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Abstract

Considering the large volume of PISA data, it is expected that data mining will often be assisted in making PISA data more meaningful. Studies show that different dimensions of ICT may reveal different relationships for mathematics achievement. The purpose of this article is to evaluate the success of the decision tree classification algorithms in predicting the effect of ICT on students' mathematics performance. The population of the research consists of 15-year-old students studying in Turkey. The sample of the study consists of 6570 students who participated from Turkey and gave adequate answers to the ICT Familiarity Questionnaire in PISA and whose mathematics score was calculated. The J48 algorithm is more successful in classifying students with low mathematics achievement than classifying students with high mathematics achievement. The rate of correctly predicting mathematics achievement with weighted average values and variables related to ICT is 66.1%. ENTUSE [ICT use outside of school (leisure)], ICTCLASS [Subject-related ICT use during lessons] and USESCH [Use of ICT at school in general] variables are the most effective variables. It is thought that the reason for the difference in the effect of the use of information and communication technologies for entertainment purposes on mathematics achievement is since the level of recreational use can have a positive effect up to a certain level, while excessive use can be harmful.

Introduction

Countries carry out national assessment studies to determine their status in the field of education. But this is not enough to determine their status compared to other countries. Therefore, international evaluation programs are needed in order to compare the level of education of the countries, to determine the deficiencies to be eliminated and the measures to be taken. PISA [Program for International Student Assessment], one of the international assessment programs, is an international student assessment program implemented by the OECD [Organization for Economic Co-operation and Development] (Schleicher, 2019). The Program aims to measure the knowledge and skills of 15-year-old students who are near the end of their compulsory education in mathematics, science and reading. In PISA questions, the use of information in real-life is at the forefront. The data collected in PISA can be covered in three categories (OECD, 2016):

1. Indicators that will reveal students ' knowledge and skills.

2. Indicators of how students' skills are related to variables collected through questionnaires in PISA.
3. Indicators on inter-student relations and inter-school relations.

In the PISA 2018 exam, the average mathematics score of OECD countries was 489, while Turkey's average score was 454 (OECD, 2018a). Therefore, Turkey's performance remained below average. In addition, Turkey's average mathematics score (454) is lower than average science score (468) and average reading score (466). The chart below shows the PISA mathematics average scores of Turkey by year.

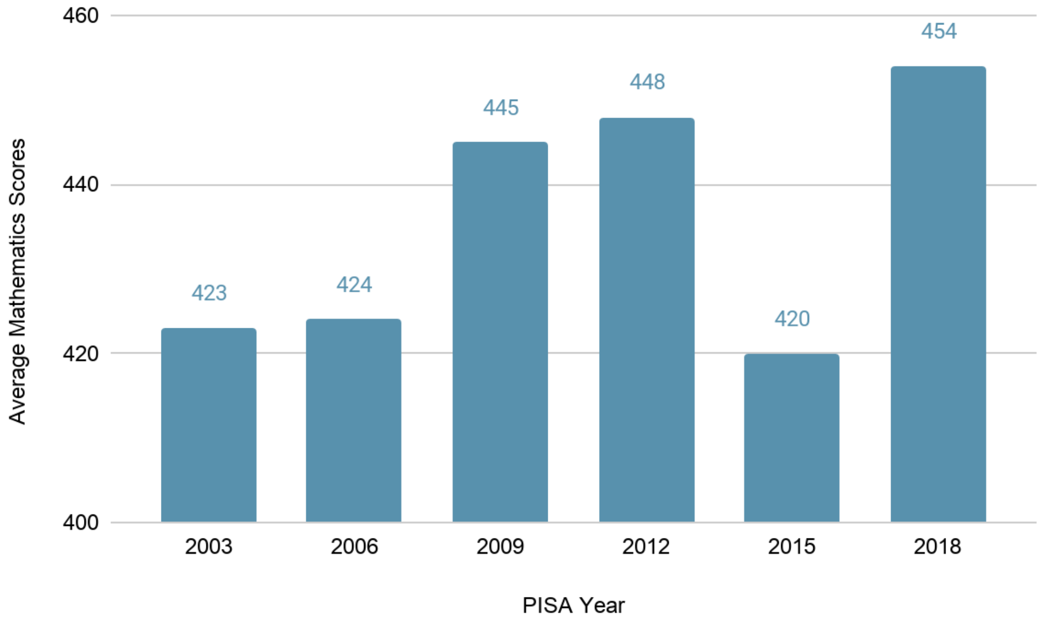

Figure 1. PISA Mathematics Average Scores of Turkey by Year

When the graph given in Figure 1 is examined, it is seen that Turkey's average mathematics scores tend to increase by year, except for 2015. In addition, according to the 2018 results, Turkey was the country that increased its mathematics average score the most in PISA 2018 compared to PISA 2015 (Suna, et al., 2018).
ICT is all the technologies used to exchange and protect digital data and to communicate with others (OECD, 2003). In PISA, data on the availability and use of information and communication technology [ICT] are collected by ICT Familiarity Questionnaire (OECD, 2017a). ICT use outside of school for schoolwork, ICT use outside of school for leisure, general ICT use at school, the student's personal interest and enjoyment of ICT, the student's perceived competence with ICT, the student's perceived autonomy related to ICT use, use of ICT as a topic in the student's social interaction, availability of ICT at home and availability of ICT at school are observed predictor variables from ICT Familiarity Questionnaire (OECD, 2017a).

The use of ICT can affect learning and teaching styles by enabling the development of high-level mental skills such as reasoning, problem solving, and communication skills, and making teaching more learner-centered rather than teacher-centered (Shaikh & Khoja, 2011). As a natural consequence of this, studies show that the use of ICT in the educational environment increases academic success (Banerjee, Cole, Duflo & Linden, 2007; Song & Kang, 2012; Petko, Cantieni, & Prasse, 2017; Meggiolaro, 2018; Tas & Gulcu, 2019). When it comes to mathematics achievement in particular, the use of technology in mathematics lessons helps to embody abstract concepts and this contributes positively to the success of students (Shirvani, 2010; Bicer & Capraro, 2016). On the other hand, in PISA applications carried out in previous years, it was found that computer use was negatively related to mathematics achievement (OECD, 2015).

Data mining aims to transform big data into meaningful information with the help of computers (Thuraisingham, 2003). Considering the large volume of PISA data, it is expected that data mining will often be assisted in making PISA data more meaningful. Such studies are the subject of educational data mining. Educational data mining can be thought of as a combination of data mining, educational sciences and statistics (Peña-Ayala, 2013). Baker & Yacef (2009) defined the goals of educational data mining as predicting students' future learning behaviors, discovering or improving domain models, studying the effects of educational support, and developing scientific knowledge about learning and learners. Therefore, the stakeholders of educational data mining are learners, teachers, researchers and education managers (Romero & Ventura, 2013).

One of the most frequently used models in educational data mining studies are decision trees, which are classification models (Sharma & Kumar, 2016). The fact that the decision tree models are easy to understand and interpret is the most important factor in the frequent use of decision trees. A decision tree consists of roots, branches, and leaves, just like a tree in nature. In a decision tree, this formation is expressed by the concepts of root node, non-leaf or internal node and leaf node, which are the endpoints of a decision tree (Akpınar, 2017).

Studies show that different dimensions of ICT may reveal different relationships for mathematics achievement. For example, according to Fuentes and Gutiérrez (2012), general ICT use at school has a negative effect on mathematics achievement, while availability of ICT at home has a positive effect. Therefore, it may be useful to determine the role of ICT on mathematics achievement. In the analysis of PISA, the results are revealed using statistical methods (OECD, 2017a). Performing secondary analysis with data mining can help reveal inductive and exploratory results. From this point on the purpose of this article is to evaluate the success of the decision tree classification algorithms in predicting the effect of ICT on students' mathematics performance.

Method

In this study, the relational survey model, one of the quantitative types of research, was used since it was aimed to examine the relationship between ICT and Mathematics Achievement. The relational survey model is one of the general survey models and is the research model used to determine the existence or degree of change between two or more variables (Büyüköztürk et al., 2014; Karasar, 2005).

Study Group

More than 10 million students aged 15 from 79 countries participated in PISA 2018. The population of the research consists of 15-year-old students studying in Turkey. The sample of the study consists of 6570 students who participated from Turkey and gave adequate answers to the ICT Familiarity Questionnaire in PISA and whose mathematics score was calculated. According to level 1 of Statistical Area Classification (SAC), taking 12 areas as the basis, 186 schools and 6890 students participated in PISA 2018 (OECD, 2018b). The selection of students in the sample was carried out randomly (based on probability) by the International Center.

Data Set

The data used in this research were collected by the OECD in the PISA 2018 application with ICT Familiarity Questionnaire (OECD, 2017b) and Student Questionnaire (OECD, 2017c). There are nine subscales related to ICT in the PISA 2018 Dataset. Table 1 describes these subscales.

Table 1. ICT Related Variables from PISA 2018 Dataset (OECD, 2018b)

Code	Explanation
ENTUSE	ICT use outside of school (leisure)
HOMESCH	Use of ICT outside of school (for school work activities)
USESCH	Use of ICT at school in general
COMPICT	Perceived ICT competence
AUTICT	Perceived autonomy related to ICT use
INTICT	Interest in ICT
SOIAICT	ICT as a topic in social interaction
ICTCLASS	Subject-related ICT use during lessons
ICTOUTSIDE	Subject-related ICT use outside of lessons

ICT related variables given in Table 1 were scaled using IRT modeling. In this way, it is ensured that the mean score is 0 and the standard deviation is 1 (OECD, 2018b). Thus, it can be said that the student with a score of 0 is in the OECD average in the relevant category. Similarly, it can be easily noticed that the score of students with negative scores is below the OECD average, and the score of students with positive scores is above the OECD average.

As a result of the application, ten different possible mathematics achievement scores (PV1MATH-PV10MATH) were calculated for each student. In this study, first, the average of these ten scores was calculated in order to obtain the categorical variable (MATHACH) from the students' mathematics achievement scores. Then, the average of the mathematics scores of the students was calculated as 455.55. Then, if the score of the students is below the average, it is coded with L, and if it is higher than the average, it is coded with H.

Data Analysis

Data analysis in data mining begins with the improvement of data quality and preliminary preparation processes (Han & Micheline, 2001). In this direction, data analysis was started with data reduction, data transformation and data cleaning steps. In the data reduction process, ICT related data and Mathematics Achievement Score data belonging to the students participating from Turkey were filtered from the PISA data for the purpose of the research. In the data transformation process, a single categorical Mathematics Achievement Score was obtained from the Mathematics Achievement Scores.

In data cleaning process, variables with high level of missing values (>%80) were removed. There was no participant whose math achievement score is missing. No action has been taken for a small number of missing values because decision tree algorithms can work with missing values (Beaulac & Rosenthal, 2020). One of the decision tree algorithms J48 (Witten et al., 2016) was used in classification. J48 is the algorithm that enables the C4.5 (Quinlan, 1992) algorithm to be used in WEKA 3.8. C4.5 and its derivative algorithms are widely used in education in terms of their simplicity and usefulness, such as allowing the use of both categorical and numerical predictor variables (Martínez-Abad, 2019).

Evaluation of classification success was made with accuracy rate, precision, recall, F-measure and kappa statistics:

- Accuracy rate indicates classification performance. It is calculated as the ratio of correctly classified samples to all samples.
- Precision is the ratio of the number of correctly classified positive samples to the total number of positively predicted samples.
- Recall is the ratio of the number of correctly classified positive samples to the number of all samples whose true class is positive. Often there is an inverse relationship between precision and recall, in which increasing the value of one may lower the value of the other.
- For this reason, the F-measure, which is the harmonic mean of both criteria, is used to obtain more precise and sensitive results (Şık, 2014).
- The Kappa statistic is a measure of the accuracy of the prediction made. Kappa results range from [0,1].

Results

Explanatory statistics for the variables used in the research are given in Table 2.

Table 2. Descriptive Statistics of Attributes

	Min	Max	$\bar{X}$
ENTUSE	-3.594	4.244	-0.112
HOMESCH	-2.301	3.310	0.122
USESCH	-1.716	3.304	-0.174
COMPICT	-2.603	2.065	-0.124
AUTICT	-2.514	2.026	-0.208
INTICT	-2.951	2.667	-0.155
SOIAICT	-2.176	2.364	0.204
ICTCLASS	-1.219	2.439	0.231
ICTOUTSIDE	-1.305	2.497	-0.021

ICT related variables given in Table 2 were scaled using IRT modeling. Considering that the situation where the average score is 0 reflects the OECD average, it is seen that the averages of the HOMESCH, SOIAICT and ICTCLASS variables of the students in Turkey are above the OECD average, and the averages of the USESCH, COMPICT, AUTICT, INTICT and ICTOUTSIDE variables are below the OECD average. In order to optimize the operation of the decision tree algorithm, optimal values are obtained. Accordingly, the confidence factor value, which is the default value of 0.25, gave the best results. The minimum number of objects worked best when used as 4 instead of the default value of 2. Accuracy indicators by class are given in Table 3.

Table 3. Accuracy by Class

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
L	0.717	0.400	0.660	0.717	0.687	0.319	0.694	0.664
H	0.600	0.283	0.661	0.600	0.629	0.319	0.694	0.671
Weighted Average	0.661	0.344	0.661	0.661	0.659	0.319	0.694	0.667

When the values given in Table 3 are examined, it is seen that the J48 algorithm is more successful in classifying students with low mathematics achievement than classifying students with high mathematics achievement. In addition, it is seen that the rate of correctly predicting mathematics achievement with weighted average values and variables related to ICT is 66.1% confusion matrix are given in Table 4.

Table 4. Confusion Matrix

Classified as L	Classified as H	
2449	969	L
1260	1891	H

According to Table 4, it is seen that 2449 out of 3418 students with low mathematics achievement were classified correctly and 1891 students out of 3151 students with high mathematics achievement were classified correctly. The decision tree resulting from the application of the j48 algorithm is given in Figure 2.

The size of the decision tree given in Figure 2 is 39 and there are 20 leaves in the decision tree. The root of the tree starts at the top and the first feature used is called ENTUSE. If ENTUSE is smaller or equal to -0.8894, then the next feature in the tree is ICTCLASS and so on. If ENTUSE is bigger than -0.8894, then the next feature in the tree is ICTCLASS and so on. As a result, it is found that ENTUSE variable has the most significant effect among the nine input variables which are covered in the study to classify students in terms of PISA Math literacy. Afterwards, it can be said that ICTCLASS and USESCH variables are also effective variables in classification.

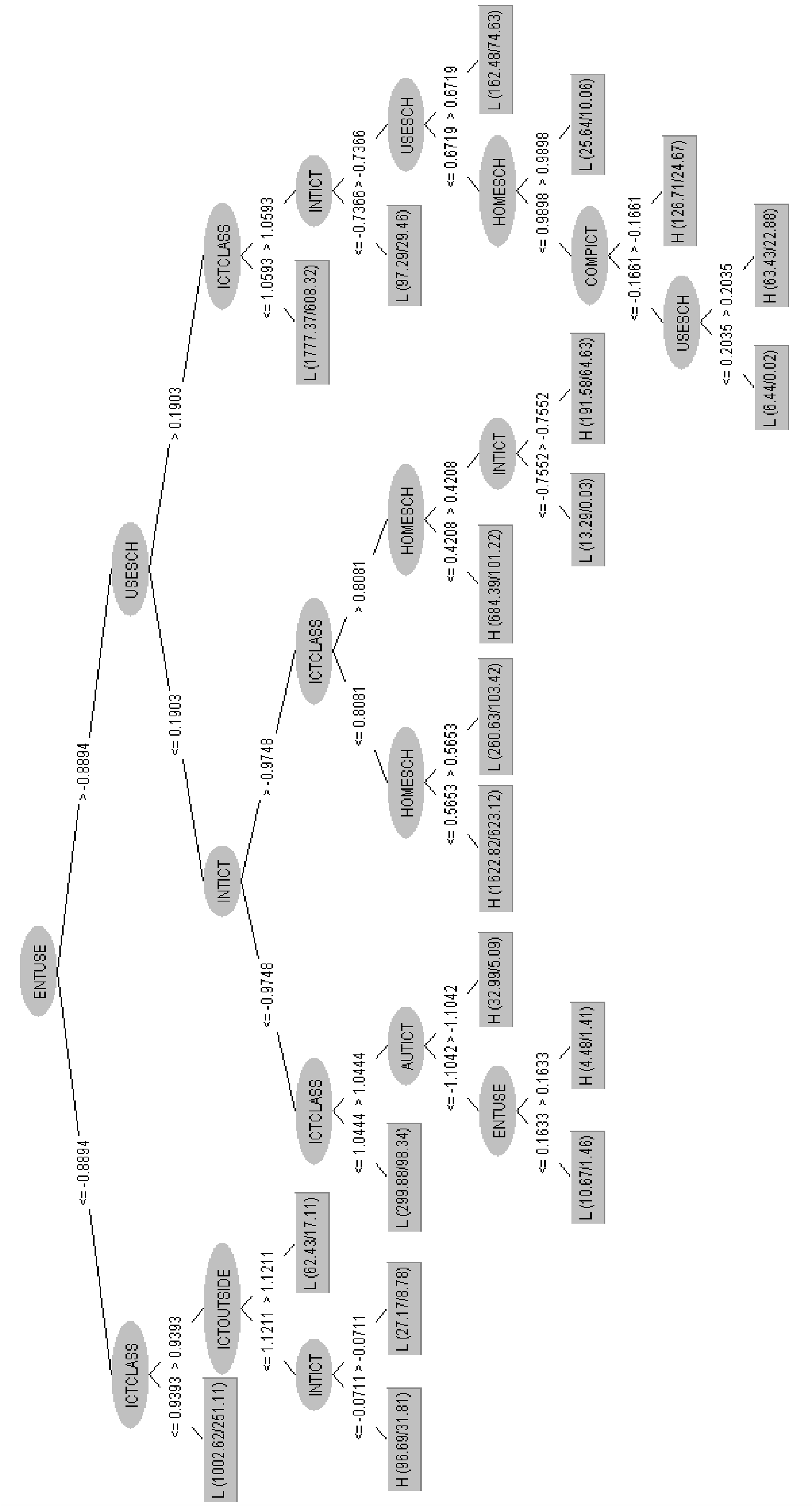

Figure 2. Decision Tree

Discussion

As a result of the research, it was concluded that the use of information and communication technologies for entertainment purposes outside of school is an important variable in classifying mathematics achievement. Bulut and Cutumisu (2018), in their study based on PISA 2012 data, stated that mathematics achievement and the use of recreational ICT are positively related. Hu, Gong Lai, and Leung (2018) stated that the relationship between recreational ICT use and mathematics achievement may be due to the fact that recreational ICT use increases students' motivation. Skryabin, Zhang, Liu, and Zhang (2015) found that recreational ICT use was negatively associated with mathematics achievement. The result of the research supports the studies regardless of positive or negative relationships.

In addition, it is thought that the reason for the difference in the effect of the use of information and communication technologies for entertainment purposes on mathematics achievement is since the level of recreational use can have a positive effect up to a certain level, while excessive use can be harmful. Another effective variable in classification is subject-related use during classroom lessons. Dynamic geometry software is used intensively in the lessons, especially in mathematics lessons. Therefore, there are various studies in the literature regarding the use of the software in lessons. Studies have shown that subject-related ICT use during classroom lessons increase the motivation towards mathematics (Abdullah et. al., 2020; Choi, 2010; Minarni, 2019) and mathematics achievement (Zulnaidi & Zambri, 2017; Arbain & Shukor, 2015; Kushwaha, Chaurasia & Singhal, 2014; Thambi & Eu, 2013).

Use of ICT at school in general is another effective variable. Studies show that Use of ICT at school in general and the use of information and communication technologies for entertainment purposes other than school have similar effects on mathematics achievement. So much so that Use of ICT at school in general can have a positive (Koğar, 2019; Meggiolaro, 2018) or negative (Kunina-Habenicht & Goldhammer 2020; Fuentes & Gutiérrez, 2012) effect on mathematics achievement, depending on the level of use. A study may be useful for the effect of recreational ICT use on the effect of recreational ICT use on mathematics achievement.

Conclusions

As a result, secondary analysis of international evaluation programs by data mining can help to reach new findings. From this point of view, in-depth analysis of the variables in this research can be made, as well as literacy and science achievement in terms of similar dimensions. In addition, it can be investigated whether it will give similar results in international student assessment programs other than PISA.

While the results for Turkey were studied in this research, similar studies can also be carried out in terms of comparing countries with each other. In this research, decision trees were used as a data mining algorithm. Examining the success of other classification algorithms for the data of this study may be the subject of another study. In general, the use of data mining in education is an important tool for us to make sense of big data.

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