ISSN: 2148-9955

International Journal of Research in Education and Science (IJRES)

www.ijres.net

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To cite this article:

Aksoy, E., Narli, S. & Aksoy, M.A. (2018). Examination of mathematically gifted students using data mining techniques in terms of some variables. *International Journal of Research in Education and Science (IJRES)*, *4*(2), 471-485. DOI:10.21890/ijres.428280

IJRES International Journal of Research in Education and Science
Volume 4, Issue 2, Summer 2018 DOI:10.21890/ijres.428280

Examination of Mathematically Gifted Students Using Data Mining Techniques in terms of Some Variables

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Article Info

Article History

Received:
04 December 2017

Accepted:
09 February 2018

Keywords

Mathematically gifted
Educational data mining
Learning style
Multiple intelligences
Personality type

Abstract

In the identification process, there may be gifted students who may be unnoticed or students who are misdiagnosed and are disappointed. In this context, this study is a step that may solve these two problems about the identification of mathematically gifted students with the help of data mining, which is data analysis methodology that has been successfully used in different areas including education. The decision tree model is one data mining technique, which was implemented using students' learning styles, multiple intelligences and personality types to identify gifted students. The sample size was 735 middle school students (234 mathematically gifted and 501 non-gifted) studying in two different cities in Turkey. The constructed decision tree model with 70% validity revealed that examination of mathematically gifted students using data mining techniques may be possible if specific characteristics are included.

Introduction

As an indicator of the development level of countries, students' success is very important. One of the fundamental elements underlying the success is to uncover students' potential abilities and educational environments which will provide to develop these abilities. The creation of this educational environment is essential for all students, and it is also important for gifted students in terms of individual rights because of their talents. However, in order to take them to appropriate educational environments, their superior talents must be determined. In this regard, the Ministry of Education in Turkey has opened Sciences and Arts Training Centers for gifted students who could receive additional training in addition to their formal education. In order to be accepted into this center, students take tests which measure their gifted abilities. For instance, mathematically gifted students were chosen for this study. Namely, if a student is mathematically gifted, he/she take tests to measure how mathematically gifted they are. One of the ways to be accepted to take these tests is to be nominated by the teacher. According to Siegle (2001), teacher nominations are generally used in the identification of gifted students because teachers are in a unique position to observe students in a variety of situations and under different conditions and to interact with them in the school for long periods of time (as cited in Hernández-Torrano, Ferrándiz, Ferrando, Prieto, & del Carmen Fernández, 2013). At this point, the problematic situation that is subject to this study begins. The problems mentioned above can be summarized as follows:

1. Failure to identify mathematically gifted students and thus not be trained in accordance with her/his talents.
2. Disappointment of the student who is not mathematically gifted but is nominated as gifted by his/her teacher.

Present study aims to reduce rates of the situations experiencing these problems by offering a model provided by data mining techniques. If this model is developed according to specific characteristics of mathematically gifted students, it may assist teachers to be able to have an idea whether a student is mathematically gifted or not.

The case of not recognizing gifted students due to various reasons is mentioned in literature. The problem is that some of gifted students cannot show their abilities. Namely, some of gifted students show the capabilities while some others may not show. Academically, these students may not be as perfect as prominently. Therefore, before identification stage, additional methods that can help to recognize gifted students may be searched. Although there are specific characteristics that have been identified by various studies in the field of mathematically giftedness, teachers may not be informed of these features. Furthermore, the procedure for measuring these characteristics is carried out only by experts. So, the features illustrating individual differences that can also be observed or measured by teachers may be investigated. And the availability of these characteristics may also be searched. In this context, learning style, multiple intelligence and personality type which have frequently taken place in literature with an emphasis on individual differences can be cited as examples of these characteristics. Individual characters between learners can be depicted by differences in preferred personality type, learning style, and strength of various multiple intelligences (Perry & Ball, 2004). In addition, this information about gifted students' characteristics may also be used at their specific education after identification. Considering all these reasons, effect of these characteristics (learning styles, multiple intelligence, and personality type) were examined to identify gifted students in mathematics in present study. A short review of these characteristics and data mining including related researches are described in next sections.

Learning Style

The term 'learning style' has been used to describe an individual's natural, habitual, and preferred way of absorbing, processing, and retaining new information and skills (Oxford, 1998). Kolb (1984) defines learning style as a preferred way of gathering information, whereas for Dunn (1984), learning style is an individual way of absorbing and retaining information or skills. The growing interest in learning styles is in recognition of the fact that learners differ in ways that need to be taken into account when teachers make decisions about course content and teaching methodology (Wu & Alrabah, 2009). Identifying the learning styles of students facilitates their understanding of themselves and hence increases teaching performance. Focusing on different aspects, there are many kinds of models and theories which allow for determination of students' learning styles. In present study, due to widespread use, Kolb's learning style model was preferred. This model is based on experiential learning theory (ELT) which is based on theories of Dewey, Lewin and Piaget. Four learning style in this model can be summarized as follows (Kolb, 2005):

> People with the diverging style are best at viewing concrete situations from many different points of view. (…) In formal learning situations, students with the diverging style prefer to work in groups, listening with an open mind to different points of view and receiving personalized feedback. (…) People with the assimilating style are best at understanding a wide range of information and putting it into concise, logical form. (…) In formal learning situations, students with this style prefer readings, lectures, exploring analytical models, and having time to think things through. (…) People with the converging style are best at finding practical uses for ideas and theories. (…) In formal learning situations, students with this style prefer to experiment with new ideas, simulations, laboratory assignments, and practical applications. (…) People with the accommodating style have the ability to learn from primarily "hands-on" experience. (…) In formal learning situations, students with the accommodating learning style prefer to work with others to get assignments done, to set goals, to do field work, and to test out different approaches to completing a project (p.5).

There is a broad range of studies about learning styles that have been addressed in literature. At the same time if we consider that learning style preferences are important as the studies on examining gifted students characteristics, we can find a lot of studies investigating the learning styles of gifted students. There are some studies that compared gifted and non-gifted students learning styles. While some of them (Chan, 2001; Kahyaoğlu, 2013; Turki, 2014) stated to find statistically significant difference between two groups in favor of gifted students, the others (Pyryt, 1998) did not. Of course, it should be mentioned that different learning style models or theories were used in these studies. For instance, in Chan's (2001) study he focused on 398 gifted and non-gifted Chinese secondary students. Gifted students were found to prefer learning styles related to discussions and independent learning. In addition, Pyryt (1998) investigated the preferred learning styles of gifted and non-gifted students in America. The study indicated that gifted students tend to be more independent in their learning and depend on self-motivators rather than exterior ones.

Multiple Intelligences

Gardner's theory of multiple intelligences (MI) is one of the proposals that have aroused more interest in the distinction of different human abilities (Chan, 2008, as cited in Hernández-Torrano et al., 2014). There is a growing awareness among teachers, however, that intelligence is a complex construct and that individuals have many kinds of abilities and strengths, not all of which can be measured by traditional IQ tests (Wu & Alrabah, 2009). Gardner's theory therefore provides a useful foundation for understanding individual differences (Gouws

& Dicker, 2011). Gardner has identified eight intelligences: verbal-linguistic, logical-mathematical, naturalistic, visual-spatial, musical, bodily-kinaesthetic, intrapersonal, and interpersonal (Gardner, 1993). Each person possesses all of these intelligences, but they typically differ in strength (Klein, 2003). These intelligences are briefly described below (Adapted from Gardner 1999; Gouws & Dicker, 2011; Wu & Alrabah, 2009, Chan, 2006):

Visual-spatial intelligence: the ability to perceive the visual-spatial world accurately and to perform transformations based on those perceptions. Musical intelligence: the ability to perceive and create pitch and rhythmic patterns, capacities such as the recognition of and use of rhythmic and tonal patterns and sensitivity to sounds from the environment, the human voice, and musical instruments, namely, the capacity to perceive, discriminate, transform, and express musical forms. Bodily-kinaesthetic intelligence: fine motor movement, athletic prowess; the ability to use the body to express emotion, to play a game, and to create a new product. Interpersonal intelligence: the ability to work cooperatively with others in a small group, as well as the ability to communicate verbally and nonverbally with other people. Intrapersonal intelligence: self-knowledge and the ability to act adaptively on the basis of this knowledge. Verbal-linguistic intelligence: ability to use words effectively whether orally or in writing, and to use abstract reasoning, symbolic thinking and conceptual patterning. Naturalist intelligence: the ability to recognize patterns in nature and classify objects; the mastery of taxonomy; sensitivity to features of the natural world, and an understanding of different species. Mathematical-logical intelligence: the capacity to use numbers effectively and to reason well.

In gifted education, MI theory has implications for identification, learning and teaching, and assessment and evaluation (Fasko, 2001). Ramos-Ford and Gardner (1991) discussed the early use of MI in the study of giftedness. Chan (2006) investigated perceived MI among male and female gifted students aged between 8 and 19 years. It showed that gifted girls rated higher their interpersonal intelligence while gifted boys rated higher in their logical-mathematical intelligence. And, Chan (2008) examined the self-perceived intelligences (multiple intelligences, emotional intelligence, and successful intelligence) of Chinese gifted students. And he found that students generally rated intrapersonal, interpersonal and verbal–linguistic intelligences. In addition, Hernández-Torrano et al. (2014) argued that MI theory has been used as a framework for the identification of gifted and talented students in different countries and educational institutions. In the same study, they provided a proposal to implement Gardner's MI theory in the identification of high-ability students in secondary education using three scales for the assessment of students, parents, and teachers' estimates of students' MI.

Personality Type

According to Corvette (2007, as cited in Gürsel, 2009), personality is the dynamic, developing system of individual's distinctive emotional, cognitive, and spiritual attributes. There are different approaches in the analysis of the personality. "One of them is Enneagram-a powerful and dynamic personality system that describes nine distinct and fundamentally different patterns of thinking, feeling and acting" (Daniels & Price, 2000/2009). It is used for analyzing and comprehending the ego mechanisms (Palmer, 1991). It's transformed into a personality type model with the contributions of Ichazo and psychiatrist Naranjo.

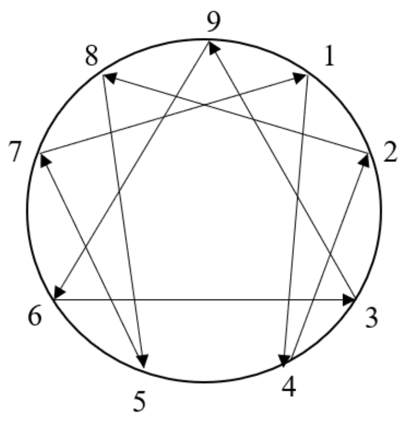

Figure 1 The enneagram system

Enneagram (see Figure 1) is comprised from (composed of) the Greek words “ennea” (nine) and “grammos” (points) (Palmer, 1991). It is a circle enclosing nine points connected by nine intersecting lines (see Figure1). Enneagram advocates that there are nine fundamental personality types, and the Enneagram System of Personality was designed to assess the degree to which an individual resembles each of these types (Riso & Hudson, 1999). One of the potentially promising features of this typology is that it captures some of the changes in our personal characteristics when we are under stress. Each type is connected to another by an arrow. Under conditions of stress, an individual takes on some of the connected types more negative characteristics. Conversely, in times of security or relaxation, an individual is inclined to take on positive characteristics of the type away from which the other arrow is pointing (Sutton, Allinson and Williams, 2013). Key characteristics of these nine types have been highlighted below (adapted Riso & Hudson, 1999; Sutten et al., 2013):

The Perfectionist (Type 1) is the principled, idealistic type, purposeful and self-controlled. They perceive the world as being judgmental and inclined towards punishing bad behaviour and impulses. People of this type believe they can only gain love through being good, correcting error and meeting their own high internal standards. Their attention is directed towards identifying error. The Giver (Type 2) is the caring, interpersonal type, generous, demonstrative, people-pleasing, and possessive. They believe that in order to have their own needs met, they must give. This type tries to gain love and get their personal needs met by giving others what they need and expecting others to give in return. Attention is directed towards identifying the needs of others. The Achiever (Type 3) is the adaptable, success-oriented type, excelling, driven, and image-conscious. They perceive that the world only rewards people for what they do, rather than who they are. People of this type believe they can only gain love through success and portray this successful image to others and themselves. Attention naturally focuses on tasks and things to accomplish. The Romantic (Type 4) is the romantic, introspective type, expressive, dramatic, self-absorbed, and temperamental. They experience a world in which an idealized love is missing. They believe the real connection can be found in a unique, special love or situation and strive to make themselves as unique as possible. Attention is directed towards what is missing rather than what is present. The Observer (Type 5) is the intense, cerebral type, perceptive, innovative, secretive, and isolated. They experience a world which they consider to be too demanding and giving too little in return. They therefore come to believe they can gain protection from intrusion by learning self-sufficiency, limiting their own needs and gaining knowledge. Attention is given to detaching themselves from the world in order to observe it. The Loyal-sceptic (Type 6) is the committed, security-oriented type, engaging, responsible, anxious, and suspicious. They perceive the world as hazardous and unpredictable. To gain security and certainty, people of this type attempt to mitigate harm through vigilance and questioning. Attention is directed towards worst case scenarios. The Epicure(Type 7) is the busy, productive type, spontaneous, versatile, acquisitive, and scattered. They perceive the world as frustrating, limiting or painful. They believe that frustration and pain can be escaped and a good life can be assured by going into opportunities and adventures. Attention focuses on options and keeping life up. The Protector (Type 8) is the powerful, dominating type, self-confident, decisive, wilful, and confrontational. They see the world as a hard and unjust place where the powerful take advantage of the weak. People of this type try to assure protection and gain respect by becoming strong and powerful and hiding their vulnerability. Attention goes towards injustices and to what needs control or assertiveness. The Mediator (Type 9) is the easy-going, self-effacing type, receptive, reassuring, complacent, and resigned. They perceive the world as considering them to be unimportant. They believe they can gain acceptance by attending to and merging with others, i.e. blending in with everyone else. Attention is directed towards others claims on them.

According to Daniels and Price (2000/2009), “discovering our enneagram personality type can help us learn how to bring positive change into our life besides; it can give us powerful assistance in integrating the personal and spiritual aspects of our life”. Although there are a lot of studies about personality, studies using Enneagram system to analyze personality types are limited. Besides, we have not found a study conducted with gifted students to analyze their personality types using Enneagram system. It is also known that studies on the Enneagram have not occurred for a very long time. More recently, scholarly works by Naranjo (1990) and Riso and Hudson (1996) have made some useful contributions to the Enneagram theory. In addition, Yılmaz, Gençer, Ünal and Aydemir (2014) represented the Nine Types Temperament Model (NTTM) and explained the similarities and differences between Enneagram and NTTM. NTTM is a new temperament model formulated with the interpretation of Enneagram System. It explains the definition, limit, scope and interrelations of temperament, character and personality concepts, as well as presenting a new perspective on studying the differences between individuals and differences within an individual. As a study about developing a measurement for personality, Yılmaz, Gençer, Aydemir, Yılmaz, Kesebir, Ünal, Örekand and Bilici (2014) conducted a study to develop a scale compatible with the Nine Types Temperament Model (NTTM) created by re-evaluating the Enneagram System. As a result of that study, they stated to have a reliable and valid scale. To explore the relationship between Enneagram types and key workplace attitudes and cognitions, Sutton et al.

(2013) conducted a study and stated that the Enneagram typology might provide a powerful tool for employee development and talent management.

Educational Data Mining

There are a lot of definitions for data mining in literature such as 'data analysis methodology used to identify hidden patterns in a large data set' (Tiwari & Vimal, 2013; Kiray, Gok & Bozkir, 2015). 'The process that analyses the data from different points of view and summarizes the results as useful information' (Şuşnea, 2009). 'A technology used to describe knowledge discovery and to search for significant relationships such as patterns, association and changes among variables in databases' (Pal, 2012). In brief, data mining can be defined as: applications of different algorithms, to identify patterns and relationships in a data set. It is similar to mining to obtain ore from the sand. That is, it can be considered that sand is data and ore is knowledge. Although it should be defined as knowledge mining, it is defined as 'data mining' to emphasize large amounts of data.

Data mining is a process that minimally has four stages (Nisbet, Elder & Miner, 2009): (1) data preparation that may involve 'data cleaning' and 'data transformation', (2) initial preparation of the data, (3) model building or pattern identification, and (4) deployment, which means subjecting new data to the 'model' to predict outcomes of cases found in the new data. Data mining techniques can be classified as below:

1. Clustering: a process of grouping physical or abstract objects into classes of similar objects (Romero &Ventura, 2007). Clustering is a type of analysis that divides data (cases or variables, depending on how specified) into groups such that members of each groups are as close as possible to each other, while different groups are as far apart from each other as possible (Nisbet et al, 2009).

2. Classification and regression (decision tree, neural network etc.): In classification, the predicted variable is a binary or categorical variable. Some popular classification methods include decision trees, logistic regression and support vector machines. In regression, the predicted variable is a continuous variable. Some popular regression methods within educational data mining include linear regression, neural networks, and support vector machine regression. Classification techniques like decision trees and Bayesian networks can be used to predict the student's behaviour in an educational environment, his interest towards a subject or his outcome in the examination (Kumar & Vijayalakshmi, 2011). Classification techniques are predictive models. And predictive modelling compares the students behaviour with past similar students behaviours to predict what she will do in order to recommend how to proceed (Lee, 2007).

3. Association rules: associates one or more attributes of a dataset with another attribute, producing an if-then statement concerning attribute values (Romero & Ventura, 2007). Association rules are characteristic rules (it describes current situation), but classification rules are prediction rules for describing future situation (Tiwari, Singh & Vimal, 2013). Association Rule mining can be used in various areas of education data to bring out the interesting rules about the learner's records. It can be used to bring out the hidden facts in understanding the behaviour of the learner in a learning environment, learning style, examination pattern and assessment. These rules can be utilized by the educator to understand the need of the learner and improve the learning skills (Kumar & Vijayalakshmi, 2013).

Data mining performs two functions: one is to identify regularities among data records (e.g., concept cluster, concept comparison, and discrimination), another to find relations among variables in the data that will predict unknown or future values of the variables. Unlike descriptive and inferential statistical analyses that rely on means and standard deviations, data mining uses both logical and mathematical (deterministic, and parametric and nonparametric statistical) reasoning to analyze data records (Liu & Ruiz, 2008).

Data mining has been used in different areas such as Marketing, Banking, Insurance, Telecommunication, Health and Medicine, Industry, Internet, Science and Engineering. Recently, one of these areas is the educational environment. As a result of the application of data mining techniques in education, the educational data mining (EDM) field has emerged.

Educational Data Mining is defined as 'an emerging discipline, concerned with developing methods for exploring the unique types of data that come from educational settings, and using those methods to better understand students, and the settings in which they learn' by the International Educational Data Mining Society.
Data mining has attracted a great deal of attention in the information industry and in society as a whole in recent years, due to the wide availability of huge amounts of data and the imminent need for turning such data into

useful information and knowledge (Han & Kamber, 2006). The education sector also has huge amounts of data and needs such techniques. EDM is an emergent discipline on the intersection of data mining and pedagogy. On the one hand, pedagogy contributes to the intrinsic knowledge of learning process. On the other hand, data mining adds the analysis and information modelling techniques (Kumar & Vijayalakshmi, 2011). Many educators and scholars have begun to pay more attention to applying data mining techniques to educational data. Three objectives could be identified to use EDM as a technology in the field of education. One of them is Pedagogic objectives – To help the students to improve in academics and designing the content of the course in a better way. (Kumar & Vijayalakshmi, 2011). Romero and Ventura (2007) summarized the role of data mining in the education sector as:

'The application of knowledge extraction techniques to educational systems in order to improve learning can be viewed as a formative evaluation technique. Formative evaluation (Arruabarrena, Perez, Lopez-Cuadrado, &Vadillo, 2002) is the evaluation of an educational program while it is still in development, and for the purpose of continually improving the program. Data mining techniques can discover useful information that can be used in formative evaluation to assist educators establish a pedagogical basis for decisions when designing or modifying an environment or teaching approach.'

As a recent conducted study, Peña-Ayala (2014) reviewed EDM with two goals; the first is to preserve and enhance the chronicles of recent EDM advances development; the second is to organize, analyze, and discuss the content of the review based on the outcomes produced by a data mining (DM) approach. Thus, as result of the selection and analysis of 240 EDM works, an EDM work profile was compiled. So, this study is very comprehensive to learn about EDM works. Liu & Ruiz (2008), reported a study on using data mining to predict K–12 students' competence levels on test items related to energy. Data sources were the 1995 Third International Mathematics and Science Study (TIMSS), 1999 TIMSS-Repeat, 2003 TIMSS, and the National Assessment of Educational Progress (NAEP). Two data mining algorithms, C4.5 and M5, were used to construct a decision tree and a linear function to predict students' performance levels. A combination of factors related to content, context, and cognitive demand of items and students' grade levels were found to predict student population performances on test items.

There are a lot of studies consisting of gifted students or data mining. But following rare studies, which enlightened this study, conclude both gifted students and data mining techniques: Nokelainen, Tirri and Merenti-Välimäki (2007), proposed a neural network model for identification of a gifted student. With a specially designed questionnaire, they measure implicit capabilities of giftedness and cluster the students with similar characteristics. They also applied data mining techniques to extract a type of giftedness and their characteristics. Data mining techniques such as clustering and classification is applied to extract the type of giftedness and their characteristics. The neural network was used to evaluate the similarity between characteristics of student and type of giftedness. They stated that in the future, they could refine their identification model using various data mining techniques and develop an intelligent learning guide system for "potential" gifted students. Gülen & Özdemir (2013), aimed to predict interest areas of gifted students and discover relationships between these areas by using educational data mining methods. By making use of the Apriori association algorithm, area pairs in which gifted students are frequently interested in are detected. They stated that results obtained from that study will provide many benefits to science and art centres, such as giving differentiated instruction by meeting individual needs and organizing course programs more effectively. Im, Kim, Bae and Park (2005) examined the influence of attribution styles on the development of mathematical talent by using the data mining technique. The results of conducted Bayesian classification modelling show that items attributing success to effort and failure and to lack of effort are the best predictors for the level of mild mathematical giftedness and gender.

Our literature research showed that very few studies have been published on both gifted students and data mining. In present study, decision tree, one of the classification techniques of data mining, was applied to data obtained from mathematically gifted students. It is described below.

Decision Tree

A decision tree is a flowchart-like tree structure, where each internal node (nonleaf node) denotes a test on an attribute. Each branch represents an outcome of the test, and each leaf node (or terminal node) holds a class label. The topmost node in a tree is the root node (Han & Kamber, 2006). During the construction of these trees, the data is split into smaller subsets iteratively. At each iteration, choosing the most suitable independent variable and branching the tree in terms of this variable is an important issue. Here, the split which creates the most homogenous subsets with respect to the dependent variable should be chosen (Güntürkün, 2007). Decision trees work by recursively partitioning the data based on input field values. The data partitions are called branches. The initial branch (sometimes called the root) encompasses all data records. The root is split into subsets, or child branches, based on the value of a particular input field. Each child branch can be further split into sub-branches, which can in turn be split again, and so on. At the lowest level of the tree are branches that have no more splits. Such branches are known as terminal branches (or leaves) (SPSS Clementine 10.1 Node Reference).

Purpose of the Study

The aim of this study is to examine mathematically gifted students in terms of their learning styles, multiple intelligences, personality types, genders and grade levels. This study would help teachers and educators to determine potential gifted students. Making this examination using different, useful and novel techniques is also one of the aims. So, unlike conventional methods, data mining techniques were applied to data collected from students. Compared to traditional statistical studies, data mining can (1) provide a more complete understanding of data by finding patterns previously not seen and (2) make models that predict, thus enabling people to make better decisions, take action, and therefore mould future events (Nisbet et al., 2009). In this context the following research question guided this study:

> Can mathematically gifted students be identified in terms of their learning styles, multiple intelligences, personality types, genders and grade levels by using data mining techniques?

Method

This study was conducted by descriptive and quantitative statistical methods. And, it was designed with relational screening model that is one of the general screening models. Relational screening is preferred because it aims to determine the existence and/or degree of joint variation between two or more variants (Karasar, 2009).

Participants

The participants of this study consist of 501 (non-gifted) students from a rural and three urban middle schools and 234 mathematically gifted students from four different Sciences and Arts Centers in two different cities in Turkey (İzmir and Manisa) by using convenience sampling and random selection. In convenience sampling participants are selected on the basis of their availability and willingness to respond (Gravetter & Forzano, 2011). Convenience sampling was preferred because of its availability and the quickness. The data were obtained in spring semester in 2013. After removing incomplete or incorrect data, the last sample size is determined to be 735 students (353 female and 382 male; 234 gifted and 501 non-gifted). In areas where data mining is practiced, millions of data are usually used. However, it is difficult to reach these numbers when the survey is conducted in education. Besides the number of mathematically gifted students that can be reached is limited. Therefore, this sample size is deemed large for the survey studies in education. These 735 participants were in grades 5 to 8 and were aged 11 to 14. Distribution of the participants according to giftedness, grade and gender can be seen in Table 1:

Table 1. Demographic characteristic of gifted and non-gifted students

Mathematically gifted or non-gifted		*Grades*				*Total*	
		5th	*6th*	*7th*	*8th*		
Mathematically non-gifted	Male	51	71	54	60	237	501
	Female	48	89	74	51	264	
Mathematically gifted	Male	43	54	34	15	145	234
	Female	37	29	16	7	89	
Total		179	243	178	135	735	

Instruments

All participants responded to a four-part questionnaire, including the ‘Learning Style Inventory’ (Kolb, 2005), ‘Enneagram Personality Scale’ (Daniels & Price, 2004), ‘Multiple Intelligences Scale’ (Selçuk, Kayılı & Okut, 2004), and a range of questions that elicited such demographic information as gender, age and grade level. Learning Style: The Turkish version of Kolb’s Learning Style Inventory (version 3.1) (Kolb, 2005), adapted by Gencel (2007), was used to assess individual learning styles. The twelve-point questionnaire had four choices for each prompt, which the student ranked by similarity to their learning style. Reliability has been proven, with Cronbach’s alpha coefficients ranging from 0.73 to 0.81.

Personality Type: In determining the personality type of the students, the Enneagram Personality scale developed in the book (translated to Turkish) by Daniels and Price (2004) was used. The scale consists of nine paragraphs describing the features of each personality type. Students were asked to choose one of these paragraphs describing their personality best. For this scale, the authors reported high level of reliability using test-retest method (Kappa=0.589 $p<0,0001$).

Multiple Intelligences: Multiple Intelligences Scale (Selçuk et al., 2004) was used to assess students’ MI. The Multiple Intelligence (MI) Inventory used in this study has 80 items. The instrument used a 5-point Likert-type scale ranging from 1 = strongly disagree to 5 = strongly agree. The items aim to measure students’ multiple intelligence preferences. The inventory includes 10 items for each of the eight multiple intelligence fields, these fields are verbal/linguistic, logical/mathematical, visual/spatial, musical, bodily-kinaesthetic, interpersonal, naturalistic, and intrapersonal. In this sample, Cronbach’s α coefficients for the MI scores were .65, .78, .75, .73, .74, .84, .69 and .85, respectively.

Data Analysis

SPSS Clementine 10.1was used to analyze collected data. Clementine is the SPSS enterprise-strength data mining workbench built by IBM. It has been used to build predictive models and conduct other analytic tasks. It has a visual interface which allows users to obtain statistical and data mining algorithms without programming. Its name has changed to the SPSS Modeller which is an extensive predictive analytics platform that is designed to bring predictive intelligence to decisions made by individuals, groups, systems and the enterprise. (IBM, n.d.). In present study, a data mining technique, decision tree, was implemented.

Results and Discussion

To answer research question about whether mathematically gifted students can be identified in terms of their learning styles, multiple intelligences, personality types, genders and grade levels or not, a decision tree technique was conducted. There are different types of algorithm that use different ‘attribute selection measure’ to construct decision tree (e.g. ID3 (Iterative Dichotomiser 3), CART (Classification and Regression Trees), C4.5, C5.0, CHAID (Chi-Squared Automatic Interaction Detector), QUEST (Quick, Unbiased, Efficient Statistical Tree) etc.). As for this study, C5.0 algorithm was used. C5.0 works by splitting the sample based on the field that provides the maximum information gain. It can also build both decision tree and rule set (SPSS Clementine 10.1 Node Reference).The represented tree is so large that the image of tree is minimized. To interpret the decision tree, it was divided into two parts and these parts are enlarged to read easily. The parts are shown using decision tree map so you can understand which part of tree it is (Figure 2 and Figure 3). In constructed decision tree, the target variable is mathematically giftedness. And independent variables are students’ learning styles, dominant intelligences, personality types, genders and grade levels. Figure 2 shows the first part of the tree for mathematically giftedness, the top level is the root of tree containing all the records of sample (N=735) (Node 0).

The second level represents the first partition of the data according to the most important factor suggested by the algorithm (Şuşnea, 2009). The first branch of the decision tree has been made with respect to grade level variable. The first branch of the decision tree shows the most influential variable in the formation of tree. Consequently, it can be said that grade level information should be examined first among a student’s such data (gender, grade level, learning styles, multiple intelligences and personality type) to determine the probability of his/her mathematically giftedness. However, 5, 6, and 7th grade students were grouped together at first branch, and 8th grade students were classed separately. This situation can be due to the fact that 8th grade mathematically gifted student ratio (9.4%) is too low. Because of this reason, interpretation of the constructed tree will start with the nodes of dominant intelligences coming after grade level variable. It is likely to be said that the C5.0 tree indicated that all of independent variables have some sort of effect on mathematically giftedness but the most effective feature is found to be dominant intelligence.

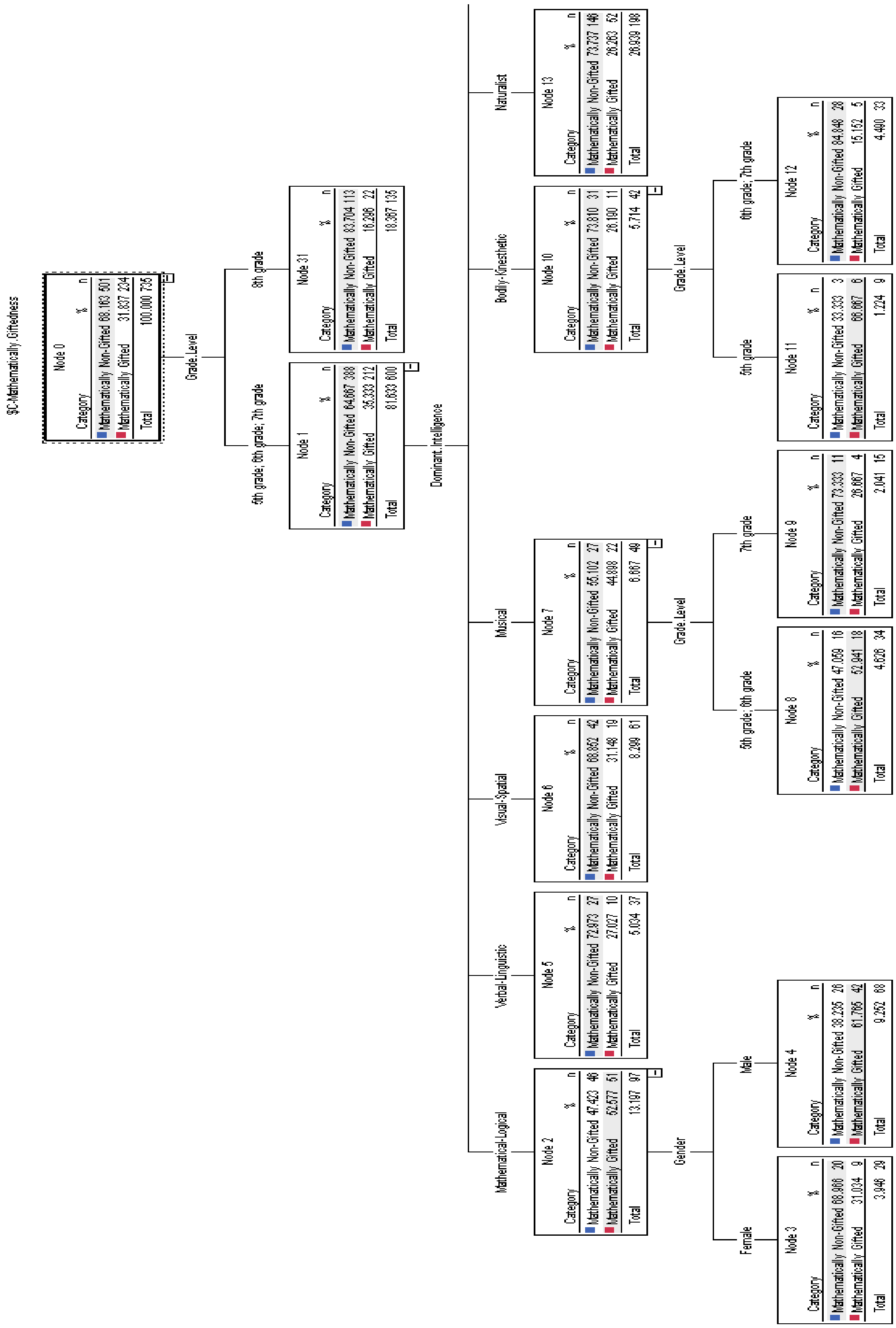

Figure 2. Decision tree for examination of mathematically gifted students (left-hand side)

The nodes which include students whose dominant intelligences are visual-spatial or verbal-linguistic (Node 5 and Node 6), did not divide into any child nodes and these nodes constructed terminal branches (leaves). At these nodes, 27 percent of the students with visual-spatial intelligence (Node 5) and 31.1 percent of the students with verbal-linguistic intelligence (Node 5) are mathematically gifted. Gender also seems to be tested at child nodes of Node 2 which contains the students whose dominant intelligence is logical-mathematical. As a result, it is likely to be said that 31 percent of girls and 61.7 percent of male students, in this node, are mathematically gifted.

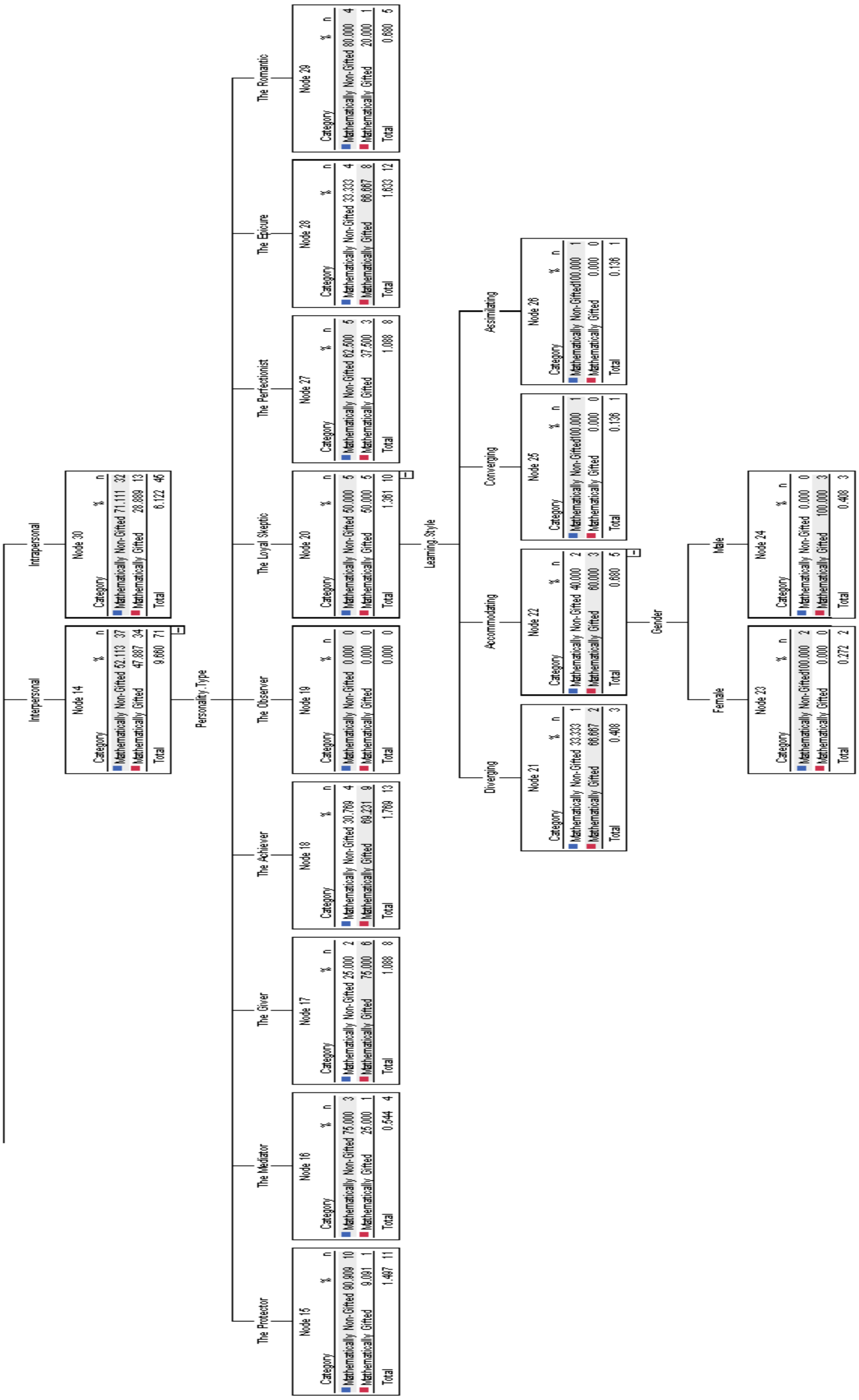

Figure 3. Decision tree for examination of mathematically gifted students (right-hand side)

The node which consists of students whose dominant intelligences are musical-rhythmic created terminal nodes after being tested with grade level variable. It can be said that 52.9 percent of these fifth or sixth grade students (Node 7) and 26.6 percent of these seventh grade students (Node 9) are mathematically gifted. It can be seen that the personality type variable was tested in the next branch of the node with students whose dominant intelligences are interpersonal (Node 14). It means personality types of students with interpersonal intelligence have an effect on this decision. Child nodes of this node (Node 14) constructed terminal branches. Decision rules of these nodes are as follows:

- 9 percent of these students with protector personality type (Node 15),
- 25 percent of these students with mediator personality type (Node 16),
- 75 percent of these students with giver personality type (Node 17),
- 69.2 percent of these students with achiever personality type (Node 18) are mathematically gifted.

There is no student whose dominant intelligence is interpersonal and is observer (Node 19). Node 20, one of the child nodes of Node 14, contains loyal-sceptic students. And, this node is also separated into four by learning style input variable. That means if a student's dominant intelligence is interpersonal and he/she is a loyal-sceptic in Enneagram system then, learning style is a distinctive feature for him/her in terms of giftedness. As for child nodes of Node 20, Node 21 contains students with diverging style, Node 25 contains students with converging style and Node 26 contains students with assimilating style stopped branching and constructed terminal leaves. Percentages for mathematically giftedness of these nodes are 66 percent, 6 percent, 0 percent and 60 percent respectively.

The last division of the decision tree occurs in this level, Node 22. The terminal nodes Node 23 and Node 24 are generated by division with respect to gender of students. Students in Node 22 have accommodating learning style, and 60 percent of these students are mathematically gifted. Besides, all of male students in this node are also mathematically gifted. That is, in Node 24, male students whose dominant intelligences are interpersonal and who have loyal-sceptic personality types and who have accommodating learning style are mathematically gifted with 100 percent in this study (Node0, Node 14, Node 20, Node 22 and Node 24).

The knowledge represented by decision tree can be extracted and represented in the form of IF-THEN rules as shown in Table 2. Using C5.0, decision rules for mathematically giftedness are extracted. Thus, these rules can be searched to understand some characteristics of mathematically gifted students.

Table 2. Decision rules for mathematically gifted students

Rule	*If;*	*Then,*
1	Learning Style: Accommodating Dominant Intelligence: Interpersonal Personality Type: Loyal-sceptic (Type 6) Gender: Male	Mathematically gifted (with 83% probability)
2	Dominant Intelligence: Interpersonal Personality Type: Achiever (Type 3) Grade Level: 5., 6., 7.	Mathematically gifted (with 66% probability)
3	Dominant Intelligence: Interpersonal Personality Type: Epicure (Type 7) Grade Level: 5., 6., 7.	Mathematically gifted (with 64% probability)
4	Dominant Intelligence: Bodily-Kinesthetic Grade Level: 5.	Mathematically gifted (with 63% probability)
5	Dominant Intelligence: Mathematical-Logical Gender: Male Grade level: 5., 6., 7.	Mathematically gifted (with 61% probability)
6	Dominant Intelligence: Musical Grade Level: 5., 6.	Mathematically gifted (with 52% probability)
7	Dominant Intelligence: Mathematical-Logical Grade level: 5., 6., 7.	Mathematically gifted (with 52% probability)

In the table2, the characteristics are written on the left side and the decision about the giftedness is on the right side. The first rule in the table2 was interpreted as follows, and the others can be interpreted similarly:

- If a student is male, and his dominant intelligence is interpersonal, and his learning style is accommodating, and his personality type is loyal-sceptic, then he is mathematically gifted with eighty three percent probabilities.
- If a student is in 5th, 6^{th} or 7^{th} grade, and his dominant intelligence is interpersonal, and his personality type is achiever, then he is mathematically gifted with sixty six percent probabilities.

Evaluation of Created Decision Tree Model

To evaluate the created decision tree model for examination of mathematically gifted students, accuracy and validity of the model were examined. Accuracy of the model was found to be 73.33 percent. To determine validity of the model, cross-validation, which allows using all data, was used. A cross validation method is a preferred method when the amount of data is limited. Because mentioning large amounts of data in data mining applications, is relatively more difficult to reach in educational areas, this evaluation analysis was preferred.

Cross-Validation is a statistical method of evaluating and comparing learning algorithms by dividing data into two segments: one used to learn or train a model and the other used to validate the model (Refaeilzadeh, Tang, & Liu, 2009). After the validation rate of this model is calculated, the same process is repeated by changing the roles of testing and training sets. Consequently, the model's validation rate is calculated by the average value of two independent validation rates (Berthold & Hand, 2000). Results of cross validation analysis for the decision tree created in this study, were found to be 70.11 percent and 71.35 percent. Consequently, the average of these two ratios was determined to be 70.73 percent.

Conclusion

The aim of this study was to examine mathematically gifted students using a data mining technique. We investigated the characteristics that facilitate to recognize mathematically gifted students before formal identification stage. Thus, the error rate of teachers in the nomination process may be reduced. Although there are some specific characteristics that mathematically gifted students have, we would like to investigate in terms of more general characteristics. So, we can also observe whether mathematically gifted students differ from others in terms of these characteristics. After literature review, because of widespread use at both gifted education and non-gifted education we decided to use characteristics such as multiple intelligences, learning style and personality type. Although these characteristics are not specific characteristics for mathematically gifted students, we were able to obtain a decision tree model and decision rules. This result showed that if the specific characteristics are used, this method could become an effective tool that can be used in the process of identifying gifted students. And, examination of the relations between these features can also be provided. The results obtained from this study cannot be generalized but it can be mentioned that they are promising.

The knowledge represented by decision tree was extracted and represented in the form of IF-THEN rules. These rules can be used in education to understand some characteristics of mathematically giftedness. It should be accepted that these rules are not adequate to decide whether a student is mathematically gifted or not. But they are important to show its usefulness. Educators can develop these rules by increasing the sample size and using more attributes. Thus, the rules can be generalized and used in an educational environment. Teachers may use these rules to have an idea whether a student is mathematically gifted or not.

The created decision tree covers much information to be used for observing characteristic profiles of students. Constructed decision tree models with C5.0 algorithm revealed that all of variables used in this study have some sort of effect on the mathematically giftedness but the most affective attribute was found to be multiple intelligence. Analysing the tree, factors effecting mathematically giftedness, can be listed respectively in decision tree as multiple intelligence, personality type, learning style and gender. The characteristics identified in this study should be searched for deeper understanding by experts. Because this study focused on using data mining techniques for the examination of gifted students, the results about these characteristics were not investigated.

There are a lot of studies including both mathematically gifted students and some of their characteristics. Most of these studies investigate whether gifted students differ from non-gifted students in terms of these characteristics. And mentioned characteristics were examined one by one. So, the relationships that may exist between characteristics were ignored. In this context, while determining mathematically gifted students in present study some of these characteristics were also examined through decision trees. For instance, learning styles and personality types of the students whose dominant intelligence are known were tested in the decision tree. And we were able to reach this conclusion that learning style a distinctive feature.

The results of the survey can also be used to increase awareness of each group's strengths and abilities. Students can identify, analyze and use their strengths to succeed in their academic studies, to develop their social relationships, and to learn. It is thought that findings of this research will be able to give opinion to researchers, mathematics educators and parents, besides contributing to the literature. It would also help educators in selecting more appropriate learning opportunities for their students and to design teaching strategies and materials that accommodate their students' learning styles, multiple intelligences and personality types.

The decision tree model's validation rate is calculated as 70.73 percent. That means the possibility of being a gifted student, identified with the help of this model using the characteristics such as learning style, multiple intelligences, personality type, gender, and grade level, was calculated as 70.73 percent. This result is not enough but it can be discussed that it is promising for further research. By increasing the number and diversity of samples it is expected to reach more definitive conclusions.

Limitations and Further Research

As a result of present study, aims to identify mathematically gifted students in terms of their learning styles, multiple intelligences, personality types, genders and grade levels using data mining, limitations and suggestions can be summarized as follows:

This study certainly has many limitations. The sample size was an important limitation of this study. The number of the sample size may be quite acceptable for educational studies, but data mining is related to large amounts of data which includes millions in general. So, the results can be more generalized with increased number of data. However, it is difficult to reach large amounts of data without using databases in educational studies.

Besides general characteristics, specific characteristics of mathematically gifted students should be used. Thus, this makes the study more comprehensive. So, this study is accepted as a step for this field by the authors. In addition to these limitations, another major limitation of this study was the complete reliance on self-report data on multiple intelligences, learning styles and personality types from students. Observations and interviews can contribute to better examination of students' characteristics. Future studies aim to test the structure of characteristics of gifted students obtaining these characteristics by multiple ways. Established models should also be tested on students at science and art centers every year and should be updated with the necessary changes.

The algorithm which has the highest accuracy rate can be determined by establishing models with different decision tree algorithms and by comparing them. The model which has the highest accuracy rate can also be determined by establishing models with different classification techniques. Mathematically gifted students were selected for this study. Similar studies can be conducted selecting gifted students from other areas such as science or arts. A model created considering all these suggestions can be made into software and given to teachers. Teachers can examine the mentioned characteristics of students through this software and can have an idea whether that student may be mathematically gifted or not. Consequently, it is likely to be said the rate of false nomination could be reduced

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