Indonesian Technology and Education Journal
E-ISSN: 2985-8216; P-ISSN: 2985-8208
https://journal.diginus.id/index.php/ITEJ

The Effects of Digital Competence, Digital Culture, and Digital Stress on Students' Academic Performance in Biology Education

Jumeiliani Sirin[1*], Indryani[2], Ahmad Syarif[3], Robi Hendra[4]
[1,2,3,4]*Magister Pendidikan Teknologi, Universitas Jambi, Indonesia*

Corresponding e-mail : jumeilianisirin@gmail.com

ARTICLE INFO

Keywords:

Academic performance in biology education;
Digital competence;
Digital culture;
Digital stress;
PLS-SEM.

Article History

Received: Feb 29, 2026
Revised : April 15. 2026
Accepted : May 02, 2026

ABSTRACT

The development of digital technology has brought significant changes in the learning process, including in Biology learning at the secondary education level. This study aims to analyze the influence of Digital Competence, Digital Culture and Digital Stress on the Academic Performance of Biology of high school students. This study uses a quantitative approach with an explanatory research design and cross-sectional methods. Data was collected from 350 high school students through a five-point Likert scale-based structured questionnaire. Data analysis was carried out using Structural Equation Modeling–Partial Least Squares (SEM-PLS) with the help of SmartPLS 4 software. The results show that digital competence has a positive and significant effect on academic performance in Biology, as well as a positive effect on digital stress. In contrast, digital culture does not have a significant effect on either academic performance or digital stress. Furthermore, digital stress was found to have a positive and significant effect on academic performance, indicating that a certain level of digital stress may enhance students' engagement in learning activities. These findings suggest that while digital competence plays a key role in improving academic outcomes, it should be accompanied by effective digital stress management. The results of this research are expected to be a reference for educators and curriculum developers in designing productive and sustainable technology-based Biology learning.

To cite this article: Sirin, J., Indryani, Syarif, A., Hendra, R. (2026). The Effects of Digital Competence, Digital Culture, and Digital Stress on Students' Academic Performance in Biology Education. Information Technology Education Journal, 4(1), 31-44. Doi. 10.61255/itej.v4i1.993

INTRODUCTION

The rapid advancement of digital technology has fundamentally transformed educational practices, particularly in science learning contexts such as biology education. The integration of digital platforms, including learning management systems, virtual laboratories, and interactive multimedia, has enabled students to access, visualize, and construct scientific knowledge more effectively (Spante et al., 2018; Falloon, 2020). Consequently, academic performance in biology education is no longer determined solely by cognitive ability, but also by students' capacity to engage productively with digital environments.

Within this context, digital competence has emerged as a critical factor influencing students' academic performance. Digital competence refers to the ability to use digital technologies critically, creatively, and responsibly, encompassing technical skills, information literacy, and problem-solving abilities (Carretero et al., 2017; Spante et al., 2018). Previous studies have demonstrated that students with higher levels of digital competence tend to achieve better academic performance, particularly in science learning, due to their ability to process complex information and engage in self-directed learning (Falloon, 2020; Zhao et al., 2021). In addition, digital competence has been associated with improved problem-solving skills and scientific literacy, which are essential in biology education (Gomes et al., 2015; Moraes & Santos, 2023).

However, students' engagement with digital environments is not shaped solely by individual competence, but also by the broader digital culture in which they operate. Digital culture refers to patterns of technology use, including habits, norms, and values that influence how individuals interact with digital tools (Nunuk et al., 2020; Cuervo et al., 2019). A supportive digital culture may enhance collaboration, expand access to knowledge, and foster learning motivation. Conversely, it may also introduce distractions, multitasking behavior, and reduced cognitive focus, which can negatively affect academic performance (Zoltán et al., 2020). These mixed findings indicate that the role of digital culture remains inconclusive and requires further empirical investigation.

In addition to competence and culture, the increasing intensity of digital engagement has led to the emergence of digital stress. Digital stress refers to psychological strain resulting from constant connectivity, information overload, and high expectations for responsiveness (Fischer et al., 2021; Winstone et al., 2023). Previous studies have generally associated digital stress with negative academic outcomes, such as decreased concentration, reduced motivation, and impaired cognitive processing (Nick et al., 2022; Wen et al., 2024). However, recent perspectives suggest that the relationship between stress and performance is not always linear. Moderate levels of stress may enhance engagement, alertness, and adaptive learning behavior, thereby improving academic performance (Wrede et al., 2023).

Despite the growing body of research, most studies have examined digital competence, digital culture, and digital stress separately. There is still limited empirical research that integrates these variables into a unified explanatory model, particularly in the context of secondary-level biology education. This gap is important because academic performance in digitally mediated learning environments is likely shaped by the interaction between individual capability, contextual influence, and psychological response.

From a conceptual perspective, digital competence functions as an individual capacity that directly enhances academic performance while also increasing students' engagement with digital environments, which may elevate digital stress (Zhao et al., 2021). Digital culture operates as a contextual factor that shapes how technology is used and may either strengthen or weaken both competence and stress (Nunuk et al., 2020). Meanwhile, digital stress represents a psychological response that influences students' cognitive readiness and learning outcomes (Winstone et al., 2023).

The relationship between digital stress and academic performance has been widely discussed in the literature, yet remains theoretically complex. Most early studies conceptualize stress as a detrimental factor that negatively affects learning outcomes. Digital stress, in particular, is often associated with cognitive overload, emotional exhaustion, and reduced concentration, all of which can impair students' academic performance (Fischer et al., 2021; Nick et al., 2022). In digital learning environments, excessive exposure to information, multitasking demands, and constant connectivity may lead to cognitive fatigue and decreased learning efficiency (Wen et al., 2024).

However, contemporary perspectives in educational psychology suggest that the relationship between stress and performance is not strictly negative, but rather non-linear. The Yerkes–Dodson principle posits that performance increases with physiological or mental arousal up to an optimal point, after which excessive stress leads to performance decline. In this sense, moderate levels of stress may function as a form of eustress, which can enhance motivation, focus, and engagement in learning activities (Wrede et al., 2023).

In the context of digital learning, digital stress can act as a cognitive activation mechanism that stimulates students' alertness and readiness to engage with complex academic tasks. When students experience manageable levels of digital pressure, such as deadlines, technological demands, or information processing challenges, they may become more actively involved in learning activities. This increased engagement can lead to improved academic performance, particularly in subjects such as biology that require high levels of cognitive processing and conceptual understanding (Ikhsan et al., 2021).

Furthermore, students with higher levels of digital competence may be better equipped to cope with digital stress through adaptive strategies. Rather than avoiding stress, these students tend to engage more deeply with digital tasks, which may increase both their exposure to stress and their academic performance simultaneously (Zhao et al., 2021). This suggests that digital stress does not operate solely as a negative factor, but may also function as a mediating mechanism that links digital engagement to learning outcomes.

Therefore, this study adopts a non-linear perspective on the relationship between digital stress and academic performance, proposing that digital stress may have a positive effect when it remains at a moderate and manageable level. This perspective provides a theoretical basis for interpreting empirical findings that show a positive relationship between digital stress and academic performance in digitally mediated learning environments.

METHOD

Research Design

This study employed a quantitative approach using an explanatory research design to examine the causal relationships among digital competence, digital culture, digital stress, and students' academic performance in biology. A cross-sectional design was adopted, in which data were collected at a single point in time to capture the relationships among variables simultaneously (Hair et al., 2021). This design is appropriate for testing structural relationships using Structural Equation Modeling–Partial Least Squares (SEM-PLS), particularly in predictive and theory-development research contexts.

Population and Sampling

The population of this study consisted of senior high school students (grades X–XII). A proportional random sampling technique was applied to ensure representation across grade levels. The minimum sample size was determined based on SEM-PLS guidelines, which recommend at least ten times the number of structural paths in the model (Hair et al., 2021). Accordingly, a total of 350 students participated in this study, exceeding the minimum requirement and strengthening the robustness of the analysis.

However, it is important to acknowledge that the sample distribution across school types was highly imbalanced, with 99.7% of respondents originating from public schools and only 0.3% from private schools. This imbalance constitutes a limitation of the study, as it may restrict the generalizability of the findings across different educational contexts. Future research is therefore recommended to include a more proportionate representation of school types in order to provide a more comprehensive understanding of the phenomena under investigation.

Data Collection

This study employed a quantitative survey design to examine the relationship between Digital Competence, Digital Culture, Digital Stress, and Academic Performance in Biology among students. Data were collected using a structured questionnaire distributed online through Google Forms. The online distribution method was selected to facilitate wider participation and improve the efficiency of data collection. The respondents of this study were students who met the predetermined research criteria, particularly those actively involved in digital-based learning activities in biology education.

The questionnaire consisted of several sections representing the research variables, namely Digital Competence (DCS), Digital Culture, Digital Stress, and Academic Performance in Biology. All measurement items were adapted from relevant previous studies and adjusted to the context of this research. The questionnaire used a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree to measure respondents' perceptions and experiences related to each construct.

Before the main data collection process, the questionnaire was reviewed and refined to ensure clarity, readability, and suitability of the items. The distribution process was conducted over a specified period, during which respondents voluntarily completed the questionnaire. Participation in this study was entirely voluntary, and respondents were informed about the purpose of the research before filling out the questionnaire.

In terms of research ethics, the study ensured respondent confidentiality and anonymity. No personal identifying information was collected, and all responses were used solely for academic purposes. Respondents were also informed that they could withdraw from participation at any stage without any consequences. These procedures were implemented to ensure compliance with ethical standards in educational research.

Data Analysis

Data analysis in this study was conducted using the Structural Equation Modeling–Partial Least Squares (SEM-PLS) approach through SmartPLS 4 software. The PLS-SEM method was selected because it is suitable for analyzing complex latent variable relationships, accommodates multiple indicators, and is appropriate for predictive research models with reflective constructs. In addition, PLS-SEM effectively examines both direct and indirect relationships among Digital Competence, Digital Culture, Digital Stress, and Academic Performance in Biology.

The analysis process involved several stages, including data preparation, assessment of measurement assumptions, and evaluation of both measurement and structural models. According to Thomas (2021), these procedures ensure that the analyzed data meet statistical requirements and are appropriate for addressing the research objectives. The significance of model parameters was tested using a bootstrapping procedure, as recommended by Solihin and Ratmono (2021), to obtain more reliable estimations of the relationships between variables. In PLS-SEM, two major evaluations were conducted: the measurement model (outer model) and the structural model (inner model). In the outer model evaluation, convergent validity, discriminant validity, and internal reliability were assessed. Convergent validity was evaluated using outer loading values and Average Variance Extracted (AVE). Indicators were considered valid if the outer loading value was ≥ 0.70, although values between 0.50 and 0.69 were still acceptable for exploratory research (Hair et al., 2021). An AVE value ≥ 0.50 indicated that the construct explained more than 50% of the indicator variance. These criteria were applied to assess the constructs of Digital Competence, Digital Culture, Digital Stress, and Academic Performance in Biology.

Discriminant validity was examined using the Fornell–Larcker criterion by comparing the square root of AVE for each construct with the correlations among constructs. A construct was considered to have adequate discriminant validity when the square root of AVE exceeded its correlations with other constructs (Musyaffi et al., 2021). This procedure ensured that each construct represented a distinct conceptual domain. Internal reliability was evaluated using Cronbach's Alpha and Composite Reliability (CR). A Cronbach's Alpha value ≥ 0.70 indicated satisfactory internal consistency, while values above 0.60 were considered acceptable for exploratory studies. Composite Reliability values ≥ 0.70 demonstrated adequate construct reliability, and values ≥ 0.80 indicated very good reliability (Musyaffi et al., 2021).

The inner model evaluation included the assessment of collinearity, coefficient of determination (R^2), and predictive relevance (Q^2). Collinearity was tested using the inner

Variance Inflation Factor (VIF), where VIF values below 5 indicated the absence of multicollinearity among predictor variables (Hair et al., 2021). The coefficient of determination (R^2) was used to assess the explanatory power of the exogenous variables on Academic Performance in Biology. R^2 values of 0.67, 0.33, and 0.19 were interpreted as substantial, moderate, and weak explanatory power, respectively.

Furthermore, predictive relevance (Q^2) was assessed using the blindfolding procedure to determine the predictive capability of the model. Q^2 values greater than 0 indicated predictive relevance, with values of 0.02, 0.15, and 0.35 representing small, medium, and large predictive relevance, respectively (Musyaffi et al., 2021). Higher Q^2 values indicated stronger predictive accuracy of the model for Academic Performance in Biology. Overall, the SEM-PLS analysis conducted using SmartPLS 4 ensured that the measurement instruments met validity and reliability requirements, while the structural model adequately explained the relationships among Digital Competence, Digital Culture, Digital Stress, and Academic Performance in Biology.

Data analysis was conducted using Partial Least Squares Structural Equation Modeling with the assistance of SmartPLS 4 software. The analysis was carried out in two main stages: evaluation of the measurement model and evaluation of the structural model (Hair et al., 2021).

Measurement Model Evaluation (Outer Model)

The measurement model was assessed based on:

Convergent Validity

Evaluated using outer loading and Average Variance Extracted. Indicators with loading ≥ 0.70 were considered acceptable, while values between 0.50 and 0.69 were retained for exploratory purposes.

Discriminant Validity

Assessed using the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio. A construct is considered valid if the square root of AVE exceeds inter-construct correlations and HTMT values are below 0.90.

Internal Reliability

Evaluated using Cronbach's Alpha and Composite Reliability, with acceptable thresholds of ≥ 0.70. Indicators that did not meet validity and reliability criteria were removed to improve model q2.

Structural Model Evaluation (Inner Model)

The structural model was assessed through:

1. Multicollinearity Test : Using Variance Inflation Factor, with a threshold of < 5.
2. Coefficient of Determination (R^2) : To assess the explanatory power of the model in predicting endogenous variables.
3. Predictive Relevance (Q^2) : To evaluate the model's predictive capability.
4. Hypothesis Testing : Conducted using a bootstrapping procedure to assess the significance of path coefficients. A relationship is considered significant if the p value is less than 0.05.

Ethical Considerations

This study adhered to standard ethical guidelines for research involving human participants. Prior to data collection, all participants were provided with clear information regarding the purpose of the study, the voluntary nature of their participation, and their right to withdraw at any time without any consequences. Informed consent was obtained from all participants before they completed the questionnaire.

To ensure confidentiality and privacy, the questionnaire was administered anonymously, and no personally identifiable information was collected. All responses were used solely for academic research purposes and were securely stored to prevent unauthorized access. In addition, the data collection procedure was conducted with the approval and permission of the respective schools, ensuring that the research complied with institutional and educational regulations.

RESULTS AND DISCUSSION

Respondent Characteristic

This study involved 350 students from public and private schools at the secondary education level in Jambi. All respondents came from school environments with a composition dominated by public schools. The demographic characteristics of the study participants are shown in Table 1.

Table 1. Respondent Characteristics

Profile	Frequency	Percentage
Gender		
Women	238	68.0%
Male	112	32.0%
Age		
≤15	137	39.1%
16	104	29.7%
17	89	25.4%
18	19	5.4%
>18	1	0.3%
School		
Public Schools	349	99.7%
Private Schools	1	0.3%

This study reviewed the characteristics of respondents based on gender, age, and school origin. The findings showed that most of the respondents were female students, which was 68.0% of the total, while male students amounted to 32.0%. In terms of age, the most represented age group is students aged ≤15 years, with a percentage of 39.1%, followed by 16-year-olds at 29.7%, and 17-year-olds at 25.4%. The 18-year-old age group comprised only 5.4%, and the >18-year-old was the smallest group with 0.3% of the total respondents. These findings show that the majority of respondents are in the middle adolescent age range, which is generally high school and vocational school students. Judging from the origin of the school, most of the respondents came from public schools, which was as much as 99.7%, while respondents from private schools were only 0.3%. This shows that this research involves more students in public educational institutions.

Outer Measurement Model

Table 2 shows the results of the outer model analysis for validity

Table 2. Outer Measurement Model for Validity

Latent Variable	Manifest Variable	Outer Loading	VIF Outer	Result
Academic Performance (AP)	AP 1	0,781	2.321	Valid
	AP 2	0,779	2.394	Valid
	AP 3	0,797	2.263	Valid
	AP 4	0.803	2.235	Valid
	AP 5	0,706	2.181	Valid
	AP 6	0,728	2.381	Valid
	AP 7	0,666	1.759	Valid
Digital Culture (CD)	CD 10	0,757	1.546	Valid
	CD 2	0,691	1.383	Valid

Latent Variable	Manifest Variable	Outer Loading	VIF Outer	Result
	CD 7	0,742	1.446	Valid
	CD 8	0,685	1.385	Valid
	CD 9	0,739	1.457	Valid
Digital Competence (DCS)	DCS 1	0,714	1.842	Valid
	DCS 10	0,672	1.601	Valid
	DCS 2	0,791	2.298	Valid
	DCS 3	0,716	1.843	Valid
	DCS 4	0.730	1.939	Valid
	DCS 5	0.712	1.804	Valid
	DCS 6	0.730	1.984	Valid
	DCS 7	0,787	2.306	Valid
	DCS 8	0,704	1.838	Valid
	DCS 9	0,726	1.919	Valid
Digital Stress (DS)	DS 1	0,673	1.712	Valid
	DS 2	0,742	2.05	Valid
	DS 3	0,681	1.784	Valid
	DS 4	0,792	2.204	Valid
	DS 5	0,687	1.844	Valid
	DS 6	0,824	2.456	Valid
	DS 7	0.831	2.565	Valid
	DS 8	0.813	2.337	Valid

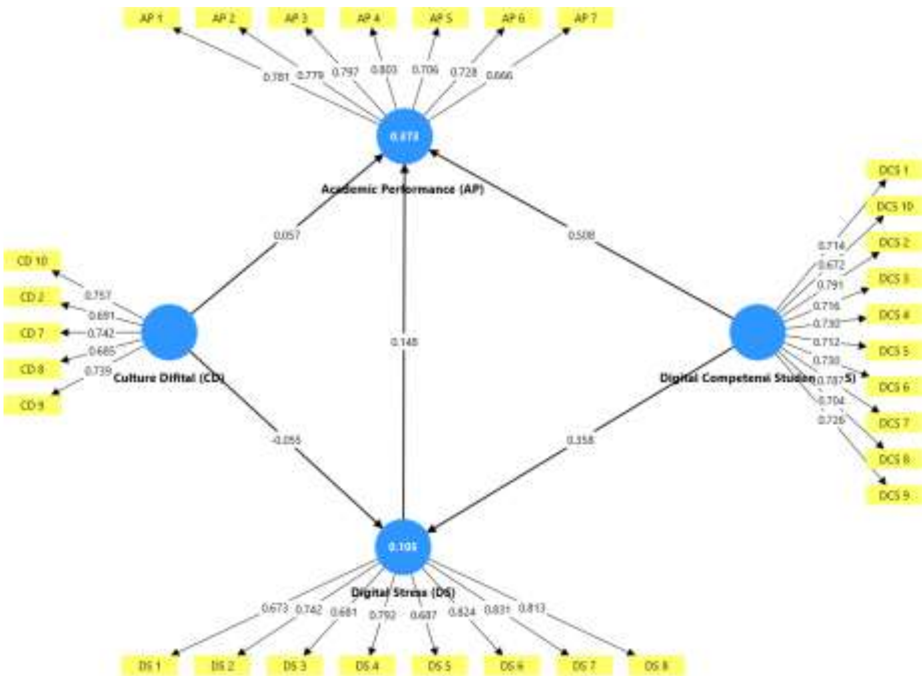

Figure 2. Outer Loading

Some of the instruments were adapted from previous research and adapted to the context of Biology learning. After the adaptation stage and preliminary test, grain quality evaluation was carried out using outer loading analysis and multicollinearity check (VIF) at the measurement model testing stage (PLS-SEM). Grains that have a low empirical contribution (outer loading < 0.50) and/or cause redundancy between indicators (VIF ≥ 5) are excluded from the model to strengthen the validity and reliability of the construct. This decision was taken based on the guidelines for instrument evaluation in PLS-SEM (Hair et al., 2021.

In table 2, the initial evaluation of the measurement model shows that some indicators do not meet the set measurement quality criteria. Specifically, the AP8 indicator has an outer loading of 0.285 and the CD1 indicator of 0.382, so it is below the minimum loading threshold (0.50) and is defined as not making a significant contribution to the related construct; Therefore, both indicators were issued. In addition, the indicators in the digital culture construct, namely CD3 (0.631), CD4 (0.640), CD5 (0.565), and CD6 (0.663), even though they have a loading > 0.50, show VIF values that exceed the tolerated limit or show significant cross-loading against other constructs thus indicating information redundancy. Since the purpose of the evaluation of the measurement model is to obtain a construct that is parsimonious, valid convergent, and has discriminant validity, the CD3–CD6 indicator is also excluded from the final model. The removal of these indicators increases the AVE and Composite Reliability (CR) values for the related constructs and decreases the VIF, so that the final measurement model meets the criteria of convergent validity (AVE ≥ 0.50), internal reliability (CR ≥ 0.70), and estimated stability (VIF < 5).

Table 3. Outer Measurement Model for Reliability

	AVE	**CR**	**Cronbach Alpha**	**Result**
Academic Performance **(AP)**	.567	.901	.872	Reliable
Digital Competence (**DCS)**	.531	.919	.902	Reliable
Digital Stress **(DS)**	.575	.915	.893	Reliable
Digital Culture **(CD)**	.523	.846	.772	Reliable

Based on the calculation results using SmartPLS 4, the AVE value for all variables is above 0.5, which ranges from 0.523 to 0.575. These results show that each variable in the study has met the criteria of good convergent validity. Thus, the research construct has an adequate ability to explain the variance of the indicators that make it up.

Furthermore, the results of the Composite Reliability (CR) test showed that all variables had values above 0.84, and most of them were in the range of 0.90, which was between 0.846 and 0.919. This value indicates that all variables in this study have met the composite reliability criteria, so it can be stated to have a high level of internal consistency.

The results of Cronbach's Alpha calculation also show that all variables have values greater than 0.7, which are in the range of 0.772 to 0.902. Thus, all variables have met Cronbach's Alpha reliability criteria, and can be declared reliable.

Overall, the results of the AVE, Composite Reliability, and Cronbach's Alpha tests show that all constructs in this study have met the standards of validity and reliability, making them suitable for further analysis.

Table 4. Heterotrait-Monotrait Ratio (HTMT)

	AP	**DCS**	**DS**	**CD**
AP				
DCS	0,662			
DS	0,355	0,345		
CD	0,518	0.801	0.222	

To assess the reliability of correlation between constructs, the HTMT test was used as recommended by Musyaffi et al. (2021). Based on the calculation results shown in Table 4, all constructs in this study have an HTMT value that is below 0.90. The HTMT value for the relationship between variables ranged from 0.222 to 0.801, indicating that there was no problem of discriminant validity between the analyzed constructs. Thus, it can be concluded that the HTMT criteria have been met.

Based on the calculations using SmartPLS 4 shown in Table 5, the Fornell-Larcker test has also been performed. The test results showed that the square root value of AVE in each variable was higher than the correlation value between the variables below it. For example, the academic performance variable has a diagonal value of 0.753, which is higher than its correlation with other constructs. Similarly, the variables of Digital Competence, digital stress, and digital culture had diagonal values of 0.729, 0.758, and 0.723, respectively, which were greater than the correlation between other constructs. Thus, all variables in this study meet the Fornell–Larcker criteria, which shows that the discriminant validity between constructs has been adequately met. The following table shows the Fornell–Larcker score in this study.

Table 5. Fornell-Larcker

Variabel	AP	DCS	DS	CD
AP	**0,753**			
DCS	0,594	**0,729**		
DS	0.321	0.321	**0,758**	
CD	0.426	0,672	0,186	**0,723**

This study also uses the Variance Inflation Factor (VIF) as a reference in testing multicollinearity. Based on the criteria put forward by Musyaffi et al. (2021), the VIF value < 5.0 indicates that there is no problem of multicollinearity. The results of the outer VIF test in Table 1 show that all indicators have a VIF value of < 5.0. Thus, it can be concluded that there is no problem of multicollinearity in all items in this study.

Inner Measurement Model

The Inner Model was also tested to ensure that there was no issue of multicollinearity between latent variables. Based on the results shown in Table 6, all Variance Inflation Factor (VIF) values in the inner model are below the threshold of 5.0. The VIF value ranged from 1,117 to 1,968, indicating that there was no problem of multicollinearity in all study variables. Thus, the relationships between constructs in the model can be considered stable and free from redundancy between predictors.

Table 6. Inner VIF

	AP	DCS	DS	CD
AP		1.968	1.117	1.828
DCS			1.825	
DS				1.825
CD				

The following table shows the results of the determination coefficient test from this study

Table 7. Coefficient of Determination

Variable	R Square	R Square Adjusted
Academic Performance	0,373	0,368
Digital Stress	0,105	0,100

Based on the results of the calculation using SmartPLS 4 presented in Table 7, a determination coefficient (R^2) test was carried out. The academic performance variable has a value of R^2 = 0.373 with a value of Adjusted R^2 = 0.368, which indicates that 37.3% of the variability of academic performance can be explained by the predictive construct in the model. Meanwhile, the Digital Stress variable has a value of R^2 = 0.105 with Adjusted R^2 = 0.100, which means that 10.5% of the digital stress variability is explained by the variables that affect it in the model. These results indicate that the model has a fairly good predictive ability, where exogenous variables contribute to explaining endogenous variables with a moderate degree of variation. In line with the standard interpretation, the R^2 value in the model can be understood as the simultaneous influence of the predictor variables, while the rest is influenced by other factors that were not included in this study.

Table 8. Predictive Relevance

	Q^2predict	RMSE	MAE
Academic Performance (AP)	0.336	0.820	0.604
Digital Stress	0.086	0.962	0.734

Based on the results of the analysis, the Q^2predict value for the academic performance variable was 0.336, which shows that the model has good predictive relevance. A Q^2predict value greater than zero indicates that the model is able to predict endogenous constructs with an adequate level of accuracy. This score also shows that exogenous variables in the model, such as digital student competence and digital culture, contribute significantly to explaining the variation in students' academic achievement.

Meanwhile, the digital stress variable has a Q^2predict value of 0.086, which is still above zero, so it can be concluded that the model has a weak to moderate predictive relevance to digital stress. This value indicates that although the model is able to predict digital stress, there are possible other factors outside the model that also affect the digital stress level of students.

Hypothesis Testing

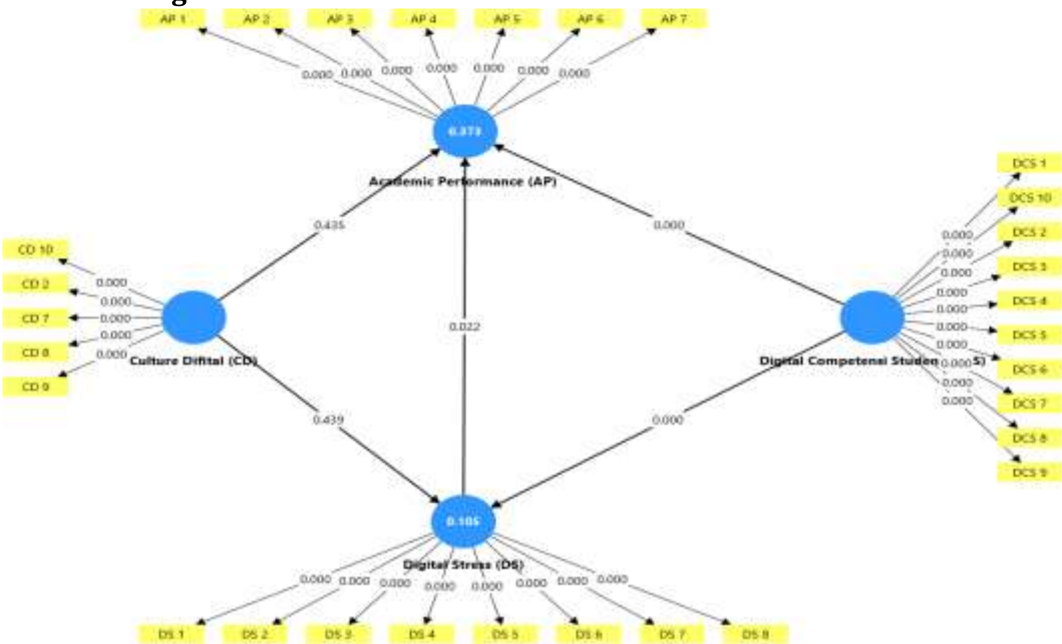

Figure 2. Hypothesis Testing of Study

Hypothesis testing is carried out based on the bootstrapping test. Furthermore, to find out whether the hypothesis is rejected or not, it is necessary to look at the results of the path coefficient. The following are the results of hypothesis testing.

Table 9. Hypothesis Testing

	Standard deviation (STDEV)	T statistics (|O/STDEV|)	Path Coefficients (O)	P values	Hypothesis
CD -> AP	0.073	0.780	0,057	0.435	Rejected

CD -> DS	0.071	0.774	-0,055	0.439	Rejected
DCS -> AP	0.074	6.881	0,508	0.000	Accepted
DCS -> DS	0.080	4.496	0,358	0.000	Accepted
DS -> AP	0.064	2.296	0,148	0.022	Accepted

Based on the results of hypothesis testing using SmartPLS, t-statistics and p-values were obtained for each relationship between variables as shown in Table 9. Using a significance level of 5% (α = 0.05), a relationship is considered significant if the p-value < 0.05. In addition, the higher the t-statistics, the stronger the influence of exogenous variables on endogenous variables.

The results showed that the influence of digital culture on academic performance had a t-statistical value of 0.780 with a p-value of 0.435. Because this value is well above 0.05, the hypothesis is rejected. This means that digital culture does not have a significant influence on academic performance. This can also be seen in the influence of digital culture on digital stress, which shows a t-statistical value of 0.774 and a p-value of 0.439. Thus, the influence of digital culture on digital stress is also not significant, so it can be concluded that digital culture does not directly increase or decrease the level of digital stress in students.

Different from these results, the Digital Competence variable was proven to have a significant influence on the other two variables. The influence of Digital Competences on academic performance resulted in a t-statistics value of 6,881 with a p-value of 0.000, so the hypothesis was accepted. These findings show that Digital Competences have an important and strong role in improving academic performance. In addition, Digital Competences also have a significant effect on digital stress with a t-statistics value of 4.496 and a p-value of 0.000. This positive influence indicates that the higher the digital competence of students, the greater the chance of them to be involved in complex digital activities, which can ultimately increase digital stress.

Furthermore, the influence of digital stress on academic performance was also found to be significant, with a t-statistics value of 2.296 and a p-value of 0.022. These results show that digital stress has an influence on academic performance, although the level of influence is not as large as other variables. Overall, the path with the strongest influence in this study is the relationship between Digital Competence and academic performance, which shows that Digital Competence is the main factor that affects students' academic performance in the context of digital-based biology learning.

Discussion

The findings of this study indicate that digital competence is positively associated with academic performance in biology education. This result suggests that students with higher levels of digital competence tend to demonstrate better learning outcomes, particularly in contexts that require the use of digital tools for accessing, processing, and interpreting scientific information. This association reinforces previous studies highlighting the importance of digital competence in supporting problem solving skills and scientific literacy in digitally mediated learning environments (Spante et al., 2018; Falloon, 2020; Zhao et al., 2021).

In addition, digital competence is positively associated with digital stress. This finding implies that students who are more actively engaged with digital technologies tend to experience higher levels of digital pressure. Rather than indicating a negative condition, this pattern may reflect increased exposure to complex digital tasks, higher learning demands, and more intensive interaction with digital platforms. In this sense, digital competence appears to be linked with both greater engagement and greater psychological demands in digital learning contexts.

In contrast, digital culture does not show a significant association with either academic performance or digital stress. This result suggests that the presence of digital habits and practices alone may not be sufficient to predict learning outcomes or psychological responses. One possible explanation is that students' digital culture is not always oriented toward academic purposes, but may also involve entertainment or social interaction activities, which do not directly contribute to academic performance. Therefore, digital culture may function more as a contextual background rather than a direct predictor within the structural model.

The most notable finding of this study lies in the positive association between digital stress and academic performance. This result indicates that higher levels of digital stress are associated with higher academic performance in biology education. This finding contrasts with conventional assumptions that position stress solely as a negative factor in learning. Instead, the result supports a non-linear perspective, in which moderate levels of stress may function as a form of eustress that enhances students' engagement and cognitive activation.

From a theoretical perspective, digital stress in this study can be interpreted as a form of cognitive activation rather than purely psychological burden. When students experience manageable levels of digital pressure, such as deadlines, task complexity, and information processing demands, they may become more focused, alert, and engaged in learning activities. This heightened engagement is particularly relevant in biology education, where understanding complex and abstract concepts requires sustained attention and active cognitive processing (Ikhsan et al., 2021).

Furthermore, the positive association between digital stress and academic performance may also reflect adaptive responses among students with adequate digital competence. Students who are capable of navigating digital environments effectively may not perceive digital demands as overwhelming, but rather as challenges that stimulate learning. In this sense, digital stress may operate as a facilitating condition that accompanies deeper engagement with academic tasks.

However, it is important to emphasize that this finding should not be interpreted as indicating that all forms of digital stress are beneficial. The relationship between digital stress and academic performance is likely to be non linear, where excessive stress may still lead to cognitive overload and reduced learning outcomes. Therefore, the positive association identified in this study may reflect a condition in which digital stress remains within a manageable and productive range.

Overall, these findings highlight that academic performance in digitally mediated biology learning is associated with the dynamic interaction between digital competence and digital stress, while digital culture plays a less direct role. This suggests that strengthening students' digital competence, while maintaining an optimal level of digital challenge, may support more effective learning outcomes.

CONCLUSIONS

This study examined the effects of digital competence, digital culture, and digital stress on students' academic performance in biology within a digitally mediated learning environment. The findings show that digital competence has a positive and significant effect on academic performance while also increasing digital stress due to greater engagement with technological demands, whereas digital culture does not significantly influence either academic performance or digital stress. Notably, digital stress was found to have a positive and significant effect on academic performance, suggesting that a certain level of digital pressure may enhance students' engagement and learning outcomes, highlighting the importance of the interaction between individual skills, learning context, and psychological responses. These results imply that strengthening digital competence is essential in biology education, particularly given its reliance on visualization, simulation, and data interpretation, while maintaining an optimal level of digital challenge. However, this study is limited by its cross-sectional design, reliance on self-reported data, and an imbalanced sample dominated by public school students, which may affect generalizability. Therefore, future research should employ longitudinal designs, incorporate objective academic performance measures, and explore mediating and moderating mechanisms as well as potential non-linear relationships, particularly the possibility of an inverted U-shaped effect of digital stress on academic performance.

REFERENCES

Argyriadi, A., Katsarou, D., Patelarou, A., Megari, K., Patelarou, E., Kotrotsiou, S., Giakoumidakis, K., Abdoola, S., Mantsos, E., Efthymiou, E., & Argyriadis, A. (2025). Digital Stress Scale (DSC): Development and Psychometric Validation of a Measure of Stress in the Digital Age. *International Journal of Environmental Research and Public Health*, 22(7), 1080. https://doi.org/10.3390/ijerph22071080

Antón-Sancho, Á., Vergara, D., Medina, E., & Sánchez-Calvo, M. (2022). Digital Pandemic Stress in Higher Education in Venezuela. *European Journal of Investigation in Health, Psychology and Education*, 12(12), 1878-1900. https://doi.org/10.3390/ejihpe12120132

An, R., Qian, G., Mumtaz, A., Alotaibi, K. A., & Wang, X. (2025). Digital fatigue and academic resilience among university students with grit and flexibility as mediators. Scientific Reports.

Carretero, S., Vuorikari, R., & Punie, Y. (2017). *DigComp 2.1: The digital competence framework for citizens*. Publications Office of the European Union.https://doi.org/10.2760/38842

Falloon, G. (2020). From digital literacy to digital competence: The teacher digital competency framework. *Journal of Educational Technology & Society, 23*(4), 244–258. https://www.jstor.org/stable/26926471

Febliza, A., & Oktariani, O. (2020). Pengembangan Instrumen Literasi Digital Sekolah Siswa Dan Guru. *Jurnal Pendidikan Kimia Universitas Riau*, *5*(1), 1-10.

Fischer, R., Peifer, C., & Häusser, J. A. (2021). *Technostress and well-being: A systematic review and meta-analysis*. Applied Psychology, 70(4), 1531–1564. https://doi.org/10.1111/apps.12282

Gomes, J., Lopes, J., & Oliveira, C. (2015). *Digital competence and problem-solving skills in science education*. Procedia – Social and Behavioral Sciences, 191, 247–251.https://doi.org/10.1016/j.sbspro.2015.04.498

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer international publishing.

Haruna, H., Zainuddin, Z., Mellecker, R. R., Chu, S. K. W., & Hu, X. (2019). *An iterative process for developing digital learning resources to improve student engagement and learning outcomes*. Educational Technology Research and Development, 67(4), 889–911.https://doi.org/10.1007/s11423-018-09639-y

Hendra, R., Putri, D. A., & Lestari, S. (2025). Academic performance measurement in AI-supported learning environments. *Jurnal Pendidikan Sains, 13*(1), 45–58. https://ejournal.unesa.ac.id/index.php/journal-pendidikan-sains

Ikhsan, M., Munzir, S., & Yusrizal, Y. (2021). The use of digital media to improve students' understanding of abstract concepts in science learning. *Jurnal Pendidikan IPA Indonesia, 10*(2), 265–274. https://doi.org/10.15294/jpii.v10i2.28488

Indriyani, I., Rizqi, U., & Mahmudah, U. (2020). Bagaimana kreativitas dan keaktivan mahasiswa mempengaruhi pemahaman materi abstrak matematika melalui e-learning. *Al Khawarizmi: Jurnal Pendidikan Dan Pembelajaran Matematika*, *4*(2), 112-131. https://doi.org/10.22373/jppm.v4i2.8130

Kalyar, M. N. (2011). Creativity, self-efficacy, and innovation behavior. *African Journal of Business Management, 5*(14), 5734–5741. https://academicjournals.org/journal/AJBM/article-abstract/8C2B43C22028

Moraes, R., & Santos, J. (2023). *Digital literacy, collaboration, and learning performance in science education*. Education and Information Technologies, 28(3), 3497–3516. https://doi.org/10.1007/s10639-022-11287-4

Musyaffi, A. M., Khairunnisa, H., & Respati, D. K. (2021). Konsep dasar Structural Equation Modeling–Partial Least Square (SEM-PLS). *Jurnal Ekonomi, Bisnis, dan Akuntansi, 23*(3), 100–114. https://ejournal.poltektegal.ac.id/index.php/monex/article/view/2326

Nick, E. A., Kilic, Z., Nesi, J., Telzer, E. H., Lindquist, K. A., & Prinstein, M. J. (2022). Adolescent digital stress: Frequencies, correlates, and longitudinal association with depressive symptoms. *Journal of Adolescent Health*, *70*(2), 336-339.

Nunuk, S., Dewi, R., & Suharno, S. (2020). Digital learning, smartphone usage, and digital culture in indonesia education. *Интеграция образования*, *24*(1 (98)), 20-31.

Rosmalinda, D., Syarif, A., Pamela, I. S., Amnie, E., & Muliawati, L. (2025). Penguatan Keterampilan Digital Guru Melalui Pelatihan Wordwall di DSN 205/IV Kota Jambi: Pengabdian. *Jurnal Pengabdian Masyarakat dan Riset Pendidikan*, *4*(1), 6367-6374. https://doi.org/10.31004/jerkin.v4i1.2809

Siagian, I. O., Linda, S., & Melia, S. (2025). Hubungan Tingkat Stres Dengan Prestasi Akademik Mahasiswa: relationship between stress levels and students'academic achievement. *Jurnal Keperawatan Muhammadiyah*, *10*(1), 114-119. https://doi.org/10.30651/jkm.v10i1.24537

Sholihin, M., & Ratmono, D. (2021). *Analisis SEM-PLS dengan WarpPLS 7.0 untuk hubungan nonlinier dalam penelitian sosial dan bisnis*. Penerbit Andi.

Spante, M., Hashemi, S. S., Lundin, M., & Algers, A. (2018). Digital competence and digital literacy in higher education research: Systematic review of concept use. *Cogent education*, *5*(1), 1519143. https://doi.org/10.1080/2331186X.2018.1519143

Syarif, A., Ahmad, E. S., & Fauziah, K. (2023). Hubungan Antara Efikasi Diri terhadap Hasil Belajar Siswa Kelas V di MIS Amaliyah Cibinong. *Mimbar Kampus: Jurnal Pendidikan dan Agama Islam*, *22*(1), 147-162.

Thomas, G. (2022). How to do your research project: A guide for students. https://books.google.co.id/books?id=uVCZEAAAQBAJ&printsec=frontcover&hl=id#v=onepage&q&f=false

Winstone, L., Mars, B., Haworth, C. M., & Kidger, J. (2023). Types of social media use and digital stress in early adolescence. *The Journal of Early Adolescence*, *43*(3), 294-319. https://doi.org/10.1177/0272431622110

Wrede, S. J., Claassen, K., Rodil dos Anjos, D., Kettschau, J. P., & Broding, H. C. (2023). Impact of digital stress on negative emotions and physical complaints in the home office: a follow up study. *Health Psychology and Behavioral Medicine*, *11*(1), 2263068. https://doi.org/10.1080/21642850.2023.2263068

Wrede, S. J., Claassen, K., dos Anjos, D. R., Kettschau, J. P., & Broding, H. C. (2023). Impact of digital stress on negative emotions and physical complaints in the home office. https://doi.org/10.21203/rs.3.rs-2394404/v2

Wen, Z., Yifan, C., & Gaohui, C. (2024). Digital stress among Chinese adolescents: a focus group study. *Information Research an international electronic journal*, *29*(2), 619-634.

Zhao, Y., Lei, J., Yan, B., Lai, C., & Tan, H. S. (2021). *What makes the difference? A practical analysis of research on digital competence*. Educational Technology Research and Development, 69(2), 1089–1107. https://doi.org/10.1007/s11423-021-09964-0

Zoltán, D., Molnár, G., & Tóth, E. (2020). Digital Culture and learning behavior in secondary education. *Journal of Educational Technology & Society, 23*(3), 133–145. https://www.jstor.org/stable/26926463