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Investigation of affective traits affecting mathematics achievement by SEM and MARS methods

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Abstract: The purpose of the study is to analyze the affective traits that affect mathematics achievement through Structural Equation Modeling (SEM) as a traditional regression model and Multivariate Adaptive Regression Splines (MARS), as one of the data mining methods. Structural Equation Modeling, one of the regression-based methods, is quite popular for social sciences due to the various advantages it offers; however, it requires very intensive assumptions. MARS method, on the other hand, is a multivariate and adaptive nonparametric statistical regression method used for data classification and modeling. MARS does not need any assumptions such as normality, linearity, homogeneity. It allows variables that do not provide linearity to be included in the analysis. The present study examines whether it is possible to use the MARS method, which is a more flexible method compared to SEM, taking both methods into account. Regarding this goal, the SEM model was created with the program R using the affective data and the achievement variable picked from TIMMS 2019 data. Then, the MARS method was created using the SPM (Salford Predictive Modeler) program. The results of the study showed that at certain points the MARS model gave similar results to the SEM model and MARS model is more compatible with the literature.

1. INTRODUCTION

TIMSS (The Trends in International Mathematics and Science Study) is an international and large-scale examination. The 4th and 8th grade students are able to participate into the examination organized in a four-year period. TIMMS 2019 was the 7th administration of the exam for the candidates from 58 different countries at the 4th-grade and the ones from 39 countries at the 8th-grade (MEB, 2019). Since TIMMS is administered at the international level, it also offers researchers the opportunity to make some possible comparisons among the countries, as well as the opportunity to make the evaluation of their educational systems. The TIMMS exam includes the surveys for the students, teachers and school administrator as well as the achievement tests. In these surveys, the affective traits of the student such as their attitudes towards the schools and the classes, their role in the family, their experience of

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bullying at school are also measured. The factors underlying students' achievement may be cognitive, affective. Many related studies show that achievement is associated with affective traits (Güngör et al., 2007). This reveals that the affective aspect of learning is of great importance (Lehman, 2006). The data obtained from such examinations provide an opportunity to reveal the reasons why students succeed or fail from different perspectives. In the various studies conducted on this subject, the impact of various affective traits on mathematics achievement has been examined (Demir & Kılıç, 2010; Wang, 2007; Zakaria & Nordin, 2008). The results are also important to show the extent to which affective traits affect achievement.

The analysis of TIMSS, which has a high number of variables and specific features, and similar large-scale exam data, can be complex. Data science provides convenience that can be advantageous in the analysis of such large-scale examinations. Accordingly, data means a piece of information and the smallest constituent that carries information (Oruç, 2019). Technology helps multidimensional and wide-ranging data develop; therefore, it has been inevitable that new means of analysis have emerged to add various meanings and dimensions to data, to extract new information that has never been extracted before from the data, and to consider data from different angles.

Data mining means using special algorithms in extracting significant models or relationships from large data stacks (Fayyad et al., 1996). Large data refers to a high amount of information with its density and volume. In other words, how big the data is, how much information it carries about the person or the item it informs, and the information it gives in a second refers to the size of the information. Data has transformed into a subject that concerns not only academics but also everyone in the 21st century. The data is gradually growing. With the use of information communication technologies in almost every corner of life, rapid technological developments trigger an increase in the size and types of data (Emre & Erol, 2017). Data mining includes automatic data extracting, processing, and modeling through a set of methods and techniques (Plotnikova et al., 2020). Methods such as ANN (Artificial Neural Networks), SVM (Support Vector Machines), CART (Classification &Regression Trees), CHAID (Chi-square Automatic Interaction Detector), MARS (Multivariate Adaptive Regression Splines) can be given as an example to the methods used in data mining. MARS data mining method, one of the data mining methods, was used in the study.

The MARS (Multivariate Adaptive Regression Splines) technique was first developed in 1991 by physicist Jerome Friedman at Stanford. The MARS model has many advantages for researchers. It is a nonparametric regression method that does not have any assumptions under the functional relationship between dependent and independent variables. MARS analyzes the effect of independent variables on the dependent variable, the interactions of independent variables with each other, and the effects of these interactions on the dependent variable together (Zhang & Goh, 2016). The interaction of independent variables with each other, which is seen as a problem of multicollinearity in regression analysis, is not considered a problem in the MARS method (Lee & Chen, 2005). The MARS model is a stepwise regression method (Özfalci, 2008). The stepwise regression method can be considered as an advanced method of forwarding selection (Anıl, 2010). According to this method, the variables that may have the highest contribution to the prediction model based on the correlation between the dependent variable and the independent variable are selected and the trivial ones are eliminated. Thus, the deviations in the model are reduced and a model with a higher prediction accuracy is obtained. Regarding the correlation coefficient between dependent and independent variables, the independent variable with the highest correlation coefficient is first included in the model. The stepwise regression model produces the least erroneous prediction model with the highest accuracy (Zateroğlu & Kandırmaz, 2018).

Structural Equation Modeling (SEM) is a model that needs a strong theoretical structure (Kline, 2015). SEM; it is a method that is successful in the testing of complex models and performs many analyses at once. Suggests new arrangements if any, for the network of relationships in the model under examination. It is also a method used in the testing of many theories and the development of new models, since it facilitates to look over the mediation and moderation impacts, and it considers the measurement errors (Dursun & Kocagöz, 2010). Thanks to the many advantages and conveniences it provides, SEM is a common method used in many areas such as marketing, education, psychology, and health. The main feature of SEM is that it decides on the models supported by experimental data; if the data model is not supported, the model is set up and tested again; meaning that a theoretical model is both setup and developed (Candemir, 2018). SEM has a strong theoretical background based on which the regression analysis of the observed variables and the factorial analysis of implicit variables lay (Kline, 2015). SEM is a statistical method that involves intensive assumptions. As with many methods of analysis, it is necessary to verify that various assumptions and requirements are met before analysis also in SEM.

Although there is little studies comparing the results of MARS and SEM, there are some studies comparing MARS with different statistical analysis methods. Deichnmann et al., (2002) made a comparision between a logistic regression and MARS in their studies. It can be concluded that MARS almost all cases produces better results than logistical regression though it is also stated that MARS gives better results when MARS and logistic regression are compared. Another study found out that prediction models created with MARS can be more reliable (Orhan et al. 2018). In the studies conducted so far, MARS has been seen as a strong regression model.

Nonlinear strong prediction models can be established and the relationships between variables can be analyzed and interpreted through MARS (Temel et al., 2010). In this study, the interactions of the affective variables were examined. In a study on the prediction of the MARS model (Zhang & Goh 2016), the advantages of MARS in the BNN method were found out and it is emphasized that the MARS prediction equation is advantageous. Furthermore, it is shown that MARS can replace many types of regression so it can completely ease the analysis and interpretation.

Bolder & Rubin (2007) noted that the MARS method yielded more successful results compared to ordinary least squares, non-parametric Kernel regression, and projection pursuit regression. AL-Qinani (2016) stated that the MARS model showed a noticeable improvement in the accuracy of prediction compared to the multiple linear regression (MLR) method, while Muzır (2011) reported that the MARS method revealed more successful results compared to the binary logistic regression and the theory of artificial neural networks. Moroever, in another study, the results of MARS and CART were compared and it was emphasized that the two types of analysis were more advantageous than other types of regression (Lee and et al., 2006). The result of another study shows that the MARS model makes a more accurate prediction at the point of the accuracy of prediction and regression than models such as artificial neural networks, regression models, regression tree models, and gives as reliable results as other models (Zhou & Leung, 2017). Furthermore, artificial neural networks and the MARS model were compared and the MARS model gave slightly better results considering the procedure than artificial neural networks, and as a result of this study, the MARS model was a strong predictor (Parsai et al., 2016). Abde-Aty and Haleem (2011) used MARS to predict traffic accidents in their study. It has been noted that the MARS model creates strong prediction equations and is an important predictor in predicting traffic accidents.

The data we obtain in international examinations or through data collection methods may tend not to provide the necessary assumptions. If these assumptions are not provided, various statistical methods cannot be used. Appropriate estimation method should be chosen according to the structure and distribution of the data. The maximum likelihood method is an estimation method that can be used for data measured at least on an equal interval scale with regard to the normal distribution; however, when these assumptions are violated, analyzes can be carried out using the estimation methods that will be preferred for data that do not show categorical and/or normal distribution (Finney et. al, 2006). In this case, the researchers may experience limitations statistically. In nonparametric data, the situation is different. Therefore, in cases where these assumptions are not provided, it is considered important to be able to use nonparametric methods. Data mining methods can be applied in a group of data that do not provide the necessary assumptions in the field of education and social sciences. In this study, it is planned to perform the analyses via SEM and one of the alternative nonparametric methods, MARS, and to discuss these two methods in terms of their advantages and limitations in the practice.

1.1. Purpose of Study

The general purpose of the present study is to examine various affective factors affecting mathematics achievements in the TIMMS 2019 study and the possible relations of such factors with achievement through MARS and SEM analysis methods over the established model. One of the regression-based methods, Structural Equation Modeling (SEM), is quite well-known for social sciences due to its various benefits; however, it requires very intensive assumptions. MARS method, on the other hand, multivariate and adaptive nonparametric statistical regression method used for data classification and modeling. MARS does not need any assumptions such as normality, linearity, and homogeneity. It allows variables that do not provide linearity to be included in the analysis. Comparisons of different statistical methods with MARS are found in the literature (AL-Qinani, 2016; Bolder & Rubin, 2007; Deichnmann et al., 2002; Lee et al., 2006; Muzır, 2011; Zhang & Goh, 2016; Zhou & Leung, 2017) but no comparison of MARS and SEM methods in terms of their advantages and limitations in practice, has been found. The present study seeks an answer to the question if it is possible to use the MARS method, which is a more flexible compared to SEM, taking both methods into account.

MARS can make it possible to study both the data obtained from large-scale exams and the complex relationships in multi-pattern research (Şevgin, 2020). With this aspect, MARS is an efficient method of analysis not only for educational sciences but also for many disciplines. For this reason, in the present study, the results of MARS, which can be considered a relatively new method, were tried to be compared with those of SEM, a conventional method. This comparison may provide convenience to the researchers in social sciences from various aspects and add perspective to analyses. This aspect of the study is expected to contribute to the literature.

Considering the TIMMS 2019 report, it was seen that the measurement of cognitive traits was addressed in general. The subject distributions in mathematics and science were given and the performance of Turkey in such distributions was stated (MEB, 2019). It was noted that cognitive traits were considered in general in the TIMMS assessments; however, the affective traits were not included enough. The effects of the affective constructs on education and the interactions among these contructs are not adequately examined (Meteroğlu, 2015). It is highly believed that the current study can contribute to the affective assessments of TIMMS.

1.2. Research Problem

In this study, the impact of various affective traits on mathematics achievement was examined. These affective traits were "*interest in mathematics*", "*attitude towards school*", "*attitude towards teachers*" and "*bullying*". For this purpose, the following question was identified as the main research question:

Do the various affective factors affecting the mathematics achievement in the TIMMS 2019 study and their possible relations with achievement have predictive differences when analyzed by MARS and SEM analysis methods?

Sub-problems

1. How are the variable interactions when data is analyzed with SEM?
2. How are the variable interactions when data is analyzed with MARS?

To respond to sub-problems, the following hypotheses have been established in light of the literature on the affective data of TIMMS 2019 in the model established.

H1: Bullying significantly affects the math achievement of the students.

H2: The students' attitude towards the school positively affects the math achievement at a significant level.

H3: The students' attitude towards the teachers positively affects their math achievement at a significant level.

H4: The students' interest in mathematics positively affects their math achievement at a significant level.

H5: A statistically significant impact was considered on the math achievement in the mediator variable of the interest in mathematics between the attitude towards the school and the attitude towards the teacher.

H6: For the moderation, a statistically significant impact was considered on the math achievement in the moderator variable of bullying between the attitude towards the school and the attitude towards the teacher.

H7: A statistically significant impact was considered on math achievement in the mediator variable of interest in mathematics and the moderator bullying variable between the attitude towards the school and the attitude towards the teacher.

2. METHOD

2.1. Research Method

The present study bears the characteristics of basic research as it aims to conduct comparative data analysis using the TIMMS 2019 assessment and in doing so, it uses the ready-made package programs. Basic research refers to experimental or theoretical investigations that have no specific applications or purposes and are carried out to gather new information, primarily about the foundations of situations and observable incidents (Karasar, 2015). Basic research is experimental or theoretical research that helps discover information focusing on the process rather than the result, and that has the goal of discovery and allows us to better understand and make sense of the world. In addition, the research where the results of the MARS data mining model and SEM analysis is based on a relational scanning model.

2.2. Population and Sample of Research

Turkey participated in the TIMMS 2019 with 180 schools and 4,028 students at the 4th-grade level. At the 8th-grade level, the application was conducted with 4,077 students at 181 schools. The sample of the present study includes the items selected among the answers of these students given to the affective survey who participated into the mathematical assessment of TIMMS 2019 and the BSMMAT01-05 variables showing the level of achievement (plausible values). (MEB, 2019).

2.3. Data Collection Tools and Process

All data used for the study have been taken from the official site of the TIMMS exam (https://timss2019.org/international-database/). TIMMS 2019 was conducted with the fourth and eighth grade students in mathematics and science. The exam included the achievement tests and the affective surveys. In the exam, the questions on mathematics and science were asked as a part of the achievement test. The affective surveys were five-point Likert-scale ones that measure the socio-economic level of the student, the attitude towards the teacher, the students' interest and motivation towards the course, and the level of bullying for the students suffered. These affective surveys were prepared not only for the students but also for the teachers and the school administrators. In this study, data consisted of the items selected from the affective surveys of the 8th-graders who participated in the TIMMS 2019 and their achievement scores. The items selected and the factors represented by these items are all given in Table 1, and in the other parts of this study, these items are given with their codes as below.

Table 1. *Selected items for the model.*

Factors	*Items*
Interest in Mathematics	BSBM16C Maths is boring. BSBM16E I love maths. BSBM16G I love maths problems. BSBM16B I wish I did not study maths
Attitude Towards Teacher	BSBM17A Teacher expects us to do. BSBM17B Teacher explains clearly. BSBM17C Teacher has clear answers. BSBM17G Teacher explains again. BSBM17F Teacher is associated with the course.
Attitude Towards School	BSBG13A I am present at school. BSBG13B I feel safe at school. BSBG13C I feel that I belong to the school. BSBG13E I am honored to attend this school.
Bullying	BSBG14B Lies about me have spread. BSBG14K I was threatened. BSBG14M I was excluded from society. BSBG14L I was hurt.

2.4. Analysis of Data

Analysis of the data took place in three steps. First, the suitability of the data for analysis was tested and the data was made suitable for analysis. Later, the established model was analyzed by SEM and MARS methods. Finally, the results of the two analyses were interpreted. For affective data, first of all, an explanatory factor analysis (EFA) was performed. A confirmatory factor analysis was then performed to confirm the model.

For the analysis, explanatory factor analysis was performed primarily for affective variables taken from the TIMMS 2019 exam. Later, the analysis was continued with confirmatory factor analysis. EFA and parallel analyzes were carried out with the Jamovi (The Jamovi Project, 2021). According to the KMO results (KMO=0.831) and Barlett Sphericity test results (p<0.05) for EFA analysis, it was decided that the data was suitable for factor analysis.

Given the parallel analysis results provided with the scree plot in Figure 1, it is seen that the model is 4-dimensional and after point 4, the Eigenvalues are similarly distributed. These values account for 54.57% of the variance.

Figure 1. *Scree plot.*

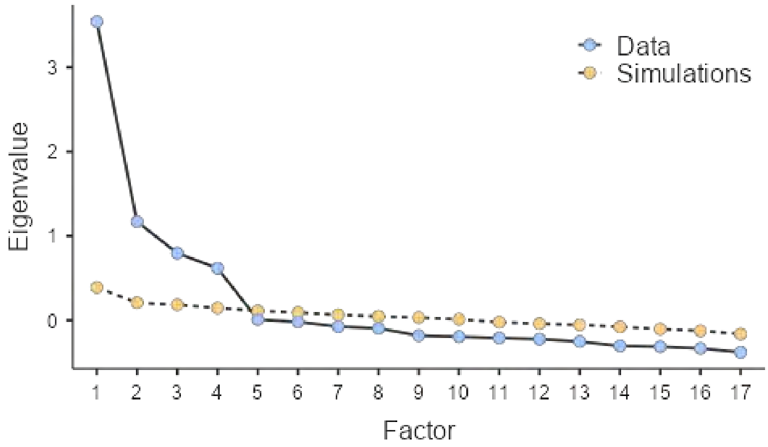


Table 2. *Measurement model dimension matrix.*

	1	2	3	4
BSBG13A			0.483	
BSBG13B			0.558	
BSBG13C			0.810	
BSBG13E			0.669	
BSBG14B				0.445
BSBG14K				0.563
BSBG14L				0.598
BSBG14M				0.435
BSBM16B	-0.679			
BSBM16C	-0.840			
BSBM16E	0.842			
BSBM16G	0.737			
BSBM17A		0.448		
BSBM17B		0.723		
BSBM17C		0.748		
BSBM17F		0.551		
BSBM17G		0.565		

When conducting EFA analysis principal axis factoring extraction method was used in combination with promax rotation. As a result of the EFA analysis, it was continued with 17 items. There were 4 items in the interest variable for mathematics; 5 items in the attitude variable for the teacher, 4 items in the interest variable for mathematics, and 4 items in the bullying variable. The achievement variable had 5 sub-dimensions. The dimensions were called "*Interest in Mathematics*", "*Attitude towards Teacher*", "*Attitude towards School*" and "*Bullying*". The analysis continued later on with 17 items and 5 dependent variables. As seen in Table 2, two items have negative factor loads. When calculating the total score, the item scores are added together to obtain the total score. These two items should not be included in the total score due to their negative factor loads. Since this study was not carried out on total scores, the negative factor loads of the items could not be taken into account. The analysis was proceeded with confirmatory factor analysis (CFA). The values of fit indices are given in Table 3 and CFA model estimations are given in Table 4.

Table 3. *Measurement model fit indices.*

Fit Index	*Calculated Value*
X^2	$p<0.05$
X^2/ sd	*2.90*
RMSEA	0.041
SRMR	0.045
GFI	0.97
TLI	0.97
CFI	0.98

Table 4. *CFA model estimations.*

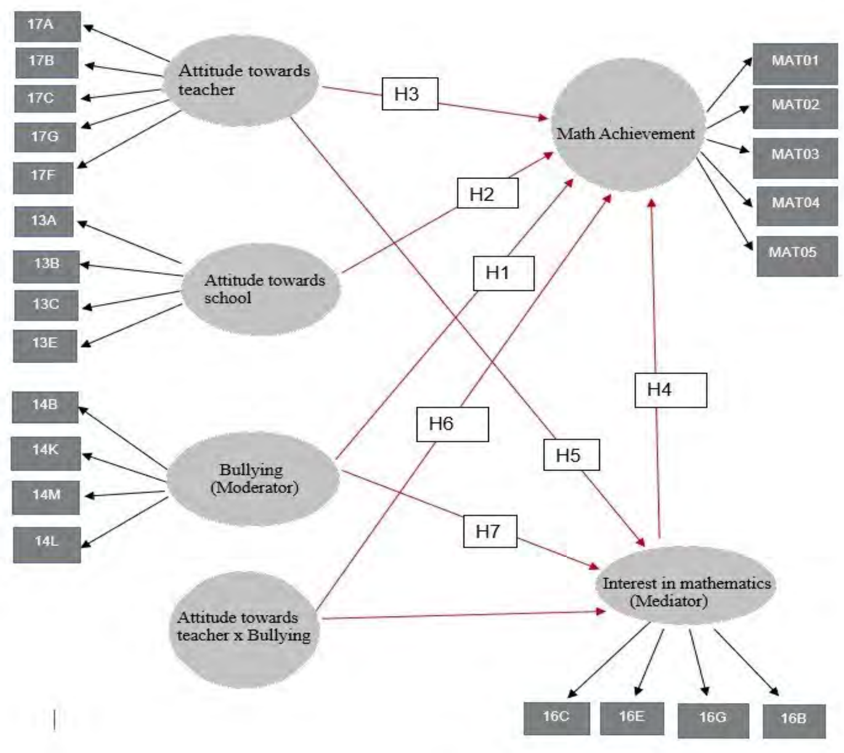
	Estimate	Std.Err	z-value	*p*
Interest in Mathematics =~				
BSBM16B	1.000			
BSBM16C	1.092	0.051	21.438	0.000
BSBM16E	-1.014	0.045	-22.673	0.000
BSBM16G	-0.969	0.045	-21.575	0.000
Attitude Towards Teacher =~				
BSBM17A	1.000			
BSBM17B	1.219	0.084	14.565	0.000
BSBM17C	1.126	0.078	14.448	0.000
BSBM17F	0.999	0.078	12.813	0.000
BSBM17G	0.615	0.05	12.377	0.000
Bullying =~				
BSBG14B	1.000			
BSBG14K	0.395	0.044	9.007	0.000
BSBG14M	0.258	0.036	7.212	0.000
BSBG14L	0.505	0.056	9.017	0.000
Attitude Towards School =~				
BSBG13A	1.000			
BSBG13B	0.958	0.066	14.586	0.000
BSBG13C	1.219	0.079	15.488	0.000
BSBG13E	1.157	0.076	15.277	0.000

As shown in the table, it seems that the degree of fit is excellent or acceptable. The model established in this part, where the four-factor structure is tested, is confirmed. The research model established after factor analysis is presented in Figure 2.

According to the research model, the following hypotheses have been established in light of the literature on the affective data of TIMMS 2019.

H1: Bullying significantly affects achievement.
H2: The attitude towards the school positively affects the achievement at a significant level.
H3: The attitude towards the teachers positively affects the achievement at a significant level.
H4: The interest in mathematics positively affects the achievement at a significant level.

Figure 2. *Research model.*



According to the model, the interest and attitude variables have a significant positive relationship with achievement, while bullying variables have a significant relationship. In other words, the students with a high level of interest towards the course, their attitudes towards the course, and the school also have a high level of achievement (*H2*, *H3*). The students who are subjected to bullying have significantly lower achievement levels (*H1)*.

It was thought that mediator and moderator effects should also be examined in the model. A mediator variable is a cause variable that has the potential to affect the result, while a moderator variable is a third variable that has the potential to affect the result. In this line, the interest in mathematics was considered as a mediator variable, while bullying was a moderator variable. The reason why these variables are selected is because the interest variable can be a cause variable that can affect the achievement, and the bullying variable can be an effect variable that can affect the achievement. The hypotheses are as follows:

H5: A statistically significant impact was considered on the math achievement in the mediator variable of interest in mathematics between the attitude towards the school and the attitude towards the teacher.

H6: A statistically significant impact was considered on math achievement in the mediator variable of interest in mathematics between the attitude towards the school and the attitude towards the teacher.

H7: A statistically significant impact was considered on the math achievement in the mediator variable of interest in mathematics and the moderator bullying variable between the attitude towards the school and the attitude towards the teacher.

3. RESULT

3.1. Results of the First Sub-Problem

In this section, the first research question *"How are variable interactions when data is analyzed with SEM?"* is dealt with.

Mediator variable analysis: Mediator analysis can be defined as the explanation of the relationships between variables that are related to another mediator variable. Mediator analysis can be explained as a process in which the variable X affects the variable Y and, accordingly, also affects the variable Z. In this case, the mediator variable Y is the cause variable. First, the predictor value between X and Z is checked, and then when the variable y intervenes, it is checked whether a certain part of this predictor value will be explained by this variable. The mediator variable is the one that affects the dependent variable (Şen, 2020). The "Interest in Mathematics" variable was determined in terms of comparison with the MARS model as a mediator variable. In the MARS model, this variable was the most interacting variable in the SPM (Salford Predictive Modeler) program. Since this variable is associated with other variables, it has been considered to what extent it predicts math achievement as a mediator.

Interest in mathematics variable has been taken as a mediator variable. The goodness of fit values of the mediator model are (χ^2:0.00, *df*:0, RMSEA:0.000, CFI:1.00, TLI:1.00, SRMR: 0.000). Given the model data-fit indices, it can be seen that model data fit provides the necessary criteria. The regression equation is as follows:

Achievement = interest x -. 393 – attitude x 5.56 + school x 6.37 + bullying x 2.81

Moderated variable analysis: A moderator variable also acts as a dependent variable and the relationship between a dependent variable and an independent variable is affected by a third variable. This third variable is called the moderator variable. The effect that occurs in moderator variable analysis occurs only in the presence of this variable (Şen, 2020). The "bullying" variable has been set as the moderator variable.

The goodness of fit values of the moderator model are (χ^2:0.000, *df*:0, RMSEA:0.000, CFI:1.00, TLI:1.00, SRMR:0.000). Given the goodness of fit values, it is possible to say that the model-data fitness has been ensured.

The regression equation is as follows:

Achievement = interest~attitude x 1.156 + interest~bullying x 1.467.

Mediated moderation analysis: In the mediator analysis, the impact of the attitude towards teacher and bullying interaction on achievement over the interest in mathematics.

As a result of the analysis, the impact of the attitude towards the teacher, interest in mathematics, and bullying variables on achievement over the attitude towards school variable was not found statistically significant (p>0.05). H7 was rejected. Since it consists of a combination of two analyses, it is not specified in the hypothesis table.

The overall results of the established model are given in Table 5. Among the hypothesis established, *H3*, *H4*, *H5*, *H7* resulted in rejection and all the other hypotheses were accepted. Since *H7* is a combination of both methods, it is not included in the table. In other words, the interest variable for mathematics is not a statistically significant variable that predicts achievement. The bullying variable is selected as the mediator variable. When the bullying variable is included in the analysis, it affects the significance of the analysis.

Table 5. *SEM results.*

	Variable	p	Hypothesis
Moderator Analysis	Interest~ attitude towards teacher	0.248	H6 Accepted
	Interest~bullying	0.142	H6 Accepted
	Interest~ attitude towards teacherxbullying	0.350	H4 Rejected
Mediator Analysis	Achievement~attitude towards teacher	0.908	H2 Accepted
	Achievement~attitude towards school	0.000	H2 Accepted
	Achievement~bullying	0.842	H1 Accepted
	Achievement~attitude towards teacherxbullying	0.381	H3 Rejected
	Achievement~interest in Mathematics	0.676	H3 Rejected

Note. $p<0.05$; Interest: interest in Mathematics

3.2. Results of the Second Sub-Problem

This part focuses on the results of the second research question "*How are variable interactions when data is analyzed with MARS?*".

At this stage, the SPM program was used to establish the MARS model. At the establishment stage of the model, variables were included in the model as 17 categorical (affective variables) and 5 continuous data (achievement variables). The same model established in SEM is also set here.

Table 6. *Mars model variable interactions.*

Variables	Basic Function Value	Coefficient
Attitude Towards teacher	1	49.97
Attitude Towards School	3	-36.23
Attitude Towards teacher	5	26.52
Bullying	7	-21.30
Interest in Mathematics	9	-49.27
Attitude Towards School	11	-19.00

The contribution of variables to the analysis was primarily studied. Table 6 shows the effects of variables on the achievement-dependent variable. The attitude variable exists with interaction values 49.97 and 26.52 in the basic equation values 1 and 5. The school variable exists with interaction values of -36.23 and-19.00 in the basic equation values of 3 and 11. The bullying variable exists with an interaction value of -21.30 in the basic equation value of 7. The interest variable exists with an interaction value of -49.27 in the basic equation value of 9.

Results of the MARS model are given in Table 7. The MARS model is a stepwise regression method and primarily analyzes all variables, and at the trimming stage, only variables that affect the dependent variable are included in the analysis. Thus, the variables that most affect the dependent variable remain in the analysis, and the others are eliminated. In other words, it does not include the variables that do not affect the dependent variable or variables that have little effect on the analysis. These variables are sorted out under the name of the importance table. It can be said that the variable taken into the final model has a statistically significant impact on the dependent variable. Here are the regression table and the relationship table formed in this way. In summary, the variable that the MARS model receives in the final model has a significant effect on the dependent variable and the level of relationship with the dependent variable is significant. Thus, "bullying significantly affects achievement." *H1* hypothesis is accepted.

Accordingly, the hypothesis that "attitude towards school significantly affects achievement in a positive way" can be explained as follows: the MARS model does not yield a positive or negative relationship. It only gives a statistically significant relationship. In this respect, the level of a relationship, such as positive or negative, can be determined in the analysis such as correlation or others. MARS gives zero to the variables which it does not take into the interaction model. It is therefore considered that the acceptance of this hypothesis is not correct. Although the variable yields a statistically significant effect, it cannot be commented on its direction, therefore the *H2* hypothesis is rejected. Likewise, the hypothesis *H3* "attitude towards teacher positively affects achievement at a significant level" is also rejected. The hypothesis that "interest in mathematics positively affects achievement at a significant level" is also evaluated in this context and the *H4* hypothesis is also rejected.

Table 7. *Results of the Mars model.*

Models	R^2	*GCVR-SQ*
MARS Model		
Mediator Analysis	0.08370	0.06397
Moderator Analysis	0.07488	0.06517
Mediated Moderation Analysis	0.07743	0.06012
Variable Importance Table	*Scores*	
Mediator Analysis		
Attitude Towards Teacher	100	
Attitude towards school	94.20	
Moderator Analysis		
Attitude Towards Teacher	100	
Attitude towards school	84.50	
Mediated Moderation Analysis		
Attitude Towards Teacher	100	
Attitude towards school	90.81	
Interest in Mathematics	33.49	

Mediation analysis in the MARS model: In the MARS model, the "interest in Mathematics" variable is regarded, which actively interacts in many analysis as a mediator variable and has a high coefficient.

Basic function equations for MARS;

Bf1 = Max (0, attit.to.teacher - 7); Bf4 = Max (0, 7 – attit.to.school); Bf6 = Max (0, 8 – attit.to.teacher) x Bf4; Bf8 = Max (0, 6 – attit.to.teacher) x Bf1

Y = 533.548 – 13.7375 x BF1 - 43.8386 x BF4 + 11.4032 x BF6 + 20.3738 x BF8

Model Mat. average = Bf1 Bf4 Bf6 Bf8

Basic function values are equations that aim to reveal the relationships among the variables. The variable constant is 533.54; the interaction of the first basic equation is -13.73; the interaction of the second basic equation is 43.83. Based on this, the relationship between the attitude towards the school and the attitude towards the teacher is 11.40. The attitude towards teacher and the attitude towards school relationship value is 20.37. The model average for the relationship value is 139.74. The relationship level here is contribution-based. A relationship level like correlation is not considered.

The amount of contribution of variables to the model can be seen in Table 6. According to the table, the contribution of the variable of attitude towards teacher to the dependent variable result is 100; while the contribution of the variable of attitude towards school is 94.20. After the variable of interest in mathematics was included in the analysis as a mediator variable, the significance of the variable and the changes in the value of the variable are indicated in Table 6. The coefficients changed after the mediator variable was included in the analysis.

Basic Function Equations for MARS Mediator Variable Analysis;

Bf1 = Max (0, attittoteacher - 7); Bf4 = Max (0,7 - attittoschool); Bf6 = Max (0,8 - attittoteacher) x Bf4; Bf8 = Max (0,6 - attittoschol) x Bf1

Y = 533.014 – 13.6083 x Bf1 – 44.1021 x Bf4 + 11.5904 x Bf6 + 20.6042 x Bf8

Model Mat. average = Bf1 Bf4

The attitude towards the teacher variable decreased from a coefficient of -13.73 to 13.60, and the attitude towards the school variable decreased from -43.83 to -44.10. The first interaction value increased from 11.40 to 11.59 and the second interaction value increased from 20.37 to 20.60. Here, it can be seen that the corresponding variable explains part of the relationship. On the other hand, the node values were 7 and 8 in the first case, while they were 6, 7, and 8 here.

After including the corresponding variable in the analysis, the basic function values also changed. The variable constant decreased from 533.548 to 533.014. The first variable value was 13.60; the second variable value was 44.10; the first interaction value was 11.59, and the second interaction value was 20.60. The average relationship value of the model was 238.75. After including the corresponding variable in the analysis, the significance table in which the contribution levels of the variables were determined also changed. The attitude towards the teacher increased from 100; the attitude towards the school increased from 94.20 to 95.82.

In conclusion, there was a 0.08344-degree interaction between the attitude towards the school and the attitude towards the teacher variables at first, while this interaction was 0.08370 when the variable of interest in mathematics was included in the analysis. The level of variable interaction was increased slightly. Therefore, it is possible to talk about mediation. Including the corresponding variable in the analysis reduced some values but increased some of them. The reason it increased slightly may be because of the low number of variables and the low variance described. As mentioned above, the amount of variance described in international exams is generally low. In this case, this can be shown as the cause of such a slight decrease. Consequently, hypothesis *H5* stating that "there is a statistically significant impact on achievement in the mediator variable of interest in mathematics between the attitude towards the school and the attitude towards the teacher" was accepted.

Moderator analysis in the MARS model: The “bullying” variable was analyzed as the moderator variable in the MARS model. It is seen in Table 6 that the model determinant value decreases when the bullying variable is analyzed (R^2=0.074). The estimated error value is also 0.06517. The lower this value, the lower the error amount. The bullying variable can be said to have a statistically significant impact on achievement. This effect is in the direction of reducing achievement.

Basic Function Equations for MARS Moderator Variable Analysis are as follows;

Bf2 = Max (0, 8- Attittoteacher); Bf4 = Max (0, 7- Attittoschool)

Y = 487.802 + 20.8284 x Bf2 - 17.5118 x Bf4

Model Mat. average = Bf1 Bf4

Looking at the basic function equations, it can be seen that the fixed term value is 487.802. The attitude value towards teacher is 20.82. The attitude value towards school is 17.51. These values are relationship coefficients. After the bullying variable is included in the analysis, it can be seen that many values, including the constant variable, has changed. Given the interaction information in Table 5, the decrease in achievement was statistically confirmed when the bullying variable was included in the analysis. Bullying has also been a mediator variable for the MARS model. Consequently, hypothesis *H6* stating that "there is a statistically significant impact on achievement in the moderator variable of bullying between the attitude towards school and the attitude towards teacher" was accepted.

Mediated moderation analysis in MARS model: The effect of the variables of attitude towards school and attitude towards teacher in mediator variable of bullying and interest in mathematics was analyzed. Table 6 shows the results.

In moderator and mediator analysis, both mediating and moderating variables were analyzed. Here, the model determinant value was found to be 0.07743. It can be seen that the value R^2 decreased due to bullying; however, it did not lose much value in mediator interest in mathematics. This analysis also shows that it is the right decision for the bullying variable to participate in the analysis as the moderator variable and the variable of interest in mathematics as the mediator variable.

Basic function equations for MARS analysis are as follows;

Bf1 = Max (0, Attittoteacher- 5); Bf2 = Max (0, Attittoschool- 4); Bf4

= Max (0,7- Interestinmaths); Bf5 = Max (0, Interestinmaths- 10)

Y = 501.186- 12.278 x Bf1 + 10.9823 x Bf2- 30.4638 x Bf4- 16.1954 x Bf5

In the variable significance table in Table 6, the attitude variable towards teacher remained the same. The attitude variable towards school was 90.81. The interest variable for mathematics is 33.49. Regarding the coefficient ranking, it is observed that the highest coefficient belongs to the variable of attitude towards the teacher and the lowest coefficient belongs to the variable of interest in mathematics. Since bullying is a weighted variable, it is not specified in the table. Consequently, hypothesis *H7* stating that "there is a statistically significant impact on achievement in the mediator variable of interest in mathematics and moderator variable of bullying between the attitude towards school and the attitude towards teacher" is accepted.

The statistical analysis result comparison of SEM and MARS model is as follows;

Table 8. *Comparison of hypotheses.*

Hypotheses	SEM	MARS
H1	Accepted	Accepted
H2	Accepted	Rejected
H3	Rejected	Rejected
H4	Rejected	Rejected
H5	Rejected	Accepted
H6	Accepted	Accepted
H7	Rejected	Accepted

As shown in Table 8, it is clear that the results of the hypotheses except *H2, H5, H7* are the same. The difference here may be due to the fact that the MARS program does not provide direction information. As a result, although there are some differences between SEM and MARS, it seems they often give similar effects to the same hypotheses.

4. DISCUSSION and CONCLUSION

The purpose of the present study is to examine various affective factors affecting mathematical achievements in the TIMMS 2019 study and the possible relations of such factors with the achievement through MARS and SEM analysis methods over the established ones. For this purpose, the following results have been reached.

As a result of the study, a significant relationship between bullying and achievement was found according to SEM and MARS analyses, and the hypothesis *H1 "Bullying significantly affects math achievement"* is accepted. Pekel (2015) noted that the academic achievement of children who were bullied fell. Also, Kestel and Akbiyik (2016) expressed that bullying negatively affected the academic achievements of the students, as well as their emotional difficulties. Özdinçer and Savaşer (2009) stated that bullying in school was a variable that negatively affected the student's academic achievement. In a research thesis by Sarier (2020), it was stated that not only the academic achievements of the students bullied but also their social and psychological were negatively influenced. In addition, Karataş (2011) agreed the negative effects of bullying and added that this effect might continue for many years. The findings in the literature support the accuracy of both models. Both of the models have similar results to each other. This study concluded that achievement rates decreased significantly when the bullying variable was analyzed in the relationship between the attitude towards the school and the attitude towards the teacher in the frame of the results of the analysis conducted through both SEM and MARS methods. In both methods, the hypothesis *H6: For the moderator variable, the attitude towards the school and the attitude towards the teacher have a statistically significant impact on math achievement in the moderator variable of bullying* has been accepted. In the literature, there has been no study in which bullying is a moderator variable, interest in mathematics is a mediator variable, and they are present together (mediator-moderator).

According to the results of the SEM analysis in the study, it was concluded that the positive attitude of the student towards school positively affects achievement at a significant level and the hypothesis *H2" The attitude towards the school positively affects math achievement at a significant level"* is accepted. The result of the MARS analysis indicated that the student's attitude towards the school significantly affected their achievement. However, the hypothesis was rejected even if it gave statistically significant results in the established MARS model so no comment on this finding could be made. Adıgüzel and Karadaş (2013) stated that the attitude towards the school significantly predicted the achievement in their study, while Bahçetepe and Giorgetti (2015) stated that the school variable significantly predicted the achievement in their study. Atik (2016) stressed that attitude towards school significantly affected the course achievement. These findings in the literature support both models. Both models significantly explained the impact of the attitude towards school on the student achievement.

According to the results of the SEM study, a negative relationship between attitude towards teacher and achievement was found and the hypothesis *H3* "*Attitude towards teacher positively affects math achievement at a significant level"* is rejected. MARS analysis gave this hypothesis a significant relationship, but since no comment can be made on the direction of this relationship, the *H3* hypothesis was again rejected. His study (Cumhur, 2018) concluded that the attitude towards the teacher positively affected the achievement. Güneş et al., (2012) found in their study that the attitude towards the teacher significantly predicted the achievement. Eraslan (2009) emphasized that educating teachers was important in the achievement in his work on PISA. Huyut (2017) stated in his study that the teacher is an important factor in the student achievement. Regarding the findings of studies in the literature, it can be said that the MARS model gives more accurate results than SEM and gives a more consistent result with the literature. In addition, based on the significance table, it can be seen that the MARS model makes a higher contribution to this variable.

According to the results of the SEM analysis, it was concluded that interest in mathematics does not positively affected the achievement at a significant level. According to the results of the MARS analysis, it was concluded that interest in mathematics affected achievement, but it could not be commented on whether it was in a positive direction. According to both methods, the hypothesis *H4* "*Interest in mathematics positively affects math achievement at a significant level"* was rejected. In his study, Güzel (2014) found that interest in mathematics significantly predicted mathematical achievement. To conclude, it can be said that the results of SEM analysis are inconsistent with the literature, while the results of MARS analysis give more consistent results with the literature.

As a result of the SEM analysis, a statistically significant impact was not found on achievement in the mediator variable of interest in mathematics between the attitude towards the school and the attitude towards the teacher. In other words, it was concluded that the interest in the course does not predict achievement and the hypothesis *H5* "*A statistically significant impact was found on math achievement in the mediator variable of interest in mathematics between the attitude towards school and the attitude towards teacher"* was rejected. As a result of the MARS analysis, a statistically significant impact was found on the achievement in the mediator variable of interest in mathematics between the attitude towards the school and the attitude towards the teacher, and the hypothesis *H5* was accepted. In other words, it was concluded that interest in the course predicts achievement in the relationship between attitude towards school and attitude towards teacher.

Considering the advantages of the MARS method, the following can be said: The MARS model does not require an assumption in the cause-effect relationship and does not seek any mathematical relationship. On the contrary, MARS establishes these relations itself. There are no definite judgments about the variables in the MARS model. Variables can be categorical or continuous. In addition, although various assumptions such as normality, linearity and homogeneity are sought in other regression models, assumptions are not sought in the MARS model. MARS is less affected by the multicollinearity problem and enables the model to be established quickly (Le et al., 2009). The MARS algorithm constructs flexible models by using simpler linear regression and data-driven stepwise searching, adding, and pruning. Furthermore, the MARS models developed are easier to interpret (Zhang & Goh, 2016). In addition, it can be said that the use of a package program for MARS analysis is limited as a disadvantage.

The results of this study showed that at certain points the MARS model gave similar results to the SEM model. Considering the advantages of MARS mentioned above, this comparison may be useful for the social science researchers in a variety of ways, including adding perspective to the analyses. Nonetheless, as this study is limited to the analysis of the current data, it is not valid to make a comparison about the estimations, the coefficients or the power of the study. Many other studies show that the MARS model is a powerful predictor but simulation studies are required to make the certain comparisons between SEM and MARS methods.

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Declaration of Conflicting Interests and Ethics

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REFERENCES

Abdel-Aty, M., & Haleem, K. (2011). Analyzing angle crashes at unsignalized intersections using machine learning techniques. *Accident Analysis & Prevention*, *43*(1), 461-470. https://doi.org/10.1016/j.aap.2010.10.002

Adıgüzel, A., & Karadaş, H. (2013). Ortaöğretim öğrencilerinin okula ilişkin tutumlarının devamsızlık ve okul başarıları arasındaki ilişki [The level of effect of high school students' attitudes towards school on their absenteeism and school success] *Yüzüncü Yıl University Journal of the Faculty of Education*, *10*(1), 49-67. https://dergipark.org.tr/en/pub/yyuefd/issue/13705/165929

Akbıyık, C., & Kestel, M. (2016). Siber zorbalığın öğrencilerin akademik, sosyal ve duygusal durumları üzerindeki etkisinin incelenmesi [An investigation of effects of cyber bullying on students' academic, social and emotional states] *Mersin University Journal of the Faculty of Education*, *12*(3), 844-859. https://doi.org/10.17860/mersinefd.282384

AL-Qinani, I.H. (2016). Multivariate adaptive regression splines (MARS) heuristic model: Application of heavy metal prediction. *International Journal of Modern Trends in Engineering and Research*, *3*(8), 223-229. https://doi.org/10.21884/IJMTER.2016.3027.7NUQV

Anıl, D. (2010). Uluslararası öğrenci başarılarını değerlendirme programı (PISA)'nda Türkiye'deki öğrencilerin fen bilimleri başarılarını etkileyen faktörler [Factors effecting science achievement of science students in programme for international students' achievement (PISA) in Turkey]. *Education and Science*, *34*(152).

Arslan Ö.S., & Savaşer, S. (2009). Okulda zorbalık [School bullying] *Milli Eğitim*, *38*(184), 218-227. https://dergipark.org.tr/en/pub/milliegitim/issue/36201/407174

Atik, S. (2016). *Akademik başarının yordayıcıları olarak öğretmene güven, okula karşı tutum, okula yabancılaşma ve okul tükenmişliği [Trust in teacher, attitude towards school,alienation from school and school burnout aspredictors of academic achievement]* (Unpublished Doctoral dissertation) İnönü University

Bahçetepe, Ü., & Giorgetti, F.M. (2015). Akademik başarı ile okul iklimi arasındaki ilişki [The relation between the academic achievement and the school climate]. *İstanbul Eğitimde Yenilikçilik Dergisi*, *1*(3), 83-101. https://dergipark.org.tr/en/download/article-file/436183

Bolder, J., & Rubin, T. (2007). Optimization in a simulation setting: Use of function approximation in debt strategy analysis, *Bank of Canada Working Paper*, 1-92. http://dx.doi.org/10.2139/ssrn.1082840

Candemir, M. (2018). *Antecedents and consequences of Turkish Millennials' ELoyalty: A Structural Equation Modeling Application* [Unpublished master's thesis]. Marmara University

Clement, K.A., Victor, A.T., & Yao, Y.Z. (2020). Multivariate Adaptive Regression Splines (MARS) approach to blast-induced ground vibration prediction, *International Journal of Mining, Reclamation and Environment*, *34*(3), 198-222. https://doi.org/10.1080/17480930.2019.1577940

Cumhur, F. (2018). The investigation of the factors affecting the mathematical success of students in the context of teachers' opinions and suggestions. *Journal of Social and Humanities Sciences Research (JSHSR)*, *5*(26), 2679-2693. http://dx.doi.org/10.26450/jshsr.647

Deichmann, J., Eshghi, A., Haughton, D., Sayek, S., & Teebagy, N. (2002). Application of multiple adaptive regression splines (MARS) in direct response modeling. *Journal of Interactive Marketing*, *16*(4), 15-27. https://doi.org/10.1002/dir.10040

Demir, İ., & Kılıç, S. (2010). Öğrencilerin matematiğe karşı tutumlarının matematik başarısı üzerine etkisi. [Effects of students' self-related cognitions on matematics achievement] *İstanbul Aydın Üniversitesi Fen Bilimleri Dergisi*, *2*(4), 50-70. https://dergipark.org.tr/en/pub/iaud/issue/30050/32446

Dursun, Y., & Kocagöz, E. (2010). Yapisal eşitlik modellemesi ve regresyon: karşılaştırmalı bir analiz [Structural equation modeling and regression: a comparative analysis] *Erciyes Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, *35*, 1-17. https://dergipark.org.tr/en/pub/erciyesiibd/issue/5892/77926

Emre, İ.E., & Erol, Ç.S. (2017). Veri analizinde istatistik mi veri madenciliği mi? [Statistics or data mining for data analysis] *Bilişim Teknolojileri Dergisi, 10*(2), 161-167. https://doi.org/10.17671/gazibtd.309297

Eraslan, A. (2009). Finlandiya'nın PISA'daki başarısının nedenleri: Türkiye için alınacak dersler [Reasons behind the Success of Finland in PISA: Lessons for Turkey] *Necatibey Faculty of Education Electronic Journal of Science and Mathematics Education, 3*(2), 238-248. https://dergipark.org.tr/en/pub/balikesirnef/issue/3369/46514

Fayyad, U., Piatetsky-Shapiro, G., Smyth, P., & Uthurusamy, R. (1996). *Advances in Knowledge Discovery and Data Mining.* AAAI/MIT Press.

Finney, S. J., DiStefano, C., Hancock, G. R., & Mueller, R. O. (2006). *Structural equation modeling: A second course.* LAP-Information Age Publishing Inc.

Güneş, S., Görmüş, Ş., Yeşilyurt, F. & Tuzcu, G. (2012). ÖSYS başarısını etkileyen faktörlerin analizi [The determinants of OSYS success] *Pamukkale Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, *11*, 71-81.

Güngör, A.A., Eryılmaz, A., & Fakıoğlu, T. (2007). The relationship of freshmen's physics achievement and their related affective characteristics. *Journal of Research in Science Teaching, 44* (8), 1036-1056. https://doi.org/10.1002/tea.20200

Güzel, H. (2004). Genel fizik ve matematik derslerindeki başarı ile matematiğe karşı olan tutum arasındaki ilişki [The relationship between success in general physics and mathematics courses and attitude towards mathematics]. *Journal of Turkish Science Education*, *1*(1), 49- 58. https://www.tused.org/index.php/tused/article/view/41/16

Huyut, M.T., & Keskin, S. (2017). Matematik başarısına etki eden faktörlerin: çevresel faktörlerin çoklu uyum analizi ile belirlenmesi [Determination of factors affecting of mathematics success: environmental factors with multiple correspondence analysis] *Türkiye Teknoloji ve Uygulamalı Bilimler Dergisi*, *1*(2), 48-59. https://dergipark.org.tr/en/pub/tubid/issue/32796/303761

Karasar, N. (2015). *Bilimsel araştırma yöntemleri* [*Science research method*]. Nobel Akademik Yayıncılık.

Karataş, H. (2011). *İlköğretim okullarında zorbalığa yönelik geliştirilen programın etkisinin incelenmesi [Examining the effect of the program developed to address bullying in primary schools].* [Unpublished Doctoral dissertation] Dokuz Eylül University

Kline, R.B. (2015). *Principles and practice of structural equation modeling*. Guilford Publications.

Lee, T.S., Chiu, C.C., Chou, Y.C., & Lu, C.J. (2006). Mining the customer credit using classification and regression tree and multivariate adaptive regression splines.

Computational Statistics & Data Analysis, *50*(4), 1113-1130. https://doi.org/10.1016/j.csda.2004.11.006

Lee, T.S., & Chen, I.F. (2005). A two-stage hybrid credit scoring model using artificial neural networks and multivariate adaptive regression splines. *Expert Systems with Applications*, 28, 743-752. https://doi.org/10.1016/j.eswa.2004.12.031

Lehman, R. (2006). The role of emotion in creating instructor and learner presence in the distance education experience. *Journal of Cognitive Affective Learning*, *2* (2), 12-26.

Li, B., Bakshi, B.R., & Goel, P.K. (2009). *Other Methods in Nonlinear Regression*. In Comprehensive Chemometrics, edited by S. D. Brown, R. Tauler, and B. Walczak, 463-476. Elsevier.

Lu, C.J., Lee, T.S. & Lian, C.M. (2012). Sales forecasting for computer wholesalers: A comparison of multivariate adaptive regression splines and artificial neural networks. *Decision Support Systems*, *54*(1), 584-596. https://doi.org/10.1016/j.dss.2012.08.006

MEB. (2019). *TIMSS 2019 Ulusal Matematik ve Fen Ön Raporu: 4. ve 8. Sınıflar* [TIMSS 2019 National mathematics and sciences preliminary report 4th and 8 th grades]. http://odsgm.meb.gov.tr/meb_iys_dosyalar/2020_12/10175514_TIMSS_2019_Turkiye_On_Raporu_.pdf

Muzır, E. (2011). *Basel II düzenlemeleri doğrultusunda kredi riski analizi ve ölçümü: geleneksel ekonometrik modellerin yapay sinir ağları ve MARS modelleriyle karşılaştırılmasına yönelik ampirik bir çalışma* [*Credit risk analysis and measurement in accordance with Basel II regulations: An empirical study to compare traditional econometric models to Artificial Neural Networks and MARS models*] [Unpublished Doctoral dissertation]. İstanbul University

Orhan, H., Teke, E.Ç., & Karcı, Z. (2018). Laktasyon eğrileri modellemesinde çok değişkenli uyarlanabilir regresyon eğrileri (MARS) yönteminin uygulanması [Application of multivariate adaptive regression splines (MARS) for modeling the lactation curves] *Kahramanmaraş Sütçü İmam Üniversitesi Tarım ve Doğa Dergisi, 21*(3), 363-373. https://doi.org/10.18016/ ksudobil.334237

Oruç, M.A. (2019). *İstihbaratın geleceği: Siber uzayda istihbarat ve karşı istihbarat faaliyetlerinde yapay zekâ ve veri bilimi kullanımı* [*Future of intelligence: The using artificial intelligence and data science in intelligence and counter intelligence activities in cyber space*] [Unpublished master's thesis]. İstanbul Aydın University

Ölçüoğlu, R., & Çetin, S. (2016). TIMSS 2011 sekizinci sınıf öğrencilerinin matematik başarısını etkileyen değişkenlerin bölgelere göre incelenmesi. [The Investigation of the Variables That Affecting Eight Grade Students' TIMSS 2011 Math Achievement According to Regions]. *Eğitimde ve Psikolojide Ölçme ve Değerlendirme Dergisi*, *7*(1), 202-220. https://doi.org/10.21031/epod.34424

Özfalcı, Y (2008). *Çok değişkenli uygulanabilir regresyon kesitleri: MARS [Multivariate adaptive regression splines: MARS]* [Unpublished master's thesis]. Gazi University.

Parsaie, A., Haghiabi, A.H., Saneie, M., & Torabi, H. (2016). Prediction of energy dissipation on the stepped spillway using the multivariate adaptive regression splines. ISH Journal of Hydraulic Engineering, *22*(3), 281 292. https://doi.org/10.1080/09715010. 2016.1201782

Pekel-Uludagli, N., & Uçanok, Z. (2005). Akran zorbaligi gruplarinda yalnizlik ve akademik basari ile sosyometrik statüye göre zorba/kurban davranis türleri [Loneliness, academic achievement and types of bullying behavior according to sociometric status in bully/victim groups]. *Türk Psikoloji Dergisi*, *20*(56), 77. https://psycnet.apa.org/record/2006-01737-005

Plotnikova, V., Dumas, M., & Milani, F. (2020). Adaptations of data mining methodologies: a systematic literature review. *PeerJ. Computer science*, 6, 267. https://doi.org/10.7717/peerjcs.267

Rodríguez, C.M., & Wilson, D.T. (2002). Relationship bonding and trust as a foundation for commitment in US–Mexican strategic alliances: A structural equation modeling approach. *Journal of International Marketing*, *10*(4), 53-76. https://doi.org/10.1509/jimk.10.4.53.19553

Sarıer, Y. (2020). TIMSS uygulamalarında Türkiye'nin performansı ve akademik başarıyı yordayan değişkenler [Turkey's performance in TIMSS applications and variables predicting academic achievement]. *Temel Eğitim, 2*(2), 6-27. https://dergipark.org.tr/en/pub/temelegitim/issue/57288/745624

Şen, S. (2020). *Mplus ile yapısal eşitlik modellemesi uygulamaları.* Nobel Yayınları.

Şevgin, H. (2020). *ABİDE 2016 fen başarısının yordanmasında MARS ve brt veri madenciliği yöntemlerinin karşılaştırılması [Predicting the ABIDE 2016 science achievement: The comparison of MARS and BRT data mining methods]* [Unpublished master's thesis]. Gazi University.

Temel, G.O., Ankarali, H., & Yazici, A.C. (2010). Regresyon modellerine alternatif bir yaklasim: MARS [An alternative approach to regression models: MARS.] *Türkiye Klinikleri Biyoistatistik*, *2*(2), 58.

The jamovi project (2021). *Jamovi (Version 1.6) [Computer Software]*. https://www.jamovi.org/

Wang, J. (2007). A trend study of self-concept and mathematics achievement in a cross cultural context. *Mathematics Education Research*, *19*(3), 33-47. https://doi.org/10.1007/BF03217461

Yoon, S., Co, M.C., Jr, Suero-Tejeda, N., & Bakken, S. (2016). A Data mining approach for exploring correlates of self-reported comparative physical activity levels of urban latinos. *Studies in Health Technology and Informatics*, *225*, 553–557. https:// doi.org/10.3233/978-1-61499-658-3-553

Zakaria, E., & Nordin, N.M. (2008). The effects of mathematics anxiety on matriculation students as related to motivation and achievement. *Eurasia Journal of Mathematics, Science & Technology Education*, *4*(1), 27-30. https://doi.org/10.12973/ejmste/75303

Zateroğlu, M.T., & Kandırmaz (2018). Türkiye için güneşlenme süresi değişiminin izlenmesi, değerlendirilmesi ve bazı meteorolojik verilerle ilişkisinin belirlenmesi [Observation and evaluation of sunshine duration changes in Turkey and determination of relations with some meteorological parameters]. *Ç.Ü Fen ve Mühendislik Bilimleri Dergisi*, *35*(3), 105-114.

Zhang, W., & Goh, A.T. (2016). Multivariate adaptive regression splines and neural network models for prediction of pile drivability. *Geoscience Frontiers*, *7*(1), 45-52. https://doi.org/10.1016/j.gsf.2014.10.003

Zhang, W., Wu, C., Li, Y., Wang, L., & Samui, P. (2021). Assessment of pile drivability using random forest regression and multivariate adaptive regression splines. *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards*, *15*(1), 27-40. https://doi.org/10.1080/17499518.2019.1674340

Zhou, Y., & Leung, H. (2007). Predicting object-oriented software maintainability using multivariate adaptive regression splines. *Journal of Systems and Software*, *80*(8), 1349-1361. https://doi.org/10.1016/j.jss.2006.10.049