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# Technology Utilization and Learning Motivation: The Mediating Role of Learning Concentration in Higher Education

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**ABSTRACT**

The integration of digital technology in higher education has transformed learning practices, yet its influence on students' learning motivation may depend on internal psychological mechanisms. This study examined the effect of technology utilization on learning motivation and investigated the mediating role of learning concentration. A quantitative explanatory survey design was employed involving 100 higher education students who actively used digital learning platforms. Data were collected using Likert-scale instruments measuring technology utilization, learning concentration, and learning motivation. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0. The measurement model was evaluated through convergent validity, discriminant validity, and construct reliability, while the structural model was assessed using path coefficients, R-square values, effect size, and mediation testing through bootstrapping. The findings showed that technology utilization had a positive and significant effect on learning concentration and learning motivation. Learning concentration also had a positive and significant effect on learning motivation. The indirect effect of technology utilization on learning motivation through learning concentration was significant, indicating that learning concentration functioned as a partial mediator. The model explained 32.8% of the variance in learning concentration and 71.4% of the variance in learning motivation. These findings suggest that technology enhances learning motivation not only through direct access to digital tools but also by strengthening students' concentration and cognitive regulation. Effective digital pedagogy should therefore focus on designing technology-based learning environments that foster focus, engagement, autonomy, and self-control.

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## 1. INTRODUCTION

The development of digital technology has brought fundamental transformation in learning practices at various levels of education. The use of technology is no longer limited to the use of hardware and software, but has evolved into the ability to analyze digital information, evaluate the credibility of sources, utilize online learning platforms, and actively produce digital content. Within the framework of

Digital Learning Theory, the use of technology is no longer just about hardware accessibility, but rather an ecosystem that demands new abilities for students to analyze digital information, evaluate the credibility of sources, and actively produce digital content (Eshet, 2012). This transformation creates great opportunities to improve the quality of learning, but also presents new challenges in the management of the learning process. Asante and Novak (2024) show that the driving and pulling factors in the use of digital education resources can produce impacts that are not always linear, and even have the potential to cause reversal effects if not supported by the right digital leadership. The findings confirm that the use of technology does not automatically improve learning outcomes without adequate support mechanisms. In the Indonesian context, technology integration through the STEAM approach has been proven to increase students' interest in technology (Huda et al., 2024), which indicates that technology has strong potential in shaping the affective aspects of learning. However, increased interest in technology does not necessarily directly increase motivation for deep learning. Therefore, a more comprehensive study is needed to understand how the use of technology can affect learning motivation through certain psychological mechanisms.

Learning motivation is an important factor that determines a student's engagement, perseverance, and academic success. Based on Self-Determination Theory (SDT), learning motivation is a manifestation of fulfilling students' basic needs for autonomy, competence, and connectedness (Niemiec & Ryan, 2009). Effective use of technology should be able to support these needs, but the connection between external factors and motivation is often not direct. Various studies show that the relationship between external factors and motivation is often indirect and involves mediating variables. In the context of entrepreneurship education, Jabid et al. (2023) found that perceptions of desirability and feasibility mediate the influence of entrepreneurship education on entrepreneurial intentions. Sucandrawati et al. (2024) also show that social capital and entrepreneurial competence form a business incubator ecosystem through complex structural mechanisms. In another field, Nguyen et al. (2024) assert that individual characteristics and the process of knowledge sharing influence perceptions of employability via certain psychological variables. Even in the context of health, Zhang et al. (2025) prove that the relationship between symptom burden and demoralization is mediated by family function, resilience, and coping behavior.

In the context of technology-based learning, the role of concentration is increasingly vital to bridge the interaction between digital tools and student motivation. According to Cognitive Load Theory (CLT), concentration serves as a crucial filtering mechanism to manage the cognitive load that arises when interacting with complex digital materials (Paas & Van Merrienboer, 2020). Without good concentration, technology can actually trigger extrinsic cognitive overload, which is a source of distraction, as alleged by Asante & Novák (2023). If technology is used appropriately, students have the potential to improve focus and self-control, which ultimately strengthens motivation to learn (Evans et al., 2024). Therefore, this study is important to test whether learning concentration really functions as a mediator in the relationship between technology utilization and learning motivation. This mediation model test is expected to be able to provide a more in-depth explanation than just testing the direct relationship between variables (Dong, 2026).

Methodologically, this study uses the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach because this method is considered suitable for analyzing complex latent constructs and causal relationships simultaneously (Demir & Uşak, 2025). A decade-long review of PLS-SEM implementation in educational technology research confirms that this method is increasingly being used due to its flexibility and ability to test complex structural models. The advantages of PLS-SEM in handling data that are not normally distributed and moderate sample sizes are also strengthened by Schamberger et al. (2020) through a robust partial least squares path modeling approach. In addition, Klesel et al. (2022) show the importance of multigroup analysis in information systems research using PLS-PM to understand the differences in group characteristics in structural models. The application of PLS-SEM is not only limited to the field of education, but is also widely used in the study of international economics and competitiveness (R. et al., 2021) as well as financial and business research (Tohari et al., 2021). This shows that PLS-SEM is an established method and has strong scientific legitimacy in various disciplines. Using PLS-SEM, this study can evaluate the outer model through the validity and reliability testing of the construct and analyze the inner model through the path coefficient, $R^2$ value, effect size, and indirect effect testing.

Theoretically, this study fills a critical literature gap related to psychological mediation mechanisms in technology-based education. Although technology adoption is widespread, the understanding of how learning concentration mediates the influence of technology on student motivation is still very limited and has not been explored empirically. In practical terms, these findings make a significant contribution to digital pedagogy by providing a foundation for educators and policymakers to move from simply providing technological infrastructure to designing learning environments that proactively foster students' cognitive focus. Thus, technology not only plays a role as a means of accessing information but also as a catalyst that strengthens the motivation for continuous learning. The relationship of this study with the existing literature lies in the strengthening of empirical evidence regarding the role of mediation in explaining structural relationships as shown in various previous studies (Chun & Abdullah, 2025; Jabid et al., 2023; Zhang et al., 2025), as well as the contribution to the development of the PLS-SEM methodology in education as discussed by (Demir & Uşak, 2025).

Based on this description, the purpose of this study is to analyze the influence of technology use on learning motivation, examine the influence of technology use on learning concentration, analyze the influence of learning concentration on learning motivation, and test the role of learning concentration as a mediator in the relationship between technology use and learning motivation. The formulation of the problem in this study is: (1) whether the use of technology has a positive effect on learning motivation; (2) whether the use of technology has a positive effect on learning concentration; (3) whether learning concentration has a positive effect on learning motivation; and (4) whether learning concentration mediates the influence of technology use on learning motivation. By answering these questions, this research is expected to be able to make a significant contribution to the development of technology-based learning models that are more effective, directed, and oriented towards increasing students' learning motivation.

## 2. METHODS

This study uses a quantitative approach with an explanatory survey design. This design was chosen to test and explain the causal relationship between the variables of Technology Utilization, Learning Concentration, and Learning Motivation. Through this approach, data is collected systematically to draw conclusions that represent the psychological dynamics of students in the context of digital learning.

The population in this study is students at IAIN Curup who actively use digital learning platforms. The total number of participants was 100 students. Sampling was carried out using the quota sampling technique. This technique was chosen because of the absence of a complete and centralized sampling frame for all students, so that quota sampling allows researchers to maintain the proportion of subgroup representation without having to rely on random population frames (Lavrakas, 2008). This approach ensures that the data collected remains adequately representative despite the constraints of limited population access.

The research instrument was developed based on indicators that have been validated in the educational literature. All variables were measured using a 5-point Likert scale (1 = Strongly Not Agree to 5 = Strongly Agree):

a. Technology Utilization: Measured using instruments adapted from Venkatesh et al. (2003), covering aspects of frequency, variety of tools, and effectiveness of use.
b. Learning Concentration: Measured on the Pintrich's (1991) scale that focuses on cognitive focus abilities, attention management, and self-control while learning.
c. Learning Motivation: Measured using the Academic Motivation Scale adapted from Vallerand et al. (1992), to capture intrinsic and extrinsic motivation.

Before being disseminated, all items of the statement have gone through a content validity test by experts (expert judgment) to ensure clarity and relevance in the context of higher education. Data analysis was carried out using Partial Least Squares Structural Equation Modeling (PLS-SEM) with the help of SmartPLS 4.0 software. The analysis procedure is carried out in two main stages:

a. Evaluation of the Measurement Model (Outer Model): This stage aims to test the validity and reliability of the construct. Testing includes:
   1) Convergent Validity: Judging from the value of outer loading (>0.70) and Average Variance Extracted (AVE > 0.50).
   2) Discriminant Validity: Verified using Fornell-Larcker criteria and Heterotrait-Monotrait ratio (HTMT < 0.90).
   3) Internal Consistency Reliability: Evaluated using Cronbach's Alpha and Composite Reliability (> 0.70).
b. Evaluation of Structural Models (Inner Model): This stage examines the causal relationships between variables. The procedures performed include:
   1) Hypothesis Testing: Using the bootstrapping technique with 5,000 subsamples to obtain t-statistical values and p-values (< 0.05).
   2) Predictive Relevance: Assess the coefficient of determination ($R^2$) and Q-square to measure the model's predictive ability.
   3) Mediation Testing: Tested the role of Learning Concentration as a mediator by looking at indirect effects and calculating Variance Accounted For (VAF) to determine the type of mediation (partial or full).

This research was carried out in compliance with academic research ethics standards. Participation is voluntary, and all respondents have provided informed consent before completing the survey. The anonymity of respondents is strictly guarded; The data cannot be traced back to a specific individual. All data collected is used solely for this research and is stored securely in a protected system to maintain confidentiality. Participants are given the full right to withdraw from the research process at any time without any consequences.

## 3. FINDINGS AND DISCUSSION

### *3.1 Findings*

The evaluation of the research model is carried out in two different phases, called the Outer Model and the Inner Model. The Outer Model deals with the assessment of the validity and reliability of indicators used for the measurement of latent variables, utilizing methodologies such as Convergent Validity, Discriminant Validity, and Construct Reliability assessment. Instead, the Inner Model investigates the linkages between latent variables and evaluates the strength and significance of these associations, using analytical techniques such as $R^2$, path coefficients, and path significance tests. Here is a picture of the latent variable models that will be analyzed in this study.

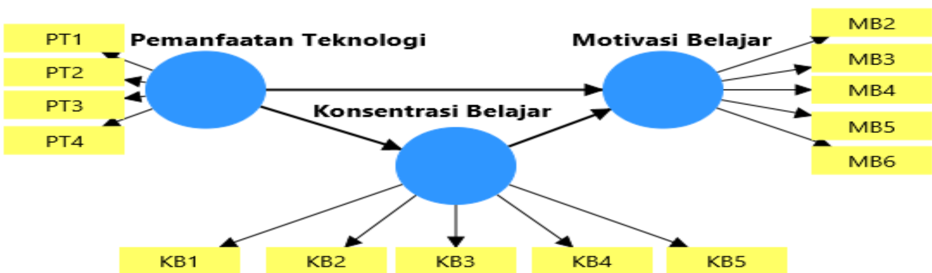


**Figure 1.** Latent Variables Model

### 3.1.1 Outer Model

Outer models focus on the relationship between latent variables and indicators. Testing on the outer model aims to ensure that the instruments used to measure latent variables have good validity and reliability. There are three main types of testing in the outer model, namely Convergent Validity, Discriminant Validity, and Construct Reliability.

**a. Convergent Validity**

1) Loading Factor/Outer Loading Score

The output of the external loading estimation results is measured from the correlation between the indicator score (instrument) and its construct (variable). The indicator is considered valid if it has a correlation value above 0.70.

**Table 1.** Outer Loading Score

| | Learning Concentration | Learning Motivation | Technology Utilization |
|---|---|---|---|
| KB1 | 0.915 | | |
| KB2 | 0.907 | | |
| KB3 | 0.868 | | |
| KB4 | 0.922 | | |
| KB5 | 0.817 | | |
| MB2 | | 0.818 | |
| MB3 | | 0.898 | |
| MB4 | | 0.734 | |
| MB5 | | 0.866 | |
| MB6 | | 0.822 | |
| PT1 | | | 0.823 |
| PT2 | | | 0.803 |
| PT3 | | | 0.818 |
| PT4 | | | 0.857 |

Based on the outer loading values of each indicator, the entire construct shows excellent convergent validity because all values are above the minimum limit of 0.70. In the Learning Concentration variable, the KB1–KB5 indicator has a loading between 0.817 and 0.922, which shows the contribution of the indicator strongly in reflecting its constructs. The Learning Motivation variable also met the criteria with a loading value of MB2-MB6 ranging from 0.734 to 0.898, so that all indicators were declared valid. Similarly, in the Technology Utilization variable, the PT1–PT4 indicator has a loading between 0.803 and 0.857, which indicates good measurement consistency. Thus, it can be concluded that all indicators are feasible to maintain in the model because they have met the criteria of convergent validity in the SEM-PLS analysis.

2) Average Variance Extracted (AVE)

The output of the estimated average variance extracted (AVE) can be seen in the table below. A variable is said to be valid if it has an average variance extracted (AVE) value of > 0.5.

**Table 2**. Average Variance Extracted

| | Average variance extracted (AVE) |
|---|---|
| **Learning Concentration** | 0.786 |
| **Learning Motivation** | 0.688 |
| **Technology Utilization** | 0.681 |

The Average Variance Extracted (AVE) value in all three constructs shows that all variables have met the convergent validity criteria because they are above the minimum limit of 0.50. The Learning Concentration has an AVE of 0.786, which means that 78.6% of the variance of the indicator can be explained by the construct, indicating a very strong measurement quality. Learning Motivation had an AVE of 0.688 and Technology Utilization of 0.681, both of which were also in the good category because more than 50% of the variance of the indicators was successfully explained by their respective constructs. Thus, it can be concluded that all constructs in the model have sufficient convergent validity and are feasible to proceed to the structural model analysis stage.

***b. Discriminant Validity***

Discriminant validity is used to ensure that the constructs or variables in the measurement model actually measure things that are different or do not overlap with each other. In other words, discriminant validity measures the extent to which different constructs in a measurement model can be distinguished from each other. Discriminant validity can be measured using one of three value criteria to be evaluated, namely cross-loading value, HTMT, and or Fornell-Larcker value, and latent variable.

1) Cross Loading

An indicator/statement is declared valid if the relationship of the indicator/statement with its construct/variable (cross-loading value) is higher than its relationship with another construct. The following are the results of data processing using SmartPLS version 4, with the results of cross-loading as shown in the table below.

**Table 2.** The results of cross-loading

| | Learning Concentration | Learning Motivation | Technology Utilization |
|---|---|---|---|
| KB1 | **0.915** | 0.744 | 0.527 |
| KB2 | **0.907** | 0.756 | 0.520 |
| KB3 | **0.868** | 0.733 | 0.564 |
| KB4 | **0.922** | 0.696 | 0.467 |
| KB5 | **0.817** | 0.670 | 0.448 |
| MB2 | 0.776 | **0.818** | 0.451 |
| MB3 | 0.700 | **0.898** | 0.624 |
| MB4 | 0.527 | **0.734** | 0.566 |
| MB5 | 0.683 | **0.866** | 0.583 |
| MB6 | 0.666 | **0.822** | 0.493 |
| PT1 | 0.494 | 0.595 | **0.823** |
| PT2 | 0.370 | 0.495 | **0.803** |
| PT3 | 0.502 | 0.531 | **0.818** |
| PT4 | 0.507 | 0.527 | **0.857** |

Based on the cross-loading table, all indicators have the highest loading value in the construct they measure compared to other constructs, thus meeting the discriminant validity criteria. The KB1–KB5 indicator has the highest loading on Learning Concentration compared to Learning Motivation and Technology Utilization. Similarly, the MB2–MB6 indicator showed the highest loading value in the Learning Motivation construct, while the PT1–PT4 indicator had the highest loading in Technology Utilization. Although there are some correlations between constructs that are quite moderate, the value is still lower than the loading in the original construct. Thus, it can be concluded that the model has met the criteria for discriminant validity based on the cross-loading approach in the SEM-PLS analysis.

2) HTMT

HTMT (Heterotrait-Monotrait Ratio) is a method for testing the validity of discriminants in SEM-PLS analysis developed by Henseler, Ringle, and Sarstedt (2015). HTMT measures the ratio between the correlations between different constructs (heterotrait-heteromethod correlations) and the average of the correlations of indicators in the same construct (monotrait-heteromethod correlations). The HTMT scoring criteria use two thresholds: HTMT < 0.85 for constructs that are conceptually very different (conservative criteria), and HTMT < 0.90 for constructs that are conceptually similar but still have to be differentiated (liberal criteria).

**Table 3.** HTMT (Heterotrait-Monotrait Ratio) value

| | **Learning Concentration** | **Learning Motivation** | **Technology Utilization** |
|---|---|---|---|
| **Learning Concentration** | | | |
| **Learning Motivation** | 0.890 | | |
| **Technology Utilization** | 0.638 | 0.756 | |

Based on the HTMT (Heterotrait-Monotrait Ratio) value, the relationship between Learning Concentration and Learning Motivation is 0.890, between Technology Utilization and Learning Concentration is 0.638, and between Technology Utilization and Learning Motivation is 0.756. In general, the HTMT criterion states that the value must be below 0.90 (or more strictly below 0.85) to demonstrate good discriminant validity. The values of 0.638 and 0.756 are well below the 0.90 limit, thus indicating that Technology Utilization has good discrimination against the other two constructs. Meanwhile, the value of 0.890 between Learning Concentration and Learning Motivation is still below the 0.90 threshold, so it is still generally acceptable, although it shows a fairly strong relationship between the two. Thus, it can be concluded that the model has met the criteria for discriminant validity based on HTMT, although the relationship between Learning Concentration and Learning Motivation is relatively high and needs to be examined conceptually.

3) Former Larcker

The Fornell-Larcker Criterion is a traditional method for testing discriminant validity in SEM-PLS analysis developed by Fornell and Larcker (1981). This method compares the square root of the Average Variance Extracted (AVE) of a construct with the correlation value between that construct and other constructs in the model.

**Table 4.** Square root value of AVE (Fornell-Larcker Criterion)

| | **Learning Concentration** | **Learning Motivation** | **Technology Utilization** |
|---|---|---|---|
| **Learning Concentration** | **0.887** | | |
| **Learning Motivation** | 0.814 | **0.830** | |
| **Technology Utilization** | 0.572 | 0.653 | **0.825** |

The table shows the square root value of AVE (Fornell-Larcker Criterion), where the diagonal values for Learning Concentration (0.887), Learning Motivation (0.830), and Technology Utilization (0.825) are greater than the correlation between constructs in the same row and column. For example, the score of 0.887 on Learning Concentration is higher than its correlation with Learning Motivation (0.814) and Technology Utilization (0.572). Similarly, the score of 0.830 on Learning Motivation is higher than its correlation with Learning Concentration (0.814) and Technology Utilization (0.653). The value of 0.825 in Technology Utilization is also greater than its correlation with the other two constructs. This shows that each construct has a better ability to explain its own variables compared to the others, so it can be concluded that the model has met the criteria of discriminant validity based on the Fornell-Larcker approach.

4) Latent Variabel

The discriminant validity test aims to ensure that each construct in the model is completely different and does not overlap with the others. One of the methods used is the Fornell-Larcker criterion, which compares the value of the square root of AVE with the correlation between constructs.

**Table 5.** Square root value of AVE (Fornell-Larcker Criterion)

| | **Learning Concentration** | **Learning Motivation** | **Technology Utilization** | **AVE** | $\sqrt{AVE}$ |
|---|---|---|---|---|---|
| **Learning Concentration** | 1 | 0.814 | 0.572 | 0.786 | 0.887 |
| **Learning Motivation** | 0.814 | 1 | 0.653 | 0.688 | 0.830 |
| **Technology Utilization** | 0.572 | 0.653 | 1 | 0.681 | 0.825 |

The table shows the results of the discriminant validity test using the Fornell-Larcker criterion, where the value of the square root of AVE ($\sqrt{}$AVE) for each construct is greater than the correlation between other constructs. Learning Concentration had an AVE of 0.786 with an AVE of 0.887 √, which is higher than its correlation with Learning Motivation (0.814) and Technology Utilization (0.572). Learning Motivation had an AVE of 0.688 with an √AVE of 0.830, which is also greater than the correlation with Learning Concentration (0.814) and Technology Utilization (0.653). Technology Utilization had an AVE of 0.681 with an √AVE of 0.825, which is higher than its correlation with Learning Concentration (0.572) and Learning Motivation (0.653). Since the overall value of $\sqrt{}$AVE is greater than the correlation between constructs, it can be concluded that each construct has good discrimination and the measurement model has met the criteria of discriminant validity.

**c. Construct Reliability**

Construct Reliability can be analyzed using one of these two methods, namely by analyzing Cronbach's Alpha or Composite Reliability values. These two methods are part of the equation used to test the reliability value of indicators on a variable.

**Table 6.** Cronbach's Alpha

| | **Cronbach's alpha** | **Composite reliability (rho_a)** |
|---|---|---|
| **Learning Concentration** | 0.931 | 0.934 |
| **Learning Motivation** | 0.886 | 0.892 |
| **Technology Utilization** | 0.844 | 0.849 |

Based on the table, all constructs have met the criteria of good internal reliability. Cronbach's alpha values for Learning Concentration (0.931), Learning Motivation (0.886), and Technology Utilization (0.844) are all above the minimum limit of 0.70, which indicates that the internal consistency of the indicators in each construct is very good. Similarly, the Composite Reliability (rho_a) values for Learning Concentration (0.934), Learning Motivation (0.892), and Technology Utilization (0.849) also exceeded 0.70, even close to or above 0.80, which indicates strong construct reliability in the PLS-SEM model. Overall, these results indicate that the research instrument has a high level of reliability and is suitable for further analysis on structural models.

**Table 7.** FIT Model on the Saturated Model

| | **Saturated model** |
|---|---|
| **SRMR** | 0.071 |
| **d_ULS** | 0.535 |
| **d_G** | 0.369 |
| **Chi-square** | 206.413 > 22.362 |
| **NFI** | 0.822 |

Based on the results of the fit model on the saturated model, the SRMR value of 0.071 indicates that the model has a good level of conformity because it is below the general limit of 0.08, so the residual model is relatively small. The values of d_ULS (0.535) and d_G (0.369) indicate a relatively low distance between the empirical covariance matrix and the model, indicating that the model estimate is quite stable. The larger Chi-square values (206.413 > 22.362) in PLS-SEM are not the main focus because this approach is predictive and is not as sensitive to sample size as in CB-SEM. Meanwhile, an NFI value of 0.822 indicates that the model has a fairly good match even though it has not reached the very good category (≥0.90). Overall, the model can be said to be feasible and meets the feasibility criteria of the model in the PLS-SEM analysis.

### 3.1.2 Inner Model

The inner model in PLS-SEM describes the relationships between latent variables and is evaluated to see the strength and significance of these relationships. The evaluation includes three main aspects: R Square, relationship significance (Hypothesis Testing), and F Square/Effect Size.

**a. Path Coefficients**

Hypothesis tests were carried out to determine the direct influence of variables in the structural model. This test uses the path coefficient (β), T-statistics, and p-values from bootstrapping on SEM-PLS.

**Table 8.** The Results of the Hypothesis Test

| | **Original sample (O)** | **Sample mean (M)** | **Standard deviation (STDEV)** | **T statistics (\|O/STDEV\|)** | **P values** |
|---|---|---|---|---|---|
| **Learning Concentration -> Learning Motivation** | 0.654 | 0.653 | 0.062 | 10.589 | 0.000 |
| **Technology Utilization -> Learning Concentration** | 0.572 | 0.564 | 0.095 | 6.03 | 0.000 |
| **Technology Utilization -> Learning Motivation** | 0.279 | 0.276 | 0.065 | 4.264 | 0.000 |

The results of the hypothesis test showed that the entire relationship between the variables was statistically significant. The effect of Learning Concentration on Learning Motivation has a coefficient of 0.654 with a T-statistic of 10.589 and a p-value of 0.000, which means that it has a positive and very significant effect; The higher the student's concentration of learning, the higher their motivation to learn. Furthermore, the use of technology had a positive effect on Learning Concentration with a coefficient of 0.572, T-statistics 6.030, and a p-value of 0.000, showing that good use of technology was able to improve students' focus and attention control. In addition, the use of technology also has a direct effect on Learning Motivation with a coefficient of 0.279, T-statistics 4.264, and a p-value of 0.000, which means significant even though the power is smaller than the influence through learning concentration. Thus, it can be concluded that all pathways in the model are accepted and show a significant positive relationship, as well as indicate a potential mediating role of learning concentration in the relationship between technology utilization and learning motivation.

**b. Specifics Indirect Effects**

Indirect effects testing was conducted to see if the Learning Concentration mediated the relationship between Technology Utilization and Learning Motivation. This analysis uses a bootstrapping procedure in SEM-PLS to test the significance of the mediation pathway.

**Table 8.** The Results of the Hypothesis Test

| | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (\|O/STDEV\|) | P values |
|---|---|---|---|---|---|
| **Technology Utilization -> Learning Concentration -> Learning Motivation** | 0.374 | 0.368 | 0.07 | 5.366 | 0.000 |

The results of the indirect influence test showed that the Technology Utilization → Learning Concentration → Learning Motivation pathway had a coefficient of 0.374 with a T-statistic of 5.366 and a p-value of 0.000, so it was statistically significant. This means that Learning Concentration is proven to mediate the influence of Technology Utilization on Learning Motivation. The positive coefficient value shows that the better the use of technology, the greater the concentration of learning increases, which ultimately has an impact on increasing learning motivation. Thus, this mediation effect strengthens the relationship between the use of technology and learning motivation through the important role of learning concentration as an intervening variable.

**c. R Square**

**Table 9.** The R-square value

| | R-square | R-square adjusted |
|---|---|---|
| **Learning Concentration** | 0.328 | 0.321 |
| **Learning Motivation** | 0.714 | 0.708 |

The R-square value shows that the Technology Utilization variable is able to explain 32.8% of the variation in Learning Concentration ($R^2$ = 0.328; $R^2$ adjusted = 0.321), which means that the effect is in the medium category. Meanwhile, the R-square value on Learning Motivation of 0.714 ($R^2$ adjusted = 0.708) shows that the combination of Technology Utilization and Learning Concentration is able to explain 71.4% of the variation in Learning Motivation, which is relatively strong. The very small difference between R-squared and R-squared adjusted on both variables indicates that the model has good stability and does not experience overfitting. Thus, the structural model built has strong predictive power, especially in explaining student learning motivation.

**d. F Square**

**Table 10.** The value of f-square (effect size)

| | Learning Concentration | Learning Motivation | Technology Utilization |
|---|---|---|---|
| **Learning Concentration** | | 1.006 | |
| **Learning Motivation** | | | |
| **Technology Utilization** | 0.487 | 0.183 | |

The table shows the value of f-square (effect size) to see the amount of contribution of each exogenous variable to the endogenous variable. The f-square value of Technology Utilization on Learning Concentration of 0.487 shows a large effect, because it is above 0.35, so it can be concluded that Technology Utilization makes a strong contribution in explaining the variation in Learning Concentration. Furthermore, the f-square value of Technology Utilization on Learning Motivation of 0.183 is in the medium category (between 0.15–0.35), which means that its contribution is quite significant but not as strong as its effect on concentration. Meanwhile, the f-square value of Learning Concentration on Learning Motivation of 1.006 shows a very large effect, indicating that Learning Concentration is the dominant predictor in explaining Learning Motivation. Overall, these results reinforce that Learning Concentration has a very strong role in the model, while affirming the importance of Technology Utilization in increasing concentration as the main pathway to increased learning motivation.

### *3.2 Discussion*

The results of this study show that all the hypotheses proposed are proven to be significant and form a relationship pattern that is consistent theoretically and empirically. The use of technology has been proven to have a positive effect on Learning Motivation, the use of technology has a positive effect on Learning Concentration, and Learning Concentration has a positive effect on Learning Motivation. In addition, the indirect influence of the use of technology on Learning Motivation through Learning Concentration is also significant. These findings expand the treasure trove of knowledge by asserting that in the era of digital pedagogy, technology does not work as a single entity, but rather as a variable that interacts complexly with individual cognitive processes to form intrinsic motivations.

Answering the first research question about whether the use of technology has an effect on Learning Motivation, the results of this study confirm the existence of a significant positive influence. These findings are in line with Huda et al. (2024) and reinforced by Digital Learning Theory, which states that the effective use of technology is not just about access to tools but rather about transforming the role of students into active actors in producing digital content. When students can analyze digital information, evaluate the credibility of sources, and actively produce digital content, according to Self-Determination Theory (SDT), it is the main driver of learning motivation (Paas & Van Merrienboer, 2020). These findings expand existing knowledge by showing that the quality of technology use (critical-productive orientation) is more determinative of motivation than just the intensity of use.

Answering the second research question about whether the use of technology affects learning concentration, the results of the study show a strong and significant coefficient. These findings expand the discussion (Asante & Novak, 2024), by applying a Cognitive Load Theory (CLT) lens. In the context of this study, the use of analytical and productive technology has been proven to improve students' ability to control their thoughts, focus their attention, and avoid distractions. This shows that technology is not always synonymous with concentration disorders, but can be a means of cognitive training if designed and used appropriately. That is, the right design of technology serves as cognitive scaffolding that helps students filter out distractions. These findings explicitly break the narrative that technology has always been a source of distraction, and prove that if designed well, technology is actually a cognitive training tool.

The third research question regarding the effect of Learning Concentration on Learning Motivation was also answered significantly. The results show that the higher the students' ability to control their thoughts and attention, the higher their motivation to learn. These findings are consistent with Chun & Abdullah (2025), which shows that a self-determined learning process involves internal psychological mechanisms that strengthen learning impulses. Good concentration allows students to engage deeply in learning activities, so that they feel the meaning and challenges in the process. With increased cognitive involvement, intrinsic motivation develops naturally. Zhang et al. (2025) also showed that mediator psychological variables have a significant role in explaining the relationships between variables in structural models, which reinforces the interpretation that concentration serves as an important psychological mechanism in building motivation. Therefore, the results of this study emphasize that learning motivation does not stand alone, but is influenced by the quality of students' cognitive regulation.

The fourth research question regarding the role of Learning Concentration mediation shows that the mediation that occurs is a partial mediation. This pattern is in line with findings that show that mediators do not always eliminate the direct influence of independent variables on dependent variables (Jabid et al., 2023). In this study, technology still had a direct influence on motivation, but concentration explained most of the mechanisms. This means that when students make optimal use of technology, they are not only motivated by the features or convenience of the technology itself, but also because it helps them improve their focus and learning engagement. This partial mediation pattern shows that the model built is realistic and non-reductionist. The significance of this finding lies in its ability to explain how cognitive processes and technological factors interact with each other in shaping student learning motivation.

From a methodological perspective, this study strengthens the argument Demir & Uşak (2025) that PLS-SEM is a relevant approach in educational technology research, especially in testing mediation models and complex relationships between latent constructs. The robustness of this approach, as discussed by Schamberger et al. (2020), supports the validity of the research results. The application of PLS-SEM in areas such as economics (R. et al., 2021), information systems (Klesel et al., 2022), and finance (Tohari et al., 2021) demonstrates the flexibility and power of this approach in analyzing complex structural models. Thus, this research not only makes a substantive contribution in the field of educational technology but also enriches methodological practices in the use of SEM-PLS in the realm of higher education.

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Theoretically, this research contributes to the development of a conceptual model that integrates aspects of technology, cognitive processes, and motivation in one structural framework. This model shows that students' learning motivation in the digital era is the result of a dynamic interaction between the use of technology and the capacity of individual cognitive regulation. Practically, the implication is that educational institutions need to design technology-based learning strategies that are not only visually appealing, but also train student concentration and engagement. The development of critical and productive digital literacy is the key to maximizing the motivational impact of technology.

These findings provide important implications in three main domains. *First*, in terms of learning strategies, educators need to move from content-centered teaching to strategies centered on cognitive regulation. Teachers should design activities that train students to focus attention in a disruptive digital environment, rather than just providing digital materials. *Second*, curriculum developers and instructors must apply the principles of Cognitive Load Theory in media design. The learning interface should be made intuitive to minimize unnecessary cognitive load, so that students' mental capacity can be fully allocated to understanding concepts (meaningful learning processes). *Third*, to increase engagement, technology must be integrated with challenging and work-creation-oriented tasks (such as digital content creation). This will trigger students' intrinsic motivation because they feel they have control over their learning process (autonomy), which is in line with SDT's principles in increasing student involvement in higher education.

However, this study has some limitations. First, the relatively limited sample count of 100 college students limits the generalization of results to a wider population. Second, the cross-sectional research design has not been able to capture the dynamics of changes in motivation and concentration in the long term. Third, this study has not tested the possibility of group differences as discussed by the multigroup analysis approach discussed by Klesel et al. (2022), so the variation in individual characteristics has not been analyzed in more depth. Therefore, further research can expand the number of samples, using longitudinal designs, and test additional moderator variables to enrich the model that has been built. However, overall, this study makes an important contribution to the development of educational technology science by showing that learning concentration is a significant psychological mechanism in bridging the use of technology and student learning motivation.

## 4. CONCLUSION

This study examined the effect of technology use on learning motivation, with learning concentration as a mediating variable. Based on SEM-PLS analysis of 100 students, the findings show that technology use positively and significantly influence both learning motivation and learning concentration, while learning concentration also has a positive and significant effect on learning motivation. The mediation results confirm that learning concentration partially mediates the relationship between technology use and learning motivation, indicating that technology enhances motivation both directly and indirectly by strengthening students' focus and cognitive regulation. Theoretically, this study contributes to understanding learning motivation in the digital era as a product of interaction between technological support and internal psychological processes. Practically, it highlights the need for technology-integrated learning designs that promote focus, engagement, autonomy, and self-control. However, due to the limited sample size and cross-sectional design, future studies should involve larger and more diverse samples, apply longitudinal approaches, and examine moderating variables or group differences to better explain the long-term effects of technology-based learning on student motivation.

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