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The Influence of Emotional Intelligence, Self-Efficacy, and Learning Motivation on Student Achievement

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Abstract

Student achievement is not only determined by cognitive abilities, but also by non-cognitive factors that influence the student's learning process. In this case, emotional intelligence, self-efficacy, and learning motivation are important aspects that deserve attention. This study examines the influence of emotional intelligence, self-efficacy, and learning motivation on the achievement of Jambi University students. Quantitative research was conducted using Google Forms survey data from 360 students, which was determined by G-Power analysis. Data were analyzed using PLS-SEM. A significant relationship was found between the factors. Academic achievement is strongly influenced by emotional intelligence and self-efficacy ($p < 0.05$). In addition, emotional intelligence and self-efficacy increase learning motivation and academic achievement ($p < 0.05$). Academic achievement is moderately influenced by learning motivation. These findings emphasize the relevance of emotional intelligence, self-efficacy, and motivation for student success. These three factors significantly influence student academic success. Emotional intelligence helps students manage emotions and build positive social relationships. Self-efficacy encourages students' self-confidence in completing tasks. Learning motivation is the main driver that increases students' commitment to learning. The novelty of this research lies in the integration of emotional intelligence, self-efficacy, and motivation which are studied holistically to understand their influence on student achievement and the direct and indirect influence of emotional intelligence, self-efficacy, and learning motivation on academic achievement among students.

Keywords: Emotional Intelligence, Learning Achievement, Learning Motivation, Self-Efficacy

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INTRODUCTION

Education plays an important role in shaping the quality of competent and competitive human resources. Quality education certainly comes from a quality learning process. This can be created if educators and students are actively involved in it through interacting in a learning activity. Student learning achievement is often used as the main indicator of success in the world of education. However, academic success is not only determined by cognitive abilities, but also by non-cognitive factors that influence the student's learning process. According to Law Number 20 of 2003 concerning the National Education System, universities are required to educate citizens who are moral, intellectual, and socially responsible. This means that education is not just a process or just knowledge, but also a process of changing ethics, norms or morals of individuals or groups (Pramana, 2020). In this case, emotional intelligence, self-efficacy, and learning motivation are important aspects that deserve attention. Learning outcomes are a measure of how much students understand the material being taught (Ningsih & Hayati, (2020). One way that can be used to see learning outcomes can be seen from the factors that influence them (Rangkuti, 2021). Many factors can influence the high and low learning outcomes of students, namely factors related to self-efficacy, intellectual intelligence, emotional intelligence, spiritual intelligence, talent, interests, motivation and metacognitive awareness (Pangestika, 2016).

According to Nurhayati (2018), emotional intelligence is the ability to express feelings, awareness and understanding of emotions, the ability to motivate oneself, the ability to regulate and control them. Emotional intelligence ensures that students think logically so that they can solve problems well (Ningsih et al., 2021). Individuals who cannot regulate and utilize their emotions well will more easily give up and give up. In addition, when emotions are uncontrolled, it will be difficult for someone to socialize. This causes someone to feel embarrassed and awkward asking for help when facing problems, thereby reducing the ability to solve the problems being faced (Leoh et al., 2019). Students also often have conflicts with their own friends because they have different opinions. This shows that students have not been able to utilize their emotions optimally. emotional intelligence involves regulating emotions, empathizing with others, and maintaining connections. This ability is important for managing academic stress and promoting collaborative learning. Students with high emotional intelligence will be able to control their emotions well so that brain performance can function better, and students will also find it easier to receive and digest lessons so that students with high emotional intelligence will also achieve high learning outcomes.

Another factor that influences students' success in improving learning outcomes is students' learning motivation. Motivation will activate and direct a person's behavior, give strength and direct a person's behavior to achieve a goal, and will affect the intensity of a person's behavior (Saenab, 2019). Lack of motivation on the part of students will prevent them from participating in learning activities and result in poor learning outcomes. Students who are motivated to learn, on the other hand, will do academic tasks well and produce superior academic results (Fatima et al., 2019). Compared to students who are less enthusiastic about learning, students who are highly motivated will complete more tasks faster. In addition, many students show a lack of learning motivation such as a lack of confidence to appear in front of the class and to express their ideas during learning.

In addition to emotional intelligence and motivation, self-efficacy is also a factor that influences student learning outcomes. Efficacy is a measure of a person's ability to perform a task successfully or unsuccessfully, correctly or incorrectly, or as needed. Self-efficacy is the belief that a person can exert some degree of control over internal processes and external events (Teguh Pambudi et al., 2019). Self-efficacy is a person's belief that he can master a situation and produce positive results and self-efficacy is one of the important things in increasing student learning activity, because students will be confident in their abilities to face problems in the learning process (Rahmi, et al. 2024). This belief affects students' courage in facing learning challenges. Students with high self-efficacy will work hard and not give up easily in learning so that students will be encouraged to find the right ways to use the right skills and strategies to solve learning problems and make estimates of the results to be obtained (Suyanti, 2016).

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Although the importance of these three factors has been widely recognized, the combined impact of these psychological dimensions on academic achievement in Indonesian higher education has been under-researched despite substantial research. Sunarti (2019) and Wahyu Pratiwi & Hayati (2021) evaluated these parameters separately and found conflicting results. Self-efficacy had a less pronounced effect on academic achievement compared to emotional intelligence and learning motivation. In Indonesia, the moderating function of learning motivation in this interaction has received less attention. We investigated the direct and indirect effects of emotional intelligence, self-efficacy, and learning motivation on academic achievement among students at the University of Jambi to fill this gap. This study examined the direct effects of emotional intelligence and self-efficacy on academic achievement, the indirect effects of learning motivation on academic performance, and the mediating role of learning motivation. This study helps improve the performance of higher education students by analyzing these psychological elements. These findings can help educators, politicians, and university administrators create interventions that improve students' emotional intelligence, self-efficacy, and learning motivation. The results of this study are expected to provide theoretical contributions to the educational psychology literature as well as practical implications for the development of more holistic learning strategies, so that they can support the improvement of the quality of education as a whole.

The role of emotional intelligence is very important in realizing educational success (Ahmad, et.al., 2019). Emotional intelligence is a person's ability to monitor their feelings and emotions both in themselves and others, then be able to distinguish between the two and then use that information to guide their thoughts and actions (Ratnasari, 2020). Emotional intelligence involves the ability to recognize, understand, and manage one's own and others' emotions (Bru-Luna et al., 2021). Emotional intelligence is an individual's ability to motivate themselves and survive frustration; control impulses and not exaggerate pleasure; regulate moods and keep stress from paralyzing the ability to think, empathize and pray. (Awang, et al. 2019). Salovey & Mayer as quoted by Guntersdorfer & Golubeva (2018) explain that emotional intelligence is a regulator and supervisor in guiding thoughts and behavior in the five basic abilities, namely self-esteem, self-regulation, motivation, empathy, and social skills. Thus, emotional intelligence is always related to one's own thoughts and behavior towards others. The growth and development of children's emotions is very important because there are so many children who are so smart in school, so brilliant in their academic achievements, but they get angry easily, give up easily or act arrogantly and arrogantly. Efforts to apply emotional intelligence in life will have a positive impact on physical health, academic success, ease in building relationships with others, and increasing resilience. Managing emotions, which is an aspect of emotional intelligence, indirectly affects aspects of resilience, namely creativity (Lestari, et al. 2021). emotional intelligence influences the success of individuals and groups in Fostering a democratic and inclusive learning environment, teaching empathy through collaborative problem solving, providing constructive feedback, and demonstrating discipline and consistency in classroom norms can help students develop emotional intelligence.

Self-Efficacy is a self-confidence in the ability to solve a problem (Septhiani, 2022). Self-efficacy greatly determines how much confidence in the ability of each individual to carry out their learning process so that they can achieve optimal learning outcomes. Individuals who have high self-efficacy will manage themselves well to learn, because there is a belief in themselves that they will be able to complete any difficult task while studying, the belief that they are able to complete various tasks and hard work to complete all tasks and also if students have good self-confidence, then even though students do not have any potential, because of self-efficacy, the achievement of something will be greater (Astantri, 2021). Therefore, students need to develop and improve self-efficacy to make it easy to solve problems. Self-efficacy is a person's belief in their abilities to achieve the expected results, including referring to the extent to which students have confidence in their ability to succeed in doing schoolwork (Putri & Juandi, 2022). self-efficacy does not always represent actual ability, but is tied to the beliefs of each individual (Oktariani, 2018). Based on the explanation above, it can be concluded that self-ability is the belief that individuals have in their ability to complete tasks or solve problems independently with good results, which are evaluated based on assessments from their environment.

Learning motivation is one of the factors that determines the effectiveness of learning (Nuryasana, & Desiningrum, 2020). Motivation is a change in energy within a person which is characterized by the emergence of affective (feelings) and reactions to achieve goals (Ratna & Yahya, 2022). Learning motivation is a drive that comes from within and from outside the student that can provide a sense of pleasure and enthusiasm in learning so that students are able to achieve very good learning achievements (Afriansyah, 2022). Motivation is the will, desire, desire, power that drives someone to do something (Sari et al., 2022; Sundayana & Parani, 2023). Learning motivation is a psychological factor that determines whether or not there is a drive from within the individual to achieve goals which is characterized by awareness in learning, high enthusiasm and attention to the learning process (Febriandar, 2018).

Motivation is very important for the success of student learning (Arnandi, Siregar, & Fitriawan, 2022). Hermans stated that the characteristics of people who have motivation (Yulianto, Sisworo, & Hidayanto, 2022) are: (1) The tendency to work on challenging tasks but not beyond their abilities; (2) The desire to try and work alone and find their own solutions; (3) A strong desire to progress and achieve a level of success that is slightly higher than the level achieved previously; (4) Orientation towards the future, learning activities are seen as a path to realizing ideals; and (5) Persistence in Working. From the previous explanation, it can be concluded that learning motivation is a factor that includes all psychological forces that encourage students both from within and outside to engage in learning activities and provide direction to their learning process with the aim of achieving the desired learning outcomes.

According to Sunarto (1996), Winkel states that learning achievement is evidence of a person's success in learning activities and reflects the student's ability to achieve learning goals according to established standards. Meanwhile, Abu Ahmadi and Widodo Supriyono (1990) explain that learning achievement is the result of the interaction between various influencing factors, both from within the individual (internal factors) and from the external environment.

Based on these definitions, learning achievement can be explained as a measurable ability that includes knowledge, attitudes, and skills, which occur through active interaction between individuals who are learning and the material being studied during the learning process. The author evaluates student learning achievement using a norm-referenced assessment approach, where a person's learning achievement is compared to the learning achievement of their classmates. Additionally, to set a minimum learning achievement threshold, the author refers to the minimum Cumulative Achievement Index (GPA) set by Jambi University, which is GPA >3.

METHOD

Quantitative research methods are frequently utilized to analyze variable interactions in a systematic and measurable way. Quantitative research uses numerical data and statistical methods to explore relationships between variables, according to Creswell (2013). This method tests hypotheses or supports theoretical claims using empirical evidence. Quantitative research, according to Wiratna

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Sujarweni (2014), uses statistical tools or other quantitative methods to provide findings for precise and replicable investigations.

This study used a questionnaire to obtain data from Universitas Negeri Medan and Universitas Jambi students. According to Creswell in Sugiyono (2016), questionnaires allow researchers to acquire standardized replies from many people. Respondents were given statements or questions and had to submit them via Google Forms, a data gathering platform.

This study uses Partial Least Squares (PLS) Structural Equation Modeling (SEM) to analyze data and assess hypothesized variable correlations. SEM-PLS is a reliable tool for assessing causal links between independent and dependent variables in latent concept and complex model investigations, according to Parashakti, Rizki, and Saragih (2016). This method is ideal for this research since it allows for the analysis of direct and indirect effects among the variables.

This study employed a structured questionnaire with two main sections to collect data. The first portion collected respondents' age, gender, academic year, and faculty. This contextualized replies and ensured a diverse student sample. The second segment covered emotional intelligence, self-efficacy, learning motivation, and academic accomplishment in 20 statements. The items in this section were adapted from prior studies for validity and relevance. Specifically: (1) Five emotional intelligence questions were taken from Muh Ilhan Jaya's (2020) study, The Influence of Emotional Intelligence on MAN Wajo Students' Learning Achievement, (2) Yustika Nur's (2021) study, The Influence of Self-Efficacy and Learning Independence on Mathematics Learning Outcomes of Class VIII Students at SMP Negeri 28 Bulukumba, yielded five self-efficacy measures, (3) Melimunah's (2020) study, The Influence of Learning Motivation of Bidikmisi and Non-Bidikmisi Students on the Learning Achievement of Economics Education Students at Sriwijaya University, provided five learning motivation components.

The Influence of Motivation and Learning accomplishment between Commuter and Boarding Students on Social Studies Education Students at UIN Syarif Hidayatullah Jakarta by Felby Famella Iffah (2017) was used to develop five academic accomplishment items. All statements were scored on a Likert scale with six responses: "Always," "Strongly Agree," "Agree," "Neutral," "Disagree," and "Strongly Disagree." Scaling allowed for standardized study of respondents' impressions across all factors.

The sample for this study included 31,205 Universitas Jambi students. A representative sample was chosen since time, resources, and logistics made investigating the full population impossible. Sekaran and Bougie (2017) define a sample as a subset of a population intended to represent the wider group, while Creswell (2012) stresses the significance of accurately reflecting the population to provide generalizable conclusions. G*Power program estimated the minimum sample size for statistical reliability and power. Based on a target power level of 0.80, 360 respondents were sufficient for this study. Online Google Forms distribution made survey distribution and response gathering efficient. The 360-person sample represented the target population and supplied enough data for statistical analysis.

Surveys were the main data gathering strategy in this study. According to Creswell (2016), questionnaires are organized instruments that collect data by having respondents answer prepared questions or statements and return them to the researcher. This method was chosen for its efficiency and capacity to standardize huge sample responses. Google Forms made data collection easier by allowing digital dissemination and secure storage.

After collecting the data, the analysis began by categorizing the replies by the variables. This study used descriptive and inferential data analysis to answer research questions and evaluate hypotheses, following Sugiyono (2017). Mean scores and standard deviations were used to summarize the data and describe the variables. We estimated Pearson product-moment correlation coefficients to analyze variable relationships. T-tests were also used to find moderating variable differences. PLS-SEM was used to analyze causal correlations between variables. According to Ghozali (2014), this method is better for predictive modeling and less sensitive to sample size than covariance-based SEM. Three steps were taken to perform statistical methods using Smart PLS version 3.2.9:

Evaluation of the measurement model or outer model is conducted to test the validity and reliability of the model used. In the outer model with reflective indicators, evaluation is conducted through convergent and discriminant validity of the indicators forming the latent construct, as well as through reliability measurement through composite reliability and Cronbach's alpha for related indicator blocks (Ghozali, 2015). The procedure to measure this validity is as follows: 1. Estimate of Loadings and Significance, 2. Indicator Reliability (items), 3. Composite Reliability (construct), 4. Average Variance Extracted (AVE), 5. Discriminant Validity – HTMT.

The inner model analysis, also known as structural model analysis, aims to estimate the relationship between latent variables (Ghozali, 2015). The steps in Structural Model Assessment are as follows: 1. Evaluate structural model collinearity, 2. Examine size and Significance of Path Coefficients, 3. R2 of Endogenous Variables (in-sample prediction), 4. F2 Effect Size (in-sample prediction), 5. Predictive Relevance Q2 (primarily in-sample prediction).

RESULTS AND DISCUSSION

Based on the research results, it was found that emotional intelligence, self-efficacy, and learning motivation have a significant influence on student learning achievement. This means that the increase and decrease in student learning achievement are influenced by emotional intelligence, self-efficacy, and learning motivation.

Research Data Description

Table 1: Demographic Profile of Participants

Variable	Demographics	Frequency (N-1719)	Percentage	Mean
Faculty	Education And Teacher Training	164	45,6	3,12
	Economy And Bussines	27	7,5	
	Cultural Science	42	11,7	
	Law	42	11,7	
	Agriculture	14	3,9	
	Animal Husbandary	22	6,1	
	Forestry	12	3,3	
	Engineering	12	3,3	
	Health Sciences	22	6,1	
	Others	3	8	
	Total	360	100,0	
Year	2019	57	15,8	2,74
	2020	64	17,8	
	2021	155	43,1	
	2022	84	23,3	

Table 1 represents descriptive statistics results, where from the demographics it can be seen that students are divided based on faculty, namely: Education and Teacher Training (164/45.6%), Economy and Bussines (27/7.5%), Cultural Science (42/11.7%), Law (42/11.7%), Agriculture (14/3.9%), Animal

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Husbandry (22/6.1%), Forestry (12/3.3%), Engineering (12/3.3%), Health Sciences (22/6.1%), Others (3/8%). Then, also divided based on year, namely: 2019 (57/15.8%), 2020 (64/17.8%), 2021 (155/43.1%), 2022 (84/23.3%).

Data Analysis

The decision to utilize PLS-SEM in this research was based on its strong predictive capability. Furthermore, the research employs Smart PLS software (Hair et al., 2017) for data analysis and hypothesis testing. The Partial Least Squares Structural Equation Modeling (PLS-SEM) technique is employed to construct a model that elucidates the interconnections among variables that impact teacher performance. Scholars recognize the intricacy of the educational system and the presence of variables that impact modifications in that system (Mital, Moore, & Llewellyn, 2014). Hence, multiple variables are recognized as elements that exert an impact on teacher performance.

To provide a robust research design in Smart PLS, it is necessary to do instrument validation. This process ensures that the instrument accurately measures the intended variables (Hair, Matthews, Matthews, & Sarstedt, 2017). The research employs the methodologies of convergent validity and discriminant validity to validate the findings. Smart PLS 3.2.9 is utilized for this purpose. This process entails a series of sequential steps: 1. Input the raw data in Excel format using the CSV comma delimited format. 2. Once the raw data is entered, perform data analysis using the following steps:

Table 2: Descriptive Statistics of the Questionnaire, loading factor, VIF, AVE, rho_A, Composite Reliability, and Cronbach's (Joe F. Hair, Howard, & Nitzl, 2020

Construct	Indikator	Mean	Loading	VIF	Rho_A	Ave	Composite Reability	Cronbach's
Emotional Intelligence (X1)	KEMO3	4,308	0,872	2,194	0,781	0,696	0,873	0,779
	KEMO4	4,286	0,751	1,302				
	KEMO5	4,256	0,874	2,196				
Self Efficacy (X2)	EFIDI1	4,078	0,752	1,584	0,820	0,577	0,872	0,816
	EFIDI2	4,139	0,734	1,506				
	EFIDI3	4,186	0,726	1,582				
	EFIDI4	4,239	0,794	1,823				
	EFIDI5	4,153	0,787	1,714				
Learning Motivation (Z)	MOBE1	4,253	0,711	1,365	0,762	0,578	0,845	0,757
	MOBE2	4,322	0,781	1,564				
	MOBE3	4,297	0,784	1,453				
	MOBE4	4,061	0,762	1,448				
Learning Achievement (Y)	PRESBE2	4,122	0,757	1,453	0,780	0,596	0,855	0,775
	PRESBE3	4,203	0,778	1,574				
	PRESBE4	4,231	0,768	1,562				
	PRESBE4	4,369	0,786	1,481				

Table 2 reveals that the learning accomplishment variable has the greatest mean score (4.369), followed by the emotional intelligence variable (4.308), and the lowest mean score is observed in the learning motivation variable (4.061). The indicators EMO1, EMO2, LM5, and LA1 in the table above have a loading factor below 0.7, indicating that they are not valid for assessing their respective constructs. Therefore, these indicators need to be eliminated. Upon recalibration, the PLS software displays the results depicted in the figure below:

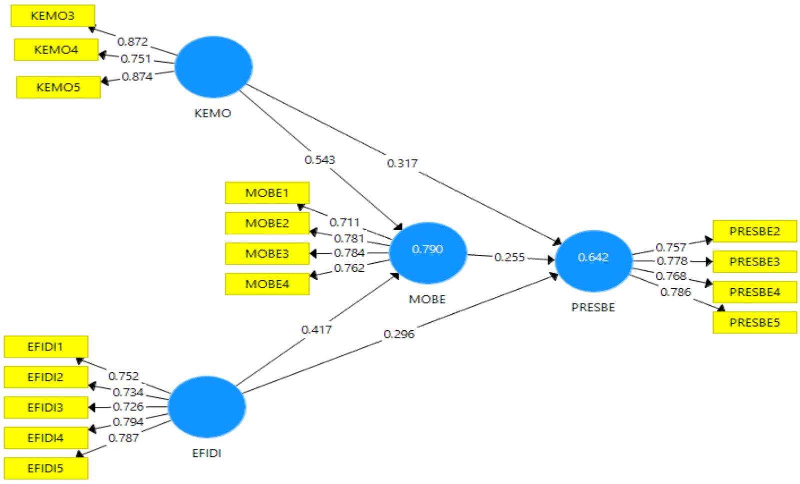

Figure 2. PLS Algorithm Management Results

After eliminating invalid indicators and performing outer loadings in the second step, all indicators in the diagram above have a loading factor greater than 0.70, indicating that they are valid for measuring their respective constructs.

Confirmatory Composite Analysis (CCA) with Reflective Measurement Model

The Standard Smart PLS 3 technique offers five suggested procedures for assessing validity, specifically: 1. Estimation of Loadings and Significance. The following are the key measures used in this study: 2. Indicator Reliability (for individual items), 3. Composite Reliability (for constructs), 4. Average Variance Extracted (AVE), and 5. Discriminant Validity - HTMT.

The CCA Model Measurement display provides further details regarding the measurement findings. First, assess the loadings of the indicators and determine their relevance in Stage 1. In order for the loading to be considered significant in a two-sided test at the 5% level, it must have a minimum value of 0.708 and a t-statistic more than ± 1.96 (Hair, Ringle, & Sarstedt, 2011). The T-statistics in PLS-SEM are derived through the implementation of the bootstrap process (Hair, et al., 2012). Wood (2005) proposed using confidence intervals in conjunction with PLS-SEM as a substitute option. Confidence intervals for indicator load can be utilized in a manner similar to t-statistics, and intervals that do not encompass 0 are considered to be statistically significant. Confidence intervals have the advantage of avoiding the binary approach to significance testing. This allows authors to explore alternative techniques for determining indicator loads that are practically significant. The indicator loading values from Cohen's study in 1994 are presented in Table 2.

Stage 2 involves calculating the squared individual indicator loads, which gives us a quantifiable assessment of the extent to which each variable indicator is associated to its corresponding construct. The concept being referred to is indicator reliability, as described by Hair et al. (2019). Table 2 displays the values for Composite Reliability, specifically X1 (0.873), X2 (0.872), Z (0.845), and Y (0.855).

Phase 3 Reliability of a construct can be assessed using two methods: Cronbach's Alpha (α) and composite reliability (CR). Both reliability criteria must exceed a threshold of 0.70. Composite reliability, a weighted measure, is considered more reliable than Cronbach's alpha, an unweighted measure, because indicators cannot be consistently examined simultaneously. Therefore, it is recommended to evaluate and report the composite reliability (CR) (Hair et al., 2019). It is important to be aware that measures of internal consistency dependability, such as Cronbach's alpha and composite reliability, can

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sometimes be excessively high. If the reliability is equal to or greater than 0.95, it indicates that the individual items are measuring the same concept and are therefore redundant. Redundancy refers to the situation where indicators measure the same notion, which leads to a lack of diversity necessary for ensuring the validity of multi-item constructs (Hair, et al., 2019). Table 2 displays the Cronbach Alpha values for the following variables: X1 (0.779), X2 (0.816), Z (0.757), and Y (0.775).

Convergent validity in Stage 4 can be assessed using the Average Variance Extracted (AVE). AVE is calculated by taking the average of the reliability of an indicator of a build. This statistic quantifies the average amount of variation that is common to both a concept and its constituent indicators. The AVE requirement requires a value of 0.5 (50%) or greater. The AVE values can be found in Table 2, specifically: X1 (0.696), X2 (0.577), Z (0.578), Y (0.596).

Discriminant validity at Stage 5 assesses the distinctiveness of a construct. Discriminant validity is established when the amount of shared variation within a particular construct (known as average variance extracted or AVE) is greater than the amount of shared variation between different constructs. The recommended approach is to utilize the heterotrait-monotrait ratio of correlations (HTMT) as proposed by Henseler, Ringle, and Sarstedt (2015). Researchers have the option to utilize cutoff values, such as 0.85 and 0.90, in order to interpret their HTMT results. In addition, Franke and Sarstedt (2019) have recently suggested conducting further significance testing that incorporates confidence intervals in order to further evaluate HTMT ratios and discriminant validity. The HTMT values may be found in Table 4.

Table 3 presents the outcomes of the validity test, which was conducted using the Smart PLS application. The test involved analyzing the cross-loading values of each study variable through statistical analysis. The results indicate that the cross-loading values of each research variable exceed 0.7. Thus, it can be inferred that all the indicators included in this study satisfy the criteria for instrument validity. The statistical measurement findings for discriminant validity assessment utilizing the Fornell-Larcker Criterion approach are presented in Table 3 below.

Table 3. Fornell-Larcker Criterion

Variabel	(X2)	(X1)	(Y)	(Z)
Self Efficacy (X2)	0.759			
Emotional Intelligence (X1)	0.707	0.834		
Learning Motivation (Y)	0.802	0.838	0.760	
Learning Achievement (Z)	0.724	0.740	0.758	0.772

The criterion of discriminant validity is demonstrated by the Fornell-Larcker method and the criterion of loading and cross-loading. The off-diagonal numbers presented in Table 4 represent the correlations between each variable, whilst the diagonal values represent the squared values of the average, indicating that the AVE value for each variable is significantly higher than that of other variables. Therefore, it can be inferred that the square root of AVE is more than the current relationships mentioned. If the square root of the average on each variable is greater than the connection values between variables in the form being evaluated, then the form can be considered to have acceptable discriminant validity (Hair et al., 2011), making it worthy of further research. The discriminant validity test findings obtained in this study utilizing the Heterotrait-Monotrait Ratio approach are displayed in Table 4 below:

Table 4. Heterotrait-Monotrait Ratio (HTMT)

Variabel	(X1)	(Y)	(X2)	(Z)
Emotional Intelligence (X1)				
Learning Motivation (Y)	0.792			
Self Efficacy (X2)	0.682	0.789		
Learning Achievement (Z)	0.664	0.791	0.714	

Several experts contend that cross-loading and Fornell-Larcker criteria exhibit reduced sensitivity in assessing discriminant validity. HTMT is a proposed alternate approach for assessing discriminant validity. This method utilizes a multi-trait and multi-method matrix as the foundation for measurement. In order to ensure discriminant validity between two reflective variables, it is necessary for the HTMT values to be less than 0.9 (Henseler et al., 2015). Based on the data presented in the table above, it can be inferred that the existing values are consistently below 0.9. Therefore, it can be determined that the research instrument utilized is deemed genuine.

Structural Model Assessment

The process of Structural Model Assessment involves the following steps: 1. Assess the collinearity of the structural model. 2. Analyze the magnitude and statistical significance of the path coefficients. 3. R2 represents the square of the endogenous variables for in-sample prediction. 4. F2 represents the square size for in-sample prediction. 5. Q2 represents the predictive relevance, particularly for in-sample prediction.

The evaluation of structural model findings in Stage 1 is greatly influenced by the fundamental concept and characteristics of multiple regression analysis. Consequently, the initial stage involves assessing the construction of the structural model to ascertain if there is a significant issue with multicollinearity. Structural models with significant multicollinearity can impact the magnitude of beta coefficients (weights) by either raising or reducing them, as well as altering the signs of these coefficients. Similar to reflective indicator structures, VIF values can be examined. If the VIF values are below 3.0, then multicollinearity will not be an issue. A different method involves examining the bivariate connection between scores of different constructs. When the bivariate correlation exceeds 0.50, the presence of multicollinearity can impact the magnitude and/or direction of route coefficients. When multicollinearity is identified as an issue, one recommended approach is to address it by creating a composite construct at a higher level. This involves combining separate constructs that are conceptually and theoretically similar, resulting in lower-level constructs that can be empirically supported (Cenfetelli & Bassellier, 2009). The structural model, depicted in Figure 3, illustrates the path coefficient values: X1->Y (0.317), X2->Y (0.296), Z->Y (0.255), X1->Z (0.543), X2->Z (0.417).

Stage 2: Assuming that multicollinearity is not an issue, the next step involves evaluating the magnitude and statistical significance of the path coefficients. This procedure enables researchers to evaluate the postulated associations between constructs. Path coefficients are standardized values that have a range of +1 to −1, although they seldom reach +1 or −1. This particularly applies to intricate models that have numerous separate constructs inside the structural model. A route coefficient value closer to 0 indicates a lesser ability to forecast the dependent construct (endogenous), whereas a value closer to the absolute value of 1 indicates a stronger ability to predict the dependent construct. The image above presents a hypothesis model that describes the partial contribution of each research variable, namely emotional intelligence, self-efficacy, and learning motivation, on student learning

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achievement. In order to assess the structural model, the study data is analyzed using the bootstrapping approach, which involves creating 500 sub-samples. The structural model for the five research hypotheses has been found to be statistically significant at a 7% significance level, as seen in Table 9.

Stage 3: Similar to multiple regression models, the predominant statistic used to assess the predictive ability of a structural model is R2. The coefficient of determination, also known as R-squared, is a statistical metric that quantifies the proportion of the variance in the dependent variable that can be explained by the independent variables in a regression model. Prediction is a metric that indicates the capacity to anticipate outcomes based on the data used for calculations. However, it is important to note that the R2 value should not be generalized to the entire population, as it is only applicable to the sample data (Rigdon, 2012; Sarstedt et al., 2014). While the minimal R2 value is theoretically 0, it is highly unlikely to be that low in practice. Similar to multiple regression, the inclusion of more independent variables (constructs) in the structural model leads to an increase in the R2 value. This is because the combined effect of the independent variables is directly associated with the dependent construct variable.

The highest possible R2 value is 1, however, such values are exceedingly uncommon. When assessing the magnitude of the R2 of the structural model, researchers should examine comparable empirical studies and utilize their findings as a benchmark, provided that the research situation is somewhat similar. Additionally, several fields of study also analyze the adjusted R2, which consistently decreases the R2 value by taking into account the sample size and the number of predictor variables. Adjusted R2 is a valuable tool when researchers include numerous predictor components in the structural model that are not statistically significant. This is similar to multiple regression analysis. The R2 values, also known as R Square, may be found in Table 5 below (Hair et al., 2017).

Table 5. (R2) R Square

	R Square	**R Square Adjusted**
Learning Motivation (Z)	0.790	0.789
Learning Achievement (Y)	0.642	0.639

Stage 4: The second measure of structural model predictive ability is effect size, which provides an estimate of the predictive ability of each independent construct in the model. To calculate this value, each predictor construct is systematically removed from the model (SmartPLS does this automatically), and a new R2 is calculated without the predictor. Then the R2 with the predictor in the model is compared to the R2 without the predictor in the model, and the difference between the two R2 values indicates whether the removed construct is a meaningful predictor of the dependent construct (Hair, et al., 2017). Effect size, called f2, is rated small, medium, and large. Values above 0.02 and up to 0.15 are considered small; values 0.15 and up to 0.35 are medium; and values 0.35 and above are large effects (Cohen, 1988). Effect size is also considered an in-sample predictive metric, F Square values can be seen in Table 6 below:

Table 6. F Square (Effect Size F2)

	Self Efficacy (X2)	Emotional Intelligence (X1)	Learning Motivation (Z)	Learning Achievement (Y)
Self Efficacy (X2)			0.414	0.086
Emotional Intelligence (X1)			0.702	0.082
Learning Motivation (Z)				0.038
Learning Achievement (Y)				

Stage 5: The third metric used to evaluate prediction is also the Q2 value, called blindfolding (Geisser, 1974; Stone, 1974). Some scholars consider this metric as an out-of-sample predictive power assessment, and to some extent, it is. But it is clearly not a strong predictive model metric like PLS-predict, explained in the next step. When interpreting Q2, values greater than zero are meaningful, while values below 0 indicate a lack of predictive relevance. Additionally, Q2 values greater than 0.25 and 0.50 represent medium and large predictive relevance of the PLS-SEM model. The variance inflation factor (VIF) is used to evaluate suitability. Multicollinearity is often found in statistics. Multicollinearity is a phenomenon where two or more independent variables or exogenous structures are highly correlated, leading to weak predictive power of the model (Shmueli et al., 2019). VIF values should be less than 5, as if more than 5 indicates the presence of inter-construct collinearity (Hair et al., 2020), Q2 Predict values can be seen in Table 7 below:

Table 7. Q2 Predict

	RMSE	**Mae**	**Q^2_predict**
Learning Motivation (Y)	0.476	0.337	0.788
Learning Achievement (Z)	0.621	0.471	0.624

The measurement of collinearity through the use of the Variance Inflation Factor (VIF) in this research can be seen in Table 4, which is the Measurement Model Table. From the table above, Validity Construct Multicollinearity occurs when predictor models are correlated and provide redundant responses.

Table 8. Model Fit

	Strated Model	Estimated Model	Model
SRMR	0.101	0.101	Fit
d_ULS	1.381	1.381	Fit
D_G	0.828	0.828	Fit
Chi-Square	1.470.191	1.470.191	Fit
NFI	0.618	0.618	Fit

Multicollinearity is measured by the variance inflation factor (VIF). If the VIF value exceeds 5.0, there is a problem with multicollinearity (Hair et al., 2017). In this research, there is no VIF value exceeding 5.0 (Table 2), which means that multicollinearity is not a problem in this research. The goodness of fit model test can be seen from the NFI value ≥ 0.662, which is declared fit. Based on the data processing conducted using the SmartPLS 3 program, the Model Fit value is obtained in Table 8 below: Based on the figure above about the hypothesis model display of the partial influence of each research variable, including emotional intelligence, self-efficacy, learning motivation, and student learning achievement. Further information about the measurement results from: 1) Path Coefficient, 2) STDEV, 3) T-Values, 4) P-Values can be seen in Table 9 below:

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Table 9. B. Results of measuring Path Coefficient, STDEV, T-Value, and P-Value

Hypothesis	Path Coefficient	P values	
H1: emotional intelligence (X1) -> student learning achievement (Y)	0.317	0.000	Supported
H2: self-efficacy (X2) -> student learning achievement (Y)	0.296	0.000	Supported
H3: learning motivation (Z) -> student learning achievement (Y)	0.255	0.011	Supported
H4: emotional intelligence (X1) -> learning motivation (Z)	0.543	0.000	Supported
H5: self-efficacy (X2) -> learning motivation (Z)	0.417	0.000	Supported

The table summarizes the results of hypothesis testing on the effects of emotional intelligence (X1), self-efficacy (X2), and learning motivation (Z) on student learning achievement (Y), as well as their interrelationships. All five hypotheses (H1 to H5) are supported, indicating that emotional intelligence and self-efficacy positively influence both student learning achievement and learning motivation, with path coefficients of 0.317 and 0.296 for learning achievement, and 0.543 and 0.417 for learning motivation, respectively, all with p-values of 0.000, showing strong statistical significance. Additionally, learning motivation has a moderate positive effect on student learning achievement with a path coefficient of 0.255 and a p-value of 0.011, which is also statistically significant. These findings suggest that emotional intelligence and self-efficacy play critical roles in enhancing both direct and indirect aspects of student achievement through increased learning motivation.

This research aims to identify and analyze the factors influencing student learning achievement at Jambi University using a sample of 360 students. The variables examined include emotional intelligence (X1), self-efficacy (X2), learning motivation (Z), and learning achievement (Y). Five hypotheses are proposed to explore the direct and indirect relationships among these variables. The findings support all hypotheses, with significant relationships aligning with the research questions.

The results indicate that emotional intelligence (X1) positively affects learning achievement (Y). This finding aligns with prior research. For example, Arum Purnaningtyas and Suharto, in their study titled The Influence of Emotional Intelligence on Student Learning Achievement in Cultural Arts Subjects at SMP, found a significant correlation between emotional intelligence and learning achievement. The calculated r-value of 0.349 exceeded the critical r r-value of 0.304 at a 5% error level, indicating that higher emotional intelligence is associated with better academic performance. Conversely, low emotional intelligence corresponds to lower academic outcomes. Emotional intelligence determines our potential to learn practical skills based on five elements: self-awareness, motivation, self-regulation, empathy, and social skills. Emotionally intelligent students have the ability to motivate themselves well and can control their emotions so they can focus on learning. (Anggraini, dkk. 2022).

Self-efficacy (X2) is found to have a positive influence on learning achievement (Y). This result is consistent with the findings of Ika Wahyu Pratiwi and Hayati (2021) in their research titled Self-Efficacy and Its Influence on Student Learning Achievement. They found that self-efficacy accounted for 7% of the variance in learning achievement among students of the 2016/2017 cohort at Borobudur University, emphasizing its partial but significant role in academic performance. The strong relationship between self-efficacy and personality makes someone with a strong personality have the confidence to solve certain problems. Self-potential will be optimally actualized if they have adequate self-efficacy. However, excessive efficacy can also have a negative impact on a person's achievement (Rustika, 2012). Students with excessive self-efficacy will feel frustrated when they fail, instead of making failure an experience that triggers an increase in their problem-solving skills (Yapono et al., 2013). Individuals with high levels of self-efficacy find it easier to understand the context of the problem, do calculations well, according to plan, and are even able to re-check the solutions obtained and interesting conclusions from the problems in the problems that have been solved (Noviza et al., 2019). In line with that, Collins (in Marasabessy, 2020) argues that individuals with high Self-Efficacy are faster at creating plans and solving problems, and choose to re-solve unresolved problems, and are even able to solve problems more accurately than students who are still unsure of their Self-Efficacy.

The study confirms that learning motivation (Z) positively affects learning achievement (Y). This aligns with research by I Gusti Ngurah Satria Wijaya (2018), titled The Influence of Learning Motivation on Student Learning Achievement at STMIK STIKOM Bali. The findings revealed a significant positive relationship between learning motivation and learning achievement, indicating that students with higher motivation tend to perform better academically. The study emphasizes the importance of fostering learning motivation as a critical factor in achieving improved educational outcomes. Learning motivation can be seen from the efforts within oneself to create learning activities, for example, diligently doing assignments, not requiring external support to achieve the best possible results so that the learning outcomes obtained will be better. Learning motivation is the overall driving force within a student that directs and maintains behavior so that he is motivated to act to do something in order to achieve learning results or goals (Yulika, 2019)

Emotional intelligence (X1) is shown to have a positive effect on learning motivation (Z). This is supported by research conducted by M. Nur and Puspita Dewi (2019), titled The Influence of Spiritual Intelligence (SQ) and Emotional Intelligence (EQ) on Learning Motivation of Students in the Management of Da'wah Study Program at the State Islamic University of Raden Fatah Palembang. The findings demonstrated that emotional intelligence significantly enhances learning motivation, even though spiritual intelligence had a stronger impact. These results highlight the role of emotional intelligence in sustaining student engagement and motivation.

Self-efficacy (X2) positively influences learning motivation (Z). This aligns with the findings of Yunita Dwi Aryanti and Muhsin (2020) in their study titled The Influence of Self-Efficacy, Parental Attention, Classroom Climate, and Teaching Creativity on Student Learning Motivation. The study found that self-efficacy significantly contributes to increased learning motivation, along with factors such as parental attention. These results emphasize the importance of fostering self-efficacy to boost student engagement and drive in academic settings.

CONCLUSION

Based on the results and discussion, it can be concluded that there is an influence between emotional intelligence variables on student learning achievement because emotional intelligence is very good, and if students' emotional intelligence is good, then their learning achievement is also good and can improve students' learning achievement. There is an influence between self-efficacy variables on student learning achievement because self-efficacy can be implemented well, and if students can recognize their abilities, it will affect the improvement of their learning achievement. There is a positive influence between learning motivation variables on student learning achievement because if there is encouragement from within oneself to increase learning enthusiasm, it will improve student learning achievement. There is a positive influence and correlation between emotional intelligence variables and learning motivation to achieve predetermined learning goals because if students' emotional intelligence is good and can influence students to achieve student learning achievement effectively, then encouragement or motivation from within oneself is needed. There is a relationship between self-

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efficacy variables and learning motivation, because if someone can recognize their abilities, then they can easily connect motivation with their self-efficacy. if self-efficacy and learning motivation are good, then the goals set will also be good, and vice versa. This research contributes to Helping teachers and schools design learning strategies that take into account students' emotional and motivational factors, as well as developing training programs to improve self-efficacy and emotional intelligence. This research supports a more holistic approach to education to produce a confident, resilient, and high-achieving generation.

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