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# The Effect of Social Media Use Intensity on Motivation-Mediated Learning Concentration: SEM Method

**Guntur Gunawan**
*Institut Agama Islam Negeri Curup, Curup, Indonesia*

Corresponding Email: gunturgunawan@iaincurup.ac.id

**Abstract.** This study aims to analyze the influence of the intensity of social media use on student learning concentration with learning motivation as a mediating variable. The study uses a quantitative approach with an explanatory survey design. The sample amounted to 100 students, which was determined through the quota sampling technique. The research instruments were compiled based on indicators of social media use intensity, learning motivation, and learning concentration that have been developed from relevant literature. Data were collected through questionnaires and analyzed using Structural Equation Modeling based on Partial Least Squares (SEM-PLS) with a bootstrapping procedure to test the significance of direct and indirect influence paths. The results of bootstrapping analysis showed that the intensity of social media use had a positive and significant effect on learning motivation ($\beta = 0.506$; $T = 4.415$; $p < 0.001$). Learning motivation also had a positive and significant effect on learning concentration ($\beta = 0.812$; $T = 17.084$; $p < 0.001$). In addition, the indirect effect of the intensity of social media use on learning concentration through learning motivation was also significant ($\beta = 0.411$; T = 3,883; $p < 0.001$), which indicates partial mediation. In conclusion, the intensity of the use of social media can increase students' learning concentration both directly through increasing learning motivation and through motivational mediation mechanisms. This shows that educators and policymakers must adopt an effective way of incorporating social media within the educational setting in order to motivate the learners and help them focus.

***Keywords:*** Intensity of Social Media Use, Learning Motivation, Learning Concentration, Partial Mediation, SEM-PLS, Bootstrapping.

## Introduction

The development of digital technology has changed the way individuals interact, communicate, and learn, especially through the increasingly intensive use of social media among students and college students. Social media is no longer just a means of entertainment, but has become an integral part of academic life, both as a source of information, a collaborative medium, and a space for self-expression. Research by Bukhari et al. (2020) shows that the use of social media has implications for students' academic performance, thus giving rise to a debate about its positive and negative impacts in the context of learning. On the other hand, Latifah et al. (2023) found that the intensity of social media use was related to students' learning motivation and academic behavior, including procrastination tendencies. These results indicate that social media can play a role as a factor that affects the psychological dynamics of learning. The findings (Supriyadi et al., 2023) also show that the intensity of YouTube use and the quality of information received can increase students' motivation to learn. However, Mariyati & Wilmar (2024) actually found that there was a negative impact of TikTok use on the learning motivation of elementary school students, thus showing that the effect of social media is ambivalent. Therefore, more comprehensive research is needed to understand how the intensity of social media use affects the psychological aspects of learning, especially motivation and concentration during learning (Muthmainnah et al., 2024; Gusmuliana & Apriani, 2021).

In the context of learning motivation, various studies have confirmed its role as a key determinant of academic success. (Budiharti et al., 2024) shows that the learning outcomes of elementary school students are greatly influenced by the level of learning motivation they have.

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(Hong & Anh, 2023) emphasized that motivation contributes to students' academic performance in the context of classroom management. (Huang et al., 2025) found that learning motivation has a significant impact on the academic performance of low-income students, even though the mediation mechanism of learning strategies and mental health. (Shao et al., 2024) show that learning motivation plays a mediating role in the relationship between peer relations and academic achievement. (T. Wang et al., 2023) also showed that learning motivation is related to online learning performance through the mediation of academic self-efficacy and experience flow. The findings (Y. Wang, 2024) and (Wangchuk et al., 2022) further reinforce that learning motivation has a consistent relationship with students' academic achievement. The series of studies confirms that motivation is not only a supporting variable but a major psychological mechanism that affects cognitive engagement and concentration in the learning process (Apriani, 2022).

Despite all that, the growing frequency of social media usage by the students presents an important problem since excessive and uncontrolled usage may disrupt cognitive processes associated with the learning process, especially learning concentration; however, research data that might help to comprehend the issue in question is rather scarce at present. Indeed, although several studies have already found both advantages and drawbacks of high social media usage intensity, it is still unclear how exactly this factor impacts the cognitive process in question.

The intensity of social media use as a behavioral variable has also been extensively researched in various contexts. (Alghamdi & Bogari, 2020) uses the Structural Equation Modelling approach to explain the influence of social media on purchasing decisions, showing that the intensity of use can be measured structurally and has a significant effect on psychological variables. (Kara, 2021) examined the intensity of mobile social media use in high school students and found the mediating role of flow experiences. (ÖZHAN, 2022) highlights that the intensity of social media use is related to conspicuous consumption behavior through the electronic word-of-mouth mechanism. (Šola & Zia, 2021) explained that social media also influences the choice of higher education institutions by students. (Du & Wang, 2024) show that social media use can predict school engagement and burnout with self-control as a moderation variable. Meanwhile, (Deng et al., 2022) found that social media multitasking outside of assignments during class has certain mediating mechanisms that impact learning engagement. (Zhang & Wei-min, 2024) also revealed that passive use of social media can increase learning burnout in high school students. These findings show that the intensity of social media use has psychological consequences that can have an impact on motivation and concentration during learning.

In a more constructive perspective, Ramzan et al. (2023) show that social media can be used to increase the academic motivation of ESL students. (Hu, 2025), through the perspective of Self-Determination Theory, emphasizes that social media feedback mechanisms can improve adolescent motivation and learning outcomes. (Le & Li, 2023) prove that digital media, including social media campaigns, can improve the quality of education in the context of sports learning. (Jiang et al., 2024) also highlights the factors that influence deep learning in the context of digital platform-based online courses. (Rochman et al., 2023) specifically found that the use of social media affects student learning achievement through motivational mediation. In addition, Dennen & Bagdy (2024) explain the dynamics of the transition to social media use in the context of academic change. (Jagtap, 2020) also emphasized that social media has a significant effect in influencing user behavior. Thus, the literature suggests that social media can play a role as a risk factor as well as a protective factor depending on the intensity, usage patterns, and psychological mechanisms involved.

Although various studies have discussed the relationship between social media and academic motivation and performance, there is still a gap in research related to how the intensity of social media use affects learning concentration through motivation as a mediating variable. Most studies have focused on academic performance or burnout, but have not specifically examined learning concentration as the main outcome in structural mediation models. In fact, concentration is a cognitive prerequisite that greatly determines the effectiveness of learning and the achievement of academic goals. Therefore, this study is important to elucidate the psychological mechanisms that bridge the relationship between the intensity of social media use and learning concentration. In the particular case of IAIN Curup, where learners tend to multitask when undertaking academic tasks as well as using social media platforms, such tendencies might affect their capacity to sustain attention and focus on their studies.

This study aims to analyze the direct influence of the intensity of social media use on learning motivation, the influence of learning motivation on learning concentration, and to examine the mediating role of learning motivation in the relationship between the intensity of social media use and learning concentration. Based on these objectives, the formulation of this research problem is: (1) whether the intensity of social media use affects learning motivation, (2) whether learning motivation affects learning concentration, and (3) whether learning motivation mediates the influence of social media use intensity on learning concentration. By integrating previous findings, this study is expected to make a theoretical contribution in elucidating the mechanisms of social media relationships and learning concentration, as well as provide practical implications for the management of social media use in educational contexts.

## Material and Methods

This study uses a quantitative approach with an explanatory design through a survey method to test the influence of the intensity of social media use on learning concentration with learning motivation as a mediating variable. The research population is active students at one university, with a sample of 100 students determined using the quota sampling technique. The determination of quotas is carried out based on certain characteristics, such as study programs or batches, so that the distribution of respondents remains proportional and in accordance with the needs of the SEM-PLS analysis. The research instrument was in the form of a closed questionnaire using a five-level Likert scale (1 = strongly disagree to 5 = strongly agree), which was compiled based on the indicators that had been attached. The variables of the intensity of social media use are measured based on the concept of Soviana and Al Aziz, quoted from the journal (Mega, 2025), including the frequency of use, duration of time of use, content consumption activities, and interest and attention to social media content. Learning motivation variables are measured based on Aritonang indicators compiled from journals (Syachtiyani & Trisnawati, 2021), namely perseverance, tenacity, interest in learning problems, independence, orientation to challenges, and a strong stance in learning. The variables of learning concentration are measured based on Kuscahyanto's concept, quoted from the journal (Putu Artha Soma, Ibnu Ikhsan, Dotrimensi, 2025), including mind control, feeling control, concentration, focus during learning, and the ability to avoid distractions.

**Table 1.**

Blueprint of Instrument

| Variable | Dimensions/Indicators | Description of Indicators | Item Codes |
|---|---|---|---|
| **Intensity of Social Media Use (X)** | Frequency of use | The extent to which students access social media in their daily lives | SM1, SM2 |
| | Duration of use | The amount of time spent on social media per day | SM3, SM4 |
| | Content consumption activity | Engagement in viewing, reading, or interacting with content | SM5, SM6 |
| | Interest and attention | Level of attraction and focus on social media content | SM7, SM8 |
| **Learning Motivation (M)** | Perseverance | Persistence in completing academic tasks | LM1, LM2 |

| | | | |
|---|---|---|---|
| | Tenacity | Resilience in facing learning difficulties | LM3, LM4 |
| | Interest in learning | Curiosity and enthusiasm toward learning materials | LM5, LM6 |
| | Independence | Ability to learn without external dependence | LM7, LM8 |
| | Challenge orientation | Tendency to seek and enjoy challenging tasks | LM9, LM10 |
| | Strong learning stance | Firm commitment toward academic goals | LM11, LM12 |
| **Learning Concentration (Y)** | Mind control | Ability to regulate thoughts during learning | LC1, LC2 |
| | Emotional control | Ability to manage feelings while studying | LC3, LC4 |
| | Focus | Degree of sustained attention during learning | LC5, LC6 |
| | Attention during learning | Consistency in following learning activities | LC7, LC8 |
| | Avoiding distractions | Ability to resist internal and external disturbances | LC9, LC10 |

The research procedure began with the preparation of the instrument grid based on the operational definition of each variable, followed by testing the instrument on respondents outside the sample to ensure the clarity of the statement items. The data was then collected through the distribution of online questionnaires using digital platforms over a certain period of time until the quota of 100 respondents was met. After the data is collected, the editing, coding, and tabulation process is carried out before analysis. Data analysis was carried out using Structural Equation Modeling based on Partial Least Squares (PLS-SEM) with the help of SmartPLS software. The analysis stages include evaluation of the outer model through convergent validity tests (outer loading > 0.70 and AVE > 0.50), discriminant validity (HTMT or cross loading), and construct reliability (Cronbach's Alpha and Composite Reliability > 0.70). Next, an internal model evaluation was carried out by looking at the R-square value, effect size ($f^2$), predictive relevance ($Q^2$), and testing the significance of the path coefficient using bootstrapping with 100 samples to obtain t-statistics and p-values. The mediation test was carried out by testing the indirect effect between independent and dependent variables through mediator variables. With these procedural stages and clear analytical criteria, the research can be replicated by other researchers in similar contexts and populations.

## Results and Discussion
### Results

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 variant models that will be analyzed in this study.

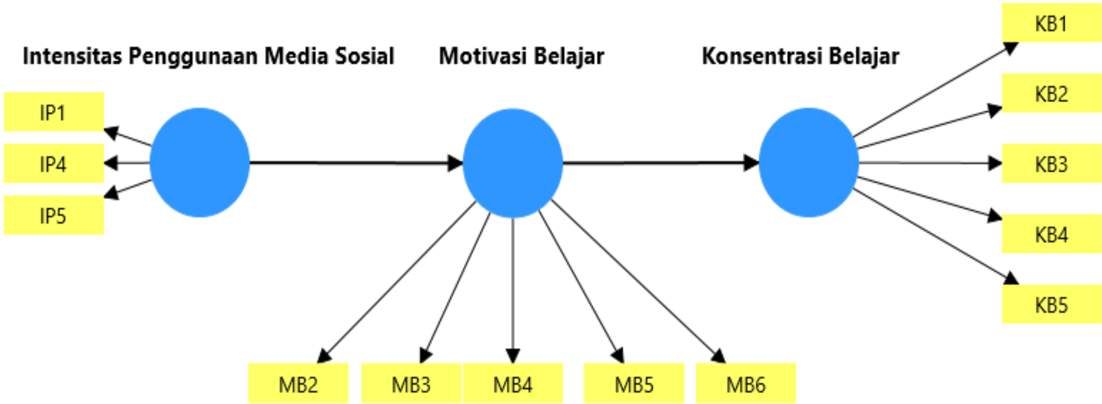

**Figure 1.** The research variable latent model

**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.

***Convergent Validity***

1. **Loading Factor Score/Outer Loading**

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 2.**

The output of the external loading estimation

| No. | Indicator | Outer Loading |
|---|---|---|
| 1 | IP1 | 0.757 |
| 2 | IP4 | 0.846 |
| 3 | IP5 | 0.769 |
| 4 | KB1 | 0.915 |
| 5 | KB2 | 0.907 |
| 6 | KB3 | 0.866 |
| 7 | KB4 | 0.922 |
| 8 | KB5 | 0.818 |
| 9 | MB2 | 0.814 |
| 10 | MB3 | 0.898 |
| 11 | MB4 | 0.733 |
| 12 | MB5 | 0.868 |
| 13 | MB6 | 0.826 |

The results of the outer loading showed that all indicators in each construct had a value above 0.70, so that they met the criteria for convergent validity in the SEM-PLS reflective measurement model. In the Social Media Usage Intensity variable, the loading values IP1 (0.757), IP4 (0.846), and IP5 (0.769) indicate that each indicator has a strong correlation with its construct. In the Learning Concentration variable, all indicators have very high values, namely KB1 (0.915), KB2 (0.907), KB3 (0.866), KB4 (0.922), and KB5 (0.818), which indicates that these indicators are very representative in explaining the construction of learning concentration. Similarly, in the Learning Motivation variable, the indicators MB2 (0.814), MB3 (0.898), MB4 (0.733), MB5 (0.868), and MB6 (0.826) also showed a strong contribution to latent constructs. In SEM-PLS, an outer loading value of ≥ 0.70 indicates that the indicator is able to explain more than 50% of the variance in its construct, so it is considered reliable and valid in a convergent manner. Since all indicators are above this limit, no indicators need to be eliminated, and the measurement model can be declared to have met the requirements of convergent validity. It is feasible to proceed to the reliability evaluation and testing stage of the structural model.

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 3.**

Average Variance Extracted (AVE)

| Variables | Average variance extracted (AVE) |
|---|---|
| **Intensity of Social Media Use** | 0.626 |
| **Learning Concentration** | 0.786 |
| **Learning Motivation** | 0.688 |

The Average Variance Extracted (AVE) value of the three variables indicates that the entire construct has met the criteria of convergent validity. In the SEM-PLS analysis, a variable is declared valid if the AVE value is greater than 0.50. This means that the construct is able to explain more than 50% of the variance of the indicators that measure it. In this study, the Intensity of Social Media Use had an AVE of 0.626, Learning Concentration of 0.786, and Learning Motivation of 0.688. All of these values are above the minimum limit of 0.50. Thus, it can be concluded that all variables in this study have met the criteria for convergent validity and are suitable for use in subsequent analysis.

***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 values, HTMT, and or Fornell-Larcker values and latent variables.

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 4.**

The results of cross-loading

| Indicator | Variables | | |
|---|---|---|---|
| | **Intensity of Social Media Use** | **Learning Concentration** | **Learning Motivation** |
| **IP1** | **0.757** | 0.326 | 0.349 |
| **IP4** | **0.846** | 0.332 | 0.41 |
| **IP5** | **0.769** | 0.312 | 0.434 |
| **KB1** | 0.352 | **0.915** | 0.743 |
| **KB2** | 0.333 | **0.907** | 0.755 |

| | | | |
|---|---|---|---|
| **KB3** | 0.434 | **0.866** | 0.733 |
| **KB4** | 0.369 | **0.922** | 0.695 |
| **KB5** | 0.319 | **0.818** | 0.668 |
| **MB2** | 0.286 | 0.777 | **0.814** |
| **MB3** | 0.480 | 0.699 | **0.898** |
| **MB4** | 0.397 | 0.526 | **0.733** |
| **MB5** | 0.489 | 0.683 | **0.868** |
| **MB6** | 0.447 | 0.666 | **0.826** |

The table shows the results of cross-loading used to test the validity of the discriminator. In principle, each indicator should have the highest loading value on the construct it is measuring compared to other constructs. Based on these data, the IP1, IP4, and IP5 indicators have the highest loading in the Social Media Use Intensity variables compared to Learning Concentration and Learning Motivation. Similarly, the KB1 to KB5 indicator has the highest loading in the Learning Concentration construct, and the MB2 to MB6 indicator has the highest loading in the Learning Motivation construct. Although there is a correlation between constructs, the main loading value is still greater than cross-loading in other constructs. This shows that each indicator represents its own construct more than the other. Thus, the measurement model has met the criteria for discriminant validity based on the cross-loading approach.

1. **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 distinguished (liberal criteria).

**Table 5.**
Heterotrait-Monotrait Ratio

| Variables | Intensity of Social Media Use | Learning Concentration | Learning Motivation |
|---|---|---|---|
| **Intensity of Social Media Use** | | | |
| **Learning Concentration** | 0.505 | | |
| **Learning Motivation** | 0.638 | 0.890 | |

The results of HTMT (Heterotrait–Monotrait Ratio) show that the value of the relationship between constructs is below the recommended critical limit. In the evaluation of discriminant validity using HTMT, a model is declared to meet the criteria if the HTMT value is < 0.90 (or stricter < 0.85). Based on the table, the HTMT value between Social Media Use Intensity and Learning Concentration is 0.505, between Social Media Use Intensity and Learning Motivation is 0.638, and between Learning Motivation and Learning Concentration is 0.890. The entire value is still below the threshold of 0.90, so it can be concluded that each construct has adequate differences from each other. Although the value between Learning Motivation and Learning Concentration (0.890) is relatively high, the value is still within acceptable limits. Thus, the model has met the criteria of discriminant validity based on the HTMT approach, which means that each variable in this study actually measures a different construct.

2. **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 6.**
The square root of the Average Variance Extracted (AVE)

| Variables | Intensity of Social Media Use | Learning Concentration | Learning Motivation |
|---|---|---|---|
| **Intensity of Social Media Use** | **0.791** | | |
| **Learning Concentration** | 0.408 | **0.887** | |
| **Learning Motivation** | 0.506 | 0.812 | 0.830 |

The table shows the results of the discriminant validity test using the Fornell-Larcker criteria. In this method, the value of the square root of AVE (shown diagonally) must be greater than the correlation between constructs in the same row or column. The diagonal value for Social Media Use Intensity was 0.791, Learning Concentration was 0.887, and Learning Motivation was 0.830. All of these values are higher than the correlation between their respective variables (for example, the correlation between Learning Motivation and Learning Concentration of 0.812 is still smaller than 0.830 and 0.887). This shows that each construct is better able to explain the variance of its own indicators compared to other constructs. Thus, the model has met the criteria of discriminant validity based on the Fornell-Larcker Criterion.

3. **Latent Variable**

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 7.**
The comparison of the square root of the Average Variance Extracted (AVE)

| Variabel | Intensity of Social Media Use | Learning Concentration | Learning Motivation | AVE | $\sqrt{AVE}$ |
|---|---|---|---|---|---|
| **Intensity of Social Media Use** | 1 | 0.408 | 0.506 | 0.626 | 0.791 |
| **Learning Concentration** | 0.408 | 1 | 0.812 | 0.786 | 0.887 |
| **Learning Motivation** | 0.506 | 0.812 | 1 | 0.688 | 0.830 |

The table shows the results of the discriminant validity test using the Fornell-Larcker criterion, where the value of the square root of AVE (√AVE) on the diagonal must be greater than the correlation between constructs. The √AVE value for Social Media Use Intensity was 0.791, Learning Concentration was 0.887, and Learning Motivation was

0.830. Each of these values is higher than the correlation between variables, such as the correlation between Learning Motivation and Learning Concentration of 0.812, which is still smaller than 0.830 and 0.887. This shows that each construct has good discrimination and is able to distinguish itself from other constructs. Thus, the research model has met the criteria for discriminant validity based on Fornell-Larcker.

***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 process used to test the reliability value of indicators on a variable.

**Table 8.**

Cronbach's Alpha

| Variabel | Cronbach's alpha | Composite reliability (rho_a) | Composite reliability (rho_c) |
|---|---|---|---|
| **Intensity of Social Media Use** | 0.702 | 0.707 | 0.834 |
| **Learning Concentration** | 0.931 | 0.933 | 0.948 |
| **Learning Motivation** | 0.886 | 0.892 | 0.917 |

The results of the reliability test showed that all variables in this study had met the good reliability criteria. In SEM-PLS, the construct is declared reliable if Cronbach's Alpha and Composite Reliability values are greater than 0.70. The Social Media Usage Intensity variable had Cronbach's Alpha of 0.702 and Composite Reliability (rho_c) of 0.834, indicating adequate internal consistency. The Learning Concentration has a very high reliability value with Cronbach's Alpha 0.931 and Composite Reliability 0.948. Similarly, Learning Motivation showed strong reliability with Cronbach's Alpha 0.886 and Composite Reliability 0.917. Thus, all constructs can be declared reliable and consistent in measuring the variables being studied.

**Model FIT**

**Table 9.**

Results of Model FIT analysis

| Model FIT | Saturated model |
|---|---|
| SRMR | 0.077 |
| d_ULS | 0.535 |
| d_G | 0.347 |
| Chi-square | 195.247 < 21.026 |
| NFI | 0.808 |

SRMR (0.077) shows a value below the limit of 0.08, so the model is considered to have a small residual error rate and belongs to the good fit category. d_ULS (0.535) is a measure of the discrepancy between the empirical correlation matrix and the model; The smaller the value, the better, and this value indicates that the model is quite viable. d_G (0.347) also measures the distance between the model and the data; A relatively small value indicates a good model fit. Chi-square (195,247 > 21,026) indicates a difference between the model and the data, but in SEM-PLS, the chi-square value is not the main indicator of model feasibility because it is sensitive to sample size. The NFI (0.808) is above 0.80, which indicates that the model has an acceptable fit, although it has not reached the very good category (>0.90).

**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.

***Direct Effect***

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-PL.

**Table 10.**

The path coefficient (β), T-statistics, and p-values

| | **Original sample (O)** | **Sample mean (M)** | **Standard deviation (STDEV)** | **T statistics (\|O/STDEV\|)** | **P values** |
|---|---|---|---|---|---|
| **The Intensity of Social Media Use - > Learning Motivation** | 0.506 | 0.507 | 0.115 | 4.415 | 0.000 |
| **Learning Motivation -> Learning Concentration** | 0.812 | 0.809 | 0.048 | 17.084 | 0.000 |

The results of the direct influence test showed that the intensity of Social Media Use had a positive and significant effect on Learning Motivation with a coefficient of 0.506, a T value of 4.415 (>1.96), and a p-value of 0.000 (<0.05). This means that the higher the intensity of social media use, the higher the student's motivation to learn. In addition, Learning Motivation also has a positive and significant effect on Learning Concentration with a coefficient of 0.812, a T value of 17.084, and a p-value of 0.000. A high coefficient value indicates that learning motivation has a very strong influence on learning concentration. Thus, the two structural relationships in this research model are proven to be statistically significant.

***Indirect Effect***

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

**Table 11.**

Indirect effects testing results

| **Variabel** | **Original sample (O)** | **Sample mean (M)** | **Standard deviation (STDEV)** | **T statistics (\|O/STDEV\|)** | **P values** |
|---|---|---|---|---|---|
| **Intensity of Social Media Use -> Learning Motivation -> Learning Concentration** | 0.411 | 0.413 | 0.106 | 3.883 | 0.000 |

Indirect effects tests were conducted to determine the role of mediation in the research model. The results of bootstrapping showed that the indirect effect of Social Media Use Intensity on Learning Concentration through Learning Motivation was 0.411 with a T-value of 3.883 (>1.96) and a p-value of 0.000 (<0.05). This shows that the effect of mediation is statistically significant. This means that the intensity of social media use can increase learning concentration through increased learning motivation. Thus, Learning Motivation has been proven to play a mediator role in the relationship between Social Media Use Intensity and Learning Concentration.

## Discussion

The results of the analysis showed that the intensity of social media use had a positive and significant effect on student learning motivation with a path coefficient of 0.506 and a t-statistic value of 4.415 ($p < 0.001$). These findings answer the first research question about whether the intensity of social media use affects learning motivation. Empirically, the results show that the higher the frequency, duration, content consumption engagement, and students' interest and attention to social media, the higher their internal motivation to learn. These results are in line with findings Ramzan et al. (2023), which show that social media can be used to increase students' academic motivation through interaction, access to information, and social support in learning. (Sunoko et al., 2025) also found that the intensity of social media use has a significant influence on students' learning motivation, especially when social media is used for educational purposes. Similarly, Supriyadi et al. (2023) explained that the quality of information obtained through platforms such as YouTube can increase students' motivation to learn. Thus, the results of this study strengthen the argument that social media is not always distracting, but can be a source of motivational stimulation if used productively. Theoretically, these findings also reinforce the view that digital media has the potential to be an informal learning environment that expands access to knowledge and academic interaction.

The second research question related to the influence of learning motivation on learning concentration was also answered strongly through the results of the analysis, which showed a coefficient of 0.812 with a t-statistic value of 17.084 ($p < 0.001$). This score shows a significant influence, so it can be concluded that learning motivation is the main determinant in increasing student concentration during the learning process. These results are consistent with Budiharti et al. (2024), which states that learning motivation plays an important role in improving the learning outcomes of elementary school students, where motivation is the main driver of cognitive involvement in learning. The findings (Huang et al., 2025) also confirm that learning motivation has a direct impact on students' academic performance, both directly and through other psychological mechanisms. (Shao et al., 2024) added that learning motivation plays an important role as a mediator in increasing student engagement and academic achievement. Conceptually, students who have perseverance, tenacity in facing difficulties, and an orientation to challenges tend to be able to control their thoughts and feelings, focus their attention, and avoid distractions during the learning process. Therefore, these results confirm that motivation is not just an affective variable, but rather a psychological foundation that strengthens the capacity for concentration in an academic context.

The third research question regarding whether the intensity of social media use affects learning concentration through learning motivation as a mediator was also answered significantly. The results of the indirect effect test showed a coefficient of 0.411 with a t-statistic value of 3.883 ($p < 0.001$), which indicates a strong mediation effect. This means that the intensity of social media use does not directly increase concentration, but rather through increased motivation to learn first. These findings are in line with research (Rochman et al., 2023), which found that the use of social media can affect student learning achievement through motivation as a mediating variable. (Deng et al., 2022) explain that undirected use of social media can lead to multitasking and distractions, but when directed to academic activities, social media can increase learning engagement. Thus, the results of this study show that learning motivation functions as a psychological mechanism that transforms social media exposure into focused learning energy.

Theoretically, this mediation model makes an important contribution to understanding the dynamics of the relationship between digital variables and psychological variables in the context of higher education.

The significance of this study lies in its contribution to explaining the internal mechanisms that link the intensity of social media use with learning concentration. Amid the debate about the negative impact of social media, this study shows that its impact is highly dependent on the motivational state of the individual. The scientific contribution of this research enriches studies in the field of educational technology and educational psychology by presenting an empirical model that integrates variables of social media use intensity, learning motivation, and learning concentration in one structural analysis framework. This research is also relevant to a study (Alghamdi & Bogari, 2020) that shows the effectiveness of the Structural Equation Modeling approach in analyzing the influence of social media on psychological and behavioral variables. The practical implication is that lecturers and educational institutions need to direct the use of social media towards activities that support motivation, such as academic discussions, sharing learning materials, and digital collaboration. In addition, students need to be equipped with self-regulation skills so that the intensity of social media use does not turn into a distraction, as reminded by Zhang & Wei-min (2024) about the risk of passive use of social media to study boredom

However, this study has limitations. First, the cross-sectional research design has not been able to explain causal relationships longitudinally. Second, the use of quota sampling techniques limits the generalization of results to a wider population. Third, variable measurement using self-report instruments allows for a biased perception of respondents. Therefore, further research is recommended to use longitudinal or experimental designs to test causal relationships in more depth, as well as expand the scope of the sample to make the results more representative. However, overall, this study provides strong empirical evidence that the intensity of social media use can be a driving factor for learning motivation that ultimately increases student learning concentration, thus enriching the scientific discourse on the integration of social media in the context of higher education.

## Conclusion

This study concludes that the intensity of social media use has a positive and significant effect on learning motivation, and learning motivation has a positive and significant effect on student learning concentration. In addition, learning motivation has been shown to mediate the relationship between the intensity of social media use and learning concentration with a type of partial mediation. This means that social media not only has a direct impact on concentration, but also works through increased motivation to learn as an internal psychological mechanism. These findings confirm that social media is not always distracting, but can be a means that supports the learning process if used productively and in a targeted manner. The contribution of this research lies in strengthening the empirical model based on SEM-PLS, which explains the relationship between digital technology variables and the psychological aspects of student learning.

For further studies, it is recommended to expand the number and characteristics of the sample so that the results can be generalized more widely. The addition of variables such as self-regulated learning, self-control, or time management is also important to enrich the conceptual model. Longitudinal research can be conducted to see the stability of the relationship between variables in the long term. In addition, distinguishing between the use of social media for academic and non-academic purposes will provide a more specific understanding of its impact on the learning process.

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