Indonesian Journal of Educational Development (IJED)
Volume 7, Issue 1, 2026, pp. 259-273
ISSN: 2722-1059 (Online); ISSN: 2722-3671 (Print)
DOI: https://doi.org/10.59672/ijed.v7i1.6057

Explaining students' learning activity: Effects of motivation, environment, and self-efficacy

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Article Info

Article history:
Received January 19, 2026
Revised March 22, 2026
Accepted April 26, 2026
Available online May 20, 2026

Keywords: Learning activity, Learning environment, Motivation, Self-efficacy, Vocational students

Abstract. This research investigated the influence of motivation, learning environment, and self-efficacy on students' learning activity through an explanatory research approach. The population consisted of 3,481 vocational students in Palu City, Central Sulawesi, Indonesia, from which 359 respondents were selected using the Slovin formula and a simple random sampling. Data were collected using a Likert-scale questionnaire and analyzed through Partial Least Squares–Structural Equation Modeling with SmartPLS 3. The assessment of the measurement model confirmed adequate validity and reliability, as all constructs met the recommended thresholds for outer loading (> 0.70), composite reliability (> 0.70), and average variance extracted (> 0.50). The structural model analysis revealed that motivation exerted a positive and significant effect on learning activity ($\beta = 0.395$; $t = 4.506$; $p < 0.001$), while self-efficacy emerged as the strongest predictor ($\beta = 0.470$; $t = 6.919$; $p < 0.001$). Conversely, the learning environment did not demonstrate a significant direct effect on learning activity ($\beta = 0.062$; $t = 0.696$; $p = 0.487$). The results indicate that internal psychological factors, particularly self-efficacy and motivation, play a more substantial role than external environmental factors in shaping students' learning activity.

Introduction

Students' learning activity is a key indicator of successful instructional processes, particularly at the vocational education level, which emphasizes active engagement in both theoretical and practical learning (Iliescu et al., 2025; J. Li & Xue, 2023). Optimal learning activities reflect students' cognitive, affective, and psychomotor involvement, which ultimately contribute to the attainment of competencies and graduates' work readiness (Firdaus et al., 2024). However, learning activity does not occur in isolation; rather, it is influenced by a range of internal and external factors that interact dynamically within the learning context. The interaction between these factors simultaneously shapes students' learning behavior, particularly in terms of engagement, persistence, and active participation throughout the learning process (J. Li & Xue, 2023).

From an educational psychological perspective, internal variables such as learning motivation and self-efficacy are key determinants of students' active involvement in learning activities (Urhahne & Wijnia, 2023). Motivation is a fundamental mechanism that shapes the strength, orientation, and continuity of students' learning behaviors, whereas self-efficacy reflects students' confidence in

their ability to complete academic tasks effectively (Kong & Kong, 2024; Suwardika et al., 2026). Meanwhile, external factors in the form of the learning environment, whether physical, social, or psychological, also influence students' comfort, support, and opportunities to participate actively in learning activities (Khalil et al., 2025). Therefore, the interaction among motivation, learning environment, and self-efficacy represents a critical aspect in understanding the dynamics of students' learning activity (Basileo et al., 2024; Widana et al., 2019).

Although learning activities play a crucial role in enhancing the quality of vocational education, empirical findings suggest that students' engagement in these activities remains inconsistent and, in many cases, insufficient (Fitria et al., 2023). Limited participation in classroom discussions, low initiative in completing assignments, and a high degree of dependence on teacher guidance suggest fundamental issues affecting students' learning. These conditions highlight the need for in-depth empirical investigation to identify the factors that significantly influence students' learning activity (Lourenço & Paiva, 2025).

Various educational reports indicate that some vocational students tend to be passive learners, do not participate in discussions, and lack perseverance in completing academic tasks (Mukhlisin et al., 2023; Mukhlisin et al., 2025). This condition is supported by research across several vocational schools, which shows that students play a more passive role as recipients of information than as active participants in the learning process (Bakri et al., 2025). In addition, results from previous studies indicate that low learning activity is often related to internal factors, such as low motivation and self-efficacy, as well as external factors, such as less conducive learning environments (AlTwijri & Alghizzi, 2024; Ariza, 2023; Dheghu et al., 2026).

A substantial body of research has investigated the roles of motivation, learning environment, and self-efficacy in shaping students' learning activity. Overall, prior studies suggest that higher levels of learning motivation are associated with increased student engagement, conducive learning environments promote comfort and active participation, and self-efficacy functions as a key determinant of learning behavior by enhancing students' confidence and sustained effort (Juita et al., 2025; Mustapha et al., 2025; Wei & Cao, 2025). However, most of these studies have examined variables separately or employed correlational designs, thereby limiting their ability to comprehensively explain causal relationships. In addition, inconsistent findings regarding the effect of the learning environment on learning activity suggest a research gap warranting further investigation (Hu & Xiao, 2025; Liu, 2024; Wu et al., 2025).

In response to these issues, the present study offers novelty by employing an explanatory approach to simultaneously examine the effects of motivation, learning environment, and self-efficacy on students' learning activity within an integrated structural model. This study uses Partial Least Squares–Structural Equation Modeling (PLS-SEM), which enables examination of causal relationships and assessment of the relative contribution of each variable (Zheng & Xiao, 2024). In addition, this research makes a theoretical contribution by strengthening the study's conceptual framework, which places motivation, learning environment, and self-efficacy as the main determinants of student learning activities (Hendra et al., 2026). Moreover, by focusing on vocational students in Palu City, Central Sulawesi Province, this study provides new empirical evidence that enriches the literature on vocational education in the Indonesian context.

Accordingly, the present study aims to examine the effects of motivation, learning environment, and self-efficacy on learning activity among vocational high school students. Specifically, this study tests the hypotheses that: (a) Motivation exerts a positive and statistically significant influence on learning activity; (b) Learning environment demonstrates a significant positive effect on learning

activity; and (c) Self-efficacy exerts a positive and statistically significant influence on learning activity.

Method

Research Method and Design

This study adopted an explanatory research design, a methodological approach that investigates causal relationships among the variables examined (Metli, 2026; Soriano-Sánchez et al., 2026). This design was selected because it is well-suited for analyzing the combined direct and indirect impacts of psychological and environmental factors on students' learning activities. An explanatory model enables the researcher to investigate the mechanisms through which motivation, learning environment, and self-efficacy function as exogenous variables that influence learning activity, the endogenous variable (Xiong et al., 2026).

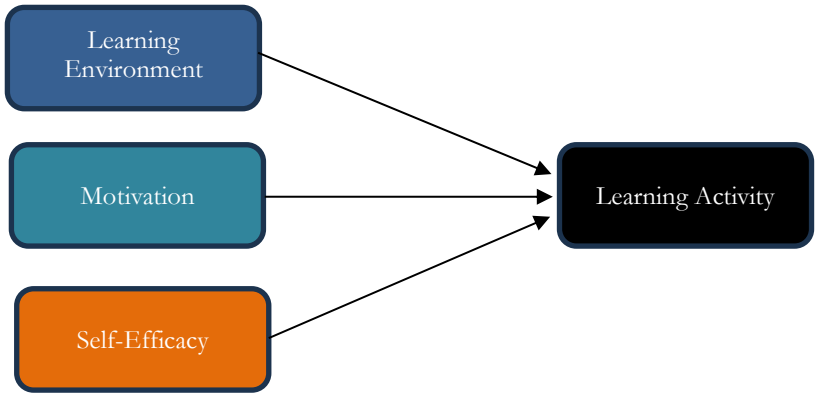

Image 1. Research Design

Participants and Technique Sampling

The population of this study comprised 3,481 vocational students enrolled in schools in Palu City, Central Sulawesi Province, Indonesia. To determine a representative sample size, the Slovin formula was applied, as it is appropriate when the population size is known, and a specific margin of error is defined (Santoso, 2023). In this study, a margin of error of 5% was used to ensure an acceptable level of precision (Lachenbruch et al., 1991). Using the Slovin formula, the minimum required sample size was determined to be 359 respondents. The participants were then selected using simple random sampling, which ensured that every vocational high school student in the population had an equal chance of being included in the study, as recommended by Endo et al. (2016) and Mulisa (2022). This procedure minimized sampling bias and enhanced the sample's representativeness of the population under study, thereby strengthening the generalizability of the research outcomes (Russell, 2025).

Research Setting and Timeline

This research was carried out at a vocational school in Palu City, Central Sulawesi Province, Indonesia. The schools in which the study was conducted represented diverse learning environments, enabling a more comprehensive analysis of the relationships among motivation, learning environment, self-efficacy, and learning activities. This research was carried out in a period of about three months. The first stage includes research preparation, such as instrument development and licensing management. The second stage is data collection, which involves distributing questionnaires to predetermined respondents. The final stage includes data processing and analysis, including data coding, statistical analysis, and interpretation of research results.

Data Collection and Research Instrument

The data collection technique in this study was conducted using an online questionnaire distributed via Google Forms. The research instrument was compiled using a 1–5 Likert scale to measure participants' approval of each statement. The scales used include: (1) Strongly Disagree, (2) Disagree, (3) Neutral, (4) Agree, and (5) Strongly Agree. The questionnaire contains 22 items, organized into four constructs: learning activity (5 items), learning environment (6 items), motivation (6 items), and self-efficacy (5 items). Each statement item is designed to represent indicators of each research variable.

The research instrument was developed based on motivation theory, learning environment theory, and self-efficacy theory. The motivation instrument was adapted from established measures by Chen et al. (2026), Dai et al. (2026), and Meng et al. (2026) and demonstrated a reliability coefficient of 0.784. The learning environment instrument was adapted from relevant theoretical frameworks (Y. Li & Singh, 2022; Pan et al., 2026) and exhibited a reliability coefficient of 0.858. The self-efficacy instrument was adapted from validated scales by Al-khresheh & Alkursheh (2024); Alkhalifah (2022); Dai et al. (2024), and showed a reliability coefficient of 0.860. The learning activity instrument was adapted from Jičínská et al. (2021); Naithani & Guleria (2024); Pasaribu et al. (2023), using appropriate measurement sources, and achieved a reliability coefficient of 0.825. The pilot test involved 65 students who were not included in the study and yielded a Cronbach's alpha reliability of 0.831, confirming the adequacy of the instrument prior to the main data collection.

Table 1. Research Instrument Grid

No.	Item Code	Indicator	Description
1	M1	Internal push	Motivation from within
	M2	Learning objectives	Clarity of purpose
	M3	Perseverance	Learning consistency
	M4	Interest in learning	Interest in the material
	M5	Hope for success	Confidence in learning outcomes
	M6	Learning efforts	Intensity of learning effort
2	LE1	Physical Environment	Comfort of the study room
	LE2	Teacher Support	The teacher's guidance and attention
	LE3	Social Interaction	Relationships with friends
	LE4	Learning Facilities	Availability of facilities
	LE5	Classroom Climate	Learning atmosphere
	LE6	Learning Safety	A sense of security in learning
3	SE1	Confidence in Ability	Academic confidence
	SE2	Overcoming Difficulties	Resilience in the face of problems
	SE3	Task Completion	Ability to complete tasks
	SE4	Confidence	Confidence in learning
	SE5	Decision Making	Confidence in learning
4	LA1	Participation	Activeness in learning
	LA2	Engagement	Involvement in study assignments
	LA3	Concentration	Focus when learning
	LA4	Discipline	Compliance in learning activities
	LA5	Initiatives	Willingness to study independently

Data Analysis Technique and Criteria

Data were analyzed using SmartPLS version 3.2.9, a variance-based Structural Equation Modeling (SEM) approach suitable for explanatory research with latent constructs. The analysis involved evaluating the measurement and structural models. The measurement model assessment focused

on indicator reliability (outer loading), internal consistency (composite reliability), convergent validity (Average Variance Extracted), and discriminant validity using cross-loading analysis, the Fornell–Larcker criterion, and the Heterotrait–Monotrait Ratio (HTMT). After confirming the adequacy of the measurement model, the structural model was evaluated by examining path coefficients, t-statistics, p-values through bootstrapping, and effect sizes (f^2) to test the hypothesized relationships among the constructs.

Results and Discussion

Measurement Model

The measurement model evaluation was conducted by examining indicator loadings, composite reliability (CR), and Average Variance Extracted (AVE). Indicator loading values exceeding 0.70 demonstrate that the measurement items adequately and reliably reflect their corresponding latent constructs (Fakhkhari et al., 2021). CR values exceeding 0.70 confirmed adequate internal consistency of the measurement items (Schermelleh-Engel et al., 2003), while AVE values exceeding 0.50 indicated sufficient convergent validity (Henseler et al., 2014). The results of the measurement model evaluation are presented in Table 1.

Table 2. Result of Measurement Model

Construct	Item Code	Loading	CR	AVE
Learning Activity	LA1	0.738	0.92	0.699
	LA2	0.869		
	LA3	0.867		
	LA4	0.876		
	LA5	0.821		
Learning Environment	LE1	0.846	0.939	0.72
	LE2	0.818		
	LE3	0.838		
	LE4	0.896		
	LE5	0.850		
	LE6	0.841		
Motivation	M1	0.867	0.945	0.742
	M2	0.880		
	M3	0.890		
	M4	0.808		
	M5	0.860		
	M6	0.862		
Self-Efficacy	SE1	0.857	0.941	0.761
	SE2	0.874		
	SE3	0.880		
	SE4	0.875		
	SE5	0.875		

Based on the measurement model evaluation presented in Table 1, all constructs demonstrated satisfactory levels of validity and reliability. The outer loading values for all indicators ranged from 0.738 to 0.896, exceeding the recommended threshold of 0.70. This indicates that each indicator was strongly associated with its respective latent construct and adequately measured the underlying concept. Specifically, indicators of learning activity, learning environment, motivation, and self-efficacy consistently showed high loading values, confirming indicator reliability across all constructs.

Regarding internal consistency, all constructs demonstrated composite reliability (CR) values that substantially exceeded the recommended threshold of 0.70, with values ranging from 0.920 to

0.945. This indicates a strong level of consistency among the indicators within each construct, confirming that the measurement items reliably represented their respective latent variables. Notably, the motivation construct achieved the highest CR value, suggesting particularly strong internal coherence among its indicators.

Furthermore, the Average Variance Extracted (AVE) values for all constructs exceeded the recommended minimum threshold of 0.50, ranging from 0.699 to 0.761. These findings confirm that all indicators met the criteria for convergent validity, indicating that each construct explained more than half of the variance in its measurement items. Notably, the self-efficacy construct exhibited the highest AVE among the constructs, suggesting particularly strong convergence among its indicators.

Overall, the findings of the measurement model evaluation indicate that all constructs satisfy the established criteria for indicator reliability, internal consistency, and convergent validity. Accordingly, the measurement model was deemed robust and appropriate for further structural model analysis. These findings suggest that the measurement indicators employed in this study were not only statistically acceptable but also theoretically sound in representing the intended constructs. The consistently high outer loading values across learning activity, learning environment, motivation, and self-efficacy indicate that the operationalization of each construct aligns well with established theoretical frameworks in educational psychology. This alignment strengthens the interpretability of the subsequent structural model results, as the relationships among constructs are based on well-measured latent variables.

Image 2. The Result of the Measurement Model

Discriminant validity was evaluated by applying cross-loading analysis, the Heterotrait–Monotrait Ratio (HTMT), and the Fornell–Larcker criterion to verify that each measurement item loaded more strongly on its intended latent construct than on any other construct within the model (Gomez et al., 2020; Voorhees et al., 2015). Furthermore, the Heterit-Monit ratio and the Fornell-Larcker criterion ratio were used to confirm discriminant validity, ensuring that each construct was distinct from the others within the conceptual framework (Zhu & Luo, 2024). The results indicate that all indicators loaded more strongly on their respective latent variables, confirming adequate discriminant validity. The results of the cross-loading analysis are presented in Table 2.

Table 3. Result of Cross Loading

Item Code	Learning Activity	Learning Environment	Motivation	Self-efficacy
LA1	0.738	0.527	0.581	0.788
LA2	0.869	0.549	0.636	0.584
LA3	0.867	0.560	0.593	0.621
LA4	0.876	0.559	0.633	0.586
LA5	0.821	0.463	0.615	0.524
LE1	0.470	0.846	0.64	0.491
LE2	0.471	0.818	0.585	0.455
LE3	0.556	0.838	0.619	0.510
LE4	0.646	0.896	0.691	0.579
LE5	0.539	0.850	0.629	0.483
LE6	0.543	0.841	0.645	0.520
M1	0.590	0.662	0.867	0.493
M2	0.648	0.619	0.880	0.548
M3	0.615	0.682	0.890	0.555
M4	0.584	0.578	0.808	0.511
M5	0.656	0.686	0.860	0.539
M6	0.688	0.646	0.862	0.567
SE1	0.621	0.524	0.469	0.857
SE2	0.674	0.619	0.598	0.874
SE3	0.666	0.503	0.551	0.880
SE4	0.621	0.536	0.529	0.875
SE5	0.695	0.439	0.562	0.875

Discriminant validity was assessed through the classification of cross-loading values, as reported in Table 2. The analysis revealed that each measurement indicator exhibited its highest loading on the construct it was intended to measure, relative to all other constructs included in the model. This pattern indicates that each indicator is more strongly associated with its respective latent construct than with any alternative constructs. Accordingly, these results confirm that the measurement model satisfies the criteria for discriminant validity, thereby reinforcing the conceptual clarity and empirical distinctiveness of the constructs examined in this study.

These findings indicate that each construct in the model represents a conceptually distinct dimension of students' learning processes. The clear separation among motivation, learning environment, self-efficacy, and learning activity suggests that the constructs capture different aspects of students' experiences and behaviors rather than overlapping or redundant dimensions (Purnadewi et al., 2023). This distinctiveness is essential for ensuring that the relationships

examined in the structural model reflect genuine theoretical associations rather than artifacts of multicollinearity among constructs (Hong et al., 2024; Pham et al., 2025).

Table 4. HTMT (Heterotrait–Monotrait Ratio)

Variable	Learning Activity	Learning Environment	Motivation	Self-efficacy
Learning Activity				
Learning Environment	0.696			
Motivation	0.802	0.808		
Self-efficacy	0.819	0.648	0.67	

Discriminant validity was further assessed using the HTMT, as presented in Table 3. The findings show that all HTMT values across constructs were below the recommended cutoff of 0.85, indicating satisfactory discriminant validity. In particular, the HTMT values for the relationships between learning activity and learning environment (0.696), learning activity and motivation (0.802), and learning activity and self-efficacy (0.819) remained within acceptable thresholds. Similarly, the HTMT values between learning environment and motivation (0.808), learning environment and self-efficacy (0.648), and between motivation and self-efficacy (0.670) further confirm sufficient construct discrimination.

Table 5. Fornell-Lacker Criteria

Variable	Learning Activity	Learning Environment	Motivation	Self-efficacy
Learning Activity	0.836			
Learning Environment	0.64	0.848		
Motivation	0.734	0.75	0.861	
Self-efficacy	0.753	0.6	0.623	0.872

Discriminant validity was further evaluated using the Fornell–Larcker criterion, as presented in Table 4. The results indicate that the square root of the Average Variance Extracted (AVE) for each latent construct learning activity (0.836), learning environment (0.848), motivation (0.861), and self-efficacy (0.872) exceeds the corresponding inter-construct correlations. This finding demonstrates that each construct explains more variance in its own indicators than in the indicators of other constructs in the model.

Specifically, the diagonal values representing the square roots of AVE are consistently higher than the off-diagonal correlation values in the same row and column. This pattern confirms that the constructs are empirically distinct and that there is no substantial overlap among the measured variables. Therefore, based on the Fornell–Larcker criterion, the measurement model satisfies the requirements for discriminant validity, providing further support for the robustness of the construct measurement and for proceeding with the structural model analysis.

These findings indicate that each construct in the model represents a conceptually distinct latent variable and that there is no substantial overlap among the constructs. Therefore, the HTMT results confirm that the measurement model meets the criteria for discriminant validity, providing a solid foundation for interpreting the structural model results. These results are consistent with the Fornell–Larcker criterion and the HTMT ratio, where the square root of the Average Variance Extracted (AVE) for each latent construct exceeds its correlations with other reflective constructs in the model, thereby ensuring adequate discriminant validity (Obiosa, 2020).

Evaluation of Structural Model

The structural model was assessed to examine the hypothesized relationships among the constructs. The structural model evaluation focused on two main criteria: path coefficients and effect size (f-square). The path coefficients were analyzed to determine the direction, strength, and significance of the relationships among the exogenous variables motivation, learning environment, and self-efficacy, and the endogenous variable learning activity (Lei et al., 2024; Zheng & Xiao, 2024). In addition, the f-square values were examined to assess the magnitude of each exogenous variable's contribution to the explained variance of the endogenous construct (Aljehani, 2024; Dai et al., 2024). Together, these analyses provide a comprehensive understanding of the structural relationships and the relative influence of each predictor within the model.

Table 6. Path Coefficient

Relationship	Original Sample	Sample Mean	Standard Deviation	T Statistics	P Values	Hypotesis
Learning Environment -> Learning Activity	0.062	0.058	0.089	0.696	0.487	Not Significant
Motivation -> Learning Activity	0.395	0.398	0.088	4.506	0.000	Significant
Self-efficacy -> Learning Activity	0.47	0.471	0.068	6.919	0.000	Significant

The results of the structural model analysis presented in Table 3 indicate that motivation and self-efficacy have positive, significant effects on learning activity, whereas the learning environment does not exhibit a significant direct effect. The path coefficient from motivation to learning activity ($\beta = 0.395$; $t = 4.506$; $p < 0.001$) indicates a statistically significant positive relationship: higher levels of student motivation lead to greater engagement in learning activities. This finding underscores the critical role of motivational factors in promoting active learning behavior among students. This finding is consistent with previous studies that emphasize the importance of motivation in enhancing students' engagement in learning (da Costa & Reis, 2025; Lei et al., 2024; Mohamed et al., 2024).

Self-efficacy exhibits the strongest influence on learning activity, with a path coefficient of $\beta = 0.470$ ($t = 6.919$, $p < 0.001$). This result indicates that students' confidence in their ability to successfully perform learning tasks substantially enhances their learning activity. The strong effect of self-efficacy highlights its importance as a key psychological determinant of student engagement. This finding is consistent with prior research in educational psychology, which suggests that students with higher self-efficacy are more likely to demonstrate greater persistence, effort, and active involvement in learning activities, as they perceive academic challenges as manageable rather than threatening (Chen et al., 2026; Lin & Zhu, 2024; Soriano-Sánchez et al., 2026).

In contrast, the path from learning environment to learning activity is not statistically significant ($\beta = 0.062$, $t = 0.696$, $p = 0.487$). This suggests that, within the context of this study, the learning environment does not directly influence students' learning activity. However, this finding does not negate the role of the learning environment, as its influence may occur indirectly through psychological factors such as motivation or self-efficacy. This result contrasts with several previous studies that have reported a significant direct effect of the learning environment on students' learning activity, particularly in contexts where instructional support, classroom climate, and learning facilities strongly shape students' engagement (Adolfo & Ducot, 2025; Pondang et al., 2025). The discrepancy may be attributed to contextual differences, measurement approaches, or the possibility that the learning environment exerts its influence primarily through mediating variables rather than through direct pathways (Bernal & Palma, 2025; Lago, 2025).

Overall, the structural model results indicate that internal psychological factors play a more dominant role than external environmental factors in shaping students' learning activity. These findings provide empirical support for the emphasis on strengthening students' motivation and self-efficacy to enhance active learning behaviors. This suggests that interventions aimed at improving learning outcomes should prioritize strategies that foster students' internal readiness, such as goal-setting, self-regulated learning, and confidence-building, rather than relying solely on improvements to physical or instructional environments (Mendoza & Yan, 2025). Furthermore, the dominance of psychological factors implies that students' perceptions and beliefs about their own abilities may serve as key mechanisms through which external conditions are translated into actual learning behaviors. Consequently, educational programs that integrate motivational enhancement and self-efficacy development are likely to be more effective in promoting sustained student engagement and active participation in learning activities (Hammoudi et al., 2025).

Table 7. Effect Size (F-Square)

Construct	Learning Activity
Learning Environment	0.005
Motivation	0.192
Self-efficacy	0.399

The effect size analysis using f-square (f^2), as presented in Table 4, provides insight into the relative contribution of each exogenous construct to learning activity. The results show that the learning environment has a negligible effect size ($f^2 = 0.005$), indicating a very weak contribution to the variance in learning activity. This finding is consistent with the path coefficient results, which suggest that the learning environment does not exert a substantial direct influence on students' learning activity in this model. In contrast, motivation has a moderate effect on learning activity ($f^2 = 0.192$), suggesting that it plays an important role in explaining students' engagement in learning activities. Furthermore, self-efficacy exhibits a strong effect size ($f^2 = 0.399$), indicating that it is the most influential predictor of learning activity among the variables examined. This result reinforces the structural model's findings, highlighting self-efficacy as a key determinant of students' active participation in learning.

Overall, the f-square analysis confirms that internal psychological factors, particularly self-efficacy and motivation, contribute more substantially to learning activity than external environmental factors within the proposed model. This finding underscores the importance of prioritizing psychological empowerment in educational interventions, as students' beliefs about their capabilities and their intrinsic drive to learn appear to exert a stronger influence on active learning than contextual conditions alone. The dominance of self-efficacy further suggests that students who perceive themselves as capable are more likely to translate learning opportunities into meaningful engagement, even in less supportive environments. Consequently, educational practices that systematically strengthen motivation and self-efficacy may yield greater impact in fostering sustained learning activity than strategies focusing solely on environmental improvements (Rimasiute-Knabikiene & Diržytė, 2025; Tu et al., 2025).

Limitation of Study

Notwithstanding its contributions, this study is subject to several limitations. First, the use of a cross-sectional research design limits the ability to draw conclusions about causal relationships over time. Although the explanatory model identified significant associations among motivation, learning environment, self-efficacy, and learning activity, longitudinal data would provide a more robust understanding of how these relationships evolve throughout students' learning experiences. Second, the data were collected using a self-report questionnaire, which may be subject to response bias, including social desirability and common method bias. Students' perceptions of their

motivation, self-efficacy, and learning activity may not fully reflect their actual behaviors in classroom settings. Third, the study focused on vocational students in selected regions of South Sulawesi, which may limit the generalizability of the findings to other educational contexts, regions, or educational levels. Differences in curriculum implementation, school culture, and socio-economic backgrounds across regions may influence the observed relationships.

Conclusion

The results of this study confirm that motivation and self-efficacy have a positive and significant effect on students' learning activities, with self-efficacy as the most dominant predictor, while the learning environment does not show a significant direct influence. These findings show that internal psychological factors play a greater role in shaping learning activities than external factors. These findings highlight the critical role of students' internal psychological factors in fostering active learning behaviors. In contrast, the learning environment did not exhibit a significant direct effect on learning activity, suggesting that its influence may operate indirectly through psychological factors such as motivation and self-efficacy. Overall, the results indicate that internal psychological factors play a more dominant role than external environmental factors in shaping students' learning activity. The findings of this study have important implications for educational practices, especially in vocational education, as improving student learning activities should focus on strengthening internal psychological factors, particularly motivation and self-efficacy.

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