, active learning, feedback interaction [prompt feedback], time on task, high expectation, and respect for diverse talents and ways of learning) [36]. The reliability coefficient of this scale was 0.94 [37].

This study used FI, one of the eight subscales of Bangert's SEOTE. FI is used to measure how well instructors can provide appropriate feedback to students through various tools. In addition, in this study, the reliability coefficient of FI was as high as 0.86.

4.4 Self-directed Learning Readiness Scale

In this study, we used a short form of the SDLR scale, which evaluated the effects of motivation, academic stress, and age on predicting SDLR [11]. We modified Guglielmino's SDLR to measure the SDLR levels of online college students.

Guglielmino's SDLR [38] is a 5-point Likert-type scale with 8 subscales and 58 items. This SDLR scale has been adapted to five subscales (openness to learning opportunities, self-concept as an effective learner, independence in learning, responsibility for one's own learning, and love of learning) and three subscales (positive orientation to the future, creativity, and ability to use basic study skills and problem-solving skills; 36 statements) were removed.

The reliability coefficient of the SDLR scale (Korean version) was Cronbach's alpha = 0.90 in eight subscales [39], and that of the short version was 0.89 [11]. In this study, a high-reliability coefficient (Cronbach's alpha = 0.90) was calculated for a short version of Guglielmino's SDLR scale.

4.5 Data Collection and Analysis

In this study, participants were recruited from an online university in Korea. A web survey was conducted from November 2 to 10, 2021, to collect data measuring LLMS, motivation, FI, and SDLR levels.

Quantitative data were analyzed by performing Pearson's correlation and multiple regression to determine whether LLMS, motivation, and FI influence SDLR level [40]. In this study, the alpha level of 0.05 was used as the confidence level for all statistical tests. From the first to the third research question, Pearson's correlation analysis was performed to investigate whether a significant correlation exists among LLMS, motivation, FI, and SDLR. In the last research question, multiple regression was used to investigate whether the three predictors (LLMS, motivation, and FI) have any significant influence on predicting SDLR.

5. Results

5.1 Correlation Analysis Among LLMS, Motivation, FI, and SDLR

A bivariate correlation analysis between LLMS and SDLR was performed. Table 2 shows a positive relationship between LLMS and SDLR level ($r(204) = 0.487$, $p < 0.01$). In addition, LLMS showed a significant correlation with the five subscales of SDLR (openness to learning opportunities: $r = 0.39$, $p < 0.01$; self-concept as an effective learner: $r = 0.39$, $p < 0.01$; independence in learning: $r = 0.37$, $p < 0.01$; responsibility for one's own learning: $r = 0.36$, $p < 0.01$; love of learning: $r = 0.38$, $p < 0.01$) (see Table 3).

Table 2 Correlation among LLMS, Motivation, FI, and SDLR.

Variables	①	②	③	④
① Literacy of Learning Management System	1			
② Motivation	0.57**	1**		
③ Feedback Interaction	0.52**	0.51**	1	
④ Self-directed Learning readiness	0.49**	0.62**	0.34**	1
M	2.95	3.96	3.63	3.97
SD	0.90	0.57	0.87	0.46

**$p < 0.01$

Table 3 Bivariate Correlation among LLMS, Motivation, FI, and SDLR.

Variable	Subscale 1[a]	Subscale 2[a]	Subscale 3[a]	Subscale 4[a]	Subscale 5[a]	Total of SDLR[a]
LLMS	0.39**	0.39**	0.37**	0.36**	0.38**	0.49**
Motivation	0.58**	0.45**	0.41**	0.48**	0.49**	0.62**
FI	0.31**	0.26**	0.28**	0.28**	0.23**	0.34**

[a](Subscale 1 = openness to learning opportunities; Subscale 2 = self-concept as an effective learner; Subscale 3 = independence in learning; Subscale 4 = responsibility for one's own learning; Subscale 5 = love of learning; total of SDLR = total score of self-directed learning readiness)
**$p < 0.01$

A significant positive correlation was observed between motivation and SDLR level among college students ($r(204) = 0.62$, $p < 0.01$). In addition, in Table 3, motivation had a significant positive correlation with the five subscales of SDLR (openness to learning opportunities: $r = 0.58$, $p < 0.01$; self-concept as an effective learner: $r = 0.45$, $p < 0.01$; independence in learning: $r = 0.41$, $p < 0.01$; responsibility for one's own learning: $r = 0.48$, $p < 0.01$; and love of learning: $r = 0.49$, $p < 0.01$).

Finally, the correlation analysis between FI and SDLR levels was performed. Table 2 shows a significant positive relationship between FI and SDLR ($r(204) = 0.34$, $p < 0.01$). Moreover, FI revealed a significant positive relationship with the five subscales of SDLR (openness to learning opportunities: $r = 0.31$, $p < 0.01$; self-concept as an effective learner: $r = 0.26$, $p < 0.01$; independence in learning: $r = 0.28$, $p < 0.01$; responsibility for one's own learning: $r = 0.28$, $p < 0.01$; and love of learning: $r = 0.23$, $p < 0.01$) (see Table 3).

Overall, there are all significant linear relationships between LLMS, motivation, and FI and SDLR level at the *p*-value of 0.01.

5.2 Influence of Three Predictor Variables (LLMS, Motivation, FI) on SDLR Level

Multiple regression analysis was performed using both the entry method and stepwise selection to determine the accuracy of LLMS, motivation, and FI in predicting SDLR. First, data were screened to identify missing data and/or outliers, and then, the significant assumptions were tested. At $p < 0.001$ with $df = 4$, there were no missing values and outliers that exceeded the critical value of Chi-square. The scatter plots were approximately elliptical, and the residual plot was not extreme. In addition, the significance of the Box's test for equality of variances was not found at 0.05 or 0.01. Therefore, normality, homoscedasticity, and linearity were assumed. All tolerances of LLMS, motivation, and FI were more than 0.1, and all variance inflation factors (VIFs) were less than 10 (see Table 3). Therefore, no collinearity problem existed.

When predicting the DV of SDLR, multiple regression analysis using the entry method revealed that the overall model of the three IVs significantly predicted the DV of SDLR ($R^2 = 0.416$, $R^2_{\text{adj}} = 0.408$, $F(3, 202) = 48.96$, $p < 0.001$) (see Table 4). This model accounts for 41.6% of the variance of SDLR. The review of the beta coefficient specified that only two variables (motivation: $\beta = 0.52$, $t(202) = 7.71$, $p < 0.001$ and LLMS: $\beta = 0.21$, $t(202) = 3.06$, $p < 0.01$) significantly contributed to the model. Whereas, the FI ($\beta = -0.03$, $t(202) = -0.52$, $p = 0.604$) does not significantly contribute to the model. In Table 5, stepwise multiple regression analysis showed that the first model with a predictor (motivation) can explain 38.9% of the SDLR variance and it had a significant effect on SDLR prediction (motivation: $\beta = 0.62$, $t(204) = 11.51$, $p < 0.001$). Moreover, the second model of two predictors adding 2.6% of adjusted R^2 can account for 41.5% and they are significantly influential in predicting SDLR (motivation: $\beta = 0.51$, $t(203) = 7.95$, $p < 0.001$ and LLMS: $\beta = 0.20$, $t(203) = 3.06$, $p < 0.01$). The results of this study indicated that LLMS and motivation could have a significant effect on predicting SDLR level.

Table 4 Multiple Regression for Predicting SDLR Using the Entry Method.

Model	Variable	B	β	T	Tolerance	VIF	F	R^2	R^2_{adj}
1	(constant)	2.06		11.82***			48.96***	0.416	0.408
	LLMS	0.11	0.21	3.06**	0.61	1.64			
	Motivation	0.42	0.52	7.71***	0.62	1.63			
	FI	-0.02	-0.03	-0.52	0.66	1.51			

**$p < 0.01$, ***$p < 0.001$

Table 5 Stepwise Multiple Regression for Predicting SDLR Using the Stepwise Selection.

Model	Variable	B	β	t	Tolerance	VIF	F	R^2	R^2_{adj}
1	(constant)	1.98		11.40***			132.45***	0.389	0.389
	Motivation	0.50	0.62	11.51***	1.00	1.00			
	Excluded Variable								
	LLMS		0.20	3.06**	0.68	1.47			
	FI		0.03	0.48	0.74	1.35			

	(constant)	2.04		11.89***					
	Motivation	0.41	0.51	7.95***	0.68	1.47			
2	LLMS	0.10	0.20	3.06**	0.68	1.47	73.57***	0.415	0.026
	Excluded Variable								
	FI		-0.03	-0.52	0.66	1.51			

$^{**}p < 0.01$, $^{***}p < 0.001$

In summary, the results of this study revealed that LLMS and motivation have a significant effect on predicting SDLR level. However, FI was not a significant predictor of SDLR level.

6. Conclusion and Discussion

In this study, the following important results were found:

First, a positive correlation was observed between LLMS and SDLR level. A significant linear relationship between LLMS and SDLR indicated that SDLR of students increased when they could efficiently handle their LMS for non-f2f learning. This result is consistent with that of previous studies wherein the use of LMS can promote learners' SDL [41-45].

In addition, Norouzi and his colleagues [42] studied 719 out of 800 postgraduate students to develop a model of LMS for SDL in an Iranian university by using a mixed-method design. This study revealed that after two semesters in the SDL posttest, significant differences were observed in SDL level between two groups, the control group, which used traditional learning, and the experimental group, which used LMS for online learning.

The results of the first research question revealed that online students would have lower SDL when they lack LLMS in non-f2f learning. Therefore, instructors should encourage learners to become proficient in an LMS or learning platforms to improve their SDL skills.

Second, the result of the second research question revealed that there was a significant positive relationship between the motivation of online students and SDLR level. The finding that a positive linear relationship exists between motivation and SDLR levels is similar to that of previous studies that learning motivation can improve SDLR levels of students [11, 28, 46-48]. Therefore, online students may have low self-direction and low autonomy in online learning because they are less motivated in a non-f2f learning environment. Therefore, it is crucial for instructors to motivate online learners to improve SDLR in online learning.

Third, a significant relationship exists between FI and SDLR level regarding the third research question. A positive correlation exists between FI and SDLR, which is consistent with previous studies that feedback has a significant effect on SDLR [49-51]. Yuan and Kim [52] also revealed that online learning is often criticized for lacking interaction because students cannot physically and easily interact with their instructors. Moreover, Karkar-Esperate [53] explained that delayed feedback and lack of clear explanations through discussion could make online students feel isolated from their instructors.

Therefore, online instructors must quickly provide critical feedback to their students within 24 h. In addition, instructors can use various asynchronous/synchronous interaction tools (i.e., bulletin board, discussion board, email, chat, etc.) to provide students with plenty of valuable feedback to help them promote their self-directed learning skills in non-f2f learning. Moreover, various e-learning tools/platforms (such as Minerva school's LMS, Schoology, Skype, Zoom, etc.) can be used to provide sufficient synchronous interaction and communication and enhance self-directed learning.

Last, several previous studies support that LLMS and motivation are crucial predictors of SDLR among online college students [28, 41, 42, 54]. Multiple regression analysis revealed that SDLR could be significantly predicted by predictors (LLMS and motivation). In addition, FI does not affect the SDLR prediction of a student. However, Lasfeto and Ulfa [55] argued that external educational variables could influence SDL predictions in distance education. In this study, correlation analysis and analysis of variance were performed on 98 students at the State University of Malang in Indonesia to study the effect of students' social interaction on SDLR. As a result, the effect of students' social interaction on SDLR in an online learning environment was confirmed [55].

A crucial finding of this study is that low LLMS and low motivation in learners can reduce their SDLS in non-f2f educational settings. Thus, online instructors should encourage students to increase LLMS and motivation for improving their SDL in online learning, although students may face challenges and problems (e.g., low LLMS and low motivation) because of non-f2f learning during COVID-19. Furthermore, online instructors can motivate students by presenting specific educational goals and targets for online courses and helping students know how to use and manage the LMS in the early stages of online learning.

7. Limitation and Suggestion

This study had some limitations and suggestions for future studies. Some problems in non-f2f classes in Korea during the COVID-19 pandemic were studied as independent variables which can significantly affect SDLR level. However, most research data and findings in countries where LMS can be actively used in e-learning may be limited. Therefore, crucial findings associated with SDLR for online educators and further studies are required to objectively be generalized by using abundant research findings of several countries that can positively use LMS to enhance the online SDL of students. Therefore, several studies on SDL and e-learning in non-f2f educational situations will be conducted worldwide with significant generalized findings even in the post-COVID-19 era.

This study had another limitation in terms of statistical methodology. There was a significant linear relationship between FI and level of SDLR. However, it was not one of the crucial predictors that had a significant influence on predicting SDLR level. It is possible that the effect of FI on SDLR was under-measured because only a few items of FI were used as the measurement tool, a subrealm of SEOTE. Therefore, for further research, it is necessary to use a measurement tool that has high discriminating power and can measure widely in the realm of FI. In addition, when studying the effect of FI on SDLR level, it is necessary to perform advanced statistical methods (such as path analysis or structural equation modeling) that can consider various research results.

Finally, the ability of LMS may significantly differ between students at cyber (or online) universities and students at offline universities. Therefore, in the study of the effects of LLMS on SDLR, it is necessary to verify the difference in SDLR level between the group that continuously used LMS and the group that did not, along with the longitudinal study method or the mixed study design to explore in detail.

Author Contributions

All authors have equally contributed to this work.

Competing Interests

The authors have declared that no competing interests exist.

References

1. Korean Association of Private University Presidents. Academic management situation relevant to COVID 19 on Korean University [Internet]. Seoul: Korean Association of Private University Presidents; 2020 [cited date 2021 November 22th]. Available from: http://kapup.org/sub/sub02_02.php?boardid=notice&mode=view&idx=28&sk=28&sw=&offset=&category=&goPage.
2. Higher Education in Korea. Academy information. The situation of distance education courses for 4 years universities in Korea [Internet]. Seoul: Higher Education in Korea; 2021 [cited date 2021 November 18th]. Available from: http://www.academyinfo.go.kr.
3. Anwar M, Khan A, Sultan K. The barriers and challenges faced by students in online education during COVID-19 pandemic in Pakistan. Gomal Univ J Res. 2020; 36: 52-62.
4. Kim HA, Lee J. Effects of Cyber Universities' career maturity on academic stress: Mediator effects of self-directed learning readiness. J Korea Contents Assoc. 2014; 14: 486-496.
5. Mahyoob M. Challenges of e-learning during the COVID-19 pandemic experienced by EFL learners. Arab World English J. 2020; 11: 351-362.
6. Rajab MH, Gazal AM, Alkattan K. Challenges to online medical education during the COVID-19 pandemic. Cureus. 2020; 12: e8966.
7. Liu H, Wang T, Lin H, Lai C, Huang Y. The influence of affective feedback adaptive learning system on learning engagement and self-directed learning. Front Psychol. 2022; 13: 858411.
8. Jeon YM, Cho JS, Kim KR. A study on the effect of LMS on the self-regulated learning competency and learning satisfaction in higher education. J Educ Inf Media. 2016; 22: 55-84.
9. Irlbeck S, Mowat J. Learning content management system (LCMS). ResearchGate; 2007 [cited date 2022 August 14th]. Available from: https://www.researchgate.net/publication/237334647_Learning_Content_Management_System_LCMS.
10. Saiyad S, Virk A, Mahajan R, Singh T. Online teaching in medical training: Establishing good online teaching practices from cumulative experience. Int J Appl Basic Med Res. 2020; 10: 149-155.
11. Heo J, Han S. Effects of motivation, academic stress and age in predicting self-directed learning readiness (SDLR): Focused on online college students. Educ Inf Technol. 2018; 23: 61-71.
12. Hargraves V. 10 strategies that promote motivation [Internet]. The Education Hub's; 2019 [cited date 2021 December 13th]. Available from: https://theeducationhub.org.nz/10-strategies-that-promote-motivation.
13. Trivena T, Harisno H. The effect of Lecturer's professionalism and student's study interest and motivation on academic achievement of bachelor degree student in online learning in Binus University. Commun Inf Technol. 2014; 8: 55-61.
14. Huebner KM, Wiener WR. Distance education in 2001. J Vis Impair Blind. 2001; 95: 517-524.
15. Barreto M, Victor C, Hammond C, Eccles A, Richins MT, Qualter P. Loneliness around the world: Age, gender, and cultural differences in loneliness. Pers Individ Differ. 2021; 169: 110066.
16. Lee DJ, Kim MS. University students' perceptions on the practices of online learning in the

COVID-19 situation and future directions. Multimedia Assist Lang Learn. 2020; 23: 359-377.
17. Aguerrebere C, Cabeza SG, Kaplan G, Marconi C, Cobo C, Bulger M. Exploring feedback interactions in online learning environment for secondary education [Internet]. Aachen: CEUR Workshop Proceedings; 2018. Available from: http://ceur-ws.org/Vol-2231/LALA_2018_paper_7.pdf.
18. Hattie J, Timperley H. The power of feedback. Rev Educ Res. 2007; 77: 81-112.
19. Brown GT, Harris LR, Harnett J. Teacher beliefs about feedback within an assessment for learning environment: Endorsement of improved learning over student well-being. Teach Teach Educ. 2012; 28: 968-978.
20. Schunk DH. Learning theories: An education perspective. Hoboken: Pearson Merrill Prentice Hall; 2008.
21. Shute VJ. Focus on formative feedback. Rev Educ Res. 2008; 78: 153-189.
22. Hrastinski S. Asynchronous and synchronous e-learning. Educ Q. 2008; 31: 51-55.
23. Offir B, Lev Y, Bezalel R. Surface and deep learning processes in distance education: Synchronous versus asynchronous systems. Comput Educ. 2008; 51: 1172-1183.
24. Shank P. The right learning modalities to deliver digital learning: Part 2 [Internet]. Cholargos: eLearning Industry; 2020 [cited date 2021 November 20th]. Available from: https://elearningindustry.com/right-learning-modalities-asynchronous-and-synchronous-interactions.
25. Dixon WB. An exploratory study of self-directed learning readiness and pedagogical expectations about learning among adult inmate learners in Michigan. Michigan: Michigan State University; 1992.
26. Zimmerman BJ, Schunk DH. Self regulating intellectual processes and outcomes: Social cognitive perspective. In: Motivation, emotion, and cognition: Integrative perspectives on intellectual functioning and development. Mahwah: Erlbaum; 2004. pp. 323-350.
27. Zimmerman BJ, Kitsantas A. The hidden dimension of personal competence: Self-regulated learning and practice. In: Handbook of competence and motivation. New York, London: The Guilford Press; 2005. pp. 509-526.
28. Grandinetti M. Motivation to learn, learner independence, intellectual curiosity and self-directed learning readiness of pre-licensure sophomore baccalaureate nursing students. Chester: Widener University; 2013.
29. Garrison DR. Self-directed learning: Toward a comprehensive model. Adult Educ Q. 1997; 48: 18-33.
30. McVay M. How to be successful distance learning student: Learning on the Internet. 2nd ed. Boston: Pearson Custom; 2000.
31. Rivenburg CR. Instructional design strategies and their effect on self-directed learning in online learning. Minneapolis: Capella University; 2015.
32. Robinson DL. Relationship of student self-directed, computer self-efficacy, and student satisfaction to persistence in online higher education programs. Louisville: University of Louisville; 2008.
33. Lee Y, Kozar KA, Larsen KRT. The technology acceptance model: Past, present, and future. Commun Assoc Inf Syst. 2003; 12: 752-780.
34. Heo J, Han S. The college students' satisfaction related to expectation and interaction in the online counseling courses. Educ Technol Int. 2011; 12: 117-134.

35. Keller JM. Manual for instructional materials motivational survey (IMMS). Tallahassee: Florida State University; 1993.
36. Bangert AW. The seven principles of good practice: A framework for evaluating on-line teaching. Internet High Educ. 2004; 7: 217-232.
37. Bangert A. The influence of social presence and teaching presence on the quality of online critical inquiry. J Comput High Educ. 2008; 20: 34-61.
38. Guglielmino LM. Reliability and validity of the self-directed learning readiness scale and the learning preference assessment. In: HB Long & Asso., Expanding horizons in self-directed learning. 1997. pp. 209-222.
39. Jeon G. The effects of an e-learning information literacy instruction program on self-directed learning ability of university student. Seoul: University of Soongsil; 2010.
40. Mertler LA, Vannatta RA. Advanced and multivariate statistical methods. 7th ed. Glendale: Pyrczak; 2022.
41. Heo J, Han S. The mediating effect of literacy of LMS between self-evaluation online teaching effectiveness and self-directed learning readiness. Educ Inf Technol. 2021; 26: 6097-6108.
42. Norouzi M, Hamid DH, Samet A, Ramezani S. Model of learning management system for self-directed learning. Int J Inf Dissemination Technol. 2014; 4: 332-337.
43. Traynor PL. Effects of computer-assisted-instruction on different learners. J Instructional Psychol. 2003; 30: 137-143.
44. Angriani P, Nurcahyo H. The influence of moodle-based e-learning on self-directed learning of senior high school students [Internet]. AIP Conf Proc 2120. 2019 [cited date 2021 December 13th]. Available from: https://doi.org/10.1063/1.5115707.
45. Biney IK. Exploring the power of the media in promoting lifelong learning and popular mobilisation drive against 'Galamsey' in Ghana. Aust J Adult Learn. 2019; 59: 435-467.
46. Cetin B. Academic motivation and self-regulated learning in predicting academic achievement in college. J Res Int Educ. 2015; 11: 95-106.
47. Mahmoodi MH, Kalantari B, Ghaslani R. Self-regulated learning (SRL), motivation and language achievement of Iranian EFL learners. Procedia Soc Behav Sci. 2014; 98: 1062-1068.
48. Merrian SB, Bierema LL. Adult learning: Linking theory and practice. San Francisco: Wiley; 2013.
49. Chou CY, Zou NB. An analysis of internal and external feedback in self-regulated learning activities mediated by self-regulated learning tools and open learner models. Int J Educ Technol High Educ. 2020; 17: 55.
50. Embo MP, Driessen EW, Valcke M, Van der Vleuten CP. Assessment and feedback to facilitate self-directed learning in clinical practice of Midwifery students. Med Teach. 2010; 32: e263-e269.
51. William D. Formative assessment. In: SAGE handbook of research on classroom assessment. Los Angeles: Sage; 2013. pp. 165-166.
52. Yuan J, Kim C. Guidelines for facilitating the development of learning communities in online courses. J Comput Assist Learn. 2014; 30: 220-232.
53. Karkar-Esperat TM. International graduate students' challenges and learning experiences in online classes. J Int Students. 2018; 8: 1722-1735.
54. Şenyuva E, Kaya H. The correlation between self-directed learning readiness and web-based learning in nursing students: A study conducted in Turkey. New Educ Rev. 2015; 41: 98-107.
55. Lasfeto D. The relationship between self-directed learning and students' social interaction in online learning environment. J E-Learn knowl Soc. 2020; 16: 34-41.


OBM Neurobiology