Factors Affecting Online Learning Satisfaction among Students in Higher Learning Institutions: An Indonesian Study

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Abstract

The study examines the tertiary students’ preparedness, motivation, internet availability, technical support, and psychological support that influence students’ online learning satisfaction in Indonesia. This study was initiated during the early Covid-19 pandemic that forced most education institutions to shift to online platforms. Data from 292 respondents were collected online across Indonesia for three months, from November 2020 until the end of February 2021. The Structural Equation Model was selected as the primary data analysis method using Smart PLS 3.2.4, where five hypotheses were tested in this study. Findings demonstrated that psychological support, motivation, and preparedness significantly affected students’ satisfaction. The result of this study contributes to updating the trend during the Covid-19 pandemic because there was limited research conducted on this topic, especially in Indonesia. However, further study should be able to provide a comparative study between different countries to understand if similar factors could have influenced their students’ online learning satisfaction in higher learning institutions, especially in the post-Covid 19 eras.

Keywords
Online Learning, Psychological Support, Students’ Satisfaction, and Technical Support.

1. Introduction

With the previous Covid 19 pandemic as a decisive push factor, many countries have been forced to implement social distancing policies across multiple sectors. This included the closure of offices, businesses, universities, and schools. As schools and universities were forced to be closed for physical sessions during this pandemic, over 1.2 billion learners in 186 countries were forced to leave their usual classroom settings (Li and Lalani, 2020). Since then, all education providers have been forced to push forward with integrating online learning as an alternative to the blackboard learning style. From being complementary, online learning has since become the primary medium of
delivery for teaching and learning for education providers at all levels, including universities. Lecturers and students on tertiary education levels were subconsciously forced to engage in synchronous and asynchronous online activities.

Although the need for mobility becomes wider throughout the pandemic, most Indonesian internet users rely heavily on the expensive and limited capacity of mobile networks, as compared to other countries which have pivoted to the broadband network, which can cater to online learning more smoothly, especially on requirements which need extensive data exchange (Harto, 2020). This was added to the situation where private education technology providers are only concentrated in Jakarta, with a typical target of tertiary education institution providers and private schools. Eventually, a significant gap emerged within Indonesia’s education sector, which has been worryingly widening since Covid-19 struck the nation in 2020 (Unicef, 2020; Mulyanto, 2021).

In tertiary education worldwide, teaching and learning delivery for various programs, which has long been done on a face-to-face basis has started to be conducted online via the emergency remote teaching (ERT) model (Hodges et al., 2020). As ERT began to be implemented with the emergence of the Covid-19 pandemic, all educators at various levels of study in Indonesia had to learn how to translate Indonesia’s curriculum for different platforms once schools were ordered to suspend face-to-face activities starting in April 2020. However, Indonesia's Ministry of Education and Culture failed to disseminate its Emergency Curriculum information until August 2020 (Helly, 2021). As the delivery content was shifted from physical to online without it being designed and developed in accordance with online learning principles, many lecturers in Indonesia tended to provide asynchronous assignments as most education technology platforms were still unfamiliar to them (Hratinski, 2020). Many teachers were also reported to have failed in translating the asynchrony approaches for online learning. In response to this situation, students could not obtain guides and feedback for the asynchronous assignments. As such, user satisfaction, especially from the perspectives of students who are receiving education in developing a nation, becomes varied across Indonesia, depending on their personal experiences.

1.1 Objectives
Learning the gap of adapting to the new mechanics, also to ensure that the quality of education for students remains a satisfactory level, the current study aims to examine the higher learning institution students’ preparedness, motivation, internet availability, technical support, and psychological support that influences students’ online learning satisfaction in Indonesia.

2. Literature Review
2.1 Student Satisfaction
Satisfaction with the educational experience is the most crucial aspect in motivating students to continue learning. Astin (1993) defines student satisfaction as a student's evaluation of their academic institution's learning experiences. Meanwhile, Muilenburg and Berge (2005) reported that considerable differences in students' perceptions of their online learning experiences continue to exist. Thus, students' perceptions of their educational experiences can influence their commitment to completing the course and their overall satisfaction with their online education learning experiences (Carr, 2000). According to Harsasi and Sutawijaya (2018), student satisfaction is one of the most critical factors that needs to be considered when evaluating accomplishments in the implementation of online learning.

Elliott and Healy (2001) contended that student satisfaction is a temporary attitude resulting from the evaluation of students' educational experiences. As such, this is a determinant of student retention and is a result of the educational system (Navarro et al., 2005). Student satisfaction is defined by Elliot and Shin (2002) as students' subjective evaluations of their academic performance and experiences. Thus, student satisfaction can also be defined in terms of the relative interaction between perceived performance and actual performance in relation to educational services provided during the study period (Mukhtar et al., 2015). When these factors are considered, student satisfaction can be characterised as a short-term behaviour generated in response to an assessment of students' experiences, services, and educational facilities (Li et al., 2016).

Over the last few decades, many scholars have made huge attempts to satisfy students in higher education by adopting diverse areas of satisfaction through a variety of frameworks and models. Primarily, researchers employed industry satisfaction models to gauge satisfaction but eventually developed models based on higher education. The models were created with a range of proportions and have been adapted to a variety of geographical regions and chronological
eras. Consequently, the same dimensions revealed paradoxical associations with students' satisfaction across contexts, but distinct dimensions demonstrated globally consistent behaviours with students' pleasure.

Several variables influence student satisfaction in a virtual environment. Bolliger and Wasilik (2009), for example, identified three essential components of online student satisfaction: the teacher or educator, the technology tools, and the interaction. This includes correspondence concerning the course and lesson components, as well as issues with the management system and websites. Additionally, Liaw (2008) identified critical constructs such as students' perspectives on assessment tasks and self-efficacy, social skills, system quality, and interactive media education. On the other hand, they highlighted several barriers to virtual learning that students experience, such as administrative issues, technical difficulties, time limits, social connection, intellectual skills, and limited access to materials.

While numerous studies have been undertaken on online learning at the university level, limited research has been conducted on the elements that influence students' happiness with online teaching and learning during COVID-19 pandemics. Many of these students have classes with their instructors face-to-face, and interactivity can simply be changed. However, COVID-19 had turned their study lives upside down. Some of them lose interest in studying since they are unable to adapt to different environments. As such, it is crucial to examine the factors that contributed to students' satisfaction in higher education during the COVID-19 pandemic. Thus, it is important to gather student perceptions of educational institutions to assist administrators in enacting policies that improve teaching and learning environments.

2.2 Students’ Preparedness and Satisfaction
The study began as a response to Arif (2001) series of questions about students' readiness for online learning. For instance, preparing students would determine if they were appropriately equipped to use computer technology and possessed the essential competencies for accessing and navigating through course information. When using educational models, the critical question is whether the student is equipped for self-evaluation and self-belief to adapt to new learning pathways. Furthermore, whether the learner is prepared to forego established study methods in favour of a new method is also unclear. Thus, in a higher education context where distance learning has become the preferred method of instruction, it may seem reasonable to believe that these technology-assisted, instinctive digital students will excel in such learning environments. However, a study by Waugh and Su-Searle (2014) found that online learning class dropout rates are typically higher than those of traditional face-to-face classes. These considerations cast doubt on students' suitability for online learning environments at the university level.

Given the rapid rise and acceptance of online learning at the university level, limited study on students' preparedness or readiness for learning environments appears to have been undertaken. Warner et al. (1998) conducted one of the first studies on student readiness for online learning, using a sample of students from the Australian Vocational Education and Training (VET) sector. According to the findings, students were neither appropriately prepared nor receptive to online learning. According to Parkes et al. (2015), students lacked perceived preparation and online learning competencies in general. While students may be prepared to handle the technology connected with online learning, they lack the necessary willingness to perform tasks such as reading and writing, responding clearly and succinctly, developing ideas, strategic planning, presenting reasoning, and working with others.

Abdous's (2019) study demonstrates the crucial necessity of generating an appealing online learning experience for students by reducing their anxiety about finishing online lessons. As a result, requiring students to undergo an orientation to online learning should increase their motivation to learn. According to prior studies and related literature, it is obvious that students' readiness may play a role in their teaching and learning satisfaction. Based on the discussion above, the following hypothesis is presented:

H1: There is a positive relationship between students’ preparedness and students’ learning satisfaction.

2.3 Students’ Motivation and Satisfaction
Motivation, according to Johnson et al. (2017), serves as the foundation for comprehending complex behaviours. Bekele (2020) says that motivation is required for constructive learning since it influences the acquisition and establishment of higher-order cognitive skills. Motivation is described as students' willingness to engage in learning activities, and it has the capacity to impact the effectiveness of learning (Tomy and Pardede, 2019). Self-determination theory's intrinsic and extrinsic motivational orientations provide a valuable framework for analysing motivation in
educational contexts. Stutz et al. (2017) show that intrinsic and extrinsic motivation are not diametrically opposed on a continuum, but rather distinct elements that can coexist and exert varied impacts on learning.

Intrinsically motivated students will engage in an activity for internal motivations such as happiness and satisfaction. Here, students will listen because the act of hearing is gratifying in and of itself or because they love undertaking listening assignments. On the other hand, extrinsic motivation is characterised by a concentration on obtaining instrumental goals that transcend the learning process itself (Stutz et al., 2017). Students that are genuinely motivated may listen to meet their teachers' expectations, acquire parental praise, earn a good grade, or gain peer recognition.

According to Johnson et al. (2017), understanding motivation may result in a more pleasurable experience for students. Motivation is crucial for task identification since it increases the possibility of positive experiences that affect pleasure and retention (Strigas and Jackson, 2003). Johnson et al. (2017) examined student motivation and satisfaction and revealed that students were driven by the opportunity to gain new knowledge, skills, and abilities while sharing their own. As a result, it is believed that the more motivated students are, the more satisfied they will be with teaching and learning. The hypothesis is constructed as follows:

H2: There is a positive relationship between students' motivation and students' learning satisfaction

2.4 Availability and Students’ Satisfaction

The internet has been described as an interactive high-speed line that links, grips, and translates the entire world into a global community in which individuals can quickly interact, locate, and converse with one another, as well as instantly transfer knowledge from one location to another (Shitta, 2002). This technology has altered academic learning practices in higher education and will continue to do so in the future (Apuke and Iyendo, 2018). According to Hussain (2012), the internet has facilitated academic advancement and research in tertiary education. Additionally, it facilitated virtual interactions for the purpose of sharing scientific findings.

Fasae and Adegbilero-Iwari (2015) discovered that science students at private universities in Nigeria who routinely utilise internet services such as e-mail, social networks, and browsers do so for the purpose of learning and engagement. However, it was determined that students' biggest challenges include poor internet connectivity and the expensive cost of data subscriptions. Additionally, studies indicated that students who lacked advanced computer and internet-related skills had a negative effect on their satisfaction with teaching and learning. Apuke and Iyendo (2018) give insight into issues such as internet access, financial constraints, and online learning implementation. Given the budgetary constraints faced by students, they want educators to make use of available resources such as the free Messenger program included in the online learning system. This finding is consistent with Allo's (2020) finding that most respondents felt that offering courses via online learning is more expensive than entirely face-to-face learning. As a result, if decision-making about learning modes were entirely based on cost, most respondents would favour traditional classroom instruction over online instruction. With widespread internet access, the current study reveals that, while individual tasks are preferred for keeping a physical distance during a pandemic, they require group tasks to aid friends who lack online access.

As demonstrated above, students eagerly endorsed the online learning system to extend their learning beyond the traditional face-to-face classroom paradigm. Students are instructed to become comfortable taking classes with or without paper under this approach. Ultimately, the issue is one of network accessibility and student financial capability. While many students can afford an Internet data subscription and a strong network, others cannot. As a result, this study will investigate the effect of internet availability on student satisfaction. The following hypothesis is presented.

H3: There is a positive relationship between internet availability and students’ learning satisfaction

2.5 Technical Support and Students’ Satisfaction

Technical support comprises aiding students with any technological issues that may occur when they are enrolled in online learning (Lee et al., 2011). Song et al. (2004) highlight that the technical problem is the significant factor that produces problems and influences student pleasure in online learning environments. Muilenburg and Berge (2005) discovered that students who were familiar with online learning technology perceived many fewer obstacles than those
who were unfamiliar. As a result, educators and instructors must ensure students' safety and security when dealing with online technologies as well as fix technological matters (Muilenburg and Berge, 2005; Song et al., 2004).

Many of these challenges are resolved when institutions provide proper technical assistance, such as laptops, mobile phones, and technical support services, and students gain a higher sense of confidence in the system, which ultimately boosts their satisfaction with educational programs (Itasanmi and Oni, 2021). Technical support is an integral part of any open or remote education system. It comprises activities that are responsive to students' requirements and provide a varied range of support to make online learning and services incredibly accessible to students. It encompasses informational assistance, institutional assistance, academic assistance, and prompt feedback to students (Aftab et al., 2019). Recent research by Aftab et al. (2019) and Itasanmi and Oni (2021) reveals that technical support services are the most important factor influencing students' satisfaction in open distance learning programs. As a result, it is concluded that technical assistance has a favourable effect on student satisfaction. Based on the explanation above, the hypothesis is as follows:

H4: There is a positive relationship between technical support and students’ learning satisfaction

2.6 Psychological Support-Enjoyment and Students’ Satisfaction
In general, student satisfaction through the enjoyment of the learning environment can be described as the feeling of pleasure related to the learning activities and the experience associated with those activities (Kangas et al., 2017). This definition emphasises optimistic attitudes and feelings toward the learning process, which are frequently inspired by learning motivation (Chang and Chang, 2012; Topala and Tomozii, 2014). Chang and Chang (2012), for example, revealed a stronger relationship between student satisfaction and enjoyment. As a result, it is logical to assume that the more students are involved in pleasant learning, the more satisfied they will be with their educational environment. Instructors may make any class more interesting and pleasant for both students and instructors by modifying it. This ability, however, requires instructors' capabilities for creativity and instructional design (Hyvonen, 2011). The findings by Hyvonen (2011) emphasize the critical role of teachers being inspired and interested in related pedagogical techniques when it comes to ensuring student happiness in a creative learning environment. This finding supports Frenzel et al.'s (2009) finding that instructor enthusiasm relates to student satisfaction in a learning environment. Additionally, research indicates that instructor pedagogical and emotional engagement is necessary for student satisfaction and the ability of schools to change sustainably (Kangas et al., 2017). Gil-Ariase et al. (2020) concluded that students who showed greater enjoyment during lessons expressed a greater sense of satisfaction. According to the explanation above, psychological support-enjoyment is expected to impact students' contentment. As a result, the final hypothesis is as follows:

H5: There is a positive relationship between psychological support and students’ learning satisfaction

3. Methods
3.1 Sampling Selection
A quantitative method was applied for the study, where students' satisfaction was considered as a dependent variable that could be measured in the survey questionnaire. This study used a cross-sectional quantitative survey method. Respondents received an online survey by university lecturers using a purposive sample technique. The study took four months to achieve, beginning from November 2020 until the end of February 2021.

Students in Indonesia were expected to be more than 2.29 million in higher learning institutions in 2020 (Statistica, 2021). However, only 384 students are required to be sampled as respondents to the current study (Krejcie and Morgan, 1970). For a medium effect size of 0.15 (Green, 1991), a minimum sample of 117 is required, which is lesser than the one proposed by Krejcie and Morgan (1970). Hence, the authors sent the questionnaire in the google form through the WhatsApp application to almost 900 students. Participation and commitment were genuinely voluntary and unidentified. In the end, 292 students from numerous disciplines of the study answered the survey completely and they became the sample of the study.

3.2 Measurement for Survey Questionnaire
The survey consisted of seven segments, which were designed to study online teaching and learning satisfaction amongst tertiary students in Indonesia. It consisted of student’s learning online satisfaction items (six items), students’ preparedness (five items), students’ motivation (four items), internet availability (four items), technical support (four
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items), and psychological support (five items) (Bolliger and Wasilik, 2009). There were five essential demographic items (i.e., age, gender, ethnicity, education background and current stage of learning). A total of 33 items were asked for seven subdivisions. Students' satisfaction with their current online learning, their internet application, tools being used in class, enjoyment, and their psychological level are among the questions asked in the survey questionnaire. A seven-point Likert-type measure varying from strongly disagree (1) to strongly agree (7) was recommended as answer options for all the components. The students were required to only choose one answer per item.

3.3 Data Analysis

The study employed the Structural Equation Model via Partial Least Squares (PLS) method to analyse the model by using SmartPLS 3.0 software (Ringle et al., 2015). It developed with the two-state analytical process recommended by Hair et al. (2019). The PLS technique is a second-generation statistical technique which was designed to analyse the interrelationships among multiple variables in a model. The objective of using PLS is to maximise the relationship between independent factors to a dependent variable (Memon, Ting, Ramayah, Chuah, and Cheah, 2017). PLS is a better option as compared to other approaches since it requires a small sample size and has the ability to handle non-normally distributed data.

The purpose of PLS-SEM is to be used for prediction-oriented analysis by using variance based, and its assumption is nonparametric (Hair et al., 2019). PLS is advantageous in terms of its ability to address the hard assumptions of traditional multivariate statistics, which are somewhat difficult to meet (Deal, 2005). In cases where there are multiple dependent variables, there is a need to use software such as Smart PLS to manage complex variables. It is considered as a predictive technique, which has the ability to handle several independent variables for a complex structural equation model. Smart PLS was used to build and validate the Partial Least Square (PLS) structural model. It determines the relationship between the variables being used. The structural model will be tested to see whether there is empirical evidence on the hypothesised relationship between the variables. There are two stages in PLS analysis. The first procedure is to evaluate a measurement model for each latent construct to assess the validity and reliability of the measures. The second procedure is to conduct a structural model assessment or path analysis by running a bootstrapping process. Structural model assessment is similar to regression in SPSS, whereby it shows the $t$ and $p$ of the factors that were being analysed.

Figure 1 indicates the study's measurement model that will be discussed further in the next section. It consists of students’ satisfaction, students’ preparedness, students’ motivation, internet availability, technical support, and psychological support.

![Figure 1. Measurement model of the study](image)

4. Data Collection

292 students in Indonesia submitted survey questionnaires that were all deemed appropriate. An overview of the respondents' demographics is shown in Table 1. In summary, male, and female respondents’ percentage are almost
equal with a non-science background and ages between 20-24 is the majority because this is the range that teenagers are in tertiary education in Indonesia.

Table 1. Demographic profile of respondents (N: 292)

<table>
<thead>
<tr>
<th>Particular</th>
<th>Categories</th>
<th>Frequency</th>
<th>Percentage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>Male</td>
<td>137</td>
<td>46.90</td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td>155</td>
<td>53.10</td>
</tr>
<tr>
<td>Age</td>
<td>15-19</td>
<td>142</td>
<td>48.60</td>
</tr>
<tr>
<td></td>
<td>20-24</td>
<td>149</td>
<td>51.00</td>
</tr>
<tr>
<td></td>
<td>25-29</td>
<td>1</td>
<td>0.30</td>
</tr>
<tr>
<td>Ethnicity</td>
<td>Jawa</td>
<td>158</td>
<td>54.10</td>
</tr>
<tr>
<td></td>
<td>Betawi</td>
<td>2</td>
<td>0.70</td>
</tr>
<tr>
<td></td>
<td>Sunda</td>
<td>46</td>
<td>15.80</td>
</tr>
<tr>
<td></td>
<td>Batak</td>
<td>1</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td>Tionghoa</td>
<td>1</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td>Melayu</td>
<td>30</td>
<td>10.30</td>
</tr>
<tr>
<td></td>
<td>Minang</td>
<td>9</td>
<td>3.10</td>
</tr>
<tr>
<td></td>
<td>Bugis</td>
<td>8</td>
<td>2.70</td>
</tr>
<tr>
<td></td>
<td>Others</td>
<td>37</td>
<td>12.70</td>
</tr>
<tr>
<td>Education level</td>
<td>SMA</td>
<td>256</td>
<td>87.70</td>
</tr>
<tr>
<td></td>
<td>S1</td>
<td>36</td>
<td>12.30</td>
</tr>
<tr>
<td>Education background</td>
<td>Science</td>
<td>124</td>
<td>42.50</td>
</tr>
<tr>
<td></td>
<td>Non-science</td>
<td>168</td>
<td>57.50</td>
</tr>
<tr>
<td>Residential Area</td>
<td>Urban</td>
<td>141</td>
<td>48.30</td>
</tr>
<tr>
<td></td>
<td>Sub Urban</td>
<td>47</td>
<td>16.10</td>
</tr>
<tr>
<td></td>
<td>Rural</td>
<td>104</td>
<td>35.60</td>
</tr>
</tbody>
</table>

5. Results and Discussion
5.1. Measurement Analysis
The convergent validity is a point where several measurements are employed to ascertain the associated thought that could be unrelated. Composite reliability (CR) and average variance extracted (AVE) are among the statistics tool to justify the convergent validity (Hair et al., 2017).

The composite reliability values shown in Table 2 reflect how well construct indicators would predict the latent construct, which is greater than the suggested value of 0.7. (Hair et al., 2019). The extracted average variance, which was greater than the necessary value of 0.5, represented the total number of overall variations in the indicators provided by the latent construct. (Hair et al., 2017). Table 2 presents the findings regarding convergent validity. It shows that all constructs have minimal AVE of 0.524 (Internet availability) and CR from 0.786 to 0.901.

Table 2. Convergent Validity

<table>
<thead>
<tr>
<th>Construct</th>
<th>Item</th>
<th>Loading</th>
<th>Cronbach Alpha</th>
<th>Composite Reliability</th>
<th>AVE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Psychological support (PS)</td>
<td>PS1</td>
<td>0.778</td>
<td>0.671</td>
<td>0.821</td>
<td>0.612</td>
</tr>
<tr>
<td></td>
<td>PS2</td>
<td>0.804</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PS3</td>
<td>0.73</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PS4</td>
<td>0.593</td>
<td></td>
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</tr>
</tbody>
</table>
The discriminant validity assessment comes next. Low correlations between the extent of interest and the measurements of other constructs indicate how little discriminant validity suggests the instruments fail to explain other variables (Cheung and Lee, 2010). Comparing the squared correlations of different constructs with their respective variances has the potential to produce discriminant validity (Fornell and Larcker, 1981). This study used the heterotrait-monotrait ratio to test discriminant validity (HTMT). All values in Table 3 were revealed to be below the recommended value of 0.90, which suggests discriminant validity had concerns when the HTMT value was larger than 0.90 (Gold, Malhotra, and Segars, 2001). This circumstance demonstrated that no discriminant validity was acknowledged. Overall, the measurement model had shown that there was sufficient discriminant and convergent validity.

### Table 3. Discriminant Validity based on HTMT criterion

<table>
<thead>
<tr>
<th>Factors</th>
<th>SIA</th>
<th>PS</th>
<th>SM</th>
<th>SW</th>
<th>SS</th>
<th>TS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internet availability (SIA)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Psychological support (PS)</td>
<td>0.673</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Students' motivation (SM)</td>
<td>0.794</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Students' preparedness (SP)</td>
<td>0.483</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Students' satisfaction (SS)</td>
<td>0.505</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Technical support (TS)</td>
<td>0.852</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Diagonals reflect the square root of the average extracted variance.

### 5.2 Structural Analysis

The second step is analyzing the structural model. The structural model revealed causal connections between its constructs. (Sang, Lee and Lee, 2010). The variance inflation factor (VIF), R-squared, F squared, Q squared, and path coefficients were first evaluated (Hair et al., 2017). The structural model's initial development should include a discussion of the collinearity issue. The VIF value was examined in order to assess this problem. To make sure there was no multicollinearity prior to hypothesis testing, the model requires the VIF value to be less than 5. Table 4 indicates that the model has no chance of being multicollinear because the VIF value is less than 5, i.e., internet...
availability (1.74), psychological support (2.209), students' motivation (1.828), student preparedness (1.739) and technical support (1.748).

Table 4. Initial Structural Model Analysis

<table>
<thead>
<tr>
<th>Item</th>
<th>Path Coefficient</th>
<th>VIF</th>
<th>F square</th>
<th>R square</th>
<th>Q square</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internet availability (SIA)</td>
<td>-0.008</td>
<td>1.740</td>
<td>0.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Psychological support (PS)</td>
<td>0.625</td>
<td>2.209</td>
<td>0.438</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Students' motivation (SM)</td>
<td>0.109</td>
<td>1.828</td>
<td>0.016</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Students' preparedness (SP)</td>
<td>0.109</td>
<td>1.739</td>
<td>0.017</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Technical support (TS)</td>
<td>0.012</td>
<td>1.748</td>
<td>0.000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

500 resamples were used in a bootstrapping process to obtain the t-values. The measurement model in Figure 1 thus displays an R-squared value of 59.7% and it indicates that another 40% factors are not from this study. The Cohen's $f^2$ measure, which gauges the proportional influence of an independent variable on the dependent variable, was used to assess the predictor's effect size. The construct from Table 4's impact size predictor showed that psychological support's $f^2$ value of 0.438 had a substantial effect size (Cohen, 1992). The other factors' $f^2$ had little or no effect sizes (0.016, 0.017, and 0.000, respectively).

Table 5. Structural Model and Hypothesis Testing

<table>
<thead>
<tr>
<th>H</th>
<th>Variable</th>
<th>Beta Coeff.</th>
<th>Std. Error</th>
<th>T Values</th>
<th>P Values</th>
<th>Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>Internet availability (SIA) -&gt; Students' satisfaction (SS)</td>
<td>-0.008</td>
<td>0.051</td>
<td>0.153</td>
<td>0.879</td>
<td>Not supported</td>
</tr>
<tr>
<td>H2</td>
<td>Psychological support (PS) -&gt; Students' satisfaction (SS)</td>
<td>0.625</td>
<td>0.051</td>
<td>12.227</td>
<td>0.000</td>
<td>Supported</td>
</tr>
<tr>
<td>H3</td>
<td>Students' motivation (SM) -&gt; Students' satisfaction (SS)</td>
<td>0.109</td>
<td>0.057</td>
<td>1.921</td>
<td>0.055</td>
<td>Supported</td>
</tr>
<tr>
<td>H4</td>
<td>Students' preparedness (SP) -&gt; Students' satisfaction (SS)</td>
<td>0.109</td>
<td>0.047</td>
<td>2.33</td>
<td>0.02</td>
<td>Supported</td>
</tr>
<tr>
<td>H5</td>
<td>Technical support (TS) -&gt; Students' satisfaction (SS)</td>
<td>0.012</td>
<td>0.056</td>
<td>0.218</td>
<td>0.828</td>
<td>Not supported</td>
</tr>
</tbody>
</table>

The results from the PLS output are presented in Table 5, which includes the path coefficients, t-values, p-values, and standard error. From the table, psychological support ($b = 0.625, p<0.05$), students’ motivation ($b = 0.109, p<0.05$), and students’ preparedness ($b = 0.109, p<0.05$) were noticed to be absolutely associated to students’ online learning satisfaction and managed to justify 59.7% of the variances. These results confirmed the current study's H2, H3, and H4. The survey also revealed that accessibility to the internet and technical assistance had no obvious influence on students' satisfaction.

6. Conclusion

In order to examine the determinants of students’ online learning satisfaction in Indonesia, this research proposed five hypotheses, and the result is that three of them are supported. Psychological support, student motivation, and student preparedness significantly affect students’ learning satisfaction. However, the other two factors, internet availability and technical support, do not influence learning satisfaction.
The result of three significant factors is relevant to prior research. Gil-Ariase et al. (2020) found that enjoyment as a positive psychological state supports students’ satisfaction during their learning. Furthermore, Strigas and Jackson (2003) and Johnson et al. (2017) proved that the more motivated the students are, the more satisfied they will be in their learning process. Lastly, research by Abdous (2019) indicated that students’ readiness contributes to higher outcomes in learning satisfaction. Connecting this result with the pandemic condition is certainly relevant because the conditions during a pandemic are unpredictable. Therefore, psychological, motivation and preparation aspects are important to consider.

Although internet availability was proven a significant factor for students’ satisfaction during their learning in previous research by Apuke and Iyendo (2018) and Allo (2020), this factor does not demonstrate the impact on students’ satisfaction in Indonesia. This contradiction could be resulted from the Indonesian government’s intervention in providing free internet access for students (Ministry of Education, Culture, Research, and Technology of Indonesia, 2021). Therefore, most Indonesian students during the pandemic generally accept that the availability of the internet is no longer an essential factor in their learning program.

Although the pandemics condition is predicted to get better and now moving to an endemic era, the trend to rely on online learning remains unchanged shortly. Formal or informal education may continue to utilize online learning in combination with face-to-face learning. Therefore, future research can focus on designing a proper learning process that combines both online and offline methods because the online delivery during the pandemic was not designed for online learning (Baber, 2020). It should be modified to the students’ condition to increase their satisfaction.

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References


