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Key Factors to Foster Academic Performance in Online Learning Environment: Evidence From Indonesia During COVID-19 Pandemic

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Abstract: The unprecedented COVID-19 pandemic has changed many aspects of society, including education. While online learning aims to avoid the transmission of viruses, however, what causes the success or failure of online learning needs to be investigated. This study tries to answer the question by analyzing how self-regulated learning, digital literacy, and the mediation of course satisfaction influence students' academic performance in online learning situations caused by the COVID-19 pandemic in Indonesia. We employed Partial Least Square Structural Equation Modelling (PLS-SEM) on 358 respondents gathered from an online survey questionnaire completed by undergraduate students during the pandemic. The study finds that self-regulated learning is the key factor, followed by digital literacy. Course satisfaction also proved to mediate self-regulated learning and digital literacy on academic performance.

Subjects: Further & Higher Education; Higher Education; Study of Higher Education

Keywords: Indonesia; PLS-SEM; online learning; self-regulated learning; digital literacy

1. Introduction

It has been two years since the COVID-19 pandemic was officially declared to have entered Indonesian territory. Many aspects of society have changed caused by social distancing, from partial until full lockdowns. Numerous things are becoming the new norm today, such as people being required to wear masks when in public spaces, places usually used as gathering places being limited in capacity and operating hours, and places of worship have been temporarily closed. Among them, the most striking thing since the pandemic is that teaching and learning activities in schools and campuses are not allowed and replaced with online learning, not only in Indonesia but school closure is also implemented throughout the global level. Following UNESCO recommendations, educational institutions are encouraged to replace the face-to-face learning process with online learning (Crawford et al., 2020).

The application of a learning management system (LMS) in online learning is challenging. This challenge comes from two sources. Firstly, it is caused by the physical absence of lecturers, and secondly is caused by the loss of the campus academic atmosphere, so that students tend to use their productive time to do other things besides studying (Elvers et al., 2003; Levy & Ramim, 2012; Michinov et al., 2011). Because online learning has powerful characteristics in self-autonomy, self-regulation has an important role in the process. If we reflect in the context of learning in regular classrooms, self-regulatory behaviors have been shown to play an important role in students' academic performance (Gonzalez-Nucamendi et al., 2021; Lan, 1996; Orange, 1999; Perry et al., 2012). If this behavior has a vital role in regular classrooms, then it can be expected that self-regulatory skills will play an even much more critical role in online learning, where students are isolated from each other in their respective rooms, because the lack of self-regulation can lead students to negative traits, such as procrastination (Hong et al., 2021). Students who lack self-regulatory learning skills are suspected of manipulating their self-autonomy so that the learning tasks they should have completed in online courses are unfinished.

In addition to self-regulated learning, the ability to use digital devices, or known as digital literacy also plays an important role here. This is because online learning is not only about using devices to access the LMS but also how to synthesize information and prevent risks that may occur when accessing the internet (Rodríguez-de-Dios & Igartua, 2016). If the understanding of literacy in the past meant demonstrating the capacity to extract sense from what they read (Prior et al., 2016), then digital literacy also has similar characteristics, because the skill to read and to write was not enough to identify a person as being literate (Miranda et al., 2018). A person can be said to have digital literacy if they have the ability to understand and use various information that they obtained from a variety of digital sources (Gilster, 1997).

Researchers have revealed that self-regulated learning influences students' course satisfaction (Kuo et al., 2014; Puzziferro, 2008; Wang et al., 2013). If explored further, course satisfaction is known to have implications for student academic performance (Blanz, 2014; Topală, 2014). Also, based on the previous study, self-regulated learning and digital literacy are known to influence academic performance directly, but previous research has only focused more on the regular classroom setting (Bail et al., 2008; Leung & Lee, 2012; Lucieer et al., 2016; Vrana, 2014). However, as far as the authors know, there is no study about how digital literacy influences course satisfaction in the online learning environment, even though in the online learning process the use of digital devices is absolutely necessary. Regarding how course satisfaction in mediating digital literacy and self-regulated learning on academic performance also has never been studied before. Thus, this study aims to fill these gaps by investigating them. Again, this study becomes important because it captures a broader understanding of how self-regulated learning, digital literacy, and course satisfaction influence students' academic performance in online learning situations caused by the unprecedented COVID-19 pandemic in Indonesia.

2. Theoretical background and hyphothesis development

2.1. *Self-regulated learning*

According to Zimmerman (2000), self-regulation is defined as self-generated thoughts, feelings, and actions that are planned and cyclically adjusted to achieve personal goals. Meanwhile, Bandura (1986) states that self-regulated learning represents the relationship between triadic processes, namely personal, behavior and environment. Furthermore, when referring to Schunk and Ertmer (2000), self-regulation is a cycle when personal, environmental, and behavioral aspects experience changes during the learning process. In online learning, students have complete control over their learning. Thus, they must do things independently related to their learning, including planning, regulating, monitoring, and evaluating. Successful self-regulated learning is characterized by active engagement, adjustment, and readjustment of learning strategies according to various factors they met.

Furthermore, even though students who carry out online learning need to be independent and autonomous, they are also expected to be able to carry out self-management. Self-regulated learning has much in common with learners' ability to exert self-control. Previous literature has shown that aspects such as resisting temptation, resisting distractions, focusing on long-term goals, and delaying short-term gratification are all part of self-regulation (Zhu et al., 2016). However, this is not easy to maintain (Elvers et al., 2003; Levy & Ramim, 2012; Michinov et al., 2011). Previous literature states that self-regulation in online learning settings tends to create learning difficulties for students compared to face-to-face learning (Lajoie & Azevedo, 2006; Lee et al., 2008; Samruayruen et al., 2013; Tsai & Tsai, 2010). Furthermore, if not managed properly, an unorganized profile from the aspect of self-regulated learning is associated with poor academic outcomes, such as a low GPA of students (Barnard et al., 2009).

2.2. *Digital Literacy*

The concept of digital literacy has changed in recent years, and even this term is often confused, as there is no general consensus among academics on its definition (Bawden, 2001, 2008; Hockly, 2012). Initially, this term expressly referred to knowledge of hardware and software. Thus, people are considered to have digital literacy if they know how to use a word processing application such as Microsoft Word. Furthermore, along with the advancement of internet technology, until around the 1990s, some academics used this term to refer to the ability to read and understand the hypertextual text and multimedia (Bawden, 2001). Nevertheless, this concept is seen as more than just using the software or the device itself. Therefore, it relates to expertise and skills in the use of mechanics as well as knowledge and skills about using these devices for different purposes (Chisholm, 2006). The importance of technology is seen not merely from the capacity to use technology but also from the intellectual, social, and ethical aspects. This is when the concept of digital literacy must take into account. It is relevant in today's class setting, while education does depend on technological use, even since primary school (Buckingham, 2015; Casey & Bruce, 2011; Unsworth, 2005). At juvenile and adult levels, digital literacy becomes a vital capacity in mastering not only for the sake of daily tasks and daily routines but also in all sectors of society, including in higher education and the professional world (Ahmed & Roche, 2021; Mohammadyari & Singh, 2015; Siddiq et al., 2017). If students have excellent digital literacy skills and, as a consequence, they know how to use technology, it will bring them several benefits for their learning because technology gives students easy access to academic resources, makes them more productive, feel connected, with more immersive, engaging, and relevant experience (Burton et al., 2015).

Digital literacy can be interpreted as an individual's awareness, attitude, and ability to use digital tools and facilities appropriately to identify, access, manage, integrate, evaluate, analyze and synthesize digital resources, build new knowledge, create media expressions, and communicate with others, in the context of specific life situations, to enable constructive social action, and for reflection (Hockly, 2012; Martin, 2005). Although today's generation is digital natives (Al-htaybat et al., 2018) and they are at the forefront of new technologies, it is not a guarantee that they will be able to use them wisely because today's generation has many difficulties managing information, assessing the credibility of information, building their digital identity, and manage privacy in their online activities (Fernández-Villavicencio, 2012). Furthermore, referring to Rodríguez-de-Dios and Igartua (2016), there are five dimensions of digital literacy, namely:

- Technological or Instrumental Skill
- Communication Skill
- Information Skill
- Critical Skill
- Security Skill

2.3. *Course Satisfaction*

Concerning terminology about satisfaction in education, it is often referred to by different names, such as student satisfaction (Xiao & Wilkins, 2015), learning satisfaction (Topala & Tomozii, 2014), and course satisfaction (Frey et al., 2003; Wang et al., 2013). However, this study uses the term of course satisfaction. In most countries, students are required to pay tuition fees, then, like consumers in business sector, their satisfaction needs to be considered by universities (Xiao & Wilkins, 2015). Referring to Rashidi and Moghadam (2014), course satisfaction can be interpreted as the relationship between students' expectations and what they actually get. Previous study has proven that students with high course satisfaction will tend to earn higher grades on their final exam (Puzziferro, 2008).

This can be imperative in online learning. With the limited interaction and many potential disruptions, course satisfaction can be in jeopardy (Dong et al., 2020; Watermeyer et al., 2022), while a large body of evidence proves that course satisfaction plays a significant role in academic performance (Abuhassna et al., 2020; Blanz, 2014; Hanus & Fox, 2015; Ko & Chung, 2014). Hence, the success of online learning can be achieved when students are satisfied with their learning experience (course satisfaction), and consequently, they will have satisfying academic performance (Chang & Smith, 2008; Marks et al., 2005; Puzziferro, 2008).

Based on the theoretical grounding and previous findings, we propose five hypotheses as follows:

H1: Self-regulated learning has a significant positive direct effect on course satisfaction

H2: Digital literacy has a significant positive direct effect on course satisfaction

H3: Course satisfaction has a significant positive direct effect on academic performance

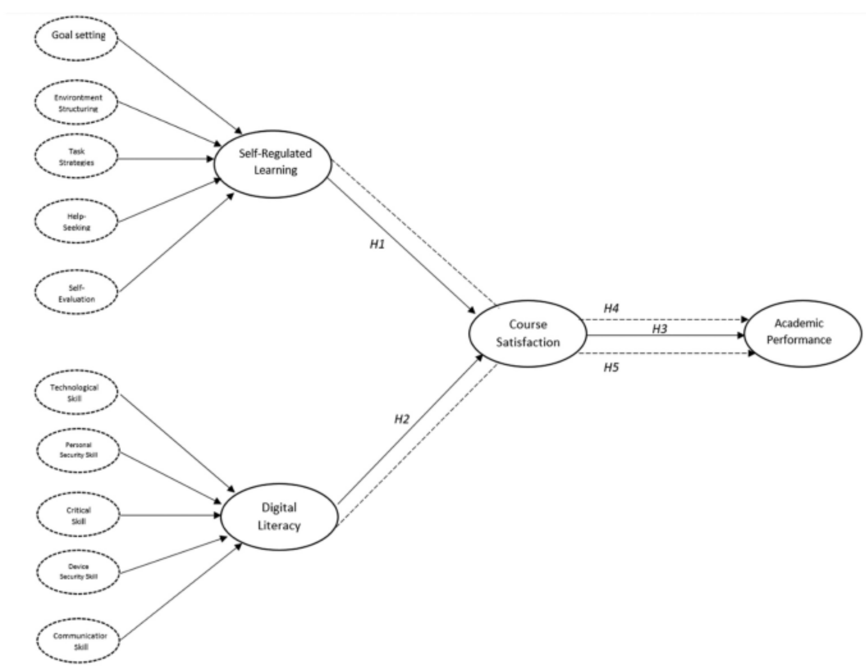
H4: Course satisfaction mediates the relationship between self-regulated learning and academic performance

H5: Course satisfaction mediates the relationship between digital literacy and academic performance

3. Research Model

The model proposed in this study can be seen in Figure 1, which generated by the theoretical grounding and hypotheses postulated. In this model, self-regulated learning and digital literacy act as an exogenous latent variable. Meanwhile, the course satisfaction variable acts as an

Figure 1. Research Model



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endogenous latent variable with a dual relationship as both independent and dependent, and the academic performance variable acts as an endogenous latent variable.

4. Method

4.1. Research design and sample

This study used survey research design as its research procedure. Survey research designs are methods in quantitative research in which researchers administer a survey to a sample or to the entire population of people to describe the attitudes, opinions, behaviors, or characteristics of the population (Creswell, 2012). Furthermore, the type of survey research design used is cross-sectional survey designs, where data is collected at one point in time (Creswell, 2012). In this study, the sample was selected using convenience sampling procedure. In determining the sample size, the authors followed the recommendations given by Hair et al. (J.F Hair et al., 2016), where to determine the required number of samples, it should be in line with the statistical power. To calculate the required sample size and the statistical power, the authors utilized G*Power software (Faul et al., 2007). The authors used error measurements of type one and two at $\alpha = 0.05$ and power $(1—\beta) = 0.95$, while the effect size = 0.15 to achieve medium effect size as the minimum threshold (Cohen, 2013; J.F Hair et al., 2016). The number of predictors as the model offered by the researcher are 3 predictors, with 2 number of tested predictors. The calculation shows that the minimum sample required in this study is 107. Furthermore, the complete settings authors used to analyze the sample size and the results can be seen in Figure 2. The sample consisted of undergraduate students who studied in two universities in Indonesia.

4.2. Instrumentation and data collection

The instruments used in data collection in this study have been validated by previous research. The self-regulated learning variable uses the Online Self-Regulated Learning Questionnaire (OSLQ; Barnard et al., 2009), the digital literacy variable uses an instrument developed by Rodriguez-de-Dios et al. (2016). Meanwhile, the learning satisfaction variable was adopted from the Course Satisfaction Questionnaire (CSQ) instrument (Frey et al., 2003), and academic performance using an instrument that has been validated by Nayak (2018). All variables were measured by utilizing five points Likert scale, where 1 refers to "strongly disagree" and 5 refers to "strongly agree".

In data collection, authors conducted a web-base survey among Indonesian students. The number of completed questionnaires was 358, where this sample size fulfilled the minimum sample calculated using the G*Power application (107 sample size).

4.3. Sample demographic background

Table 1 shows the background of the sample who participated in this study. The categories of all samples (n = 358) are divided into gender, university, and the most frequent devices used in online learning. More than half were female (69.55%), and the remaining were male (30.45%). In terms of universities, the number of samples from the two universities was still relatively comparable in size, with 201 samples from Universitas Negeri Medan (56.15%), while those from Universitas Islam Negeri Sumatera Utara were 157 (43.85%). Interestingly, based on the devices used in attending online lectures, the majority of the samples participating in this study used mobile phones in online learning, with a total of 300 (83.8%), and the remaining using laptops (16.2%).

4.4. Data analysis procedure

Because the constructs authors want to examine are complex and contain two layers of constructs thus, the hierarchical component models (HCMs) in Partial Least Square Structural Equation Modeling (PLS-SEM) were employed for data analysis. HCMs have two elements: the higher-order component (HOC), which captures the more abstract higher-order entity, and the lower-order components (LOCs), which capture the subdimensions of the higher-order entity (J.F Hair et al., 2016). Furthermore, the type of HCMs used in this study is reflective-formative type models (Type II). Regarding the approach to estimate the HCMs, there are three approaches to estimate the

Figure 2. Power results for required sample size

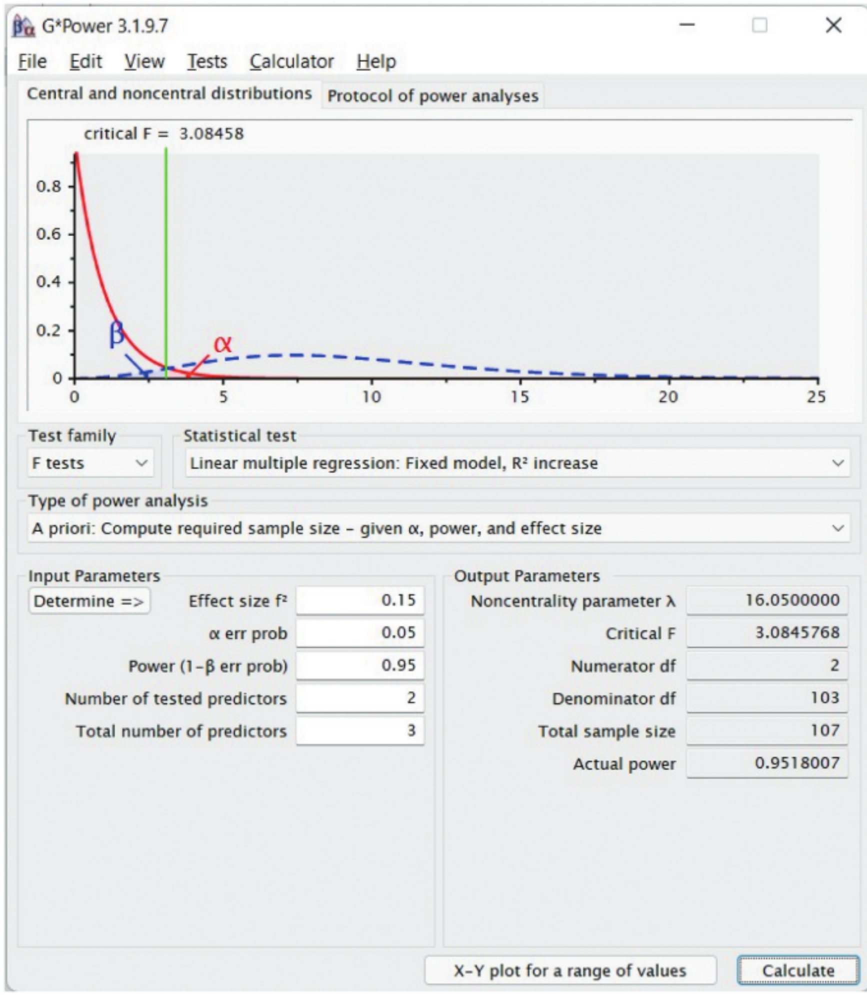

Table 1. Sample demographic background

		Frequency	Percentage
Gender	Male	109	30.45
	Female	249	69.55
University	Universitas Negeri Medan	201	56.15
	Universitas Islam Negeri Sumatera Utara	157	43.85
The most frequent devices used	Laptop	58	16.20
	Handphone	300	83.80

parameters in HCMs models using PLS-SEM, they are the repeated indicator approach (Lohmöller, 2013; Wold, 1982), the two-stage or sequential approach (Ringle et al., 2012; Wetzels et al., 2009), and the hybrid approach (Becker et al., 2012; Ciavolino & Nitti, 2013). However, authors used repeated indicator with Mode B formative measurement to estimate the parameters in HCMs in this study. The advantage of the repeated indicator approach is its capability to assess all constructs simultaneously instead of assessing lower-order and higher-order dimensions separately (Becker et al., 2012). Mode B for the repeated indicator also consideres to more appropriate referring to Becker et al. (2012).

In general, PLS-SEM chosen with the reason of the nature of this research is exploratory and predictive (Henseler et al., 2016; J.F Hair et al., 2016). In addition, the utilization of PLS-SEM is also preferred because it allows researchers to approximate complex models with many constructs, indicators, and structural paths without having to worry about distributional assumptions on research data since PLS-SEM is non-parametric in nature (J.F Hair et al., 2016). Three main steps were conducted in analyzing the results: (1) evaluation of measurement models for first-order constructs, (2) evaluation of the first-order constructs on the second-order constructs, (3) evaluation of the structural model (Becker et al., 2012; J.F Hair et al., 2016; Ringle et al., 2015). The explanation for both evaluations will be explained in the next session.

5. Results

5.1. Evaluation of measurement models for first-order constructs

The first-order constructs in this study have reflective constructs. The assessment of reflective constructs involves convergent validity, internal consistency reliability, and discriminant validity (J.F Hair et al., 2016). Convergent validity is the degree to which a measure correlates with other measures of the same construct (J.F Hair et al., 2016) requiring both loading factors and Average Variance Extracted (AVE) to exceed 0.5. Furthermore, internal consistency reliability is a form of reliability used to determine whether the items measuring a construct are similar in their scores. It required composite reliability and Cronbach's alpha to be above 0.6 (J.F Hair et al., 2016). The last aspect in evaluating the measurement models for first-order constructs is discriminant validity. While there are many approaches to evaluating the discriminant validity, such as cross-loading (Henseler et al., 2009), Fornell-Larcker criterion (Fornell & Larcker, 1981), and Heterotrait-monotrait ratio (HTMT; Henseler et al., 2015). HTMT is considered to have a more accurate examination since cross loading and Fornell-Larcker criterion suffer to recognize discriminant validity issues (Henseler et al., 2015). For the threshold, the HTMT confidence interval must not include 1. For a more conservative threshold, 0.85 seems warranted (Henseler et al., 2015).

However, the results shown in Table 2 are the second run analysis. In the first analysis (all indicators can be seen in Table A1), the measurement that does not meet the requirements has been removed, namely SRL13, SRL14, SRL15, DL6, DL 7, DL8, DL22, DL23, DL24, and DL25. SRL13, SRL14 and SRL15 were parts of Time Management sub-construct from Self-Regulated Learning. DL6 and DL7 were parts of Technological Skill sub-construct from Digital Literacy. DL8 was one of the Personal Security Skill sub-construct from Digital Literacy. While DL22, DL23, DL24, and DL25 were parts of Information Skill sub-construct from digital literacy. Therefore, two sub-constructs were discarded completely: Time Management from Self-Regulated Learning, and Information Skill from Digital Literacy. Table 2 shows that all constructs have adequate convergent validity, internal consistency reliability, and discriminant validity. Nonetheless, the details of HTMT results can be seen in Table 3. Once it is confirmed that the evaluation of measurement models for first-order constructs is viable, then it can proceed to the evaluation of the second-order constructs.

5.2. Evaluation of the first-order constructs on the second-order constructs

The evaluation of the second order follows the same process or analogy used to evaluate the first-order constructs (Chin, 1998a). However, since the second order is formative, several researchers have emphasized that traditional validity assessments do not apply like its reflective counterpart (Götz et al., 2010; Henseler et al., 2009; J.F Hair et al., 2016; Petter et al., 2007). Fundamentally, formative models assume that the indicators have an influence or shape the construct (J.F Hair et al., 2016; Jarvis et al., 2003). It makes a different interpretation and evaluation of the measurement (Götz et al., 2010; J.F Hair et al., 2016). Thus, in general, the evaluation of the second-order

Table 2. Convergent validity and internal consistency reliability measures

Latent Variable	Indicators	Loadings	AVE	Composite Reliability	Cronbach's Alpha	Discriminant Validity
		>0.50	>0.50	0.60–0.90	0.60–0.90	HTMT confidence interval does not include 1
Academic Performance	AP1	0.85	0.70	0.87	0.81	Yes
	AP2	0.83				
	AP3	0.63				
Self-Regulated Learning						
Goal Setting	SRL1	0.55	0.60	0.88	0.83	Yes
	SRL2	0.72				
	SRL3	0.72				
	SRL4	0.81				
	SRL5	0.70				
Environment Structuring	SRL6	0.77	0.74	0.89	0.82	Yes
	SRL7	0.78				
	SRL8	0.78				
Task Strategies	SRL9	0.65	0.65	0.88	0.82	Yes
	SRL10	0.77				
	SRL11	0.74				
	SRL12	0.77				
Help-Seeking	SRL16	0.71	0.65	0.88	0.82	Yes
	SRL17	0.73				
	SRL18	0.68				
	SRL19	0.80				

(*Continued*)

Table 2. (*Continued*)

Latent Variable	Indicators	Loadings	AVE	Composite Reliability	Cronbach's Alpha	Discriminant Validity
Self-Evaluation	SRL20	0.80	0.72	0.88	0.80	Yes
	SRL21	0.73				
	SRL22	0.76				
Digital Literacy						
Technological Skill	DL1	0.49	0.59	0.88	0.82	Yes
	DL2	0.65				
	DL3	0.67				
	DL4	0.59				
	DL5	0.65				
Personal security skill	DL9	0.73	0.65	0.88	0.82	Yes
	DL10	0.64				
	DL11	0.74				
	DL12	0.80				
Critical Skill	DL13	0.82	0.68	0.91	0.88	Yes
	DL14	0.82				
	DL15	0.77				
	DL16	0.82				
	DL17	0.65				
Device Security Skill	DL18	0.77	0.69	0.90	0.85	Yes
	DL19	0.76				
	DL20	0.79				
	DL21	0.73				

(Continued)

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Table 2. (*Continued*)

Latent Variable	Indicators	Loadings	AVE	Composite Reliability	Cronbach's Alpha	Discriminant Validity
Communication Skill	DL26	0.78	0.65	0.85	0.73	Yes
	DL27	0.66				
	DL28	0.62				
Course Satisfaction	CS1	0.70	0.62	0.97	0.97	Yes
	CS10	0.77				
	CS11	0.85				
	CS12	0.74				
	CS13	0.75				
	CS14	0.78				
	CS15	0.77				
	CS16	0.74				
	CS17	0.77				
	CS18	0.80				
	CS19	0.73				
	CS2	0.73				
	CS20	0.85				
	CS21	0.89				
	CS3	0.74				
	CS4	0.78				
	CS5	0.84				
	CS6	0.69				
	CS7	0.80				
	CS8	0.66				
	CS9	0.81				

Table 3. HTMT values for discriminant validity

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Academic Performance														
2. Communication skill	0.09													
3. Course Satisfaction	0.12	0.61												
4. Critical skill	0.10	0.80	0.56											
5. Device security skill	0.05	0.72	0.56	0.78										
6. Digital Literacy	0.09	0.94	0.60	0.98	0.92									
7. Environment Structuring	0.15	0.59	0.55	0.56	0.56	0.60								
8. Goal Setting	0.13	0.58	0.65	0.55	0.50	0.60	0.62							
9. Help-Seeking	0.08	0.56	0.62	0.54	0.56	0.59	0.64	0.70						
10. Personal security skill	0.07	0.72	0.42	0.84	0.71	0.94	0.45	0.45	0.37					
11. Self Regulated Learning	0.12	0.68	0.70	0.66	0.63	0.72	0.84	0.96	0.95	0.52				
12. Self-Evaluation	0.09	0.66	0.62	0.66	0.62	0.73	0.65	0.80	0.87	0.56	0.99			
13. Task Strategies	0.10	0.65	0.65	0.64	0.61	0.69	0.72	0.82	0.81	0.50	1.01	0.91		
14. Technological Skill	0.09	0.76	0.54	0.76	0.72	0.95	0.52	0.61	0.62	0.73	0.71	0.76	0.68	

Table 4. Weights of the first-order constructs on the second-order constructs

Construct level		Weight	t	Mean	Standard Deviation
Second-order construct	**First-order construct**				
Self regulated learning	Goal setting	0.29	29.13***	0.29	0.01
	Environment structuring	0.19	22.97***	0.19	0.01
	Task strategies	0.26	36.34***	0.26	0.01
	Help-seeking	0.25	29.44***	0.25	0.01
	Self-evaluation	0.21	34.55***	0.21	0.01
Digital literacy	Technological skill	0.26	32.18***	0.25	0.01
	Personal security skill	0.21	27.05***	0.21	0.01
	Critical skill	0.32	36.71***	0.32	0.01
	Device security skill	0.24	28.30***	0.24	0.01
	Communication skill	0.16	23.90***	0.16	0.01

Notes: ***Significant at 0.001 level based on 5,000 bootstraps; **significant at 0.01 level based on 5,000 bootstraps; *significant at 0.05 level based on 5,000 bootstraps

constructs contains two steps: the indicator level (in which the first-order constructs now act as indicators), and the second-order constructs (Henseler et al., 2009).

In the first stage, we need to assess whether every first-order construct contributes to forming the second-order construct (Chin, 1998a; Hair et al., 2011). However, as a reminder, we treated the path as weights instead of loading factor. Note that the weights obtained are the scores we obtained in the first stage. Referring to Andreev et al. (2009), the indicators' weight should exceed 0.1. Furthermore, bootstrapping should be employed to verify the significance (Hair et al., 2011; Henseler et al., 2009). Table 4 shows that all first-order constructs' weights are higher than 0.10 and have a significant level based on 5,000 bootstrapping, which means there is empirical support for the first-order constructs in terms of the construction of the formative second-order constructs (Hair et al., 2011).

Furthermore, it is necessary to assess the nomological validity at the second-order construct level. This validity manifested in the magnitude and significance of the relationships between the second-order formative construct with the other constructs in the model (Henseler et al., 2009). The results in Table 5 indicate a significant relationship between second-order formative constructs in this study and other constructs in the model. It means the nomological validity has been met.

5.3. Evaluation of the structural model (inner model)

After the outer model is proven to be reliable and valid, then the inner model estimates should be examined for the sake of hypothesized relationships among constructs in the model (Hair et al., 2012; J.F Hair et al., 2016). However, PLS-SEM is different from CB-SEM. It makes the goodness-of-fit of CB-SEM not fully transferrable to PLS-SEM. Therefore, the inner model goodness-of-fit in this study was evaluated following Chin & others (Chin, 1998a, 1998b), Henseler et al. (2009), and Hair Jr et al. (J.F Hair et al., 2016) by assessing the f^2 and Q^2 effect size. Furthermore, the standardized path coefficients and significance levels with 5,000 bootstrapping allow researchers to test the proposed hypotheses.

Table 5. Hypotheses tests and effect size results

Hyphotheses	Coefficient	Mean	Standard Deviation	t	Result
H1: Self Regulated Learning -> Course Satisfaction	0.51***	0.51	0.04	12.02	Supported
H2: Digital Literacy -> Course Satisfaction	0.24***	0.24	0.05	4.85	Supported
H3: Course Satisfaction -> Academic Performance	0.11**	0.11	0.04	2.46	Supported
H4: Self Regulated Learning -> Course Satisfaction -> Academic Performance	0.05*	0.06	0.02	2.38	Supported
H5: Digital Literacy -> Course Satisfaction -> Academic Performance	0.03*	0.03	0.01	2.16	Supported
f^2 effect size					
Self Regulated Learning -> Course Satisfaction	0.27***	0.27	0.06	4.44	Medium
Digital Literacy -> Course Satisfaction	0.06*	0.06	0.03	2.13	Small
Course Satisfaction -> Academic Performance	0.02*	0.02	0.01	1.10	Small
Q^2 effect size					
Self Regulated Learning	0.46				Large
Digital Literacy	0.45				Large
Course Satisfaction	0.29				Medium

Notes: ***Significant at 0.001 level based on 5,000 bootstraps; **significant at 0.01 level based on 5,000 bootstraps; *significant at 0.05 level based on 5,000 bootstraps

Many researchers rely on R2 to examine the explained variance of the endogenous constructs. However, since the second-order constructs in the model of this study use repeated indicators, surely the variance of the second-order construct will be perfectly explained and the explained variance will be equal to 1. Therefore, another approach is used, known as the Stone-Geisser's Q^2 (Geisser, 1975; Stone, 1974). In the PLS-SEM application, this approach follows a blindfolding procedure and then tries to estimate the omitted part using the estimated parameters (Vinzi et al., 2010). In this study, researchers used SmartPLS blindfolding feature with the omission distance used was 7. This value follows the recommendation by Chin (Chin, 1998a) and Henseler et al. (2012) that omission distance should be between 5 and 10. For interpretation, if Q^2 > 0, it means the model has predictive relevance. However, if $Q^2 < 0$ it represents a lack of predictive relevance (Henseler et al., 2009; Vinzi et al., 2010).

Besides Q^2, numerous scholars (Henseler et al., 2009; J.F Hair et al., 2016; Ringle et al., 2020) also recommended evaluating the effect size of each path using f^2 (Cohen's effect size; Cohen, 2013). Values between 0.02 and 0.15, between 0.15 and 0.35, and over 0.35 represents small, medium, and large effect size, respectively (Henseler et al., 2012; Vinzi et al., 2010). Similar to f^2, this three level can be applied to Q^2 as well (Henseler et al., 2009).

Table 5 presents the path coefficients and the significance levels. The direct effects show that self regulated learning has a stronger effect ($\beta = 0.51$, $p < 0.001$) on course satisfaction than digital literacy ($\beta = 0.24$, $p < 0.001$). In terms of the influence of course satisfaction on academic performance, the path coefficient shows a significant effect, with $\beta = 0.11$, $p < 0.01$. Thus, hypothesis 1, hypothesis 2, and hypothesis 3 are supported. Regarding the indirect effect on academic performance through course satisfaction, the coefficient reveals that self-regulated learning ($\beta = 0.05$, $p < 0.05$) has proven to be important as well as digital literacy ($\beta = 0.03$, $p < 0.05$) in influencing academic performance of students. Therefore, hypothesis 4 and hypothesis 5 are supported. The calculation of f^2 effect size in Table 5 also shows that the path of self-regulated learning on course satisfaction has a medium effect size, while digital literacy on course satisfaction and course satisfaction on academic performance has a small effect size. The results in Table 5 also indicate that Q^2 effect size of exogenous constructs in the model of this study have an adequate effect size. Self-regulated learning and digital literacy were revealed to have large predictive relevance, while course satisfaction revealed to have a medium effect size

6. Discussion and implications

This study aimed to explore how self-regulated learning, digital literacy, and course satisfaction shaped academic performance in online learning settings during the unprecedented COVID-19 pandemic in Indonesia. From the literature review, the authors hypothesized that both self-regulated learning and digital literacy directly affect course satisfaction, while course satisfaction directly influences students' academic performance. Furthermore, self-regulated learning and digital literacy are intervened by course satisfaction in the relationship to students' academic performance.

Our results found that self-regulated learning positively impacts the level of students' course satisfaction. This finding supports the idea of Kuo et al. (2014) that interaction, internet self-efficacy, and self-regulated learning roles as predictors of student satisfaction in online education courses. Furthermore, in Massive Open Online Courses (MOOCs) setting, Li (2019) finding also shows a similar result, that self-regulated learning strategy was a key variable in students' course satisfaction. Also, the empirical evidence in this study found that digital literacy predicted students' course satisfaction. This finding corroborates the ideas of Eshet-Alkalai (2004), who stated that digital literacy is a survival skill in this digital era, including in the learning process. That is why having an understanding of how to use digital tools in the learning process is crucial. Because if students do not have adequate digital literacy, students may experience a tendency to depression in the use of technology, or what is known as technostress, which will surely decrease the academic productivity of university students (Upadhyaya, 2021). Another important finding was that course satisfaction positively impacts the students' academic performance. These results match those observed in recent studies. A study conducted by Bossman and Agyei (2022) proved that technology and instructor dimensions, e-learning satisfaction influence the academic performance of distance students in Ghana.

The mediating effects of course satisfaction proposed in our study suggest that self-regulated learning does not straightforwardly lead to a higher level of academic performance of students, but through course satisfaction. Similar results also applied to digital literacy. These results suggest

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that nurturing digital literacy and self-regulated learning ignites the students' course satisfaction, which in turn positively affects academic performance. These results support the idea of other scholars that course satisfaction has a crucial role in mediating one variable to another. Take an example of the research conducted by Ko and Chung (2014) that found student satisfaction has a mediating role of teaching quality of teachers and students' academic performance. Furthermore, Nye et al. (2021) also reported similar pattern.

The present results are significant in at least two major aspects. First, in the sample and setting in this study, digital literacy and course satisfaction do not only act as a stand-alone variable that impacts students' academic performance; it also needs a high level of student satisfaction at the prior, so that students' academic performance can be fostered. And second, in the time of online learning, self-regulated learning acted as the biggest predictor of the students' academic performance. It means success online learning needs a high level of self-regulated learning from students. Practically speaking, in the community of students with low self-regulated learning, authors are really doubtful that online learning can run smoothly or have the expected outcome.

These findings may help us to understand the online learning situation in Indonesia. The discovery of this study found that digital literacy, while it acted as the second biggest predictor of academic performance, but it still held a high coefficient. It means digital literacy is important. However, as we can notice, Indonesia is a country with high inequality in many education indicators, let alone socioeconomic status (Ikeda & Echazarra, 2021; OECD, 2018). Imagine, is it possible to have a high level of digital literacy while, in fact, many Indonesian children do not have access to the digital device in their home? Again, we doubt, except the government can guarantee the accessible of the digital devices. In terms of self-regulated learning, this study has important implications for using or developing the teaching strategies that can foster students' self-regulated learning. Dignath et al. (2008) suggest using what is called as self-regulated learning training programs. These programs proved to be effective, even at the primary school level. So the educator needs to realize that self-regulated learning is more likely to be nurtured than nature. The educator can not just teach how to understand the subject matter but need to stimulate the self-regulated learning of students.

While COVID-19 is still around, but in Indonesia, the teaching and learning process started to be conducted in schools or campuses. Thus, online learning is no longer fully implemented. Many parties think that online learning should continue to be carried out to reduce the number of transmission and droughts caused by COVID-19. However, this study gives a glimpse that online learning can be successfully implemented, but still with a high level of caution of every stakeholder involved, in order not to let the noble ideals to be achieved actually plunge students into the abyss of ignorance. This study suggests that the government and educational policymakers move the learning process from the "virtual world" to the actual classroom as soon as possible, especially in Indonesia, where online learning readiness is not too good (Afrianti & Aditia, 2020). If online learning really needs to be conducted, blended learning platform is preferable to fully online learning because blended learning combines the benefit of both worlds (Dziuban et al., 2018), but still, the implementation needs an enormous amount of caution. As the finding from this study indicates, academic performance in an online environment really depends on digital literacy capacity. If the students cannot use the digital device well, do not rely on technological devices to deliver your learning.

As a closing statement to hinder us from doing malpractice in education, we need to put what the distinguished scholar in pedagogy, Paulo Freire, said into heart: "We have methods to approach the content, methods to make us get closer to the learners. Some methods of approaching students can in fact push us very far from the student." (Horton & Freire, 1990).

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Appendix A

Table A1. Item questionnaire coding

Code	Sub-construct	Variable
SRL1	Goal setting	Self-Regulated Learning
SRL2		
SRL3		
SRL4		
SRL5		
SRL6	Environment structuring	
SRL7		
SRL8		
SRL9	Task strategies	
SRL10		
SRL11		
SRL12		
SRL13	Time management	
SRL14		
SRL15		
SRL16	Help-seekng	
SRL17		
SRL18		
SRL19		
SRL20	Self-evaluation	
SRL21		
SRL22		

(Continued)

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DL1	Technological skill	Digital Literacy
DL2		
DL3		
DL4		
DL5		
DL6		
DL7		
DL8	Personal security skill	
DL9		
DL10		
DL11		
DL12		
DL13	Critical skill	
DL14		
DL15		
DL16		
DL17		
DL18	Device security skill	
DL19		
DL20		
DL21		
DL22	Information skill	
DL23		
DL24		
DL25		
DL26	Communication skill	
DL27		
DL28		

(Continued)

Table A1. (*Continued*)

CS1	No sub-construct	Course satisfaction
CS2		
CS3		
CS4		
CS5		
CS6		
CS7		
CS8		
CS9		
CS10		
CS11		
CS12		
CS13		
CS14		
CS15		
CS16		
CS17		
CS18		
CS19		
CS20		
CS21		
AP1	No sub-construct	Academic performance
AP2		
AP3		

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