Article History
Received: 21.10.2022
Received in revised form: 06.03.2023
Accepted: 17.03.2023
Article Type: Research Article

International Journal of Contemporary Educational Research (IJCER)

www.ijcer.net

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To cite this article:

Bezek-Gürü, Ö., Şevgin, H. & Kayri, M. (2023). Reviewing the Factors Affecting PISA Reading Skills by Using Random Forest and MARS Methods. *International Journal of Contemporary Educational Research, 10*(1), 181-196. https://doi.org/10.33200/ijcer.1192590

IJCER International Journal of Contemporary Educational Research
Volume 10, Number 1, March 2023, Page 181-196 ISSN: 2148-3868

Reviewing the Factors Affecting PISA Reading Skills by Using Random Forest and MARS Methods

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Abstract

The research aims to determine the factors affecting PISA 2018 reading skills using the Random Forest and MARS methods and to compare their prediction abilities. This study used the information from 5713 students, 2838 (49.7%) male and 2875 (50.3%) female, in the PISA 2018 Turkey. The analysis shows the MARS method performed better than the Random Forest method. In both methods, the most significant factor affecting reading skills in Turkey is "the number of books in the house." The variables the MARS method finds significant are "students' perception of difficulty, motivation for reading skills, father's educational status, reading pleasure, bullying experience of the student, mother's educational status, attitude towards school, classical artifacts at home, supplementary school books at home, competition at school, competitive power, cooperation perception at school, reading frequency, self-efficacy, poetry books at home, anxiety about reading skills, and teacher support." However, the other variables had no relationship to prediction. This study is expected to serve as a model for the use of data mining in educational research.

Keywords: Educational Data Mining, MARS, PISA, Random Forest, Reading Skills

Introduction

Along with the national assessment studies in the field of education, applications such as TIMSS, PISA, and PIRLS are carried out to enable countries to see their position on an international scale (Chang & Bangsri, 2020; Ministry of National Education [MoNE], 2019). One of these exams, the Program for International Student Assessment (PISA), which was developed by the Organization for Economic Cooperation and Development (OECD), is educational research that measures the ability of an age group of 15 students enrolled in formal education to apply the knowledge and skills they have acquired throughout their school life into daily life. In the PISA applications conducted every three years, students' reading skills, mathematics literacy, and science literacy levels are measured, and a different field is emphasized in each application period. In PISA applications, apart from three fields, information about the student's motivation, thoughts about himself, learning styles, school, and family environment is collected (MNE, 2019). In the last PISA application in 2018, reading skills were determined as the main field (MNE, 2019).

Reading skills are defined as the individual's capacity to understand, use, evaluate, think about, and communicate about the texts to achieve his or her goals, develop his/her knowledge and potential, and participate in society (Ikhsanza et al., 2019; OECD, 2019; Urfalı Dadandı et al., 2018). The definition of reading skills has changed in line with economic, cultural, and technological developments. Reading should not only be understood as a skill acquired during childhood. Reading skills are significant tools in lifelong learning that enable individuals to interact with their peers and society (OECD, 2019). In other words, reading skills are a key to success not only in the academic field but in all fields of life (Ikhsanza et al., 2019). Therefore, reading skills can be considered the power to understand and use printed information in daily activities that help individuals reach their goals and increase their knowledge and potential. Therefore, within the framework of PISA reading skills, such aspects as a student's ability to access, select, interpret, combine, and evaluate information are considered (OECD, 2019).

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In the PISA 2000 application, which was the first cycle of PISA, the reading skills competence levels were determined under five categories; this number was then increased to six in the 2009 application. In this period, the name of level 1 has been changed to level 1a, and level 1b categories have been added. Unlike these, in the PISA 2018 application, the scope was expanded by adding Level 1c to the reading scale, which better defines the competencies of the lowest-achieving students. The aim here is to increase sensitivity in measuring reading skills and to try to understand what students in this situation can do while reading (Arıcı & Altıntaş, 2014; OECD, 2019). Besides, in the reading skills category in previous PISA applications; there were three sub-scales named "accessing and obtaining information", "integrating and interpreting texts" and "reflecting on and evaluating texts". In the PISA 2018 application, the names of these scales were changed to "finding information", "understanding" and "evaluating and reflecting". Also, in this period; two new sub-scales that define students' literacy with single-source and multi-source texts were also developed.

Thanks to large-scale examinations such as PISA, countries have the opportunity to see where they rank among the participating countries and draw comparisons with other countries on specific areas relating to education (Torney-Purta & Amadeo, 2013). Turkey participated in a PISA application for the first time in 2003, and in these applications made in the field of reading skills so far, it has been seen that Turkey is below the OECD average (Bozkurt, 2016; Urfalı Dadandı et al., 2018). In the 2018 PISA reading skills field, the average for Turkey is 466, the average for the OECD is 487, and the average for all countries is 453 points. In this cycle, Turkey has increased its average score according to PISA 2015. Despite this, it ranks 40th out of 79 participating countries in the field of reading skills. When the performance was examined according to their competence levels, it was seen that students concentrated on levels 1a and 2 (MoNE, 2019). In PISA applications, Turkey trails behind OECD countries in terms of mathematics and science literacy, as well as reading skills. In the literature, there are studies suggesting that reading skills affect mathematics and science achievement (Güleç & Alkış, 2003; Güre et al., 2020; Gürsakal, 2009; İnal & Turabik, 2017; Kaya, 2017). Therefore, it is clear that the data to be obtained in the analysis of multifaceted information gathered at a large scale level through the applications carried out at an international level like PISA are of vital importance. In the analysis of such data, it is likely to unveil the hidden structure and analyze the big data through powerful methods without errors due to the existence of data mining methods. In fact, in the examination of the data obtained from such large-scale applications, it has been seen that there are numerous studies in the literature in which data mining methods are used (Aksu & Doğan 2018; Gamazo & Martínez-Abad, 2020; Güre et al., 2020; Martínez-Abad et al., 2020). Among these studies, there are several that utilize the Random Forest method, one of the existing methods that use PISA data (Aksu & Doğan 2018; Güre et al., 2020; Han et al., 2019; Saarela et al., 2016; Yi & Na, 2020). In addition, it has been found that there is a study in which the MARS method is used (Kılıç Depren, 2018). However, in the related literature, there is no study encountered in which the two methods are used together in the field of education. It has been observed that although a limited number of studies using the MARS method have been encountered (Kayri, 2010; Şevgin & Önen, 2022), there are numerous studies utilizing the RF method (Behr et al., 2020; Mahboob, Irfan & Karamat, 2016; Pelaez, 2019; Petkoviç et al., 2016).

In the present study, it is aimed to investigate, using data mining methods, the factors affecting the reading skills of 15-year-old students who are enrolled in formal education in Turkey. The PISA 2018 data were examined utilizing data mining methods such as Random Forest and MARS, and the classification performance of the approaches as well as the factors affecting students' reading skills according to both approaches were revealed according to their importance. To that end, RF and MARS were used to analyze the relationships between the factors influencing students' reading skill levels in Turkey, and answers to the following questions were sought:

1. What is the significance level of the variables in the model according to these Random Forest and MARS methods?
2. Do the classification performances of these two methods differ?

Methodology

The present research is a descriptive study using a relational survey model, which is one of the most common survey models. The relational survey model is a research methodology that aims to describe the existence of the interaction between many variables as it is (Karasar, 2006).

Data Set

More than 600,000 students participated in the PISA 2018 application, representing 32 million students in the age group of 15 and studying in 79 participating countries (of which 37 are OECD members) (MoNE, 2019). A random selection of 6890 students from 186 schools attended to PISA 2018 Turkey application based on 12 regions according to Nomenclature of Territorial Units for Statistics (NUTS) Level 1 (MoNE, 2019). Students with missing data from demographic characteristics were excluded from the data set prior to analysis. The regression method was used for the student characteristics collected at the Likert type scale level for the variables that were found to be significant as a result of the missing data analysis at each scale level and contained less than 5% missing data, and deletion was used for the variables that contained more than 5% missing data. As a result of the missing data procedures, the data collected from 5713 students—2838 (49.7%) male and 2875 (50.3%) female — who took the PISA 2018 were used.

Measuring Tools

In this study, as a data collection tool as well as a PISA 2018 student survey of Turkey , the scales, the difficulty perception, the competitiveness perception at school, the cooperation perception at school, the attitude towards school, the sense of belonging to the school, the students' bullying experience variables, and the scores obtained from the reading skills test were used.

In the research, first of all, the variables that had the likelihood of being associated with one another and that were thought to affect reading skills were examined and selected based on the theoretical framework. In the scope of the research, the scores obtained from the scales Teacher Support, Reading Frequency, Reading Pleasure, Reading Fluency, Student Motivation Scale, Student Anxiety Scale, and Self-Efficacy Scales were used. Moreover, within the scope of the study, in addition to the scales used, certain demographic and personal information about the students was also used. (Table 1).

Table 1. Descriptive statistics of predictor variables

Predictor	Categories	%
Gender	Female	50.3
	Male	49.7
Mother's Educational Level	High School	23.8
	Vocational / Technical High School	15.6
	Secondary school	22.4
	Elementary school	28.2
	Not Graduate from Elementary school	10.0
Father's Educational Level	High School	25.4
	Vocational / Technical High School	21.8
	Secondary school	27.4
	Elementary school	21.6
	Not Graduate from Elementary school	3.8
Do you have your own room in your home?	Yes	74.9
	No	25.1
Do you have classic artefacts in your home?	Yes	74.1
	No	25.9
Do you have poetry books in your home?	Yes	59.6
	No	40.4
Do you have supplementary textbooks at home?	Yes	88.6
	No	11.4
Do you have a dictionary in your home?	Yes	96.4
	No	3.6
Do you have art, music and design books in your home?	Yes	44.3
	No	55.7
How many books do you have in your home?	0-10 book(s)	15.6
	11-25 books	26.1
	26-100 books	31.2
	101-200 books	14.2
	201-500 books	9.1
	More than 500 books	3.9

As the dependent variable in the study, reading skills at the student level were used by taking the average of ten different possible (PV1READ-PV10READ) values in terms of cognitive domain competence. The average scores were grouped according to the threshold values of the PISA 2018 reading skills competence levels, and then the competence levels were converted into a two-level categorization as successful and unsuccessful (Table 2). In this case, the predicted variable in the model was transformed into a categorical structure.

Table 2. PISA 2018 threshold values and categories of reading skills competence levels

Competence levels	Score (X)	Category
level 1c	189 <**X** <261	Unsuccessful
level 1b	262 <**X** <334	
level 1a	335 <**X** <406	
level 2	407 <**X**<479	
level 3	480 <**X**<552	Successful
level 4	553 <**X**<625	
level 5	626 <**X**<697	
level 6	above 697	

Analysis

Within the scope of the study, in the application of RF and MARS methods, SPM (Salford Predictive Modeler), SPSS, and MS Excel programs were used. The SPM program uses the source codes written by Breiman and Cutler in the Fortran programming language (Akman et al., 2010). In the program; algorithms such as CART, Random Forest, MARS, and Gradient Boosting can be run. In the study, the educational version of the SPM program was used. After downloading the data file containing the PISA data, it was first converted to Excel format and transferred from Excel to the SPSS environment. Data deletion was performed in SPSS, descriptive statistics of the variables in the model were obtained, and the Likert-type scales used in the research were converted into a Z-point with the same mean value and standard deviation due to the various numbers of categories. With the demo version of the SPM 8.0 program, predictions were made for the RF and MARS methods based on default values, and performance indicator values related to the predictions were obtained.

Random Forest Method

The Random Forest (RF) method, developed by Breiman in 2001, is a well-known method as a classification and regression method. The method, one of the Ensemble methods, is based on the idea of combining decision trees with clustering and bootstrapping ideas (Biau & Scornet, 2016; Genuer et al., 2017).

The RF method has high prediction performance even in cases where the number of variables is greater than the number of observations, there are many missing observations, and compliance is excessive (Biau & Scornet, 2016; Cutler et al., 2007). The method is fast, simple to use, has high classification accuracy, can work with small samples, and can be applied directly to high dimensional problems (Biau & Scornet, 2016; Cutler et al., 2011). The RF method attracts attention with its features such as measuring the proximity between samples in two ways, determining the significance levels of variables, assigning missing values, determining outliers, and unsupervised learning (Cutler et al., 2011). The ability to work with the desired number of trees and the absence of pruning or stopping rules make the method advantageous (Breiman, 2001; Quinlan, 1993).

The RF method can model complex interactions between predictor variables and work with statistical analysis methods such as regression, classification, and survival analysis (Cutler et al., 2007). It is reported that it is consistent compared to other methods due to its small generalization error (Breiman, 2001). RF method; while creating each tree, it uses different bootstrap samples according to the classification or regression trees it has composed. In standard trees, each node is divided by providing the best division among all variables; in the RF method, variables that provide the best division among the predictors randomly selected among all nodes, are used (Güre et al., 2020; Liaw & Wiener, 2002).

In the RF method, each tree sampled from the original data set in the decision forest is selected by using both the bootstrap sampling method and the random and replacement method (Breiman, 2001). In the method, each tree shows a similar distribution with all trees in the forest. Also, the method combines predictions based on the values of an independently sampled random vector. The generalization error of a tree classifier forest depends on the strength of each tree in the forest and the correlation between them. As the correlation increases, the error rate in the forest increases (Breiman, 2001). The method uses the CART algorithm to produce maximum size trees without pruning (Akman et al., 2011; Breiman, 2001).

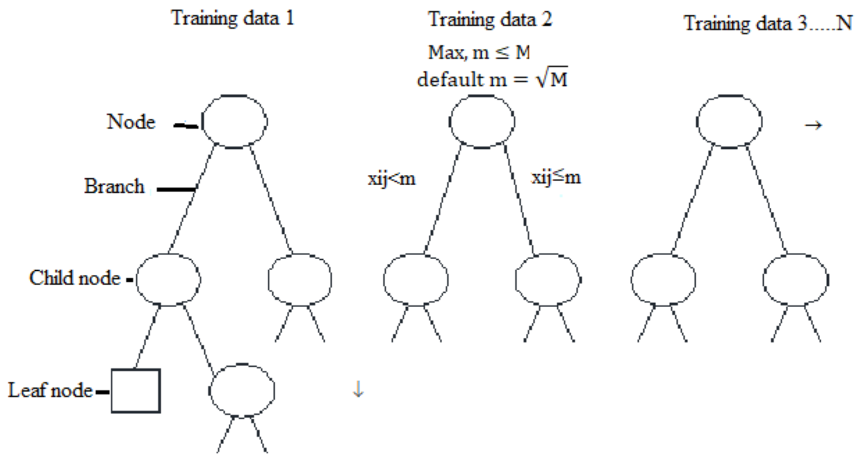

Figure 1. The tree structure of the RF method (Özdarıcı Ok et al., 2011).

RF is accepted as a collection of predictors consisting of random-based regression trees defined as $\{r_n(x, \Theta_m, D_n), m \geq 1\}$ with outputs $\Theta_1, \Theta_2 \ldots\ldots\ldots\ldots$ of the random variable. These random trees are combined with clustered regression estimates. The corresponding equality is shown below.

$$\bar{r}_n(\boldsymbol{X}, \mathcal{D}_n) = \mathbb{E}_{\Theta}[r_n(\boldsymbol{X}, \Theta, \mathcal{D}_n)] \quad (1.1)$$

In the equality; $\mathbb{E}_{\Theta}$ conditionally indicates the expectation for the random parameter on X and the data set $\mathcal{D}_n$. Θ random variable is used to determine how to make successive partitions in the creation of individual trees, for example, choosing the coordinate to be split and the split position. In the model in mind, it is assumed that the variable is independent of X and that the training example is $\mathcal{D}_n$. This shows that, especially, any bootstrapping or resampling steps in the training set are not accepted (Biau, 2012; Güre et al., 2020).

In the method, a model can be established by taking the entire data set as well as separating it into test and learning data sets. To create the RF algorithm; first, n pieces of bootstrap samples are selected from the original data set. Among these, 1/3 is used as training data, and the other 2/3 is used as learning data. Next, the un-pruned classification and regression trees are grown for each bootstrap sample. Instead of choosing the one that provides the best division among all the variables in the learning (inBag) data set, first m pieces of random samples are selected, and the one that will provide the best division among them is determined. Finally, by collecting the estimates of n pieces of decision trees, the new data set is estimated by considering the average for regression and the majority of votes for classification (Akman et al., 2011; Liaw & Wiener, 2002).

MARS (Multivariate Adaptive Regression Splines–MARS)

The MARS method is a nonparametric regression method developed by statistician Jerome Friedman in the early nineties. This analysis method, abbreviated and known as MARS, is generally translated into Turkish as "multivariate adaptive regression extensions". The MARS method, which has great significance in both classification and regression, is successfully applied, especially in science fields where complex relationships among many variables are modeled (Kuter et al., 2015). The MARS analysis method (Lindner, 2011), which is a particularly popular method in the field of data mining, enables more accurate estimation, easy understanding, and elaboration of regression models (Statsoft, 2017).

MARS determines the relationships between the dependent variable(s) and independent variables based on the "smoothing splines" logic. MARS is a very popular method used to develop models that can make accurate predictions, especially when there is no simple or monotonous relationship between the dependent variable and the independent variables, or when there are complex relationships with another expression (Lindner, 2011; Nisbet et al., 2009). Besides, the MARS analysis is a method that does not contain any assumptions regarding the functional relationship between dependent and independent variables (Friedman 1991).

MARS transforms nonlinear relationships between dependent and independent variables into a linear structure using appropriate transformation techniques (Deichman et al., 2002). MARS, which can automatically find connections and perform modeling between independent variables by creating nonlinear models, is based on the principle of revealing the model hidden in the database. This model is known to give good results, especially in data sets with more than one dependent variable (Statsoft, 2017). Besides, MARS, which effectively processes the loss data in the data set, can be regarded as unbiased due to its ability to divide nonlinear models into linear particles and make parameter estimates separately in each particle (Kayri, 2009).

The MARS analysis method essentially goes to create the most suitable model in two steps. In the first step, MARS creates the sum of basic functions, which are transformations of independent variables, taking into account deviations (nonlinear) and interactions in the model. In the second step, MARS estimates the basic functions as independent variables using the least-squares method (Deichman et al., 2002). Again, it tries to construct a flexible regression model by using basic functions corresponding to different intervals of independent variables (Friedman 1991). Besides, the selection of basic functions is data-based and specific to the problem studied, which makes MARS an adaptable regression technique for solving multidimensional problems. When creating the MARS model, partial linear basic functions are added to each other to determine the dependent variable, taking into account the additive and interactive effects of the independent variables (Kuter et al., 2015).

When creating the MARS model, partial linear basic functions are added to each other to take into account the additive and interactive effects of independent variables to determine the dependent variable (Kuter et al., 2015).

MARS is an ideal data modeling method for researchers who want to fully explain the relationships between variables besides using strong and accurate estimation (Friedman, 1991). Thus, the researcher gets the chance to gain insight into the business and make more strategic decisions.

Performance Criteria

As for performance criteria in the study, Accuracy rate, specificity rate, sensitivity rate, precision rate, F1 statistic values and AUC values of the ROC curve were used. Equations for performance criteria are given below.

Table 3. Complexity Matrix

		Predicted Class Unsuccessful	Successful	Total
Real Class	Unsuccessful	TN	FP	TN+FP
	Successful	FN	TP	FN+TP
	Total	TN+FN	FP+TP	TN+FN+FP+TP

$$Correct\ classification\ rate = \frac{(\mathrm{TP+TN})}{(\mathrm{TP+FP+TN+FN})} \quad (1.2)$$

$$Specificity\ rate = \frac{(TN)}{(TN+FP)} \quad (1.3)$$

$$Sensitivity\ rate = \frac{(TP)}{(TP+FN)} \quad (1.4)$$

$$Precision\ rate = \frac{(TP)}{(TP+FP)} \quad (1.5)$$

$$F1 - Statistics = \frac{2 + Sensitivity + Precision}{Sensitivity + Precision} \quad (1.6)$$

Before the PISA 2018 data set was analyzed with RF and MARS methods, it was tested whether there was a multi-correlativity problem among the variables included in the analysis. In the multi-correlativity test, the Variance Inflation Factor (VIF) and the Tolerance values of the multi-correlativity are taken into account. If the VIF value is greater than 10 or the Tolerance value is less than 0.1, it is understood that there is a problem of multi-correlativity between variables (Güre et al., 2020; Keller et al., 2012). In this study, it was observed that VIF values varied between 1.059 and 5.458 and Tolerance values varied between 0.183 and 0.944. Therefore, it was understood that there was no problem with multi-correlativity among the variables used in the study.

Results and Discussion

Results

Significance levels of variables in the model according to both methods

The RF method is also an iterative method like the MARS method. In this method; the researcher can decide on the number of trees and the number of variables to be used. In the study, to determine the most appropriate number of trees for creating the decision forest; the analysis was repeated with the numbers of trees 250, 500, 750, and 1000. The value with the lowest error rate expresses the number of trees from which the most suitable model will be composed. The number of random variables to be selected in each node is taken as 5, which is the square root of 25, which is the total number of variables. The graph showing the error rates in the decision forest according to the number of trees is shown in Figure 2.

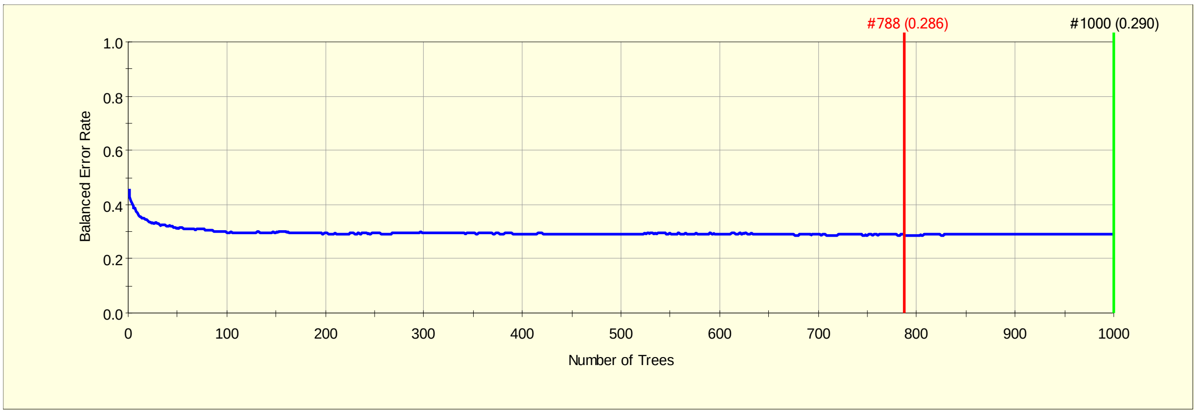

Figure 2. The overall error rate of the decision forest according to the number of trees

As can be seen in Figure 2, the error rate decreases starting from the first tree until the 788th tree, and it rises again after the 788th tree, where it has the lowest (0.286) value. This value refers to the number of trees required to build the new model. Thus, to create the most suitable model, the model was rebuilt with 788 trees, which had the lowest error rate. Predictor variables that affect the predicted variable in the established model are given in Table 4 in order according to their significance level.

Table 4. Significance levels of variables according to the RF method

Predictor Variables	Score	
Number of books at home	100.00	||||||||||||||||||||||||||||||||||||||||||||||||||||||
The presence of classical artefacts at home	35.81	||||||||||||||||||
Difficulty perception	34.34	|||||||||||||||||
Father's educational status	29.15	||||||||||||||
Mother's educational status	14.31	||||||
Reading pleasure	13.38	||||||
Presence of supplementary books supporting the school at home	11.41	|||||
Motivation about reading skills	9.33	||||
Bullying experience of the student	7.40	|||
Reading fluency	6.33	|||
Sense of belonging to the school	5.77	||
Competence perception	4.02	|
Attitude towards school	3.33	|
Competition power	3.14	|
Self-efficacy	1.86	
Presence of poetry books at home	1.76	
Competition environment at school	1.61	
Cooperation perception at school	1.50	
Reading frequency	1.23	
Teacher support	1.18	
Gender	1.18	
Anxiety about reading skills	1.00	
Having his/her own room at home	0.91	
Presence of art, music, design books at home	0.50	
Presence of a dictionary at home	0.21	

When Table 4 is examined, it is seen that the most significant predictor affecting the predicted variable is the variable "number of books at home," with 100 points. Other variables that have a significant effect on reading skills are the presence of a classical artifact at home, the difficulty perception of the student, the educational status of the father, the education level of the mother, the pleasure of reading, and the presence of school-supplied books at home. It can be said that other variables in the model are not highly effective on the reading skills variable. For the MARS model, firstly, the maximum number of basic functions must be determined based on the Generalized Cross Validation (GCV) value. The lowest GCV value obtained expresses the number of basic functions to start with to get the best model. The number of basic functions represented by the lowest GCV value was obtained as 73, and the MARS model with 73 basic functions was established. The forward-looking phase started with 0 basic functions and became the most complex when it reached 48 basic functions. As it can be seen in Table 5, the most suitable model, which is the final model with 35 basic models, has been composed, by removing the basic functions that do not contribute to the model by pruning in the forward step phase.

Table 5. Final Model

	Basic Function	Coefficient	Variable	Sign	Node Point
	0	0.35615			
1	1	0.23569	Number of books at home	+	SubSet1
2	3	1.35528	Perception of difficulty	+	-0.52400
3	5	0.14072	Motivation about reading skills	+	-0.59540
4	6	0.07957	Motivation about reading skills	-	-0.59540
5	7	-0.05515	Father's educational status	+	SubSet1
6	9	-0.07931	Reading pleasure	+	-0.17957
7	11	0.09539	Presence of classical artefacts at home	+	SubSet1
8	13	0.12931	Mother's educational status	+	SubSet1
9	15	1.75482	Bullying experience of the student	+	0.29070
10	17	0.61480	Attitude towards school	+	-1.16640
11	19	-0.09828	Presence of supplementary books supporting the school at home	+	SubSet1
12	21	-0.05397	Competition environment at school	+	0.69120
13	23	-0.07147	Number of books at home	+	SubSet2
14	25	-0.22140	Bullying experience of the student	+	1.44540
15	28	0.02327	Competition power	-	1.18110
16	29	-0.07106	Father's educational status	+	SubSet2
17	31	0.07427	Mother's educational status	+	SubSet2
18	33	0.02647	Cooperation perception at school	+	-0.21190
19	34	0.04717	Cooperation perception at school	-	-0.21190
20	35	-0.14738	Difficulty perception	+	0.70670
21	37	-0.06406	Reading frequency	+	0.87489
22	40	0.10253	Teacher support	-	-0.69421
23	41	-0.04144	Presence of poetry books at home	+	SubSet1
24	45	-0.35653	Self-efficacy	+	-0.26168
25	47	0.13797	Self-efficacy	+	-0.60318
26	49	0.24270	Self-efficacy	+	0.08767
27	51	-2.65539	Difficulty perception	+	-0.63110
28	53	1.46755	Difficulty perception	+	-0.69490
29	57	-2.02060	Attitude towards school	+	-0.70250
30	59	1.70827	Attitude towards school	+	-0.61980
31	61	-0.23624	Attitude towards school	+	-2.07380
32	63	0.25355	Motivation about reading skills	+	0.94904
33	65	-0.14264	Motivation about reading skills	+	0.17682
34	67	0.01592	Anxiety about reading skills	+	-1.62913
35	72	-1.56159	Bullying experience of the student	+	0.23080

In the final model, the node values were composed by each predictor variable independently from other variables, and the model coefficients that give their contribution to the regression equation as a result of multiplication with the basic function, the directions of their slopes, and the information showing which variables are distributed to the basic functions are included. The multiplication of the 35 basic functions used in creating the most suitable model with the model coefficients composed the regression equation in Table 6.

Table 6. Regression Equation for the Most Suitable Model

$$
\begin{aligned}
Y = {} & 0.356151 + 0.235689 * BF1 + 1.35528 * BF3 + 0.140716 * BF5 \\
& + 0.0795665 * BF6 - 0.0551473 * BF7 - 0.0793062 * BF9 \\
& + 0.09539 * BF11 + 0.12931 * BF13 + 1.75482 * BF15 \\
& + 0.614802 * BF17 - 0.0982762 * BF19 - 0.0539656 * BF21 \\
& - 0.0714741 * BF23 - 0.221403 * BF25 + 0.0232724 * BF28 \\
& - 0.0710607 * BF29 + 0.0742705 * BF31 + 0.0264696 * BF33 \\
& + 0.0471711 * BF34 - 0.147377 * BF35 - 0.0640643 * BF37 \\
& + 0.102527 * BF40 - 0.0414432 * BF41 - 0.356529 * BF45 \\
& + 0.137969 * BF47 + 0.242702 * BF49 - 2.65539 * BF51 \\
& + 1.46755 * BF53 - 2.0206 * BF57 + 1.70827 * BF59 \\
& - 0.236242 * BF61 + 0.253551 * BF63 - 0.142644 * BF65 \\
& + 0.0159187 * BF67 - 1.56159 * BF72;
\end{aligned}
$$

In Table 6, the equation starts with a constant value and then the result of the sum of the multiplication of each basic function with the coefficients in Table 5, so the regression equation for reading skills was obtained. The order of the predictor variables represented by the basic functions in this equation according to their significance levels is given in Table 7.

Table 7. Significance levels of variables according to the MARS method

Predictor Variables	Score
Number of books at home	100.00
Difficulty perception	71.91
Motivation about reading skills	70.91
Father's educational status	52.49
Reading pleasure	48.13
Bullying experience of the student	46.60
Mother's educational status	45.79
Attitude towards school	43.19
Presence of classical artefacts at home	38.69
Presence of supplementary books supporting the school at home	30.37
Competition environment at school	24.34
Competition power	16.86
Cooperation perception at school	15.05
Reading frequency	14.70
Self-efficacy	14.53
Presence of poetry books at home	14.25
Anxiety about reading skills	8.76
Teacher support	8.16
Competence perception	0.00
Sense of belonging to the school	0.00
Having his/her own room at home	0.00
Reading fluency	0.00
Presence of art, music, design books at home	0.00
Presence of a dictionary at home	0.00
Gender	0.00

When Table 7 is examined, it is seen that the most significant predictor affecting the predicted variable in the MARS method is "the number of books at home," with 100 points, similar to the result of the RF method. Other variables that have a significant effect on reading skills are "the presence of classical artifacts at home", the student's perception of difficulty, motivation for reading skills, the father's education level, reading pleasure, the student's bullying experience the mother's education status, attitude towards school, the presence of classical artifacts, presence of supplementary books supporting the school at home. Competition at school, competitiveness, perception of cooperation at school, frequency of reading, self-efficacy, and presence of poetry books at home. On the other hand; it can be said that the other variables in the model have little or no effect on reading skills variable.

Classification performances of both methods

The performance of students who were classified as successful or failed in terms of reading skills in PISA 2018 when assigning them to these categories with the MARS data mining method is presented in Table 8.

Table 8. Classification Table composed for the MARS method

		Predicted Value		
		Unsuccessful	Successful	Total Number of Students
Real Value	Unsuccessful	2150	899	3049
	Successful	667	1997	2664
	Total Number of Students	2817	2896	5713

The performance of students who were classified as successful or failed in terms of reading skills in PISA 2018 when assigning them to these categories with the RF data mining method is presented in Table 9.

Table 9. Classification Table composed according to the RF method

		Predicted Value		
		Unsuccessful	Successful	Total Number of Students
Real Value	Unsuccessful	1952	1097	3049
	Successful	601	2063	2664
	Total Number of Students	2553	3160	5713

In the study, to compare the estimation abilities of RF and MARS methods; accuracy rate, specificity rate, sensitivity ratio, precision ratio, F1 statistic values, and AUC values of the ROC curve were used. In the final section of the study, performance indicators of the RF and MARS methods in terms of accurate estimation are given in Table 10.

Table 10. Performance of RF and MARS Methods

Performance Criteria	MARS	RF
Correct classification rate	% 72.59	% 70.28
Specificity rate	% 74.96	% 77.44
Sensitivity rate	% 70.51	% 64.02
Precision rate	% 76.32	% 76.46
F1-Statistics	% 73.30	% 69.69
Area Under ROC Curve (AUC)	% 79.80	% 78.29

When Table 10 is examined, it is seen that the MARS method performs better than the RF method in terms of correct classification rate, sensitivity rate, F1 statistics, and AUC values, and the RF method performs better than the MARS method in terms of specificity and precision rate.

Discussion

In the current study, the variables that were considered to be related to the reading skills of a 15-year-old student in the Turkish language field in the PISA 2018 application were examined through MARS and RF data mining methods, and the classification performances and prediction capacities of both methods were compared. As a result of the analysis, it has been seen that the MARS method gives better results than the RF method in terms of performance criteria. Therefore, the variables that were considered important by the above-mentioned method are discussed in this section by taking two dimensions into account.

In the first dimension, MARS and RF data mining methods were compared in terms of their classification performances. The RF method gives better results in terms of specificity and certainty rate; however, the MARS method performs better in terms of accurate classification and sensitivity rates, F1 score, and AUC value. Likewise, et al. (2012) reported that the RF method performed better in terms of Kappa coefficient and specificity rate, but, added that the MARS method gave better results in terms of sensitivity criteria. Yao, Yang, and Zhan (2011) stated that the MARS method performed better in terms of accuracy and sensitivity, and the RF method was more successful in terms of specificity. Chen et al. (2018) and Golkarian et al. (2018) noted that the MARS method performed better in terms of AUC value compared to the RF method, although Munkhdalai et al. (2019) and Østergård et al. (2018) stated that the MARS method was more successful in terms of accurate classification rate compared to the RF method. On the contrary, Lawrence and Moran (2015) and Shirzad and Safari (2019) reported that the RF method performed better in terms of accurate classification rate; Arabameri et al. (2018) and

Youssef and Pourghasemi (2021) noted that the RF method gave better results in terms of AUC value compared to the MARS method. Similarly, Kundu et al. (2021) stated in their study that the RF method showed better classification performance compared to the MARS method in terms of accuracy, specificity, sensitivity, and precision rate.

In the second dimension, both methods have revealed that the quantity of books at home was the greatest predictor variable that had a significant effect on reading skills, according to the importance level in the mentioned study, using both methodologies. When the literature is examined, many studies show that the number of books in the house has an effect on reading skills (Chiu & Mc-Bride Chang, 2006; Urfalı Dadandı et al., 2018; Gündüver & Gökdaş, 2011; Kahraman & Çelik, 2017; Karatekin et al., 2012; Kurnaz &Yıldız, 2015; Kutlu et al., 2011; Türkan et al., 2015).

According to the MARS method, the variable that has a significant effect in the second place in terms of importance is the perception of difficulty (Fulmer & Tulis, 2013; Işık, 2016; Xu, 1991). It is stated that the perception of difficulty has a positive effect on success (Işık, 2016). Studies show that high-level perceptions of difficulty may produce less positive effects or negative effects such as anxiety and anger (Acee et al., 2010; Efklides and Petkaki, 2005; Fulmer and Tulis, 2013; Pekrun et al., 2002).

According to the MARS method, other predictive variables that are effective on reading skills according to their importance are the variables of motivation for reading skills and the father's education level. It is evident from many studies that the motivation variable has a positive effect on student achievement. (Aksu & Güzeller, 2016; Güre et al., 2020; İnal & Turabik, 2017) Some studies state that there is a direct relationship between motivation and student achievement (Bayraktar, 2015; Mendi, 2009; Uzun & Keleş, 2010). Therefore, it is important to carry out studies to increase the motivation of students. On the other hand, another variable considered significant in our study is the father's education level. In parallel with the findings of our study, Anıl (2009) also found that a father's education level is more effective than a mother's education level in determining the success of students.

According to the MARS method, other predictive variables that are effective on reading skills based on their importance include the variables of reading pleasure and the student's bullying experience. It is known that there is a positive relationship between reading pleasure and achievement (Chiu & Mc-BrideChang, 2006; Smith et al., 2011). Another variable that is considered significant in the present study is the student's experience with bullying. In parallel with the results of our study; in the study conducted by Şevgin (2020), it was seen that the bullying variable was significant in predicting science achievement. But; in the study conducted by Açıkgöz (2017), no significant difference was found between bullying and academic achievement. Teachers should pay special attention to their students who are faced with bullying, and take approaches that make them feel valued.
The variables of maternal education level and attitude towards school are two further predictive variables that the MARS approach finds significant in the predicted variable. In many studies; it is shown that the education levels of the students' mothers are related to the success of the students (Anıl, 2009; Güre et al., 2020; Karabay et al., 2015; Savaş et al., 2010). In this context, it can be considered significant that parents take part in educational activities within the scope of lifelong learning in terms of being a role model for the student. On the other hand, another variable considered significant in the study is the students' attitude toward school. It is known that student attitudes affect academic achievement. It has been observed that if the student's attitude towards school is positive, the student is successful, if it is negative, the student is unsuccessful (Açıkgöz, 2017).

Other variables that have a major effect on reading skills, according to the MARS method, include the presence of classical works at home and the existence of school-aided resources at home, in order of importance. Many studies support our results (Erdoğan & Acar Güvendir, 2019; Kaya, 2017). Arıcan and Yılmaz (2010) concluded that reading classical works partially increases the reading habit; however, in the study conducted by Okur and Arı (2013), the effect of reading a classical book on whether the student gains or develops a reading habit could not be determined with certainty. On the other hand, another variable that is considered significant in the present study is the variable "presence of resources supporting the school. In parallel with the results of the study, in the study of Erdoğan and Acar Güvendir (2019), it is stated that students' having supplementary resources can contribute to the improvement of their reading skills. Unlike the study results, in the study conducted by Urfalı Dadandı et al. (2018), it was found that supplementary sources do not have a significant effect on reading skills. Taş and Minaz (2018) stated that students prefer supplementary resources more because they find them simple and concise, have more activities, and attract attention. Therefore, textbooks should be supported by supplementary resources.
Other variables that the MARS method considers important for reading skills in the present study are the variables of competition environment and competitiveness in school, in order of importance. It should be seen that activities

that allow students to compete with each other are significant. Students with high competitive power have high academic success (Bing, 1999; Frymier & Houser, 2000; Shimotsu-Dariol et al., 2012).

According to the MARS method, other important predictive variables on reading skills include the perception of cooperation at school and the frequency of reading, in order of importance. It should be considered significant to organize activities in the school environment where students can collaborate. On the other hand, another variable that seems significant is reading frequency. Studies have reported that reading habits have a positive effect on academic achievement (McQuillan & Au, 2011; Kurulgan & Çekerol, 2008; Tercanlıoğlu, 2001).

Other predictive variables that the MARS method finds important are self-efficacy and the presence of poetry books at home, in order of importance. Self-efficacy perception shows students' belief that quality results will be achieved when an effort is made. Many studies show a significant relationship between self-efficacy perception and achievement (Chang & Bangsri, 2020; Maier & Curtin 2005). On the other hand, the other variable that seems significant is "having poetry books at home". It is stated that having poetry books at home increases reading skills (Erdoğan & Acar Güvendir, 2019; Kaya, 2017).

Finally, according to the MARS method, the factors of anxiety and teacher support for reading skills are, in order of significance, predictive variables that have a significant effect on the predicted variable. It is known that there are studies reviewing students' anxiety levels in the literature (Aksu & Güzeller, 2016; İnal & Turabik, 2017; Yücel & Koç, 2011). On the other hand; another variable that is considered significant is the teacher support variable. In parallel with our study results, in the study of Chang and Bangsri (2020), it is stated that teacher support indirectly affects success. When students feel the support of teachers in the classroom, they think they are cared for and feel valued, which will increase their commitment to the school and the teacher, and this will bring success with it.

Conclusion

Within the scope of this research, MARS and RF data mining methods were discussed in order to examine the data obtained by large-scale tests, and they were recommended as alternatives for use in the field of education. In this study, MARS from the family of nonlinear regression methods under the umbrella of data mining and the RF analysis method using the Bagging algorithm from Ensemble methods were used together. Therefore, it is valuable in terms of demonstrating the use of data mining approaches in the educational research process. Unlike the MARS data mining method, the RF data mining method is easier to access. For the MARS method, there are paid programs such as STATISTICA, SAS, SPM, and free package programs such as R (Earth Package), while many paid programs such as SPSS Modeler, STATISTICA, SAS, SPM, and free package programs such as Orange, WEKA, and R (Random Forests package) are available for the RF method.

Recommendations

In addition, new studies may be considered on different samples for the generalizability of the obtained findings. Again, different from RF using the Bagging algorithm, it is also recommended to use data mining methods using the Boosting algorithm, such as Boosted Regression Trees (BRT), Multiple Additive Regression trees (MART), or Additive Boosting (Adaboost), in the process of educational research.

Author (s) Contribution Rate

The authors contributed equally.

Conflicts of Interest

There is no conflict of interest for individuals or institutions in this research.

Ethical Approval

Ethical permission (20.11.2020-E.18139) was obtained from Batman University institution for this research.

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