The interplay of factors affecting online learning experience in higher education

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ABSTRACT

Education has undergone a profound transformation, transitioning significantly from traditional face-to-face instructional approaches to a predominant reliance on online learning methodologies. This sudden change leaves questions on how to provide an affective and satisfying online leaning for students. As prior studies revealed, many factors affect the success of implementing online learning, specifically for higher education students. As a response, this quantitative study was intended to investigate the interplay of factors affecting online learning experience in higher education namely anxiety, motivation for learning, self-directed learning, online learning attitude, and computer-internet self-efficacy. An exploratory factor analysis (EFA) included 20 items of online survey distributed to undergraduate students (n=329) from several faculties at one Indonesian university to explore this issue. This study used the partial least squares structural equation modeling (PLS-SEM) application to explore the interplay among six constructs. The results showed that all six constructs namely anxiety, motivation for learning, self-directed learning, online learning attitude, computer-internet self-efficacy, and online learning experience were positively associated. It meant that those factors were statistically proven to affect students' online learning experiences. Educators could use these results as a consideration in implementing online learning more effectively. Further implications of pedagogical practice and further research are discussed.

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1. INTRODUCTION

The advancements of technology change people on how to communicate and interact, and educational sector is not an exception. Education today has experienced a transition from face-to-face classroom learning to online learning. Online learning philosophy "anytime, anywhere, and for everyone" which allows students to further their study at distance [1]. Also, Zou *et al.* [2] found that online learning should be an alternative to substitute face-to-face classroom learning which is unable to conduct. However, many students struggle in this transition [3] due to many factors. Educators need to pay attention to how students adapt to this sudden change in learning methods. Many researchers have proven the effectiveness of online learning [4]. However, some argue that online learning is still a challenge for students and teachers [5]. The effectiveness of online learning could be different depending on its location, culture, facilities, and students' readiness. Regarding location, online learning is surely more effective to be implemented in big cities with enormous technological supports than in remote area with limited supports. In remote area, in which this study took place, the available facilities may affect students' attitudes towards online learning. Many researchers have continuously conducted studies on this issue for years.

Symeonides and Childs [6] found that students often consider online learning unreal and unnatural. The students struggle in expressing themselves, establishing relationships, and often comparing themselves to others. However, some factors were found to have affected online learning success. Jan [7] discovered that students with high self-efficacy and prior online learning experiences tend to have more satisfaction in online learning. Continuously, students with prior online learning experiences were more likely to choose online learning [8]. Besides, prior learning experiences also positively affect students' learning attitudes and motivation to learn [9]. However, regarding self-efficacy and prior learning experiences, Kreth *et al*. [10] surprisingly found that students with prior learning experiences have lower learning self-efficacy and more negative view of online learning. Still, other studies result differently. Lim *et al*. [11] discovered that high self-efficacy supports students' online learning processes. They proved that online learning self-efficacy results in positive learning outcomes. Conclusively, it is still arguable how these factors affect online learning implementation. Considering prior studies as such, it seems that researchers pay less attention to the interrelated factors affecting online learning experience, specifically viewed from a quantitative study's perspective using an exploratory factor analysis (EFA). Thus, it raises our curiosity about how those factors actually interplay in achieving successful online learning. Finally, this study is intended to investigate the interplay of constructs namely anxiety, motivation for learning, self-directed learning, online learning attitude, computer-internet self-efficacy, and online learning experience by employing an EFA.

Self-efficacy is known as the students' beliefs in their own abilities to succeed. Computer internet self-efficacy is identified as students' beliefs in their own abilities to use computers and internet to help them succeed in their studies. It plays a critical role in online learning since their learning is highly supported by technology, in this case, computers, and internet. High computer self-efficacy contributes positively to students' learning outcomes [11]. It gives them more satisfying learning outcomes since they believe that they can make use of computers and internet effectively. Furthermore, students' high technological self-efficacy improves their motivation in learning [12]. It seems that students' beliefs in using technology trigger their motivation to continue learning online, leading them to successful outcomes of learning. Online learning experience is highly influenced by many factors. It may come from the students, learning environment, or facilities. Researchers found that online learning experience is affected by anxiety [6], [13], teacher presence [11], computer self-efficacy [7], prior learning experience [8], [9], motivation for learning [14], self-directed learning [15], and many other factors. Their findings are somehow mixed, and such a condition needs further studies to confirm and strengthen prior findings on achieving a successful online learning.

Considering those theories and prior studies' results, it is likely that the six constructs namely anxiety, motivation for learning, self-directed learning, online learning attitude, computer-internet self-efficacy, and online learning experience are interrelated to one another. Students' anxiety is correlated with self-efficacy. It seems that high computer-internet self-efficacy makes students less anxious in online learning. Furthermore, other factors also affect one another. Mastering computer-internet for learning puts more motivation to the students. It also eases students in managing their online learning as they know what they should do with the media of learning, computers, and internet. Last, learning attitude has been found to be able to predict students' learning outcomes and satisfaction. It is clearly seen that those factors are also interrelated with one another. However, these factors' interplay has not been clearly and statistically proven. Thus, this study formulates eight hypotheses regarding this issue as: i) anxiety is associated with computer-internet self-efficacy in online learning (H1); ii) anxiety is associated with motivation for learning in online learning (H2); iii) anxiety is associated with self-directed learning in online learning (H3); iv) motivation for learning is associated with online learning attitude in online learning (H4); v) computer-internet self-efficacy is associated with self-directed learning in online learning (H5); vi) self-directed learning is associated with online learning experience (H6); vii) self-directed learning is associated with an online learning attitude (H7); and viii) online learning attitude is associated with online learning experience (H8).

2. METHOD

This quantitative study employed an EFA. The factors analyzed consisted of anxiety, motivation for learning, self-directed learning, online learning attitude, computer-internet self-efficacy, and online learning experience in online learning, specifically in this pandemic era of COVID-19. There were eight hypotheses formulated in this study which are represented in the conceptual model in Figure 1.

The participants of this study were undergraduate students of one Indonesian university in Papua, Indonesia. They were from the Faculty of Teacher Training and Education, Faculty of Engineering, Faculty of Social Science and Law, and Faculty of Economy and Business. This study employed random sampling to select the participants who attended online learning in COVID-19 pandemic. The data were collected by delivering online questionnaire using Google form in which the link was administered by each department chairperson given to the students. The data were collected in July 2022. The participants in total were 329 students. This respondent is a sample of the student population of 1,645 people. The determination of this sample refers to the criteria, which is as much as 20% of the total population [16]. We adapted the previous study in formulating the questionnaire. The variables of this study were anxiety using SASE; computer internet self-efficacy, motivation for learning, self-directed learning; online learning attitude; and online learning experience. The questionnaire consisted of 20 item questions. After the data were collected, we validated the data using face validation with linguistic and teaching media experts to appraise the questionnaire contents and linguistic features. They used Linkert scale from 1=very poor to 5=very good. The face validation showed an average of 4.3 in results. We, then, held questionnaire pilot testing to 50 students in English major. The results were then tested for the validity and reliability using SPSS 23 application. The results showed that the instrument had a good degree of reliability with the Cronbach alpha of .823. Furthermore, every question was categorized as a valid item with the r values in the range from .61 to .83 compared with r table of .138. This study employed survey using partial least squares structural equation modeling (PLS-SEM) analysis model by three steps namely model specification, outer model evaluation, and inner model evaluation. The first step was done by constructing inner and outer model (exogenous and endogenous construct). The second step was by compositing reliability evaluation, convergent validity assessment, and discriminant validity assessment. The last step was the analysis of the coefficient, cross-validated redundancy, path coefficient, and effect size.

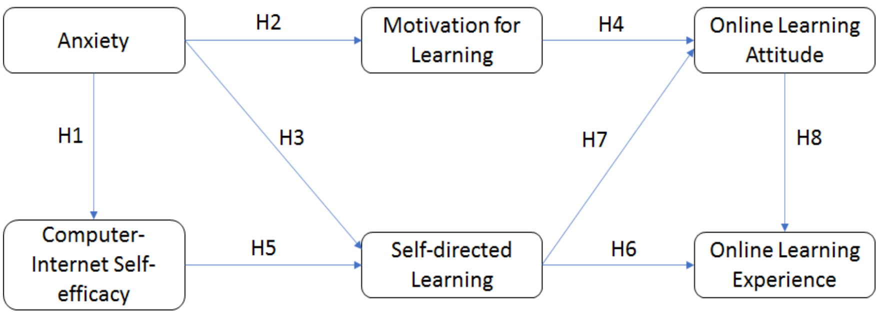

Figure 1. Conceptual model

3. RESULTS AND DISCUSSION

The first step of data analysis was to construct the variable model. Figure 2 shows that this study had six inner model with 17 outer models. Furthermore, anxiety took a role as the exogenous construct, while computer internet self-efficacy, motivation for learning, self-directed learning, and online learning attitude were functioned as endogenous and exogenous constructs, and last, online learning experience took a role as the endogenous construct. This step began by testing the indicator and internal consistency reliability. The result of item loading was used to test the indicator reliability, as seen in Figure 2. The suggested threshold was more than .5 [17]. The item loading of CIS_3, MFL_3, and SDL_1 had a value less than .5, so the items were dropped. The rest of item loading values were categorized as good with the values ranging from .612 to .906. Those results showed that the indicator of reliability was established. The next step was to test the composite reliability to know the internal consistency reliability with suggested threshold within .70 to .90 [18]. The obtained values from composite reliability, as seen in Table 1, were between .775 to .889 which was categorized as reliability satisfactory.

Convergent and discriminant validity analyses were conducted to ensure the model validity. We employed it to find out the average variance extracted (AVE) with suggested threshold more than .50. The obtained AVE value lied within .538 to .766, meaning that convergent validity was obtained. The last step in this second phase was to test discriminant validity to gain heterotrait-monotrait ratio (HTMT) value with the suggested threshold less than .85. The obtained value of HTMT, as shown in Table 2, was within .504 to .756, meaning that the discriminant validity was obtained. Inner model analysis began with testing collinearity to gain variance inflation factor (VIF) value with suggested threshold less than three. Table 3 shows that the obtained VIF was within 1.000 to 1.373. It means that there was no issue in collinearity.

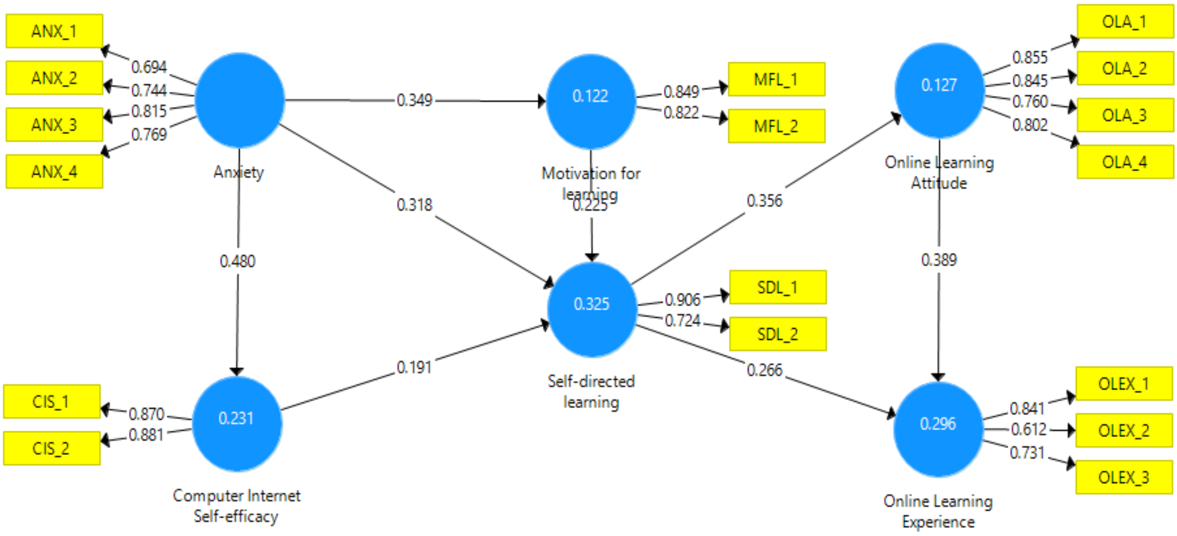

Figure 2. Confirmatory factor analysis

Table 1. Composite reliability and AVE

Variables	Composite reliability	AVE
Anxiety	0.842	0.573
Computer internet self-efficacy	0.868	0.766
Motivation for learning	0.822	0.699
Online learning attitude	0.889	0.666
Online learning experience	0.775	0.538
Self-directed learning	0.802	0.673

Table 2. HTMT

Variables	Anxiety	Computer internet self-efficacy	Motivation for learning	Online learning attitude	Online learning experience
Anxiety					
Computer internet self-efficacy	0.667				
Motivation for learning	0.537	0.526			
Online learning attitude	0.582	0.751	0.566		
Online learning experience	0.504	0.526	0.642	0.640	
Self-directed learning	0.756	0.631	0.695	0.503	0.650

Table 3. VIF

Variables	Anxiety	Computer internet self-efficacy	Motivation for learning	Online learning attitude	Online learning experience	Self-directed learning
Anxiety		1.000	1.000			1.373
Computer internet self-efficacy						1.352
Motivation for learning						1.184
Online learning attitude					1.146	
Online learning experience						
Self-directed learning				1.000	1.146	

The next step was coefficient determination analysis to find out the value of predictive accuracy (R2). There were three categories in predictive accuracy (R2), namely great (.75), moderate (.50), and substantial (.25) [17]. Table 4 shows that online learning experience and self-directed learning were the only variables having substantial value. Then, cross-validated redundancy was employed to find the value of predictive relevance. This process was done by calculating the Q2 value in the inner model. There were three categories of predicative relevance value namely small (0.), medium (0.25), and substantial (0.50) [17]. Table 5 shows that the predicative relevance value was categorized as small (<.25).

Table 4. R-square (R^2) value

Variables	R-square	R-square adjusted
Computer-internet self-efficacy	0.231	0.228
Motivation for learning	0.122	0.119
Online learning attitude	0.127	0.124
Online learning experience	0.296	0.292
Self-directed learning	0.325	0.319

Table 5. R-square (R^2) value

Variables	Sum Square Observation (SSO)	Sum square error (SSE)	Q^2 (=1-SSE/SSO)
Anxiety	1.316.000	1.316.000	
Computer-internet self-efficacy	658.000	544.801	0.172
Motivation for learning	658.000	603.948	0.082
Online learning attitude	1.316.000	1.208.231	0.082
Online learning experience	987.000	843.097	0.146
Self-directed learning	658.000	524.801	0.202

The next step was to test the hypotheses of the inner model. First, we determined the kind of relationship based on path coefficient -1 (strong negative relationship) to +1 (strong positive relationship) [17]. Table 6 shows that the values were of .191 to .480. It means that all paths had positive relationships.

We employed bootstrapping with setting a significance level of 5% for the model. We used threshold to test the hypotheses by T-Statistics >1.96 to determine that outer model loadings are highly significant. T-Statistics (see Table 6 or path value in Figure 2) values show that the eight hypotheses were accepted for T Statistics >1.96. The analysis was, then, continued to find the effect size (f2) by categorizing the values of .02, .15, and .35 which indicate small, medium, and large effect [17]. Table 7 shows that the model having medium effect size was anxiety to computer internet self-efficacy and online learning attitude to online learning experience. The rest of the models had a small effect size. Furthermore, the description of the Structural model assessment formed based on the results of the analysis is shown in Figure 3.

The present study employed an explanatory factor analysis of anxiety, motivation for learning, self-directed learning, online learning attitude, computer-internet self-efficacy, and online learning experience. Our analysis showed that there was a positive and significant relationship between anxiety and computer internet self-efficacy, anxiety and motivation for learning, anxiety and self-directed learning, computer internet self-efficacy, and self-directed learning, motivation for learning and self-directed learning, online learning attitude and online learning experience, self-directed learning and online learning attitude, and also self-directed learning and online learning experience. As a result, all eight hypotheses were accepted.

Table 6. Structural model assessment

The hypotheses within the inner model	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Anxiety→Computer internet self-efficacy	0.480	0.485	0.049	9.903	0.000
Anxiety→Motivation for learning	0.349	0.354	0.055	6.359	0.000
Anxiety→Self-directed learning	0.318	0.320	0.058	5.463	0.000
Computer internet self-efficacy→Self-directed learning	0.191	0.192	0.058	3.279	0.001
Motivation for learning→Self-directed learning	0.225	0.225	0.052	4.304	0.000
Online learning attitude→Online learning experience	0.389	0.396	0.055	7.115	0.000
Self-directed learning→Online learning attitude	0.356	0.362	0.055	6.435	0.000
Self-directed learning→Online learning experience	0.266	0.267	0.052	5.097	0.000

Table 7. Effect size

Variables	Anxiety	Computer internet self-efficacy	Motivation for learning	Online learning attitude	Online learning experience	Self-directed learning
Anxiety		0.300	0.139			0.109
Computer internet self-efficacy						0.040
Motivation for learning						0.064
Online learning attitude					0.188	
Online learning experience						
Self-directed learning				0.146	0.088	

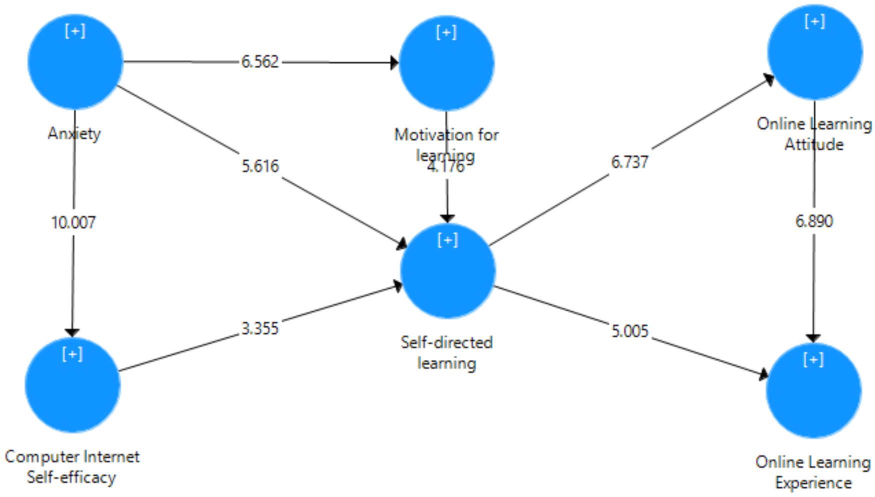

Figure 3. Structural model assessment

The first result was that students' anxiety was positively associated with computer internet self-efficacy (β=0.480, t=9.903, and p=<0.05). It indicates that students' anxiety is highly affected by their beliefs in their ability in using computer and internet. Students with low efficacy in using computer and internet were likely to be more anxious in online learning than the ones with high efficacy. Similarly, Valle *et al*. [19] reported that good a belief in computer use influences students' anxiety. Furthermore, it surely affects their learning outcomes. Students with good control of anxiety are predicted to have more successful online learning. However, how this anxiety contributes to learning outcomes is beyond our scope, so it needs to be studied further. Other studies have also revealed different findings delineating on various variables other than anxiety that potentially affect computer internet self-efficacy. For instance, learners' autonomy of using computers, their capacities of learning, and supports from their colleagues could predict the degree of computer self-efficacy. Studies demonstrated that the extent of self-efficacy in using computers is affected by experiences and time spent for operating computers. Study suggested that attitudes towards using internet to some extent affect computer self-efficacy. Also, it can be learned from study that internet self-efficacy is affected by ones' personal possessions of computer and internet connection. The foregoing highlights of different findings exhibit a number of non-individual factors underlying computer internet self-efficacy. However, the current study's result contributes to the literature by adding another individual factor, the so-called anxiety, which may cause computer internet self-efficacy in such a way that ones with lower anxiety may have higher self-efficacy in using computers and accessing the internet.

The second result revealed that students' anxiety was positively associated with motivation for learning (β=0.349, t=6.359, and p=<0.05). It means that students' anxiety affects their motivation for learning. High anxiety will give students uncertainty feeling of their success in learning. This finding somehow confirms Aguilera-Hermida's study [20] that students' high anxiety will eventually decrease their motivation for learning. Their low anxiety in online learning, which can be caused by prior experiences, keeps them motivated to continue learning online. Our finding significantly provides another factor influencing students' motivation for learning where students with low anxiety probably have high motivation for learning. It seems that peers and teachers are often failed to give force to the students to keep motivated in online learning. Further studies are needed to know the effective ways to maintain students' motivation for learning.

The third result was that students' anxiety was positively associated with self-directed learning (β=0.318, t=5.463, p=<0.05). It indicates that students with high anxiety will encounter more difficulties in monitoring and evaluating their learning progress. This finding is in line with previous finding [21] that students with good control of anxiety have higher abilities in their self-directed learning. It probably means that students who can manage their anxiety can also have better learning strategies than those who have anxiety issues. Thus, they can have better learning outcomes and experiences. Prior studies reported that students' anxiety is commonly influenced by their demographics, prior learning experiences, and learning situations [22]. Educators need to consider these factors to reduce students' anxiety in learning. The findings highlight the importance of controlling students' anxiety by considering factors influencing students' anxiety as for controlled or low anxiety creates high self-directed learning which impacts on better learning outcomes.

The fourth result revealed that there was a positive relationship between computer internet self-efficacy and self-directed learning (β=0.191, t=3.279, and p=<0.05). It indicates that students with high beliefs in their ability in using computer and internet will find it easier to handle online learning. These beliefs will ease them in managing, controlling, and maintaining their progress in online learning as they have abilities to use computer and internet effectively. Also, these beliefs affect their motivation for learning. Computer internet self-efficacy is also affected by their views of computer role and prior knowledge of using computer and internet [23]. It indicates that to gain a good self-directed learning, educators need to consider those factors influencing computer internet self-efficacy. Furthermore, self-directed learning is affected by external factors such as family support and academic environment and internal factors such as motivation [24]. Thus, to help students obtain good self-directed learning abilities, educators need to consider these factors.

The fifth result reported that students' motivation is found to be associated with their self-directed leaning abilities (β=0.225, t=4.304, and p=<0.05). Motivational beliefs influence students' learning strategies. Motivated students are likely to have more effective learning strategies which lead to better learning outcomes and satisfaction. Also, this finding is somehow similar to Samanthula *et al.* [25] finding that students' motivation is closely related to their self-monitoring abilities to learn. The students' self-monitoring ability increases when they are motivated in learning. Self-directed learning is influenced by students' motivation. In their study, high motivated students perform high self-directed learning, so they perform good and high learning strategies. Furthermore, students' motivation is affected by academic and social supports [6]. These supports will keep students motivated to learn, specifically in online learning. Educators need to pay attention to this factor to maintain students' motivation that they can have high self-directed learning abilities as found by our study. Students' motivation, specifically in non-blended learning environment, is not affected by their self-directed learning abilities. The possible reason was their students prefer face-to-face classroom learning rather than online learning. It indicates that students' motivation also depends on their preferences for teaching methods. However, further research is needed to investigate this matter.

The sixth result was that there was a strong positive relationship between self-directed learning and online learning attitude (β=0.356, t=6.435, and p=<0.05). It means that self-directed learning affects online learning attitudes. As found by Hofer *et al.* [21], students with good work ethics and interests are more likely to handle online learning easier. Students' positive attitudes toward online learning make online learning less threatening, so that they can cope with it easier. Lamb and Arisandy [9] reported that students' attitudes toward online learning are highly affected by their prior online learning experiences such as experiences for online informal learning of English (OILE). The students with prior experiences have more positive views of online learning. Furthermore, online learning attitudes are also affected by external factors such as locations and learning supports [26]. The locations where students live have an important role in online learning as the proper technological supports are mostly found in big cities rather than in border areas. It seems that when they have good learning supports, they will gain good online learning attitudes. It indicates that students' prior experiences and those external factors in online learning also affect self-directed learning indirectly.

The seventh result reported that self-directed learning also associates positively with online learning experiences (β=0.266, t=5.097, and p=<0.05). It means that students with good self-directed learning are predicted to have better online learning experiences. Students' positive views, perceptions, and behavior in online learning are predicted to give them satisfying online learning experiences. Students' online learning experiences are influenced by students' leaning strategies. Students with good learning strategies are likely to have more pleasant and satisfying online learning experiences. Also, as found by van Alten *et al.* [27], students with high self-directed learning is predicted to have higher learning outcomes and experiences as well. Meanwhile, students' online learning experiences are also affected by other factors such as students' demographics (i.e., gender and location), prior online learning experiences, and also their sense of preparedness for the course [28]. He also reported that those factors also influence students' anxiety in learning. It may infer that anxiety is associated with students' online learning experiences. Our finding proves another factor influencing online learning experiences apart from the factors found by prior studies.

The eighth result showed a strong positive relationship between online learning attitude and online learning experience (β=0.389, t=7.115, and p=<0.05). It indicates that students' online learning experiences are influenced by their learning attitudes. Students who have positive views of online learning are likely to be more motivated in learning, leading to a more successful and satisfying online learning experience. This finding somehow supports finding that students' positive attitudes toward the benefits of online learning affects their learning satisfaction [29]. Students with positive learning attitudes are highly believed to have more satisfying online learning experiences than those with more negative learning attitudes. However, Aguilera-Hermida [20] reported that students often consider online learning as an unpleasant experience and show negative attitudes toward it. They prefer face-to-face classroom learning as they can have real and direct interactions with other students and teachers. Thus, it should be a concern for future research to find the effective ways to handle students' attitudes toward online learning.

Another interesting finding is that the model of our study also demonstrates that anxiety, motivation for learning, and computer-internet self-efficacy indirectly affect online learning experiences. These findings partially support findings that students' anxiety affects their performances [28]. High anxiety has a negative impact on students' performances and learning outcomes. Then, students' online learning experiences are also indirectly affected by their motivation for learning. This finding is consistent with prior studies [14] that motivated students are found to have more successful and satisfying learning experiences. Students perceive online learning as beneficial and effective when they are comfortable with using computers-internet, are well-acquainted with the learning system, and face no difficulties in its usage [30]. Also, computer-internet self-efficacy was found to be able to predict students' learning experiences. It may imply that students who find it easier to use computer and internet will experience more effective and satisfying online learning. Students perceive online learning as beneficial and effective when they are comfortable with using computers-internet, are well-acquainted with the learning system, and face no difficulties in its usage.

Our finding may imply that students with low anxiety are expected to have more pleasant online learning experiences. It indicates that high anxious feelings probably make the students face more threatening online learning experiences. However, it is somehow in contrast with Hilliard *et al.* [13] finding as the students there perceived anxiety more positively. They argue that high anxiety will be perceived by students as a challenge to make them more motivated in their learning. The explanation for this issue probably lies on each individual difference. A possible reason is that every student must have a different view on anxiety and different ways to overcome anxiety. It seems that our students tend to have negative views on anxiety as for students with low and controlled anxiety are predicted to have more pleasant online learning experiences. However, still, further researchers are needed to complete and confirm this finding.

4. CONCLUSION

In conclusion, the results revealed that six constructs in this study namely anxiety, motivation for learning, self-directed learning, online learning attitude, computer-internet self-efficacy, and online learning experience were positively and significantly associated with one another. Hence, all eight hypotheses of this study were accepted. It indicates that students' online learning experiences are affected by their anxiety, motivation for learning, self-directed learning, computer-internet self-efficacy, and also online learning attitudes. However, our study has some limitations. The ratio of male and female student participants was quite different in total that it is somehow difficult to generalize the results in a larger context. Similar studies with participants in a balanced ratio of gender as well as in different ages are worthwhile to conduct. Also, the data of this study were obtained from one source, which was online survey. Future studies may include multiple data sources such as students' reflection or interview to obtain more sophisticated data and results. Last, this study only focuses on the students' perspectives. Studies on a similar topic from different perspectives may be worthwhile to conduct for confirming, completing, or comparing the results to obtain a more solid interpretation.

REFERENCES

[1] S. Naidu, "Openness and flexibility are the norm, but what are the challenges?," *Distance Education*, vol. 38, no. 1, pp. 1–4, Jan. 2017, doi: 10.1080/01587919.2017.1297185.

[2] B. Zou, H. Li, and J. Li, "Exploring a curriculum app and a social communication app for EFL learning," *Computer Assisted Language Learning*, vol. 31, no. 7, pp. 694–713, Sep. 2018, doi: 10.1080/09588221.2018.1438474.

[3] J. Trespalacios, L. Uribe-Flórez, P. Lowenthal, S. Lowe, and S. Jensen, "Students' perceptions of institutional services and online learning self-efficacy," *American Journal of Distance Education*, vol. 00, no. 00, pp. 1–15, 2021, doi: 10.1080/08923647.2021.1956836.

[4] L. Harasim, *Learning Theory and Online Technologies*. Routledge, 2017.

[5] C. M. D. Hart, D. Berger, B. Jacob, S. Loeb, and M. Hill, "Online learning, offline outcomes: online course taking and high school student performance," *AERA Open*, vol. 5, no. 1, p. 233285841983285, Jan. 2019, doi: 10.1177/2332858419832852.

[6] R. Symeonides and C. Childs, "The personal experience of online learning: An interpretative phenomenological analysis," *Computers in Human Behavior*, vol. 51, pp. 539–545, Oct. 2015, doi: 10.1016/j.chb.2015.05.015.

[7] S. K. Jan, "The relationships between academic self-efficacy, computer self-efficacy, prior experience, and satisfaction with online learning," *American Journal of Distance Education*, vol. 29, no. 1, pp. 30–40, Jan. 2015, doi: 10.1080/08923647.2015.994366.

[8] W. A. Zimmerman and J. M. Kulikowich, "Online learning self-efficacy in students with and without online learning experience," *American Journal of Distance Education*, vol. 30, no. 3, pp. 180–191, Jul. 2016, doi: 10.1080/08923647.2016.1193801.

[9] M. Lamb and F. E. Arisandy, "The impact of online use of English on motivation to learn," *Computer Assisted Language Learning*, vol. 33, no. 1–2, pp. 85–108, Jan. 2020, doi: 10.1080/09588221.2018.1545670.

[10] Q. Kreth, M. E. Spirou, S. Budenstein, and J. Melkers, “How prior experience and self-efficacy shape graduate student perceptions of an online learning environment in computing,” *Computer Science Education*, vol. 29, no. 4, pp. 357–381, Oct. 2019, doi: 10.1080/08993408.2019.1601459.
[11] J. R. N. Lim, S. Rosenthal, Y. J. M. Sim, Z. Y. Lim, and K. R. Oh, “Making online learning more satisfying: the effects of online-learning self-efficacy, social presence and content structure,” *Technology, Pedagogy and Education*, vol. 30, no. 4, pp. 543–556, Aug. 2021, doi: 10.1080/1475939X.2021.1934102.
[12] C. Y. Hung, J. C. Y. Sun, and J. Y. Liu, “Effects of flipped classrooms integrated with MOOCs and game-based learning on the learning motivation and outcomes of students from different backgrounds,” *Interactive Learning Environments*, vol. 27, no. 8, pp. 1028–1046, 2019, doi: 10.1080/10494820.2018.1481103.
[13] J. Hilliard, K. Kear, H. Donelan, and C. Heaney, “Students’ experiences of anxiety in an assessed, online, collaborative project,” *Computers & Education*, vol. 143, p. 103675, Jan. 2020, doi: 10.1016/j.compedu.2019.103675.
[14] R. Kaufmann and M. M. Buckner, “Revisiting ‘power in the classroom’: exploring online learning and motivation to study course content,” *Interactive Learning Environments*, vol. 27, no. 3, pp. 402–409, Apr. 2019, doi: 10.1080/10494820.2018.1481104.
[15] A. Maksum, I. W. Widiana, and A. Marini, “Path analysis of self-regulation, social skills, critical thinking and problem-solving ability on social studies learning outcomes,” *International Journal of Instruction*, vol. 14, no. 3, pp. 613–628, Jul. 2021, doi: 10.29333/iji.2021.14336a.
[16] R. B. Johnson and L. Christensen, *Educational research: quantitative, qualitative, and mixed approaches*, 7th ed. Sage, 2020.
[17] J. F. Hair Jr, M. Sarstedt, L. Hopkins, and V. G. Kuppelwieser, “Partial least squares structural equation modeling (PLS-SEM),” *European Business Review*, vol. 26, no. 2, pp. 106–121, Mar. 2014, doi: 10.1108/EBR-10-2013-0128.
[18] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, “When to use and how to report the results of PLS-SEM,” *European Business Review*, vol. 31, no. 1, pp. 2–24, Jan. 2019, doi: 10.1108/EBR-11-2018-0203.
[19] N. Valle, P. Antonenko, D. Valle, K. Dawson, A. C. Huggins-Manley, and B. Baiser, “The influence of task-value scaffolding in a predictive learning analytics dashboard on learners’ statistics anxiety, motivation, and performance,” *Computers & Education*, vol. 173, p. 104288, Nov. 2021, doi: 10.1016/j.compedu.2021.104288.
[20] A. P. Aguilera-Hermida, “College students’ use and acceptance of emergency online learning due to COVID-19,” *International Journal of Educational Research Open*, vol. 1, p. 100011, 2020, doi: 10.1016/j.ijedro.2020.100011.
[21] S. I. Hofer, N. Nistor, and C. Scheibenzuber, “Online teaching and learning in higher education: lessons learned in crisis situations,” *Computers in Human Behavior*, vol. 121, p. 106789, Aug. 2021, doi: 10.1016/j.chb.2021.106789.
[22] N. Chaku, D. P. Kelly, and A. M. Beltz, “Individualized learning potential in stressful times: How to leverage intensive longitudinal data to inform online learning,” *Computers in Human Behavior*, vol. 121, p. 106772, Aug. 2021, doi: 10.1016/j.chb.2021.106772.
[23] O. E. Hatlevik, I. Throndsen, M. Loi, and G. B. Gudmundsdottir, “Students’ ICT self-efficacy and computer and information literacy: Determinants and relationships,” *Computers & Education*, vol. 118, pp. 107–119, Mar. 2018, doi: 10.1016/j.compedu.2017.11.011.
[24] N. Ramli, P. Muljono, and F. M. Afendi, “External factors, internal factors and self-directed learning readiness,” *Journal of Education and e-Learning Research*, vol. 5, no. 1, pp. 37–42, 2018, doi: 10.20448/journal.509.2018.51.37.42.
[25] B. K. Samanthula, M. Mehran, M. Zhu, N. Panorkou, and P. Lal, “Experiences toward an interactive cloud-based learning system for STEM education,” in *2020 IEEE Integrated STEM Education Conference (ISEC)*, Aug. 2020, pp. 1–6, doi: 10.1109/ISEC49744.2020.9280688.
[26] S. M. Ojetunde, “Online learning platforms’ induced education inequalities and special education students’ learning attitude during Covid-19 pandemic homestay in the University of Ibadan,” *Journal of Education and Practice*, no. August, 2021, doi: 10.7176/jep/12-23-08.
[27] D. C. D. van Alten, C. Phielix, J. Janssen, and L. Kester, “Secondary students’ online self-regulated learning during flipped learning: A latent profile analysis,” *Computers in Human Behavior*, vol. 118, p. 106676, May 2021, doi: 10.1016/j.chb.2020.106676.
[28] M. Abdous, “Influence of satisfaction and preparedness on online students’ feelings of anxiety,” *The Internet and Higher Education*, vol. 41, pp. 34–44, Apr. 2019, doi: 10.1016/j.iheduc.2019.01.001.
[29] S. I. Lei and A. S. I. So, “Online teaching and learning experiences during the COVID-19 pandemic – a comparison of teacher and student perceptions,” *Journal of Hospitality & Tourism Education*, vol. 33, no. 3, pp. 148–162, Jul. 2021, doi: 10.1080/10963758.2021.1907196.
[30] T. Zobeidi, S. B. Homayoon, M. Yazdanpanah, N. Komendantova, and L. A. Warner, “Employing the TAM in predicting the use of online learning during and beyond the COVID-19 pandemic,” *Frontiers in Psychology*, vol. 14, pp. 1–14, Feb. 2023, doi: 10.3389/fpsyg.2023.1104653.

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