The Influence of Academic Stress, Internet Addiction, and Sleep Quality on Student Academic Achievement in Indonesia

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ABSTRACT

This study investigates how academic stress, internet addiction, and sleep quality affect the academic performance of Indonesian students. Data were collected through an online survey completed by 209 students from various universities in Indonesia. This study, which was conducted using the Partial Least Squares-Structural Equation Modeling (PLS-SEM) method, found that internet addiction and academic stress have a significant negative impact on academic achievement, while sleep quality has a significant positive impact. This study suggests that stress management, wise use of the internet, and good sleep quality are essential for improving students' academic performance.

INTRODUCTION

Improving academic quality is an increasing need in the contemporary world of education. Indonesian university students often face various difficulties, leading to academic stress, which impacts their performance (Oktavia, Urbayatun, Mujidin, 2019; Kaur, 2020). Academic stress is caused by the pressure of excessive coursework as well as concerns about their inability to manage these tasks well due to the many other activities that occur on and off campus (Munir, 2015; Dixit, 2020).

The study conducted by Nur Hamizah Hj Ramli et al. (2018) found that academic stress is an emotional or mental condition that students often experience during their studies. A dense curriculum, a different education system, concerns about future plans after graduation, and a heavy exam load create anxiety to achieve high grades cause this stress. Thoughts about career prospects increase the pressure, and changes in the education system make it difficult to adjust.

A study conducted by Bedewy and Gabriel (2015) found that academic stress can improve creativity and learning quality, which, if managed well, can have a positive impact on students' self-development. The study found that when students face academic challenges

that trigger controlled stress, they tend to be more motivated to learn and find new ways to solve problems, which helps them achieve their academic goals.

However, poorly managed academic stress can have a negative impact. According to Bataineh (2013) and Waqas, Khan, Sharif, Khalid, and Ali (2015), academic stress can negatively impact alcohol consumption, sleep disturbances, mental health issues, and eating disorders. Students who experience severe stress may seeking ways to escape by consuming alcohol, having sleep problems or insomnia, experiencing mental health issues such as anxiety and depression, and changing their diet which adversely affects their physical and mental health. Modern technology is developing rapidly, making the world more open. The internet allows us to communicate and interact with others easily. However, as many people prefer to interact via the internet, in-person interactions are becoming less and less frequent. As a result, internet usage is increasing and difficult to control.

The internet has become an important part of students' lives in both education and non-education. As a result, it is difficult for them to avoid using the internet in their daily lives (LaRose, Cannplly, Lee, & Hales, 2014). Accessing the internet easily provides many benefits and changes education (Yung, Eickhoff, Davis, Klam, & Doan, 2015). But accessing the internet too much can cause problems such as internet addiction (Rahmawati, 2018).

According to Yang et al. (2019), internet addiction often leads to social isolation. Addicted individuals prefer online interactions over face-to-face. This reduces their ability to interact in real social situations. They feel more comfortable communicating over the internet, so they tend to avoid in-person interactions. As a result, their social skills are reduced, and they face difficulties in building and maintaining social relationships in the real world. In education, the internet affects students' academic outcomes, according to Hia and Ginting (2019). During the learning process, students are required to gather as much information as possible. The internet makes college fun. The internet, however, has many benefits, including positive things that encourage academic spirit, but also many negative benefits, such as pornography, online gaming, and addiction to cyber relationships that can lead to apathy and abuse.

Fernández-Ozcorta et al. (2020) conducted a study that emphasized the relationship between students' academic performance and their sleep quality. They found that students who had poor sleep quality had lower academic grades, suggesting that sleep disorders affect a person's health in addition to their academic performance. According to the results of this study, good sleep is essential to support students' academic performance. According to Nilifda et al. (2016), sleep quality (hours of sleep) and sleep depth (hours of sleep) are two factors that make up the need for adequate sleep. One of the most important human needs is sleep. However, everyone's sleep needs are different. In general, humans need seven to eight hours of sleep every night (Ratnaningtyas, 2019).

According to Dewi (2015), a busy college schedule increases the likelihood of students experiencing poor sleep quality. In addition, according to Taylor et al. (2016) investigated how adolescents' nighttime eating habits relate to their sleep quality. They found that unhealthy nighttime eating patterns, such as consuming fatty foods or caffeinated drinks, can affect adolescents' sleep quality. This study increases our knowledge of how lifestyle components, such as diet, can affect sleep and have a significant impact on adolescent health.

Good quality sleep is essential as lack of sleep can reduce the ability to concentrate. Not getting enough sleep can cause students to be sleepy and tired, which can hinder their learning process and lower their academic performance. This needs to be taken seriously as lack of sleep, also known as sleep deprivation, can affect students' memory, learning process, and emotional health. Memory is closely related to the ability to concentrate. Remembering, recording, and developing lecture material requires concentration, which enables students to achieve good academic performance.

Learning achievement, also known as academic achievement, is the result that a person achieves after following various learning processes, according to Slameto (2003). Many changes occur during this process, including changes in attitudes, knowledge, and learned skills. Hawadi (2006) defines academic achievement as a process in which students transform knowledge, understanding, analysis, synthesis, and evaluation. According to Haripoernomo (2003), academic achievement is also an important measure that shows how well students understand what they are learning.

Achieving good performance is the responsibility and desire of all students. According to Sahputra (2009), the grades students receive determine their success. According to Azwar (2002), there are two components that influence academic achievement: internal and external. Academic achievement in formal education is a complex issue and requires many steps. Therefore, academic achievement becomes a scientifically validated measure of student achievement.

2. Theoretical Background and Hypothesis Development
2.1 Academic Stress

Academic stress has become part of a student's problem, Sarafino (2006: 65) explains that the stress experienced by everyone is diverse and varies from one person to another. In other words, what makes one person feel stressed is not always the same as what makes another person feel stressed. Therefore, it is important for each individual to understand what makes them stressed and how to manage it in order to better cope with stress. Sarafino (2006: 61) explains that pressure from certain demands can make students feel stressed if they cannot fulfill them.

Carveth, et al (in Misra and McKean, 2000) state that academic stress includes students' perceptions of the amount of knowledge that must be mastered and sufficient time to develop it. For this reason, academic competition and high academic demands are a deep reason for why a student experiences stress. In this case, there is a significant relationship between the level of academic stress experienced by students and their achievement in terms of academic performance. A study by Misra and McKean (2000) showed that students who experience high levels of academic stress tend to have lower levels of academic achievement compared to those who have lower levels of stress. In addition, research by El Ansari et al. (2013) found that academic stress can affect students' psychological well-being, which in turn can affect their learning motivation and overall academic outcomes (El Ansari et al 2013). Therefore, it can be concluded that the higher the level of academic stress experienced by students, the lower their likelihood of achieving high academic performance, and conversely, lower or well-managed stress levels are likely to have a positive impact on students' academic performance.

H1 : Academic stress has a negative influence on the academic performance of university students in Indonesia.

2.2 Internet addiction

When they are in college, many students use the internet to study. However, after returning home, they continue to use the internet non-stop. They can sit in front of a laptop or computer for a very long time, even hours. This suggests that they may already be addicted to the internet. Internet addiction can have a negative impact on one's health and daily life. Therefore, it is important to regulate internet use so that it is not excessive and remains balanced with other activities.

In 1998, Young and Rodgers stated that the internet has a negative impact on a person's ability to communicate in person in everyday life. This means that when someone uses the internet too much, they may become lazy to interact with others in the real world. Dewi (2011) explains that a person can become addicted by using the computer excessively. When the person suddenly stops the activities they are doing with the computer, they can experience withdrawal symptoms, such as restlessness, difficulty concentrating, or even feeling uncomfortable.

Thus, it is important that we remain balanced in our use of the internet. While the internet can provide many benefits, we also need to spend time interacting with others in the real world in order to build healthy social relationships.

Kandell (1998) pointed out that excessive internet use can lead to a decline in academic performance as it interferes with study time. In addition, research by Junco and Cotten (2012) found that college students who use social media with high intensity tend to have a lower GPA than those who use with low intensity. Thus, there is a negative relationship between the level of internet addiction and student academic achievement, where the higher the level of internet addiction, the lower the academic achievement achieved by students.

H1 : Internet addiction has a negative influence on academic performance of university students in Indonesia.

2.3 Sleep Quality

Sleep quality is very important for success in school or college, because sleep helps our brain remember the information that has been learned. According to hidayat (2006) Sleep quality is a person's satisfaction with sleep, so that a person does not show feelings of fatigue, easily aroused and restless, lethargy and apathy, blackness around the eyes, swollen eyelids, red conjunctiva, sore eyes, fragmented attention, headaches and frequent yawning and sleepiness.

Sleep is an unconscious state of restful inactivity, with repetitive cycles that include different cerebral and bodily phases. (tartowo and wartonah, 2011). According to nashori and diana (2005), sleep quality is when a person sleeps well and wakes up fresh and fit. So, the quality of sleep is important to ensure our body and mind are ready for daily activities. For example, when we sleep well at night, we will feel fresh and energetic when we wake up in the morning. If our sleep quality is poor, we may feel tired and unfocused throughout the day. So, it is important to ensure we get quality sleep so that we can function well every day.

Gomes et al. (2018) found that college students who experienced sleep disturbances had lower levels of academic performance, including decreased grades and increased failure in exams. Irregular sleep patterns can cause disruptions in the body's biological clock (circadian rhythm) and result in a lack of quality sleep that can interfere with cognitive function and academic performance (short, gradisar, lack, wright, and carskadon 2012). Therefore, it can be assumed that there is a negative relationship between poor or irregular sleep quality and students' academic performance.

H1 : Sleep quality has a positive influence on academic performance of university students in Indonesia.

METHODS

This analysis uses a quantitative approach with a survey design, using the Partial Least Squares - Structural Equation Modeling (PLS - SEM) technique to analyze and explain the relationship between variables and the suitability of the research model. This technique is suitable for reports that combine and test predictors and theoretical frameworks that have never been tested before.

3.1 Sample and Population

This study uses a Cross-Sectional research approach to collect data at one specific point in time. This approach makes it possible to analyze the relationship between the variables under study at the same time period. The population of this research is all students at several universities in Indonesia, which is estimated to be approximately 9,000,000 students. In this study, we have taken a sample of 209 students. A simple random sampling method will be used to ensure proper representation of the population. This sample will be selected from different universities and years to obtain a balanced picture of the student population. Data was collected through an online survey that has been conducted from mid-March-April. The survey was distributed through email, social media platforms, and student forums at the selected universities. The survey questionnaire included questions about students' academic stress levels, internet addiction, sleep quality, and academic performance. In this study, the confidence level used is 80%, with a margin of error of 5%, and a population proportion of 50%. The analysis method that will be used is smartpls version 4, an effective statistical analysis tool to examine the relationship between variables in a structural model of controlled equations (SEM). By using this tool, it is expected to gain in-depth insight into the influence of academic stress, internet addiction, and sleep quality on the academic performance of university students in Indonesia.

3.2 Data Analysis

Partial Least Squares-Structural Equation Modeling (PLS-SEM) technique was applied using SMARTPLS 4 and SPSS to analyze and test the effect of moderators on the relationship between academic stress, internet addiction, sleep quality, and academic performance of university students in Indonesia. The selection of PLS-SEM as the main analysis method was based on its ability to handle models involving complex interactions between the variables. Assumptions about data distribution do not affect the results of the analysis. The approach of this study is predictive in nature to gain causal insights from the constructed model, with PLS-SEM chosen because it is able to handle the relationship between previously related and predicted variables. The advantages of PLS-SEM remain relevant in

predicting student academic performance. The statistical power of PLS-SEM allows the identification of correlations between the variables in the population. The user-friendly features of PLS-SEM are particularly beneficial for exploratory research that examines complex relationships between the variables involved. SMARTPLS 4 provides easy-to-use latent variable modeling tools and advanced techniques such as Bootstrapping. The main objective is to predict the interrelationships between the variables to improve understanding of students' academic performance. PLS-SEM is more suitable for testing relationships between variables and modeling new pathways in complex study contexts. The analysis is conducted through a series of steps involving the evaluation of convergent and discriminative validity, as well as multicollinearity assessment. The structural model was evaluated through a bootstrapping process after reliability and validity testing was conducted.

Results
4.1 Normal Data Analysis

Table 1. Descriptive statistical data for data normality testing.

Name	Mean	min	max	Standard deviation	Excess kurtosis	Skewness
STA1	4.459	1.000	5.000	0.855	5.180	-2.112
STA2	4.314	1.000	5.000	0.788	3.555	-1.516
STA3	4.275	1.000	5.000	0.832	1.846	-1.265
STA4	2.208	2.000	5.000	0.652	8.706	3.126
STA5	4.42	1.000	5.000	0.830	3.757	-1.790
STA6	4.198	1.000	5.000	0.865	0.791	-0.982
STA7	4.256	1.000	5.000	0.838	2.604	-1.406
STA8	3.966	1.000	5.000	1.023	-0.114	-0.749
STA9	4.068	1.000	5.000	0.935	0.966	-1.028
STA10	4.237	1.000	5.000	0.894	1.303	-1.180
KCI1	4.242	1.000	5.000	0.884	2.536	-1.465
KCI2	4.208	1.000	5.000	0.874	2.762	-1.425
KCI3	4.232	1.000	5.000	0.848	2.818	-1.421
KCI4	4.208	1.000	5.000	0.851	2.917	-1.454
KCI5	4.232	1.000	5.000	0.898	3.105	-1.564
KCI6	4.251	1.000	5.000	0.837	0.665	-1.001
KCI7	4.242	1.000	5.000	0.868	2.073	-1.339
KCI8	4.208	1.000	5.000	0.857	1.721	-1.249
KCI9	4.266	1.000	5.000	0.852	2.014	-1.295
KCI10	4.237	1.000	5.000	0.921	2.629	-1.499
KLT1	4.082	1.000	5.000	1.011	0.779	-1.070
KLT2	3.894	1.000	5.000	1.072	-0.444	-0.664
KLT3	4.005	1.000	5.000	0.985	1.183	-1.108
KLT4	4.179	1.000	5.000	0.880	1.250	-1.086
KLT5	4.203	1.000	5.000	0.905	2.086	-1.320
KLT6	4.246	1.000	5.000	0.907	1.842	-1.329

KLT7	4.217	1.000	5.000	0.899	1.530	-1.248
KLT8	4.271	1.000	5.000	0.903	2.782	-1.553
KLT9	4.29	1.000	5.000	0.918	1.887	-1.400
KLT10	4.126	1.000	5.000	0.924	0.936	-1.067
PTA1	4.092	1.000	5.000	0.936	0.972	-1.040
PTA2	4.145	1.000	5.000	0.889	0.968	-0.995
PTA3	4.106	1.000	5.000	0.878	0.774	-0.942
PTA4	4.121	1.000	5.000	0.890	1.210	-1.068
PTA5	4.319	1.000	5.000	0.903	2.335	-1.507

4.2 Measurement Modal

Hair recommends evaluating convergent validity, composite reliability, and AVE values for measurement model analysis. These estimation steps are then performed in the PLS algorithm for CFA (Confirmatory Factor Analysis); the analysis of the loading factor values can be seen in Figure 1. It thoroughly describes the internal consistency analysis related to the assessment of reliability, validity, and DV based on CFA.
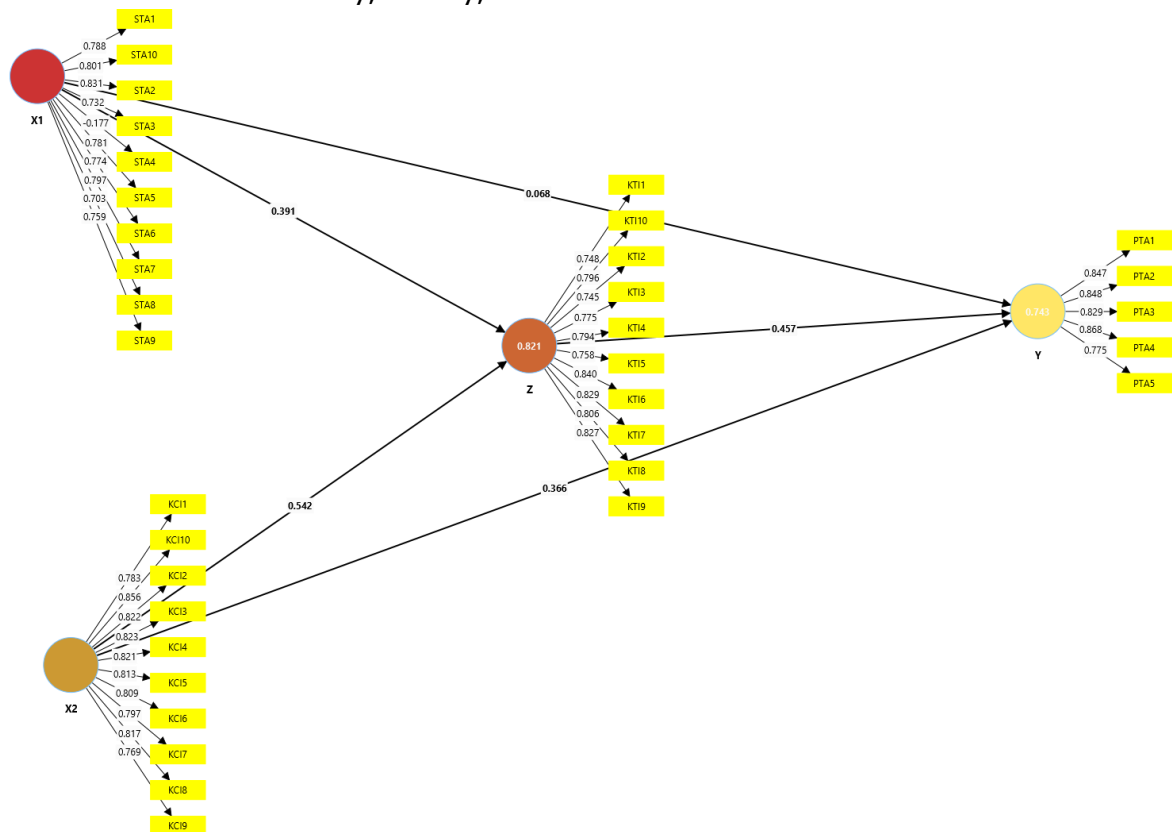
Gambar 1. Nilai CFA dan R-square dalam PLS.

4.3 Konsistensi, Keandalan, dan Validitas Internal

Analysis of the outer loading values of each measurement item was conducted using the CFA-based PLS algorithm as shown in Figure 4. However, SmartPLS was used to analyze the factor loading values for all items. Based on the results, the outer loading values were between 0.732 and 0.868, and there was one invalid value of -0.177. This shows that all constructs exceed the value recommended by Hair, where the estimated outer load should

be higher than 0.708. In the next step, Rho-A values were used to determine the internal consistency of reliability, with other studies (e.g. Smith et al., 2010) stating that higher estimates lead to greater levels of model reliability. This proves that values above 0.7 are sufficient to define satisfaction, although issues related to decreased construct validity are observed when estimates exceed 0.86. Rho-A values above this estimate also indicate the presence of redundant items. Based on the results, the research model had the lowest and highest Rho-A values of 0.890 and 0.943, respectively. In this condition, Cronbach alpha was also used as an option to analyze internal reliability consistency, although it should be higher than 0.700. From the analysis, the lowest Cronbach alpha value was 0.877, as the full estimation in collaboration with Rho-A is shown in Table 3. For all constructs, both Cronbach alpha and Rho-A values met the criteria, indicating that they have satisfactory internal reliability consistency. This is because all values were not less or more than 0.700 and 0.868. This study refers to the contribution of Smith et al. [2010].

Table 2. Cronbach Aplha, CR, AVE, and Rho-A values for internal consistency reliability and validity analysis.

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
STA	0.877	0.919	0.910	0.544
KCI	0.942	0.943	0.951	0.658
KLT	0.890	0.890	0.919	0.696
PTA	0.934	0.935	0.944	0.628

The next step emphasizes the evaluation of CV (convergent validity), which is used to determine the extent to which convergent constructs explain item variation in accordance with another study by Anderson et al. (2010), where CV analysis is observed from AVE values. Using the PLS algorithm, the AVE had the lowest and highest estimates of 0.544 and 0.695 on values and innovations, respectively. This is in accordance with the criteria of Anderson et al. (2010), where the AVE value should be greater than 0.5. For each construct, the Rho-A, CR, and AVE values prove that internal consistency is achieved for a more complete measurement model, as shown in Table 2.

The final step emphasizes the analysis of discriminant validity (DV), which is defined as the extent to which each construct is empirically distinct from the others. This is analyzed using two methods, namely the Fornell-Larcker criterion [79] (see Table 3) and the heterotrait-monotrait ratio (HTMT). This method was used because some studies consider that DV analysis is less effective when using only one method.

Table 3. Fornell-Lacker criterion value of smart PLS software.

	STA	KCI	KTI	PTA
STA	0.870	0.887	0.841	0.792
KCI	0.789	0.832	0.834	
KLT	0.883	0.811		
PTA	0.737			

Notes: Bold and diagonal values indicate the square root of AVE and the correlation between constructs that cannot exceed the square root of AVE, respectively.

Based on the Fornel-Larcker criteria, the cross-loading value (bold) should be higher than the other construct loading values, according to the Fornell-Larcker criteria [79]. For example, the cross-loading value for constructs is 0.953, which is higher than the loading values for other constructs, such as knowledge, PBC, perceived benefits, subjective norms, and values, which are 0.526, 0.563, 0.657, 0.518, and 0.571, respectively. The heterotrait-monotrait correlation ratio (HTMT) is one assessment of discriminant validity. Using a Monte Carlo simulation study, Henseler et al. [1] proposed improving the performance of this technique. They found that HTMT has higher specificity and sensitivity (97% to 99%) compared to the cross-loading (0.00%) and Fornell-Lacker (20.82%) criteria. Using HTMT as a criterion means comparing it to a predefined threshold. An HTMT value close to 1 indicates that there is no discrimination validity. If the HTMT value is greater than this threshold, no discrimination is valid. A threshold of 0.85 was proposed by several authors. In addition, Gold et al. [14] discussed it and suggested a value of 0.90.

Table 4. Heteroit-monotrait (HTMT) values for discrimination validity testing

	STA	KCI	KTL	PTA
STA				
KCI	0.876			
KLT	0.868	0.806		
PTA	0.843	0.844	0.822	

4.4. Structural Model

According to Hair (75), the assessment of the structural model starts by looking at the collinearity problem, which is when two or more independent variables in the regression model have a high correlation with each other. High collinearity can interfere with the estimation of regression coefficients and make the model unstable and difficult to interpret, so it is important to check it first. Next, the path coefficient, t value, and p value are used to analyze the relationship. The path coefficient measures the strength and direction of the relationship between the independent and dependent variables, and the t value and p value indicate the probability that the observed results occurred by chance. To obtain the power in this research model to explain academic achievement, further analysis was conducted on the coefficient of determination ($R2$), effect size ($F2$), and predictive relevance ($Q2$).

4.5. Correlation

The Variance Inflation Factor (VIF) value is used to test the correlation between latent variables. In this condition, the degree of correlation is higher with higher VIF values; VIF values higher than 5.00 indicate that there is a correlation problem between the structural model variables; however, all VIF values below 5.00 indicate that there is no correlation problem between the variables in the model.

Based on the analysis results, academic stress has a relationship with students' academic performance, internet addiction, and sleep quality (H1, β = 0.130, t = 2.062, p-value < 0.05; H3, β = 0.177, t = 1.924, p-value < 0.05; H4, β = 0.161, t = 1.975, p-value

< 0.05), although it has no effect on internet addiction (H2, β = 0.114, t = 1.459, p-value > 0.05). Internet addiction also affected academic performance and had a relationship with sleep quality and academic stress (H5, β = 0.538, t = 7.070, p-value < 0.001; H6, β = 0.415, t = 5.637, p-value < 0.001; H7, β = 0.586, t = 9.159, p-value < 0.001). In addition, sleep quality had a relationship and strongly influenced students' academic achievement and academic stress, respectively (H8, β = 0.487, t = 7.646, p-value < 0.01; H10, β = 0.487, t = 7.646, p-value < 0.001). Academic performance also had the strongest positive significance and relationship with sleep quality and academic stress, respectively (H9, β = 0.580, t = 10.257, p-value < 0.001; H12, β = 0.224, t = 3.335, p-value < 0.01). Furthermore, academic stress, internet addiction, and sleep quality had no significant relationship with internet addiction (H11, β = 0.066, t = 1.083, p-value > 0.05; H13, β = 0.045, t = 0.776, p-value > 0.05; H14, β = 0.080, t = 1.103, p-value > 0.05). Nevertheless, sleep quality still has a relationship with students' academic performance (H15, β = 0.131, t = 2.045, p-value < 0.05).

Construct	VIF Value	Construct	VIF Value
KCI1	1,082	PSA1	1,156
KCI2	1,368	PSA2	1,444
KCI3	1,030	PSA3	1,810
KCI4	1,752	PSA4	1,450
KCI5	1,675	PSA5	1,273
KCI6	1,562	STA10	1,61
KCI7	1,598	STA2	1,698
KLT1	1,198	STA3	1,591
KLT2	1,516	STA4	1,406
KLT3	1,631	STA5	1,698
KLT4	1,316	STA6	2,000
KLT5	1,834	STA7	2,536
KLT6	1,465	STA8	1,816
KLT7	1,713	STA9	2,006
KLT8	1,514	STA1	1,818
KLT8	1,1070		

4.6 Coefficient of Determination

The coefficient of determination (R^2) is a measure often used to evaluate model structure in research because it shows how well the dependent variable can be predicted by the independent variables. R^2 values less than 0.25 are considered weak, values between 0.25 and 0.5 are considered moderate, and values above 0.75 are considered substantial.

The use of Smart PLS software to conduct structural model analysis for research on the effect of internet addiction, sleep quality, and academic stress on academic performance. The results show that all dependent variables in the model have R^2 values that are in the moderate category, which is between 0.25 and 0.75. This indicates that the

model has good predictive power and is able to explain most of the variation in academic performance studied.

With moderate R2 values, it can be concluded that although the model is effective in explaining how internet addiction, academic stress, and sleep quality affect academic performance, there is still room for improvement. For example, to improve the predictive ability of the model, further research may need to investigate additional variables or other components that may contribute to the variation in academic performance. These results suggest that the variables analyzed in this study have a significant influence and may provide important insights into efforts to improve academic performance through stress management, internet addiction, and improved sleep quality.

Table 6. Coefficient of Determination (R2)

Construck	R2	Interpretation
STA	0.779	Moderate
KCI	0.755	Moderate
KLT	0.739	Moderate

4.7 Effect Size (F2)

Based on the evaluation of the structural model, it is also necessary to analyze the F2 value. This construct explains the effect of exogenous on endogenous variables to determine the change in R2 value when certain exogenous determinants are excluded from the model. F2 values below, between, and above 0.15, 0.15 and 0.35, and 0.35 are categorized as small, medium, and large effects, respectively. Based on the results, perceived usefulness has the largest F2 for attitude, as shown in Table 7.

Tabel 7. Value of Effect Size

Relationship	f-square	effect size
STA->PTA	0,01	Small
STA->KLT	0,035	Medium
KCI->PTA	0,083	Large
KCO->KLT	0,771	Large
KLT->PTA	0,295	Small

Discussion

The aim of this research is to find out how much influence the quality of systems, information and services has on student satisfaction with e-learning platforms in the increasingly advanced era of digitalization in Jambi Province. Apart from that, this research also aims to analyze and explain how the quality of systems, information and services influences student satisfaction at online universities in Jambi Province. Quantitative methods are used to show the relationship between research variables. This study uses a survey design and Partial Least Squares structural equation modeling (PLS-SEM) method.

This research utilized a quantitative approach designed as a survey design. The convenience sampling method was used to collect samples, where the student population in Jambi Province was 114,134 students and the sample used was 207 students. This

sample determination uses Calculate Sample Size with a confidence level of 85% and a margin of error of 5%. The partial least squares fractional equation modeling technique (PLS-SEM) was used to analyze the data obtained through SmartPLS.

A sufficient kurtosis skewness value indicates that the data in this study are normally distributed. Measuring the quality of systems, information and services shows that they are valid and reliable. Information quality (0.942), service quality (0.934), user satisfaction (0.890), and system quality (0.877) each construct received a Cronbach's alpha value. In addition, convergent validity for all structures is demonstrated by AVE (Average Variance Extracted), although the AVE for system quality is slightly lower (0.544). Discriminant validity was measured by the Fornell-Lacker criterion and the Heterotrait-Monotrait (HTMT) ratio. The results show that each construct has good discriminant validity, which means that the constructs in the model are different from each other. The model's variation inflation factor (VIF) value is below the threshold, according to collinearity analysis. This proves that the analysis of the structural model results is reliable.

This research shows that student satisfaction with e-learning at universities in Jambi Province is significantly influenced by the quality of systems, information and services. This shows that improving the quality of this third element will increase student satisfaction. Higher education institutions in Jambi Province are advised to continuously develop and improve their e-learning systems with a focus on improving systems, information and services so that students feel better.

Discussion

One of the main components that affect students' academic performance is academic stress. Results show that academic stress has a significant negative influence on academic achievement ($\beta = -0.361$, $p < 0.05$). That is, the level of academic stress that students experience is negatively correlated with their academic outcomes. There are many reasons for this. Firstly, excessive stress can lead to mental health issues such as depression and anxiety, which can hinder learning. Secondly, students who experience excessive stress may lose the desire to study and attend classes, which negatively impacts their academic outcomes. Thirdly, excessive stress can also interfere with students' concentration when they are studying, making it difficult for them to understand lessons.

In addition, it was found that internet addiction has a significant negative impact on academic achievement ($\beta = -0.284$, $p < 0.05$). Excessive use of the internet that interferes with daily activities, including studying, is called internet addiction. There are several reasons why internet addiction can interfere with students' academic achievement, one of which is the diversion of study time; students who are addicted to the internet may spend a lot of time online for social media, gaming, or other unproductive activities, thus reducing their time for studying. With easy access to the internet, students are often distracted by notifications and other online activities, making it difficult to focus on their academic tasks.

In contrast, good sleep quality has a significant positive effect on academic achievement ($\beta = 0.405$, $p < 0.05$). Good sleep quality includes adequate and restful sleep. Some of the reasons why good sleep quality can improve academic performance are cognitive recovery, where adequate sleep helps the brain process and store information learned during the day, which is important for remembering exam material. Students who

sleep poorly also tend to have lower energy levels and concentration than students who sleep poorly. In addition, adequate sleep improves physical and mental health, aiding learning and achievement.

The results suggest that stress management, wise use of the internet, and good sleep quality are essential to improving students' academic performance. The following are some suggestions for educational institutions and students. Educational institutions should offer support and counseling to help students cope with academic stress. Education should be increased about the negative effects of internet addiction and the importance of using the internet carefully. In addition, awareness of the importance of adequate and quality sleep for health and academic success should be increased.

CONCLUSION

This study emphasizes that to support students' academic performance, stress management, wise internet use, and good quality sleep are essential. It is evident that too much academic pressure and internet addiction have significant negative effects on academic outcomes. This is due to impaired concentration, lack of desire to study, and reduced study time due to excessive internet use. Maintaining a good quality of sleep, on the other hand, has a significant positive effect. Adequate and high-quality sleep helps students in cognitive recovery, improves their concentration ability, and enhances their memory.

Counseling programs, which help students manage stress and teach wise internet use, are essential for educational institutions. In addition, awareness of the importance of quality and sufficient sleep should be increased. It is hoped that these recommendations will help students reach their academic potential and create a more productive and healthy learning environment. These results also give educators and policymakers a better understanding of how important these things are in supporting students' academic success.

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