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Social Support, Learning Load, Emotional Intelligence, Boredom, and Mathematics Learning Achievement

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ABSTRAK

Dukungan sosial, beban belajar, kecerdasan emosional, kejenuhan belajar siswa merupakan hal-hal yang siswa alami secara psikologis dalam mempelajari matematika. Penelitian ini bertujuan untuk menganalisis hubungan dukungan sosial terhadap beban belajar, kecerdasan emosional, kejenuhan belajar, dan prestasi belajar matematika siswa. Penelitian ini menggunakan desain penelitian survei. Subjek penelitian yaitu siswa SMP dengan besar sampel 377 dari populasi sebesar 6.658. Sampel dalam penelitian sebanyak 377 siswa yang didapat dari total anggota populasi 6658 siswa menggunakan teknik area proportional simple random sampling. Pengumpulan data dengan menggunakan kuisioner untuk mengetahui kertekaitan tersebut. Teknik analisis data menggunakan Structural Equation Modeling (SEM), terdiri dari measurement model dan structural model melalui program Analysis of Moment Structure (AMOS) digunakan untuk menganalisis data yang diperoleh. Hasil penelitian menunjukkan bahwa dukungan sosial memiliki pengaruh terhadap beban belajar, kecerdasan emosional, kejenuhan belajar, dan prestasi belajar matematika; beban belajar memiliki pengaruh terhadap kejenuhan belajar; kecerdasan emosional memiliki pengaruh terhadap beban belajar dan kejenuhan belajar. Simpulan penelitian menunjukkan hubungan antara dukungan sosial, beban belajar, kecerdasan emosional, kejenuhan, dan prestasi belajar matematika saling terkait. Implikasi penelitian ini memberikan informasi kepada guru dan para pendidik bahwa dukungan sosial kepada siswa mempengaruhi prestasi belajar siswa.

ABSTRACT

Social support, learning burden, emotional intelligence, and student learning boredom are things that students experience psychologically when learning mathematics. This study aims to analyze the relationship between social support and learning burden, emotional intelligence, learning boredom, and students' mathematics learning achievement. This study uses a survey research design. The subjects of the study were junior high school students with a sample size of 377 from a population of 6,658. The study sample was 377 students, obtained from a total population of 6658 students, using the area proportional simple random sampling technique. Data collection will be done using a questionnaire to determine the relationship. Data analysis techniques using Structural Equation Modeling (SEM), consisting of measurement models and structural models through the Analysis of Moment Structure (AMOS) program, were used to analyze the data obtained. The results of the study showed that social support had an effect on learning burden, emotional intelligence, learning boredom, and mathematics learning achievement; learning burden had an impact on learning boredom; emotional intelligence had an effect on learning burden and learning boredom. The conclusion of the study shows that the relationship between social support, learning burden, emotional intelligence, boredom, and mathematics learning achievement are interrelated. The implications of this study provide information to teachers and educators that social support for students affects student learning achievement.

1. INTRODUCTION

Schools are formal institutions that provide services and facilities to support the educational process. The benchmark for the success of education in schools is the high and low quality of students produced. One of the ways that students can be measured is through the learning achievements of each student. Academic achievement refers to students' academic achievements at school (Andryani Putri &

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Trianita Wilman, 2023; Cadime et al., 2016). Meanwhile, learning achievement is the result of learning efforts achieved by a student, in the form of skills from academic learning activities at the place of study for a certain period of time which is recorded at the end of each semester in the report card (Akpur, 2020).There are two factors that affect student learning achievement, namely internal and external factors. Internal factors are factors that exist within the individual, including physical, psychological, and fatigue or stress factors. External factors are factors that arise from the family environment, school environment, and community environment (Akrim, 2020; Yan, 2020). Excessive stress will have a negative impact on an individual's ability to interact normally with their environment. Individuals will suffer from fatigue if they experience long-term stress with a high enough intensity, both physically and mentally. This condition is called burnout (Jacobs & Dodd, 2003; Yang, 2004).

Burnout is used to describe a syndrome that occurs beyond physical exhaustion from overwork. Emotional exhaustion is part of it, but the hallmark of burnout is the slackness that occurs in response to overload (Shirazizadeh & Moradkhani, 2018). From the phenomena that occurred, researchers saw many students who studied under quite a lot of pressure and had excessive study loads that resulted in students experiencing learning saturation. Learning saturation is a saturation that occurs in students who experience a time span that brings saturation many times in a certain learning period. Learning saturation is the same as learning saturation. In this study, saturation will later be referred to as learning saturation. Learning load is an increase in the level of emotional exhaustion and release. The problem of excessive learning load is one of the factors that has an impact on the emergence of saturation (Fakih Khusni et al., 2022; Lin & Huang, 2012; Maulida, 2022). Excessive study load can include dense classes, many assignments, routine exercises, and other routine exercises that exceed the capacity and abilities of individual students. In addition, excessive study load can include the level of learning difficulties that must be addressed. Students will feel emotional when studying so that they can direct fatigue behavior caused by excessive study load. When students are in the learning process facing many problems, of course they feel overloaded and result in learning saturation (saturation). Where the study load also affects learning achievement. This is in accordance with research showing that the study load has a significant effect on entrepreneurship learning achievement (Fakih Khusni et al., 2022; Khoirin & Syah, 2017).

The current reality is that many students do not have big dreams, meaning they do not have the desire to achieve in their future studies. Most of them think everything is easy without having to try harder. However, there are also quite a few students who do not have a high IQ who actually have quite good academic achievements. From this, it can be concluded that there is an indication of low emotional intelligence. On the other hand, there are some students who have quite high emotional intelligence who always make all the demands of the assignments given by their teachers able to achieve good academic achievements. Emotional intelligence includes different abilities, but affects academic intelligence. People will not be able to use their cognitive abilities according to their maximum potential without having emotional intelligence (Maharani, 2014; Priskillaa, 2020). Learning activities, students will not be able to escape from the conditions of their learning environment. Students also need social support in motivating them to achieve the desired learning achievements. Seeing that students are currently experiencing quite a lot of pressure from learning loads. So the role of the learning environment, especially social support from the family, is very necessary because the family environment can affect a student's academic performance (Garcia & Skrita, 2019; Toor, 2018). Boredom is influenced by social support and personality (Noordin et al., 2012; Oktaviani & Dewi, 2021). One of the factors that causes boredom in students is the poor environmental conditions. The mismatch between what students expect regarding their learning achievements will cause boredom in students. The emergence of boredom can also arise due to lack of support from the environment and unhealthy competition in the learning process. Social support has been related to boredom, with greater social support can reduce the level of boredom in students. Sources of social support are from family, friends, and society. Social support is one of the important factors in influencing boredom in students (Puspitasari et al., 2021). Research shows that social support is a key resource in maintaining an individual's psychological health in response to stress (Rae, 2014).Unbalanced relationships can cause emotional tension. Emotions play an important role because they are a bridge for self-awareness in relationships, both personally, with others and with the cosmos. Emotional maturity, cooperation and empathy are commonly referred to as emotional intelligence (Ardianti & Efendi, 2021; Sa et al., 2019). Social support also affects learning achievement.

The relationship between social support on emotional and mental health. Social support can affect a person's emotional (Thompson et al., 2016). Students who are more emotionally intelligent are more self-directed, which leads to higher achievement in both academic and general development (Zhoc et al., 2018). Student networks including family, ethnic and religious affiliations play a role in academic success (Mishra, 2020). Further research on school burnout results in lower academic scores when school burnout levels are higher (Seibert et al., 2016). Previous research on self-control has investigated what factors must be in place to help students succeed, one of which is mathematics achievement emotions (i.e., anxiety, anger, shame, hopelessness, boredom, enjoyment, pride) which shows that there is a relationship between these factors (C. Kim et al., 2014).There is an influence of the variables of study load and social support on boredom (Khoirin & Syah, 2017).

Previous studies have discussed the influence of each variable, but there has been no study that discusses three variables at once, namely the relationship between social support, emotional intelligence, and learning burden in learning achievement, especially in learning mathematics. In the practice of learning mathematics, for example, it is done by providing drill questions to hone and high logical abilities. Whereas based on the results of the study, the high learning burden and aspects of emotional intelligence are considerations in learning achievement. Research that carries the aspect of novelty in the relationship between social support, learning burden, emotional intelligence, boredom, and mathematics learning achievement will have significant differences from previous studies. Previous studies have explored these variables more generally, this study has a more specific focus on the influence of these variables on mathematics learning achievement in particular. The link that binds all these elements is an attempt to present a more integrated method approach and a deeper understanding of the relationship between social support, learning burden, emotional intelligence, boredom, and its impact on mathematics learning achievement. Analysis using the application described in this study allows for a deeper and more responsive understanding of these complex dynamics in real-time, which may not have been achieved by previous studies as seen in the results of the research path diagram output. So in this case, further research is needed to find out and explore the relationship between these aspects in mathematics learning. The purpose of this study is to analyzethe relationship between social support and learning burden, emotional intelligence, learning boredom, and students' mathematics learning achievement.

2. METHOD

This study uses a survey research design. The subjects of the study were junior high school students in Gresik Regency with a sample size of 377 from a population of 6,658. The sample in the study was 377 students obtained from a total population of 6658 students using the area proportional simple random sampling technique. The questionnaire with 84 questions consisting of 30 social support questionnaire questions, 14 study load questionnaire questions, 30 emotional intelligence questionnaire questions, and 10 study saturation questionnaire questions where each item was provided with five answer choices. The lowest answer was given a score of 1 and the highest answer was given a score of 5. The data analysis technique used Structural Equation Modeling (SEM), consisting of measurement models and structural models through the Analysis of Moment Structure (AMOS) program. First, the development of a theoretical model, at this stage conducting a search or development of a theoretical model by means of scientific exploration through a literature review, in an effort to obtain justification for the theoretical model being developed. Second, the development of a path diagram, the constructs in the path diagram are divided into two groups, namely exogenous variables (exogenous constructs) namely transformational leadership and organizational culture and endogenous variables (endogenous constructs) namely factors predicted by one or more constructs. Third, compiling structural equations Figure 1. Fourth, selecting the input matrix and Estimation Technique, AMOS will convert the raw data into a covariance matrix or correlation matrix. Analysis of outliers is carried out in two stages, namely the Estimation Measure Model is used to test the unidimensionality of exogenous and endogenous constructs using Confirmatory Factor Analysis and the Structural Equation Model estimation stage is carried out through a full model to see the suitability of the model and the causal relationship built in this model. Fifth, assessing the identification of the structural model, during the estimation process using a computer program, illogical or meaningless estimation results are often obtained and this is related to the problem of identifying the structural model.

Identification problem is the inability of the proposed model to produce unique estimates. The way to see whether there is an identification problem is to look at the estimation results. If it is known that there is an identification problem, then there are three things that must be seen, the large number of estimated coefficients relative to the number of covariances or correlations, which is indicated by a small degree of freedom value, the use of reciprocal or reciprocal influences between constructs (non-recursive models) or (3) failure to set a fixed value on the construct scale. Sixth, assessing the Goodness-Of-Fit criteria, the test of suitability between the theoretical model and empirical data can be seen at the level (Goodness-of-fit statistics). A model is said to fit if the covariance matrix of a model is the same as the covariance matrix of the data (observed). Model fit can be assessed based on testing various fit indices. Model fit can be assessed based on testing various fit indices obtained from AMOS based on the evaluation of the fulfillment of SEM assumptions (normality assumptions, outlier assumptions, multicollinearity and singularity assumptions), measurement models and full structural equation model analysis and goodness of fit criteria. Seventh, interpretation and modification of the model. In SEM analysis, interpreting a model that has met the requirements is guided by the goodness-of-fit criteria. If the model does not meet these criteria, it is recommended to make modifications. In the AMOS program, a modification index has been provided. One indication that the modified model is getting better is the decrease in the chi-square value.

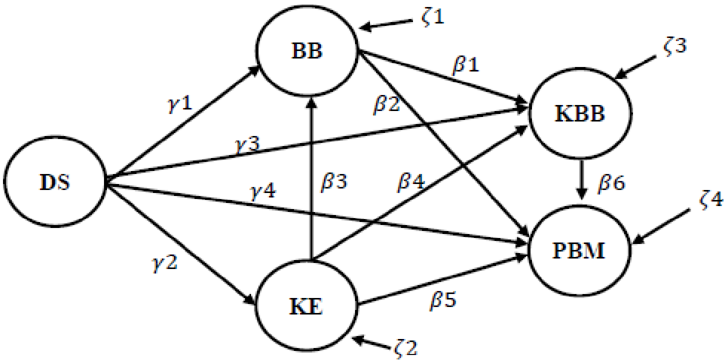

Figure 1. The Structural Equations

Information

DS	exogenous variables (Social Support)	ζ(Zeta)	for measurement errors of endogenous variables
BB	endogenous variable (Study Load)	β(Beta)	The coefficient of influence of endogenous variables on endogenous
TO	endogenous variable (Emotional Intelligence)	γ(Gamma)	The coefficient of influence of exogenous variables on endogenous variables
KBB	endogenous variable (learning saturation)	λ (Lambda)	factor loading
PBM	endogenous variable (Mathematics Learning Achievement)	ε(Epsilon)	Measurement error on manifest variables

3. RESULT AND DISCUSSION

Result

This study uses a survey research design.The structural equation model is obtained as seen in the AMOS 24 Notes For Model output. Based on the analysis output, the resulting degree of freedom value is 199 > 0. So the model is overidentified, so the model can be identified by its estimation and testing on the model can be carried out. This SEM assumption test consists of three parts, namely the assumption of data normality, the assumption of outliers, and the assumption of multicollinearity. The three assumptions will be explained as follows: The provisions for the normality test are by comparing the cr (critical ratio) value in the assessment of normality with the critical value$\pm$2,58at level 0.01. If there is a cr value that is greater than the critical value, then the data distribution is not normal in univariate. While in multivariate it can be seen in the last row cr with the same provisions. The results of the normality test in this study are presented in Table 1.

Table 1. The Normality Test Results

Variable	min	max	skew	cr	kurtosis	cr
$X12$ = Performance	6.000	30.000	0.558	4.427	0.973	3.857
$X13$ = Recognizing your own emotions	10.000	30.000	-0.347	-2.751	0.416	1.648
$X14$ = Managing emotions	10.000	27.000	-0.032	-0.251	-0.369	-1.464
$X15$ =Motivate yourself	11.000	27.000	-0.028	-0.221	-0.124	-0.490
$X16$ = Recognizing other people's emotions	13.000	30.000	-0.075	-0.593	-0.001	-0.003
$X17$ = Building relationships	11.000	26.000	-0.706	-5.600	1.891	7.493
$X22$ = Psychomotor aspects	22.500	26.400	-0.017	-0.133	-1.069	-4.237
$X21$ = Cognitive aspects	22.500	26.400	0.042	0.333	-1.076	-4.263
$X20$ = Low personal achievement	6.000	24.000	0.667	5.289	0.190	0.754
$X19$ = Personalization	6.000	25.200	0.771	6.111	0.874	3.463
$X18$ = Emotional exhaustion	8.000	30.000	0.699	5.544	0.904	3.585

Variable	min	max	skew	cr	kurtosis	cr
$X11$ = Frustration level	6.000	27.000	0.225	1.785	-0.222	-0.880
$X10$ = Temporal demand	12.000	30.000	0.600	4.757	0.256	1.013
$X9$ = Mental demand	6.000	24.000	0.136	1.081	-0.709	-2.811
$X8$ = Effort	6.000	30.000	0.513	4.064	-0.337	-1.337
$X7$ = Physical demand	6.000	28.000	0.484	3.833	0.082	0.325
$X1$ =A reliable alliance	12.000	30.000	0.184	1.462	0.135	0.533
$X2$ =Guidance	15.600	30.000	-0.118	-0.934	0.057	0.225
$X3$ =Guarantee of fair value	9.600	30.000	-0.594	-4.709	0.793	3.144
$X4$ =Attachment	9.600	30.000	-0.719	-5.695	0.844	3.347
$X5$ =Social integration	13.200	30.000	-0.152	-1.201	0.111	0.441
$X6$ =Chance	13.200	30.000	0.225	1.781	-0.466	-1.848
Multivariate					**97.701**	**29.188**

Based on Table 1, shows that there is a value in the critical ratio (cr) that is not in the range. So the data distribution is not normal univariately$\pm 2, 58$. Since the data is not normally distributed, one way to deal with the problem of normality is to remove outliers. Univariate and multivariate outliers have been removed from the data, after removing the outlier data, the model is re-executed until no outlier data is found.Outlier detection can be done by looking at the mahalonobis distance of the data, namely by looking at the AMOS output in the Observations Farthest from The Centroid (Mahalanobis distance) section. Data is said to be an outlier if the Mahalanobis d-squared value is greater than the chi-squared table value. From this explanation, it can be seen that the chi-square value of this study is 0.001 (probability) x 22 (number of items used) = 48.27. The AMOS output in the Observations Farthest from The Centroid (Mahalanobis distance) section

Based on data analysis, it shows that there is a Mahalanobis d-square value > 48.27, namely in samples 86, 107, 145, 62, 78, 52, 211, 193, 76, 111, and 106. So that there is no outlier data, samples that have a Mahalanobis d-square value > 48.27 are eliminated (deleted) so that the data is normally distributed. The output of Observations Farthest from The Centroid (Mahalanobis distance) after elimination. Based on data analysis, shows that there is no longer a Mahalanobis d-squared value >48.27, meaning that there is no outlier data. Furthermore, multicollinearity can be detected from the determinant of the covariance matrix. To find out, the correlation between constructs must be$<$ 0.90. If between constructs reaches 0.90 or more, then there will be multicollinearity between constructs. If the data experiences multicollinearity, it means that the data is not singular.

The output results of Standardized Regression Weights in the Estimate column which states that the correlation between constructs$<$ 0.90.So it can be concluded that the data does not experience multicollinearity, meaning the data is singular. The initial stage in this test is to look at the AMOS output in the notes for model section to get the valuenotes for model, degree of freedom values $>$ 0 in other words, the model can be continued to estimate and test the hypothesis. The chi-square value is at the probability level. Based on the chi-square results, the null hypothesis stating that the model is the same as the empirical data is rejected, which means that the model does not fit. Therefore, other model fit measures are sought, namely GFI, AGFI, RMSEA and so on. The Summary of AMOS output results showed in Table 2.

Table 2. The Summary of AMOS Output Results

Goodness of Fit(GOF) Index	Cut-off Value	Values In Research Models	Information
AGFI	> 0.90	0.786	Not Fit model
CMIN/DF	< 2.0	3,835	Not fit model
(Probability)	> 0.05	0,000	Not fit model
RMSEA	< 0.08	0.089	Not Fit model
GFI	> 0.90	0.832	Not Fit model
TLI	> 0.90	0.783	Not fit model
RMR	< 0.08	1,037	Not fit model
RFI	> 0.90	0.727	Not fit model
AIC	expected to be small	871.329	Not Fit model
ECVI	expected to be small	2.420	Fit model
HOELTER	< 200	110	Fit model

Based on Table 2, above is a summary of AMOS Output on the Summary Fit Model, TLI and RFI values, then, TLI and RFI values, RMR values obtained and CMIN/df values are. Overall the model is not acceptable, therefore the data cannot be continued to the next analysis. Because the data is not normally distributed, one way to deal with the problem of normality is to remove outliers. Outliers in univariate and multivariate have been removed from the data, after removing the outlier data, the model is executed again until no outlier data is found. In the Mahalanobis Distance table, data is considered not an outlier if the Mahalanobis d-square value is > 48.27. Based on the output results, there is no data that is considered an outlier. If there is still outlier data, then the data should be discarded. Although the outlier data has been discarded, the Goodness of Fit value has not changed $= 0{,}783 = 0, 727 < 0{,}91{,}037 \geq 0{,}083{,}835 \geq 2$

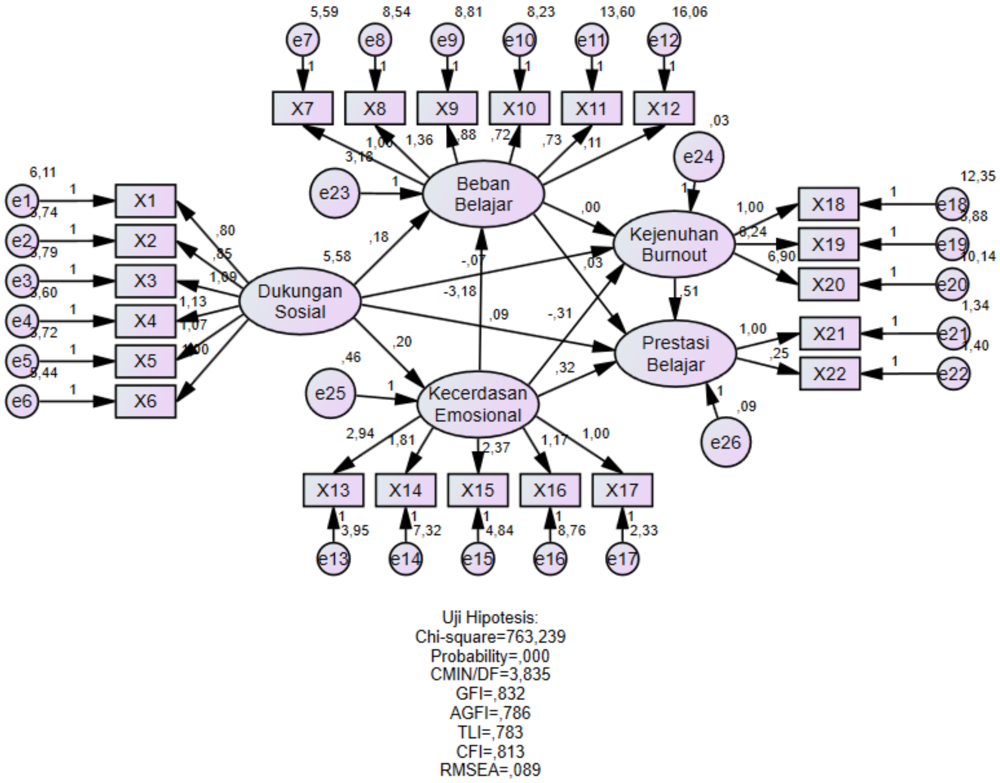

Figure 2. The Path Analysis Output on AMOS 24

Based on Figure 2, the data is successfully estimated and produces a hypothesis test, but the data is invalid or the data does not support the model because the data is not normally distributed. The last step to improve the Goodness of Fit in the model is to carry out the modification stage. The output in Amos displays the suggested modifications to the Modification Indices. By connecting the suggested variables, it can reduce the chi-square value and increase the probability level value. However, in making modifications there must be an accompanying theory. Modifications between variables cannot be done without a strong theory, for example from previous research. Modifications can only be done between error indicators on fellow exogenous variables. The greater the modification indices that are changed, the greater the change in the chi-square value. However, this study did not carry out index modifications because there was no theoretical support to strengthen the modification. Based on the results of the tests that have been carried out, the data used does not meet the assumptions needed to proceed to the hypothesis testing stage. The data used does not support the existing model, so it will produce a model that does not fit even though the hypothesis test can still be known. For this reason, alternative actions are taken to test the model with existing data using PLS-SEM.

Evaluation of the measurement model is carried out to assess the validity and reliability of the model which is carried out with convergent validity, composite reliability and discriminant validity. The convergent validity value is the loading factor value on the latent variable with its indicators, the minimum validity of which can be accepted is . This value will show how big the correlation is between the indicator and the latent variable. The loading factor results for each indicator can be seen in> 0.4. Based on data analysis, outer loading the loading factor value can be seen in the Original Sample column (O) in each indicator there is a value that exceeds the required standard, so it is necessary to delete the indicator in the model. After deleting the indicators X12, X18, and X22. Based on data analysis, outer loading the loading factor value can be seen in the Original Sample (O) column for each indicator has exceeded the required standard value, namely . The loading factor value can also be seen from the magnitude of the value that leads from each variable to each of its reflection indicators. The loading factor results for each indicator can be seen in the path diagram output in SMART-PLS, as> 0,4 Figure 3:

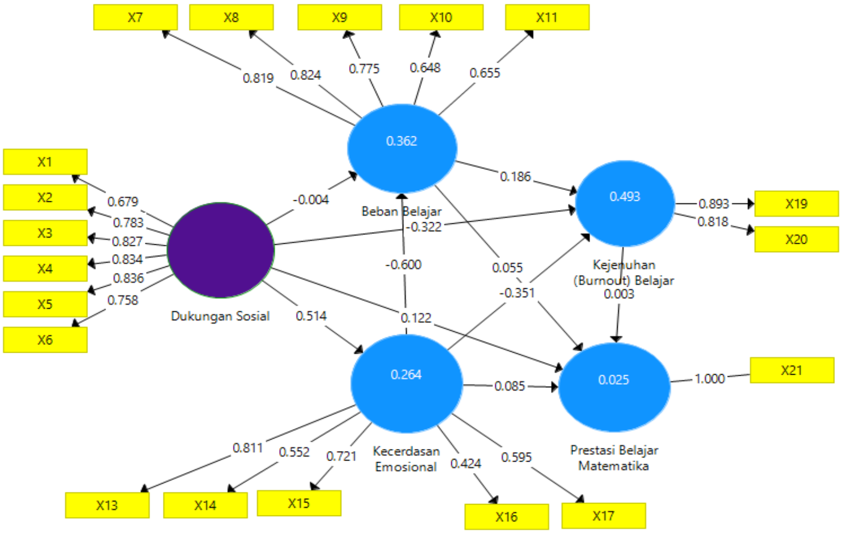

Figure 3. The Output Loading Factor in Path Analysis in SMART-PLS

The next test is to calculate the reliability of the indicator. The level of reliability is measured by the composite reliability value and the AVE value. In composite reliability, the minimum value set to identify that the construct is acceptable is 0.7. If the composite reliability value is greater than 0.7, then the construct passes the reliability test. The results of the composite reliability test show that the composite reliability value for each construct is greater than . This indicates that the construct being tested is reliable. Another measurement that is also used to test reliability is by using the AVE value. The aim is to measure the level of variance of a construct component collected from its indicators by adjusting the error rate. The minimum recommended AVE value is . Based on the test results with the AVE value, it shows that all constructs in the model have good reliability values. This can be seen from the AVE value for all constructs that have a value greater than 0,70. After the convergent validity test is passed, the next test is carried out, namely the discriminant validity test.To test discriminate validity, cross loading and fornell-lacker criterion can be examined.

Based on data analysis, that the cross loading value atcorrelation of indicator X1 to variable social support of . This value is greater than the correlation value of the X1 indicator on the variables of learning load, emotional intelligence, saturation, and learning achievement. Applicable to other indicators, n0,679value cross loading on the indicatorThis identifies the suitability of an indicator to explain the variable itself, showing a larger number compared to the correlation between other variables.Thus, the discriminant validity requirement with cross loading has been fulfilled.Meanwhile, in the Fornell-Lacker criterion, the discriminant validity test is carried out by comparing the correlation between variables with$\sqrt{\text{AVE}}$. The measurement model has good discriminant validity if the variable itself is greater than the correlation between other variables. The results of the discriminant validity test with$\sqrt{\text{AVE}}$ fornell-lacker criterion can be seen on Table 3.

Table 3. The Discriminant Validity with Fornell-Lacker Criterion

	Study Load	Social Support	Emotional Intelligence	Bornout Saturation	Learning achievement
Study Load	0.748				
Social Support	-0.312	0.788			
Emotional Intelligence	-0.602	0.514	0.635		
Bornout Saturation	0.497	-0.56	-0.628	0.857	
Learning achievement	-0.033	0.147	0.113	-0.092	1.000

In the fornell-larcker criterion table, it can be seen that the value of the emotional intelligence correlation variable is . This value is greater than the correlation value of the emotional intelligence variable with social support and other variables. Applicable to other variables, the value of the variable itself shows a number greater than the correlation between variables. Thus, the discriminant validity requirement has been met. After testing the measurement model (outer model), the next step is to test the structural model (inner model) to determine whether the hypothesis is accepted or rejected. The structural model is evaluated using the Estimate for Path Coefficients, which is the value of the path coefficient or the magnitude of the relationship/influence of latent variables, carried out using the bootstramping and R-Square procedures to determine the effect of the independent latent variable on the dependent latent variable. To conclude whether the hypothesis is accepted or rejected, the p-value is used in the significance. If the p-value is rejected, in other words there is a significant influence between the variables. However, if the p-value is accepted, it means there is no significant influence between the variables. The results of bootstramping data processing in Table 4.

Table 4. The Bootstramping Data Processing Results

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Study Load -> Bornout Boredom	0.186	0.182	0.043	4.305	0
Study Load -> Study Achievement	0.055	0.057	0.06	0.919	0.358
Social Support -> Study Load	-0.312	-0.314	0.047	6,646	0
Social Support -> Emotional Intelligence	0.514	0.517	0.043	11,978	0
Social Support -> Bornout Burnout	-0.56	-0.564	0.048	11,558	0
Social Support -> Learning Achievement	0.147	0.152	0.052	2,853	0.005
Emotional Intelligence -> Study Load	-0.6	-0.604	0.043	13,885	0
Emotional Intelligence -> Bornout Saturation	-0.463	-0.46	0.051	8,999	0
Emotional Intelligence -> Learning Achievement	0.051	0.05	0.058	0.869	0.385
Bornout Saturation -> Learning Achievement	0.003	0.008	0.074	0.041	0.967

Based on Tabel 4, it can be seen that 3 variables have a p-value meaning rejected, in other words there is a significant influence between the variables. Meanwhile, 5 variables have a p-value meaning accepted, in other words there is no significant influence between the variables. To find out how much influence the exogenous variables have on the endogenous variables, an evaluation is carried out on the R-square value. The latent variables of social support and emotional intelligence that affect the learning load in the structural model have an R-square value of which indicates that the model is "moderate". The latent variables of social support, learning load and emotional intelligence that affect saturation saturation in the structural model have an R-square value of which indicates that the model is "moderate". The latent variables of social support, learning load, emotional intelligence, and saturation saturation that affect learning achievement in the structural model have an R-square value of which indicates that the model is "weak". Based on boots tramping data processing results the results of the hypothesis testing are presented in Table 5.

Table 5. The Hypothesis Test Results

	Original Sample (O)	P Values	Information
Study Load -> Bornout Boredom	0.186	0	H_0 rejected
Study Load -> Study Achievement	0.055	0.358	H_0 accepted
Social Support -> Study Load	-0.312	0	H_0 rejected
Social Support -> Emotional Intelligence	0.514	0	H_0 rejected
Social Support -> Bornout Burnout	-0.56	0	H_0 rejected
Social Support -> Learning Achievement	0.147	0.005	H_0 rejected
Emotional Intelligence -> Study Load	-0.6	0	H_0 rejected
Emotional Intelligence -> Bornout Saturation	-0.463	0	H_0 rejected
Emotional Intelligence -> Learning Achievement	0.051	0.385	H_0 accepted
Bornout Saturation -> Learning Achievement	0.003	0.967	H_0 accepted

Based on Tabel 5, it can be seen that social support has an influence on learning load, emotional intelligence, learning saturation, and mathematics learning achievement; learning load has an influence on learning saturation; emotional intelligence has an influence on learning load and learning saturation.

Discussion

The results of the study show that social support has an influence on learning load, emotional intelligence, learning saturation, and mathematics learning achievement. Learning load has an influence on learning saturation. Emotional intelligence has an influence on learning load and learning saturation. The results of this study can be analyzed that several factors revealed by previous studies are related to mathematics achievement, especially related to character (Liu et al., 2020; Martínez-Martí & Ruch, 2017). The lower the social support of students, the higher the study load, and vice versa. The social support in question can include attention, comfort, appreciation, or assistance received by individuals from others, where others here are individuals or groups. Social support can be in the form of love, affection, concern, attention, appreciation from teachers that have an impact on student satisfaction during school (Danielsen et al., 2009). Individuals who receive such support will feel cared for, respected, loved, and appreciated. The individual will be more competent and confident in carrying out their activities. People who have high social support can reduce the level of the person's learning burden. Thus, they will succeed in dealing with the pressure of the burden that arises (Kaharuddin & Tulak, 2022; Muhtadi et al., 2022; Putri & Desyandri, 2019) (Greenglass et al., 1997; Ray & Miller, 1994). School type (secondary school and college) influences the relationship between overall social support and student burnout (B. Kim et al., 2017).

High levels of social support are closely related to students' emotional intelligence levels. A positive correlation between social support and mental health, which indirectly illustrates a possible relationship between social support and emotional intelligence (Sa et al., 2019; Suryani & Jama, 2020). Emotional intelligence has a significant influence on a person's behavior, which is then reflected in their social interactions (Adegboyega et al., 2017; Ntalakos et al., 2023; Parker et al., 2021). Mental health is closely related to how a person manages and responds to their personal emotions. Emotional intelligence is not a static trait; it can develop and change over time, greatly influenced by the surrounding environment (Zhang et al., 2024). This indicates that the environment, especially the role of parents in childhood, has an important role in shaping emotional intelligence. Studies show that students who are raised in a family environment that offers good social support and well-being tend to have greater life satisfaction, higher levels of emotional intelligence, better academic performance, and face fewer problems (Núñez et al., 2023; Zawadzki, 2024). This confirms that environmental factors, especially parental influence, play an important role in shaping aspects of emotional intelligence and students' success in various aspects of life.

Low social support is closely related to high levels of learning boredom in students, and conversely, high levels of support can reduce the tendency of learning boredom. Low levels of social support can be a predictor of high levels of learning boredom (Madigan & Curran, 2021). Learning boredom can be explained as a state of an individual who experiences physical, emotional and mental fatigue which can hinder the learning process (Maslach & Schaufeli, 1993). This concept of saturation is often associated with the term burnout, which according to Firth & Britton (1989), is a negative internal condition that includes psychological experiences, usually indicating fatigue or loss of motivation to learn. Based on Firth & Britton's explanation, burnout behavior is a type of psychological disorder that can appear in the school environment, especially among students and teachers. This disorder can be found as a response to learning stress that may occur at almost all stages of education. Thus, the relationship between low social support, learning saturation, and the concept of burnout underscores the importance of a supportive social and psychological environment in the educational context. Lack of social support can be a risk factor for the tendency of learning saturation, while greater support may reduce the risk of burnout in students. Burnout that occurs among students refers to a feeling of emotional exhaustion caused by learning demands, having cynical behavior and leaving lessons, and feeling like an incompetent student (Cazan, 2015). Burnout is a syndrome of emotional exhaustion and cynicism with frequent frequency in someone whose work is related to people or the like. The main source of burnout is the presence of stress that develops cumulatively due to individual involvement in an activity in the long term. The experience of stress in students if left untreated and not immediately addressed can give rise to new impacts such as symptoms of burnout.

The results of this study indicate that the higher the social support of students, the higher the learning achievement, and vice versa. Students who feel greater social support for mathematics and science from parents, teachers, and friends have more positive attitudes towards mathematics and science (Duffin et al., 2020; Rice et al., 2013).However, it should be noted that, although social support is positively related, its influence is not that great when associated with learning. The relationship between social support and learning depends on the academic environment in which students attend school (Jacobsen et al., 2024). Specifically, social support was associated with better academic achievement, which was true only for women. This is because women felt more support than men from all sources, except from teachers (Iglesia et al., 2014).However, other studies have shown that a person's emotional intelligence level does not depend on gender. Students who have low mathematical resilience and emotional intelligence can hinder them during the mathematics learning process (Faradillah & Wulandari, 2021). By building relationships with students and allowing students to build relationships among themselves, mathematics educators have the potential to significantly influence student achievement and motivation.

The results of the study confirmed that the higher the learning load, the higher the tendency of learning saturation in students, while there was no significant relationship between the level of learning load and learning achievement. This finding indicates that although learning saturation can increase with a high learning load, its influence on students' mathematics achievement tends to be limited. Furthermore, the factor that seems to have a greater influence on students' mathematics achievement scores is their perception of their mathematics ability. Students who have a positive view of their learning ability tend to achieve higher mathematics achievement scores. In addition, this positive perception is also related to a more positive global self-concept, more intellectual and behavioral competence, and more social acceptance. In this context, peer tutoring approaches, both formative and conventional, have an important role in improving students' learning achievement and reducing their cognitive load (Chu et al., 2017). Research also shows that adaptive approach techniques, as expressed by (Liu et al., 2020) associated with lower levels of academic burnout, higher learning engagement, and lower test anxiety. Thus, the results of the study highlight that although high learning load may increase learning burnout, internal factors, such as perceptions of learning ability and types of learning approaches, have a stronger impact on students' mathematics achievement outcomes. Focusing on developing positive perceptions and using adaptive learning approaches may be a more effective strategy in improving students' learning achievement than simply reducing learning load.

The limitations of this study are that it is correlational, making it difficult to determine cause and effect. While correlations provide valuable insights, they do not necessarily indicate a direct cause-and-effect relationship. Further research using longitudinal studies or experimental designs could provide stronger evidence to address these limitations. The findings from this study may differ across students of different ages, cultural backgrounds, or academic levels, limiting the generalizability of the findings. Measurements of variables such as emotional intelligence or perceived social support often rely on self-report measures. These subjective assessments may be subject to individual bias, social desirability, or varying interpretations, affecting the accuracy of the data. Other factors not considered in this study may influence the observed relationships. Variables such as prior academic achievement, personality traits, socioeconomic status, or external stressors may have an impact on the variables under investigation but were not accounted for in the study. Addressing these limitations could increase the depth and reliability of research in this area. Combining multiple methodologies, considering different demographic factors, and refining measurement tools could contribute to a more nuanced understanding of how these variables interact and impact students' learning experiences.

4. CONCLUSION

Students with high levels of emotional intelligence may be better able to cope with high learning pressure and find strategies to reduce boredom, which in turn can affect mathematics learning achievement. The relationship between social support, learning burden, emotional intelligence, boredom, and mathematics learning achievement is interrelated. High levels of emotional intelligence can help students utilize social support better, reduce boredom, and ultimately affect mathematics learning achievement. Implementing programs that improve students' emotional intelligence and create a supportive environment in schools can help reduce learning boredom. Strategies to manage learning burden, such as time management and adaptive learning, can also help students cope with learning pressure. Related to the results of this study in an effort to improve mathematics learning achievement, it is important for educators to pay attention to the interaction between social support, learning burden, emotional intelligence, and boredom.

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