THE EFFECT OF COMPUTER ASSISTED INSTRUCTION ON EIGHT GRADE STUDENTS' PERMUTATION-COMBINATION-PROBABILITY ACHIEVEMENT AND ATTITUDES TOWARDS COMPUTER ASSISTED INSTRUCTION

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES OF
MIDDLE EAST TECHNICAL UNIVERSITY

BY

TUĞBA KAPUCU

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
STATISTICS

DECEMBER 2016

Approval of the thesis:

THE EFFECT OF COMPUTER ASSISTED INSTRUCTION ON EIGHT GRADE STUDENTS' PERMUTATION-COMBINATION-PROBABILITY ACHIEVEMENT AND ATTITUDES TOWARDS COMPUTER ASSISTED INSTRUCTION

submitted by **TUĞBA KAPUCU** in partial fulfillment of the requirements for the degree of **Master of Science in Statistics Department,** Middle East Technical University by,

Prof. Dr. Gülbin Dural Ünver
Dean, Graduate School of **Natural and Applied Sciences** _____

Prof. Dr. Ayşen Dener Akkaya
Head of Department, **Statistics** _____

Prof. Dr. İnci Batmaz
Supervisor, **Statistics Department, METU** _____

Assoc. Prof. Dr. Özlem İlk Dağ
Co-advisor, **Statistics Department, METU** _____

Examining Committee Members:

Assoc. Prof. Dr. Ceylan Talu Yozgatlıgil
Statistics Department, METU _____

Prof. Dr. İnci Batmaz
Statistics Department, METU _____

Assoc. Prof. Dr. Özlem İlk Dağ
Statistics Department, METU _____

Assoc. Prof. Dr. Bülent Çetinkaya
Mathematics and Science Education, METU _____

Assoc. Prof. Dr. Serpil Aktaş Altunay
Statistics Department, Hacettepe University _____

Date: _____

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last Name : TUĞBA KAPUCU

Signature :

ABSTRACT

THE EFFECT OF COMPUTER ASSISTED INSTRUCTION ON EIGHT GRADE STUDENTS' PERMUTATION-COMBINATION-PROBABILITY ACHIEVEMENT AND ATTITUDES TOWARDS COMPUTER ASSISTED INSTRUCTION

Kapucu, Tuğba
M.S., Department of Statistics
Supervisor : Prof. Dr. İnci Batmaz
Co-Advisor : Assoc. Prof. Dr. Özlem İlk Dağ

December 2016, 161 pages

The purpose of this study was to examine the effects of computer assisted instructional material prepared in R programme, on eight grade students' permutation-combination and probability achievement and attitudes towards computer assisted learning. In this study, we have survey data for 74 randomly selected students which consists of 45 highly correlated explanatory variables with different measurement levels to model whether CAI material has been effective or not. For data reduction, we firstly presented pairwise comparison between schools and as a second method, we presented Categorical Principal Components Analysis to deal with multicollinearity problem among explanatory variables. Next, we used uncorrelated components instead of original correlated variables to fit regression model. While the program CATPCA in SPSS has been used in the analysis of data reduction, MINITAB 17 has been used in the analyses of linear models.

Results of the first data reduction technique showed that only previous mathematics grade of the students was statistically significant factor in explaining probability achievement of the students. According to the results of CATPCA, general success of the students and basic socio-economic and technological factors affecting this situation and interaction of those factors with the secondary social situation of the family had a statistically significant effect on probability achievement of the students. Instruction method was found statistically significant factor in explaining students' achievement in permutation-combination subjects in both data reduction techniques. None of the explanatory variables mentioned in the study were found statistically significant in explaining attitudes towards CAI in both techniques.

Keywords: Computer Assisted Instruction, R Software, Categorical Principal Components Analysis, Multicollinearity, Linear Models

ÖZ

BİLGİSAYAR DESTEKLİ EĞİTİMİN 8. SINIF ÖĞRENCİLERİNİN PERMÜTASYON-KOMBİNASYON-OLASILIK BAŞARISINA VE ÖĞRENCİLERİN BİLGİSAYAR DESTEKLİ EĞİTİME İLİŞKİN TUTUMLARINA ETKİSİ

Kapucu, Tuğba
Yüksek Lisans, İstatistik Bölümü
Tez Yöneticisi : Prof. Dr. İnci Batmaz
Ortak Tez Yöneticisi : Doç. Dr. Özlem İlk Dağ

Aralık 2016, 161 sayfa

Bu çalısma, R programı ile geliştirilmiş bilgisayar destekli materyalin 8. Sınıf öğrencilerinin permütasyon-kombinasyon-olasılık başarısına ve öğrencilerin bilgisayar destekli ögrenmeye karşı tutumlarına etkisini incelemeyi amaçlamıştır. Bu çalışmada, bilgisayar destekli öğretim materyalinin etkili olup olmadığının modellenmesi için farklı ölçme seviyelerine sahip, 45 birbiyle ilişkili açıklayıcı değişkenden oluşan 74 rasgele seçilmiş öğrenci için anket verileri bulunmaktadır. Veri azaltımı için öncelikle okullar arasında eşli karşılaştırma yapılmış ve ikinci bir yöntem olarak, açıklayıcı değişkenler arasındaki çoklu ortak doğrusallık sorununun üstesinden gelmek için kategorik temel bileşenler analizi yapılmıştır. Daha sonra, çoklu doğrusal regresyon modeli kurmak için özgün korelasyon değişkenleri yerine, ilişkisiz bileşenler kullanılmıştır. Veri azaltma analizlerinde SPSS'de bulunan

CATPCA programı kullanılırken, doğrusal modellerin analizinde MINITAB 17 kullanılmıştır.

Birinci veri azaltma tekniğinin sonuçları, yalnızca öğrencilerin önceki matematik notlarının olasılık konusundaki başarılarının açıklanmasında istatistiksel olarak anlamlı bir faktör olduğunu göstermiştir. CATPCA sonuçlarına göre, öğrencilerin genel başarısı ve bu durumu etkileyen temel sosyo-ekonomik, teknolojik faktörler ve bu faktörlerin ailenin ikincil sosyal durumu ile etkileşimi öğrencilerin olasılık başarısı üzerinde istatistiksel olarak anlamlı bir etkiye sahiptir. Öğretim materyalinin öğrencilerin permütasyon-kombinasyon konularındaki başarısını açıklamada istatistiksel olarak önemli bir faktör olduğu iki yöntemle de bulunmuştur. İki veri azaltma tekniği sonuçlarına göre, bahsedilen açıklayıcı değişkenlerin hiçbiri öğrencilerin bilgisayar destekli öğretim materyaline yönelik tutumlarının açıklanmasında istatistiksel olarak anlamlı bir faktör olarak bulunmamıştır.

Anahtar Kelimeler: Bilgisayar Destekli Öğretim, R yazılımı, Kategorik Temel Bileşenler Analizi, Çoklu Doğrusallık Sorunu, Lineer Modeller

To my dear mum and father...

for their everlasting love and support.

ACKNOWLEDGMENTS

First of all, I would like to express my deepest appreciation to my thesis supervisor Prof. Dr. İnci Batmaz for her making distances close, everlasting patience, advice and motivation during my research. I would like to present my special thanks my thesis co-advisor Assoc. Prof. Dr. Özlem İlk Dağ for her support, detailed reviews and constructive comments. It has been a great honor for me to be a students of them and work with them.

I would like to present my grateful thanks to my examining committee members: Assoc. Prof. Dr. Ceylan Talu Yozgatlıgil, Assoc. Prof. Dr. Serpil Aktaş Altunay and Assoc. Prof. Dr. Bülent Çetinkaya for their constructive comments and suggestions.

I would like to present my grateful thanks to administrator and teachers of Mardin Bahçeşehir College, Ankara Bilkent College and Mardin Şehit Ögretmen Fasih Sögüt Elementary School for their support, hospitality and smiling faces.

Finally, my greatest gratitude to my beloved family. I owe my special thanks to my wonderful sister Hacer Pınar Kapucu for her endless energy and motivation throughout my life. I also owe my special thanks to my elder sister Seher Kapucu for her unconditional support and encouragement.

TABLE OF CONTENTS

ABSTRACT v

ÖZ vii

ACKNOWLEDGMENTS x

TABLE OF CONTENTS xi

LIST OF TABLES xv

LIST OF FIGURES xvii

LIST OF ABBREVIATIONS xix

CHAPTERS 1

1. INTRODUCTION 1

1.1 Main and Sub-Problems of the Study and Associated Hypotheses 4

1.2 Significance of the Study 5

2. LITERATURE REVIEW 7

2.1 Educational and Instructional Technology 7

2.2 The Utilization of Computer in Education-Instruction 8

2.3 Computer Assisted Instruction 9

2.3.1 Advantages of Computer Assisted Instruction 11

2.3.2 Restrictions of Computer Assisted Instruction 12

2.4 Mathematics Instruction 13

2.5 Computer Assisted Mathematics Instruction 16

2.6 Probabilistic Thinking 19

2.6.1 Theoretical Background for Probability 20

2.6.2 Research Studies on CAI Method in Probability Instruction 23

3. METHODOLOGY 29

3.1 Categorical Principal Components Analysis 29

3.1.1 Definition of CATPCA 30

3.1.2 Analysis Levels 32
3.1.3 Discretizing 34
3.1.4 Analysis Levels and nonlinear relationships between variables 34
3.2 CATPCA Output 35
3.2.1 Model Summary of CATPCA 35
3.2.2 Quantification Tables 35
3.2.3 Variance Accounted for Table 36
3.2.4 Correlations between Transformed Variables 36
3.2.5 Component loadings 36
3.2.6 Object Scores 36
3.3 Multiple Linear Regression Model 37
3.3.1 Definition of the Model 37
3.3.2 The Use of Dummy Variables in Multiple Linear Regression Analysis 38
3.3.3 Multiple Linear Regression Model Adequacy Checking 39
3.3.4 Analysis of residuals 40
3.3.5 Diagnostic check and remedies 42
4. APPLICATION 43
4.1 Research Design of the Study 43
4.2. Participants of the Study 45
4.3 Description of Variables 46
4.4 Preparation of Animations 46
4.4.1 R Project for Statistical Computing 46
4.4.2 Animations 47
4.5 Data Collection Instruments 50
4.5.1 Objective Comprehension Tests 50
4.5.2 Computer Assisted Learning Attitude Scale 51

4.5.3 Demographic Survey 52
4.5.4 School Technology Equipment Survey 54
4.6 Data Collection Procedures 54
4.7 Limitations 59
5. ANALYSIS AND RESULTS.....61
5.1 Data Description.....61
5.2 First Data Reduction Method.....62
5.3 Second Data Reduction Method.....84
5.3.2 Multiple Linear Regression Model.....100
6. CONCLUSION.....111
6.1 Results Concerning First Data Reduction Method.....111
6.1.1 Results of OCT2 Scores.....111
6.1.2 Results of CALAS Scores.....113
6.1.3 Results of OCT1 Scores.....113
6.2 Results Concerning Second Data Reduction Method-CATPCA.....115
6.2.1 Results of OCT2 Scores.....115
6.2.2 Results of CALAS Scores.....116
6.2.3 Results of OCT1 Scores.....116
6.3 Limitations of the study.....117
6.4 Implications of the study 118
REFERENCES 120
APPENDICES 128
A. OBJECTIVE COMPREHENSION TEST 1- OCT1.....128
B. OBJECTIVE COMPREHENSION TEST 2- OCT2.....130
C. COMPUTER ASSISTED LEARNING ATTITUDE SCALE (CALAS) 132
D. DEMOGRAPHIC SURVEY 133

E. SCHOOL TECHNOLOGY EQUIPMENT SURVEY 137

F. THE CONSEST FOR PERMISSIONS 140

G. ACTIVITY SHEETS 142

H. TRANSFORMATION PLOTS OF THE 20 VARIABLES TREATED AT AN ORDINAL SCALING LEVEL IN CATPCA 148

I. R CODES FOR ANIMATIONS 153

LIST OF TABLES

TABLES

Table 4. 1 *Quasi-Experimental Posttest-Only Design* 44

Table 5. 1. *Schools∗Income Test Result* 63

Table 5. 2. *One way ANOVA Results: OCT2 TR vs School* 66

Table 5. 3. *One way ANOVA Results: CALAS TR vs School* 68

Table 5. 4. *Regression Analysis: OCT2 vs First Term Mathematics Grade vs Gender* 71

Table 5. 5. *Regression Analysis: CALAS vs V10; V13* 73

Table 5. 6. *Regression Analysis: OCT1 vs V13; V14* 76

Table 5. 7. *Comparison of state-village schools* 77

Table 5. 8. *Regression Analysis on OCT2 Scores between state schools* 78

Table 5. 9. *Regression Analysis on CALAS between state schools* 81

Table 5. 10. *Description of the 43 variables in the analysis* 85

Table 5. 11. *Highly correlated variables* 86

Table 5. 12. *KMO and Bartlett's Test Result* 88

Table 5. 13. *Model Summary of CATPCA for 6-dimensional solution with 29 variables.* 91

Table 5. 14. *Variance Accounted For table for 6-dimensional solution with 29 variables.* 92

Table 5. 15. *Model Summary of CATPCA for 6-dimensional solution with 20 variables.* 93

Table 5. 16. *Variance Accounted For table for 6-dimensional solution with 20 variables.* 95

Table 5. 17. *Correlation between dimensions in 6-dimensional CATPCA with 20 variables.* 95

Table 5. 18. *Rotated component loadings from a 6-dimensional CATPCA on 20 variables, with all variables analyzed ordinally.* 97

Table 5. 19. *Model Summary of CATPCA for 5-dimensional solution with 21 variables.* 98

Table 5. 20. *Regression Output with PC1, PC2 and PC1∗PC2 variables* 101

Table 5. 21. *Stepwise Regression* 104

Table 5. 22. *Regression analysis OCT1 vs Instruction Method* 105
Table 5. 23. *Regression analysis* $CALAS *$ *vs Gender, City,...* 107
Table 6. 1. *Grouping Information Using the Tukey Method and 95% Confidence* 112
Table 6. 2. *Mean for CALAS Score* 113
Table H. 1. *Unrotated component loadings of the 6-dimensional CATPCA solution on the 20 variables, with all variables analyzed ordinally.* 151
Table H. 2. *Rotated component loadings from a 5-dimensional CATPCA on 21 variables, with all variables analyzed ordinally.* 152

LIST OF FIGURES

FIGURES

Figure 4. 1. *Animation result for "Addition Rule" R codes* 47
Figure 4. 2. *Animation result for "Multiplication Rule" R codes* 48
Figure 4. 3. *Animation result for "Combination" R codes* 48
Figure 4. 4. *Animation result for to "Combination" R codes* 49
Figure 4. 5. *Animation result for "rolling dice" R codes* 49
Figure 4. 6. *Animation result for "drawing ball" R codes* 50
Figure 5. 1. *Residual Plots for OCT2 TR* 67
Figure 5. 2. *Residual Plots for CALAS TR* 68
Figure 5. 3. *Box-Cox Plot of OCT2* 69
Figure 5. 4. *Boxplot of OCT2 for School and Gender* 70
Figure 5. 5. *Residual Plots for OCT2* 72
Figure 5. 6. *Residual Plots for CALAS* 74
Figure 5. 7. *Residual Plots for OCT1* 76
Figure 5. 8. *Boxplot of OCT1* 77
Figure 5. 9. *Residual Plots for OCT2* 79
Figure 5. 10. *Probability Plot of OCT2* 80
Figure 5. 11. *Residual Plots for CALAS*.....82
Figure 5. 12. *Probability Plot of CALAS* 82
Figure 5. 13. *Scatterplot of score vs V15, V16 in different plots.*.....83
Figure 5. 14. *Transformation plot after discretizing variables "Math Average Grade" and "Overall GPA"* 89
Figure 5. 15. *Scree plots with lines denoting the eigenvalues for a four-, five-, six-, and seven-dimensional CATPCA solutions on 29 variables analyzed at an ordinal analysis level.* 90
Figure 5. 16. *Scree plots*.....99
Figure 5. 17. *Residuals Plots for OCT2* 102
Figure 5. 18. *Normal probability plot of residuals* 102
Figure 5. 19. *Residuals Plots for OCT1* 105
Figure 5. 20. *Normal probability plot of residuals* 106
Figure 5. 21. *Residuals Plots for CALAS* $*$ 109

Figure 5. 22. *Normal probability plot of residuals* 109

LIST OF ABBREVIATIONS

AECT	Association for Educational Communications and Technology
ANOVA	Analysis of Variance
BTS	Bartlett's Test of Sphericity
CAI	Computer Assisted Instruction
CAIM	Computer Assisted Instructional Material
CALAS	Computer Assisted Learning Attitude Scale
CATPCA	Categorical Principal Components Analysis
CBE	Computer-Based Education
PC1-PC6	Principal Components 1 through 6
CV15	Centered V15 Variable
CV15CB	Cube of the Centered V15 Variable
CV16	Centered V16 Variable
CV17	Centered V17 Variable
D-W	Durbin Watson
GPA	Grade Point Average
KMO	Kaiser-Meyer-Olkin
MEB	Ministry of Education of Turkey
MLR	Multiple Linear Regression
MoNE	Ministry of National Education
NCTM	National Council of Teachers of Mathematics
NLPCA	Nonlinear Principal Component Analysis
OCT1	Objective Comprehension Test 1
OCT2	Objective Comprehension Test 2

PCA	Principal Component Analysis
PMG	Previous Mathematics Grades
R	Statistical Software and Language
TEOG	Examination of Transition to Secondary Education from Elementary Education
TIMSS	Trends in International Mathematics and Science Study
TM	Traditional Method
TR	Transformed
V1-V17	Variables 1-17
VAF	Variance Accounted For
VARIMAX	Type of a Rotation in Factor Analysis
VIF	Variance Inflation Factors
WLS	Weighted Least Squares

CHAPTER 1

INTRODUCTION

Probability is an old branch of mathematics dealing with calculating probability of a variety of events (HodnikČadež and Škrbec, 2011). With the change of world conditions, the importance of probability knowledge has also gained importance. As Lopes and Moura (2002) indicated, knowledge of facts of probability is significant not only to make decisions and predictions; but also to provide an earlier accession of population to social and economical arguments in which tables and graphics synthesize studies and analysis and comparison of indexes are done to support ideas. Due to the fact that teaching of Probability and Statistics advances students' ability of collecting, organizing, interpreting and comparing data to acquire and support conclusions, it is appropriate to be placed in Mathematics curriculum in the Elementary Education (Lopes and Moura, 2002). Researchers from numerous countries (e.g., Farnworth, 1991; Fischbein and Schnarch, 1997; Freudenthal, 1973; Gardner, 1989; Jones, 1995; Koshy, Ernest and Casey, 1999; Shaughnessy, 1992; Sobel and Maletsky, 1988; as cited in Tsakiridou and Vavyla, 2015), detected that probability is a crucial branch of mathematics education, by reasons of

- providing participation of students in attractive and intentional learning activities,
- comprehension by distinct aged and distinct capacities of students,
- its benefits of daily life, contributory function to the other disciplines and significant role to decision making (Gal, 2005).

In the light of the researches, the importance of probability in mathematics school curriculum is more of an issue. Although the importance of probability in mathematics school curriculum is proved, teaching of probability has received less

focus in the literature (Keeler and Steinhorst, 2001). As Keeler and Steinhorst (2001) stated that even though lack of people's ability in learning the concepts encompassing judgement under uncertainness is mentioned so much over the last three decades, the research on solutions is insufficient. Another research done by Batanero et al. (2005) showed that teachers have lack of experience in probability and transport their probabilistic misconceptions to their students. *The Principles and Standards for School Mathematics* document published by the National Council of Teachers of Mathematics (NCTM) (2000) submits that elementary grades students should comprehend probability as a means of quantifying the likelihood of an event. However, teachers are lack of or have little probability experience in either their educational background or teaching practice (Dollard, 2011). Most teachers find it difficult to teach probability and they do not rely on their ability of teaching probability and they are unconfident in the activity of probability including uncertainty (Stohl, 2005). A case study conducted by Souza (2015) in the state of Sao Paulo, Brazil, shows that teachers are hesitant to introduce probability concepts in elementary education generally because of their deficient knowledge about probability and statistics. Probability is difficult to teach due to a variety of reasons, such as difference between instinct and conceptual improvement even if they are fundamental concepts (Batanero et al., 2005). Garfield and Ahlgren (1988) stated that students dislike probability due to exposing highly abstract study of it in a formal way. Introducing probability through activities and simulations; not in an abstract way, is among the recommendations given by Garfield and Ahlgren (1988) for overcoming difficulties for teaching probability. Simulation is a new and fundamental tool in all aspect of education today. Chance and Rossman (2006), as reported in Zieffler and Garfield (2007), said that the use of simulation in probability and statistics course as a supportive of instructional efforts is highly recommended by statisticians and researchers. Simulation is a powerful instrument giving the opportunity of repetition of a study many times (Burrill, 2002). Using simulation provides students to perceive active processes, rather than stable configurations and representations (Zieffler and Garfield, 2007). Using probabilistic simulations and games by teachers in their lectures can be very beneficial for students, thus, students

can learn how to make a statement based on evidence and enlightened decisions on data which may cause a smaller chance of error (Souza, 2015).

Although it is emphasized that using simulation in mathematics instruction is beneficial, the number of research studies conducted to examine effectiveness of simulation on mathematics achievement is not sufficient both in Turkey and abroad. Furthermore, there are only a few research studies conducted to examine the effects of simulation in probability instruction (e.g. Garfield and Zieffler, 2007; Andiç, 2012; Braun, White and Craig, 2013). One of the purposes of the present study is to examine the effect of instruction with simulation on elementary school students' probability achievement. Besides the use of simulation, the present study also investigates the effect of simulation to learning environment. MoNE (2009b) highlights the provision of learning environment in which students find out and improve their interests and abilities so that they would be happy and mentally healthy individuals. According to the vision for mathematics education described in *Principles and Standards for School Mathematics* of NCTM (2000), students are expected to be flexible and creative problem solvers. In this sense, it is important that students be flexible in all aspects of instruction to be active in lectures. To achieve this goal, according to MoNE (2009b), both students and teachers have responsibilities in the elementary school mathematics curriculum. The role of students is to participate learning process actively; asking questions, thinking and discussing. Ensure students to ask question, comprehend and discuss and also using the existing materials or developing the new one, applying them effectively in the lecture are among the responsibilities of teachers (MoNE, 2009b). As a result of expectation of both MoNE and NCTM, it is necessary to create an effective learning environment and measure its effects on students' mathematics achievements.

Another concern of the present study is to investigate how students' attitudes towards computer assisted instruction (CAI) changes while animation and simulation are used as a material in the mathematics education. The present study also aims to create a learning environment in which students can be motivated and enjoy the process of learning probability concepts with simulation.

1.1 Main and Sub-Problems of the Study and Associated Hypotheses

In this section main and sub-problems of the present study are stated.

The first main problem of the study is: "What is the effect of instruction with computer assisted education (simulation-animation) on eight grade students' permutation-combination and basic probability achievement and attitudes toward CAI when the previous mathematics grades (PMG), overall grade point average (GPA), socio-economic and cultural factors and interaction of the students with technology are controlled?"

It consists of two sub-problems. They are stated below:

S.1. What is the effect of CAI on eighth grade students' permutation-combination and basic probability achievement?

The following hypotheses are stated in order to test the problem:

H1: There is no significant difference among the mean scores of the students instructed by CAI (simulation-animation), and those instructed by the traditional method (TM) with respect to academic performance when PMG and overall GPA of the students are controlled.

H2: There is no significant difference among the scores of the students instructed by CAI (simulation-animation) with respect to academic performance across the culture when PMG and overall GPA of the students are controlled.

S.2. What is the effect of CAI via simulation-animation on eighth grade students' attitudes toward CAI?

The following hypothesis is stated in order to test the problem:

H1: There is no significant difference among the mean scores of the students instructed by CAI (simulation-animation), and those instructed by TM with respect to attitudes towards CAI.

1.2 Significance of the Study

Probability and statistics have been involved in curriculum of school mathematics for less than 40 years and they supplement the traditional topics of arithmetic, algebra and geometry (Borovcnik and Kapadia, 2010). Although almost all countries accept statistics as an inseparable part of mathematics curriculum, the concept of probability is just introduced to older students (Borovcnik and Kapadia, 2010). According to Ferreira et al. (2014) students are required to show more advanced skills while learning probability concepts compared to traditional school tasks, because as Borovcnik and Kapadia (2010) indicated that conceptual errors in probability affect all aspects of people's decisions such as assessment, medical tests and etc. Therefore, it is important that probability should be a vital part of elementary school mathematics and effective teaching strategies and materials should be utilized while teaching probability concepts. In the current elementary school mathematics curriculum in Turkey, however, probability is included only in grade eight (MoNE, 2013), while probability education should be started in grade three according to NCTM instructional program. Besides, students do not show success in questions related to probability both in national and international exams. For instance, Turkey ranked 30th among 38 countries in terms of probability and data analysis subject's score (TIMSS, 1999). According to the 2015 TIMSS results, Turkey ranked 24th among 39 countries in mathematics achievement among eight grade students (TIMSS, 2015). Furthermore, students have low scores in mathematics in the examination of transition to secondary education from elementary education (TEOG). According to the data of General of Educational Technologies in Ministry of National Education (MoNE), the average mathematics score in TEOG is 29.34 out of 100 in the first exam and 37.47 in the second exam in 2014-2015 academic year. This score is not specific to only probability concept, but all mathematics lesson. Therefore, these scores show that new teaching methods should be used in mathematics lessons.

There is a number of difficulties that confronted in teaching and learning the concept of probability (Gürbüz, 2008). The lack of suitable teaching materials is among the reasons of these difficulties (Aksu, 1990; Gürbüz, 2006). The traditional instruction

in teaching probability is not successful to overcome these difficulties (Gürbüz, 2008). Computer technology can be a solution to these problems. According to the new developments in the education area, developing materials that influences students' learning positively is essential (Gürbüz, 2008). The improvement in the computer technology provides new teaching materials in education such as simulation, animation. The aim of this study is to present a computer-assisted material designed for teaching 'probability' topics for eight grade level students, to examine how CAI and the socio-economic and cultural factors affect the achievement of the students. For this purpose, we have developed computer-assisted instructional materials consisting of animations and simulations by using R language. It is expected that these computer-assisted instructional materials would be effective in teaching and learning of probability topics.

CHAPTER 2

LITERATURE REVIEW

This chapter begins with the definition of Educational and Instructional Technology and the role of computers in education-instruction and then continues with the definition of CAI. Following this, advantages and restrictions of CAI are discussed. Later, the use of CAI in mathematics, and specially CAI in probability subject are presented. In doing so, research studies both in Turkey and abroad reviewed. This chapter ends up with the implication of CAI in probability teaching.

2.1 Educational and Instructional Technology

The first definition of “Educational Technology” is defined as an audio-visual communications which is an arm of educational technology, by the Department of Audiovisual Instruction (the predecessor of Association for Educational Communication and Technology) in 1963 (Meifeng, Jinjiao and Cui, 2010). However, today, educational technology is more than audio-visual communications and is a field in all over the world without dispute (Meifeng et al., 2010). Educational technology also has the meaning of the media intension which concentrates on materials and equipment, i.e., delivery systems (Ely and Plomp, 1986). Tickton (1970), as reported in Ely and Plomp (1986), gave the definition of educational technology like that: “the media born of the communications revolution which can be used for instructional purposes alongside the teacher, textbook and blackboard... The pieces that make up instructional technology: television, films, overhead projectors, computers and the other items of 'hardware' and 'software'.”

Education and instruction are connected to each other in academic area, in fact instruction is a subset of education. Therefore, it is required to define instructional

technology at the same time. Earle (2002) reported, as in the Commission on Instructional Technology (1970), that media has burned with the communications revolution which might be utilized for instructional aims among the educator, textbook and blackboard; alongside instructional technology is defined as a well-organized aspect of scheming, accomplishing, and appraising the whole period of learning and teaching in recognition of intention, based on studies in individual learning and communications, and functioning of all human and nonhuman access to provide more effective instructions. Lately, Association for Educational Communications and Technology (AECT) has defined instructional technology as "the theory and practice of design, development, utilization, management, and evaluation of processes and resources for learning."

As it is seen, instructional technology is a component of educational technology. While educational technology is a broader concept, instructional technology is a more specific concept that contains mechanism of learning and instruction. Computers and computer software are among the most known teaching materials, but instructional technology is not limited by these tools. Cameras, CD players, Personal digital assistants (PDA's), GPS devices, computer-based probes, calculators and electronic tools are all instructional technology tools used in the teaching and learning process.

2.2 The Utilization of Computer in Education-Instruction

Computers are becoming an important factor in teaching and learning environment. The abbreviation CAI is generally used in the terminology area, however it distinctly denotes for computer-assisted instruction, computer-aided instruction, computer-augmented instruction, or computer-administered instruction (Kulik et al., 1985). Computer-managed instruction, computer-based learning, and computer-based instruction and computer-based education, or CBE are among the other terms used in this area (Kulik et al., 1985). Taylor (1980), as reported in Bull (2009), identified three utilization of computers (Tutor, tool and tutee) in schools. First of all, due to providing presentation of materials, evaluation of students' process and deciding what to demonstrate next and keeping the transactions of student's process, computer

is seen as tutor in education area. Secondly, computers are defined as a tool which are utilized for statistical analysis, calculations or word processing, for example students can use it as a calculator in mathematics lesson, as a map-maker in geography lesson, as a musician in music lesson or as a text editor in English lesson. The last utilization of computer defined by Taylor (1980) is as a tutee; that means when it is given directions by students in programming language, it serves as a tutee.

The history of the computers in education is not old-timer; in fact computers are firstly used in education as a tool to solve mathematics, science and engineering problems (Dudeney, 2000). However, today, computers are used in every aspect of human activity as a learning material of reality, mechanization of designing and education process (Dementiev et al., 2015). Computer technologies in instructional viewpoint have an enormous occasion in acquiring of capacities to set and solve the applied problems in education (Dementiev et al., 2015). According to Postnikov et al. (2005), as stated in Dementiev et al. (2015), computer technologies resolve several contradictions occurring in education such as;

- There is a huge amount of knowledge gathered in all branches of science and technics, but not enough consumption of knowledge attached with delivery, comprehension and improvement of this knowledge;
- There is a demand of quick, easy and high-quality knowledge, but deprivation of proper procedure and system in educational and instructive process at experts like engineers, technicians and so on for creation of training.
- There is a requirement of an appropriate method for applying mathematical modeling, but lack of its application in education process.

2.3 Computer Assisted Instruction

CAI, which is formed by self-learning in another words interactional learning principles with the computer technology, is a teaching method in which computer is utilized as a supportive tool for teacher in learning environment so that teaching process and students' motivations are strengthen by making possible for student to learn with respect to his/her learning speed (Şahin and Yıldırım, 1999; Uşun, 2000).

It is vital to improve and use instructional materials and activities that evoke students' visual and intellectual frame (Köse et al., 2003). CAI, as reported by Çelikler and Aksan (2011), is one of the methods utilized for this aim (Ertepınar et al., 1998). By extension of technological advances, technological devices, especially computers are started to be used in educational environments to develop audiovisual materials such as animation and simulation (Serin, 2011). The use of simulations and animations associated with abstract concepts, enable students to participate in learning process and enable students to structure the concepts easily in their minds when the concepts have difficulty in understanding (Karamustafaoğlu et al., 2005).

When it is looked the researches done by the aim of investigating the effect of CAI, Köse et al. (2003) searched the effects of CAI to overcome students' misconceptions related to photosynthesis at the last year of lycee. According the results of the research, it is stated that CAI is more effective than TM on remediating students' misconceptions related to photosynthesis. Toros and Yeşiltaş (2015) carried out the researched named "the effect on overcoming misconceptions of CAI in teaching social studies" to determine the misconceptions of elementary sixth grade students about the concepts of weather condition, climate, map, scale, geographical position, specific position and math position and to demonstrate the effectiveness of the CAI in overcoming these misconceptions. With regard to the research, it is detected that CAI is more effective than existing instructional methods to eliminate students' misconceptions. Another research named "The effect of CAI in science and technology course to teachers and students' attitudes and achievements" carried out by Kırılmazkaya et al. (2014) to discover science and technology teachers' attitudes towards using information and communication technologies and to determine attitudes and achievements of the students towards science and technology courses using CAI. According to the result of the study, there is a significance change on students' achievement score when Chemical Bonds subject is taught by CAI, however attitudes towards CAI is not found significant. It is also seen that a portion of the teachers engaging in the study could not gain benefit and have negative attitudes towards Information and Communication Technologies. A dissertation study (Pilli, 2008) titled "the effects of computer-assisted instruction on the achievement, attitudes and retention of fourth grade Mathematics course" is

conducted to examine the effects of the computer software *Frizbi Mathematics 4* on 4th grade students' mathematics achievement. Control group was taught using lecture-based traditional instruction and experimental group was taught using educational software, namely *Frizbi Mathematics 4*. Result of the study indicates that there are statistically significant differences between the groups on the achievements tests and attitude scales in favor of experimental group. In the light of the researches comparing traditional instruction with CAI, it is seen that CAI motivates students to learn and increases students' academic performance.

2.3.1 Advantages of Computer Assisted Instruction

In today's world, computer is an inseparable part of life and by implication it is an important and inseparable part of education area.

According to Cingi (2013), there are various advantages of computer use in education including the followings;

- In the beginning of the education starting in preschool level where students have no ability to read and write,
- Using colorful software with animations rather than reading a book is more interesting and attractive according to children,
- Computer education module including pictures, diagrams and movie clips provides deeper understanding of the content,
- Carrying, copying and distribution of software are easy,
- There is more opportunity of sharing individual experiences, ideas and new approaches,
- There is more opportunity of searching and receiving in seconds.

Demirel et al. (2001), as indicated in Kibar (2006), defined the advantages of CAI as below;

- CAI keeps students active; the need to respond to the questions and thinking on the subject in order to pass the next step requires students to be continuously active.

- Subjects are taught to students in a less time and in a systematic way with CAI.
- Dangerous and expensive experiments required to be tested in a laboratory environment can be done easily with the simulation method.
- Due to instruction is divided into smaller units, success on these units is performed by aligning.

Kaptan (1999), as indicated in Kibar (2006), identified contributions of computers to the educational environments as follows;

- CAI engages students in the learning-teaching environment and increases their motivation.
- CAI has the unlimited repetition ability.
- CAI contributes the development of high-level skills.
- CAI reduces the charge of teachers so that teachers can allocate more time to their students.
- Using audio, video, text and animation techniques together in multimedia facilitates learning by appealing more than one sense of students.

2.3.2 Restrictions of Computer Assisted Instruction

Although there are various advantages of computer aided education, there are also restrictions. According to Şahin and Yıldırım (1999), the restrictions of CAIs are as below:

- CAI requires special equipment and talents; before anything else to use an educational software, it is necessary to have hardware to be used. It is difficult and expensive for schools and classes to access the hardware which is needful for CAI.
- Every material used in teaching should support the training program and be the supportive of the aims and objectives set out in the program. This type of programs and software are needed to be continuous renewaled and developed.
- Weak educational qualifications of CAI. Besides compliance of the programs, instructional software must be able to offer an active learning

environment for students. Due to the fact that software are not improved by educators, it is faced with problems.

Halis (2002), as indicated in Kibar (2006), identified restrictions of CAI as follows;

- **Expenditure Height:** It is not easily afforded by people to have computer and computer software. When this is thought for school, the requirements of variety of software to be used by school causes to be considered as a limitation of the costs.
- **Not Supporting the Educational Program:** Each material used in education should be supportive of the educational program, compatible with the objectives specified in the program and has the qualification of gaining the objectives to the students.
- **High Expectations of Computer Users Related to Computer:** Both students and teachers may have unrealistic expectations from computers. When these expectations are not occurred, negative attitudes towards computers are comprised in that person, as a result working motivation is reduced.
- **Obstacle for Social Interaction:** Computers decrease the social interaction among people in general as well as in the class environment.
- **Health Problems:** Computers cause some health problems due to radiation scattering.
- **Computer Challenges in Usage:** The rapid developments in computer field makes it difficult to use in instruction environment.

2.4 Mathematics Instruction

Mathematics is an excellent appliance to identify the nature and relations between natural phenomena (Salout et al., 2013). In fact, mathematics is not only in the nature, but also in many daily activities of human being. Mathematics has a significant function in forming how individuals overcome the different domain of private, social and civil life (Anthony and Walshaw, 2009). Conveyance of mathematics knowledge and skills obtained in the school to real life necessitates the

individual to think rationally, figure out, estimate and put into practice in real life problems and convey mathematically (Baki et al., 2009). According to Moellwald (1997), as indicated in Salout et al. (2013), “the embedding of mathematics within the context of the learner is fundamental to the establishment of a meaningful association between personal beliefs and meaning-making processes.” Çağlar and Ersoy (1997), as Arslan (2008) indicated, mathematics is a branch of science that provides individual to create and solve the problems, to comprehend objectively, to explain the problems faced in the relationship of cause and effect and provides self-confidence. According to Yıldırım et al. (2006), as reported in Andiç (2012), stated that it is important to gain children and young people the required knowledge and skills for daily life, to teach how to solve problems and thinking approaches and prepare them for the future.

Mathematics plays an important role in the information age and in the future of societies aimed to develop. Due to the width of the application field of mathematics, it is used today as an indispensable source in all sciences. Aksu (2008) indicated that mathematics is not only the main tool of science and technology but at the same time mathematical system is used in the science of medicine, social, political, economic, operation and management and so on. Due to the wide usage of mathematics in every field of life, learning and teaching mathematics is more of an issue.

The effective teaching and learning of school mathematics is one of the important purpose of mathematics education. There is a wide range of researches carried out to address how effective mathematic teaching and learning can be implemented. According to Van de Walle (2004) a suitable structure of mathematics instruction should be directed to the following three objectives; conceptual knowledge of mathematics, procedural knowledge of mathematics and connections between conceptual and procedural knowledge. Due to the fact that mathematics is itself a system consisted of structure and relations and it is an abstract concept with sequential abstraction and generalization processes that create the relationship, it is difficult for students (Alakoç, 2003). Therefore, Alakoç (2003) emphasized that a proper education on the nature of mathematics should be on the purpose of helping students to comprehend concepts and procedures of mathematics and establish the

links between these concepts and functions. Schoenfeld (1989) advocated that mathematics instruction must improve the following skills (cited Alakoç, 2003);

- Students should understand mathematical concepts and methods
- Students should be aware of the mathematical relationships
- Students should have the ability to reach logical conclusions

Students should apply mathematical concepts, methods and relationships for the solution of unusual, various problems.

The role of teachers and students in teaching and learning mathematics created a research area focus in mathematics education in the past decade (Sulaiman, Abdurahman and Rahim, 2010). In the light of the researches, as Sulaiman et al. (2010) stated, teachers need to apply more alternative and cooperative teaching approaches in mathematics instruction (Galton and Eggleston, 1979; Nelson, 1996). The designated teaching methods is more than a simple and technical procedure including teaching objectives and learning consequences, therefore teachers adjust progressive teaching methods to associate various abilities of students to increase students' learning (Sulaiman et al., 2010). For mathematics teaching and learning, it is not expected from students to just learn the knowledge of numerical facts, rather to be a good problem solvers according to their individual mightiness and inadequacies (Jones and Tanner, 2002). According to Sulaiman et al. (2010), a mental and oral introduction, the main teaching and activity and a conclusion should be parts of the lesson that should be structured. Addition to the structure of instructional strategy, effective teaching of mathematics requires active and interactive two way process in which students take part by answering questions, involving discussion, interpreting and showing their own methods to class mates (Sulaiman et al., 2010). According to Anthony and Walshaw (2009) effective mathematics pedagogy is a factor that influences the effective teaching and learning environment of mathematics. They stated a set of principles that support students' mathematical capability and tendency within an effective learning environment including;

- Acknowledgement that all students, regardless of age can have positive approach to mathematics and can learn mathematics.

- Optimizing a variety of wanted academic outcomes that comprises conceptual understanding, procedural smoothness, principal adequacy and adaptive reasoning.
- Contribution to the holistic development of students by enhancing a range of social outcomes within mathematics classroom.

Mathematics is the most abstract science but affecting human lives directly in a comprehensive manner, so it is important to avoid a mathematics instruction which is away from real life and full of memorization given in clusters for not to cause negative attitudes and anxiety towards mathematics (Yenilmez and Uysal, 2007). When the child cannot associate the mathematical concepts with concrete examples in real life, the child disregards and unlike mathematics by asserting that mathematics is not a work for him or her and she has no mathematical thinking ability (Yenilmez and Uysal, 2007). With the change of mathematics program in 2006, The Ministry of Education indicated that only instruction of conceptual knowledge would not be enough in mathematics education. Therefore, it is a necessity to create concrete and real life models to teach abstract mathematical concepts.

2.5 Computer Assisted Mathematics Instruction

Technology is an important tool in mathematics instruction due to providing new opportunities for the process of creating and solving problems (Ersoy, 2003). Using cognitive tools, which mathematical concepts in teaching-learning mathematics on computers are based on, is concerned in mathematics education due to the fact that software has an effective position in acquiring problem solving and thinking skills (The Ministry of Education [MEB], 2005). In addition to gain analytical and critical thinking abilities, the use of technologies in mathematics instruction provides students to develop positive attitude towards mathematics, increase students' interest and reduce the math anxiety (Alakoç, 2003).

21st century is called information and technology era and impressions of technology is seen in every field of life and instinctively it is seen in education too. According to

Köse (2008), technologies used in mathematics education can be grouped under three main headings;

- General technological tools: The tools do not just include the requirements of mathematics instruction, but all technology such as web-based communications.

- Technological tools to do the math: The technological tools such as calculator and excel, developed in order to make easier and accurate mathematics.

- Technological tools for teaching mathematics: Software programs developed in order to improve students mathematics achievements such as Cabri 3D, Geometry Sketchpad, Geogebra.

According to Bayturan (2012), the impression of computer is not as speed as improvements in information technologies, therefore presentation of the interactive materials to the students with appropriate software and activities is emphasized. By the virtue of the general judgement that mathematics is a difficult lesson to comprehend, away from real life and even ominous, it is vital to use computers as materials with mentor of teachers in learning environment (Bayturan, 2012). Instruction supported with the use of mathematics software provides students to associate and internalize the mathematics knowledge with each other in addition to features that help learning (Tutkun et al., 2011). Visualization is a useful approach for attracting students attention, making learning meaningful by concretizing, providing students' own organization of the information, associating the abstract and concrete expression of the concept (Işık and Konyalıoğlu, 2005). Departing from the principle that usage of visualization in mathematics education will affect students positively in both the cognitive and affective aspects, it is clear that the use of visualization should begin in the first stage of primary education (Tutkun et al., 2011). By the advantage of visualization of computer, even more abstract subjects in software such as animation and simulation, the requirement of usage of computer in mathematics instruction is visible. Simulation is a very useful type of CAI enhancing teaching and learning. According to Aydın (2005), simulation is an integral part of

mathematics curriculum. For example numerous three dimensional objects, which are very difficult to be visualized by the students, can be presented through the screen of a computer (Aydın, 2005). Akinsola and Animasahun (2007) showed use of simulation games which is illustration with physical object coupled with dramatization in mathematics instruction improve students mathematical understanding.

Aqda, Hamidi and Rahimi (2011) indicated that under the favor of computers capability to create highly interactive learning environments, providing a variety of learning activities, offering independence to students in the process of learning, improving students' self-confidence, encouraging and motivating students to learn in a better manner with technology-based tools, students' creativity in mathematics is developed. Yushau, Mji and Wessels (2003) have found that CAI improves teaching mathematics by reviewing numerous researches relevant to influence of computer assisted education on mathematics. Jeffery (2000), as reported in Aqda et al. (2011), pointed out that CAI affects students' learning in different grades and many different school subjects, at least as the same level with traditional teaching by comprising positive attitudes in students towards school subjects, reducing the time and duration of learning compared to traditional teaching.

Besides the numerous advantages of CAI of Mathematics, there are also some constraints about usage of it. The findings from Göktas, Yildirim, and Yildirim (2009) show that due to lack of in service training, lack of appropriate software and materials and lack of hardware are the primary obstacles for implementing CAI (as cited in Han, Halim, Shariffuddin and Abdullah, 2013). While some educational software programs are free and downloadable through the internet, some of them are not. Therefore, it is not always possible to find an appropriate and free software program for the instruction. Technological infrastructure of schools is another barrier against the CAI. Although, interactive whiteboards and tablet applications launched in 2014 with Fatih Project in Turkey, it is not reached to all area of Turkey. Therefore, usage of CAI everywhere in Turkey does not seem possible for now. The most important barrier against the computer assisted mathematics instruction is teachers. As Han et al. (2013) stated only a few teachers are confident in using a

wide range of CAI materials in mathematics education. Reluctance of teacher in integrating computer to the instruction affects the learning environment, therefore the main objectives of the lecture cannot be gained by students. As a result of that teacher's view point of CAI implicitly will determine the quality of instruction.

Teachers' role in CAI is tracking, guiding and improving learning (Arslan, 2008). Software technology is not a tool that replace the teacher in the classroom, yet facilitate visualization, calculation and allow to perform errorless experiments that can be repeated (Can, 2010). Birgin, Çatlıoğlu, Çoçtu and Aydın (2009) found that interest to computer, the frequency of computer usage and having experience of CAI make differences on the views of mathematics teachers about computer assisted education. Because of this reason, it is very important a mathematics teacher to have competence in computer and the related software programs to provide an effective course.

2.6 Probabilistic Thinking

Probability has a strong relationship with the other fields of mathematics such as proportional reasoning, multiplicative reasoning (Dooren, 2014 as cited in Chernoff and Sriraman, 2014). However, probability has additional features such that the outcome of an event is variable and defined by randomness and uncertainty (Dooren, 2014 as cited in Chernoff and Sriraman, 2014). Piaget and Inhelder worked on the development of chance and randomness in the early 1950s, and presented two main results about the study. First result is about that chance is in opposition with determination, and the second is that chance might have some physical laws or causality to express (Savard, 2014 as cited in Chernoff and Sriraman, 2014). Those results shows that an intuition of probability does occurs and might be formed (Savard, 2014 as cited in Chernoff and Sriraman, 2014). San Martin (2007) indicates that the intuition of probability and chance might be derivation of facts if compared with the order and its results (Savard, 2014 as cited in Chernoff and Sriraman, 2014).

2.6.1 Theoretical Background for Probability

In the literature there are various researches on students' understanding of probability. While a group has dwelled on school children's probabilistic thinking (e.g., Fischbein, 1975; Green, 1983; Piaget and Inhelder, 1975; as cited in Garfield and Ahlgren, 1988), the other has dwelled on college students' and adults' probabilistic thinking (e.g., Konold, 1983; Tversky and Kahneman, 1982; as cited in Garfield and Ahlgren, 1988).

Piaget and Inhelder (1975), as reported in Yağcı (2010), explained children's development of probabilistic thinking in three stages:

1. Stage: Sensory Motor (up to 7 years old): Children are not able to comprehend the probability concepts and they have tendency to make changeable predictions in this stage.

2. Stage: Concrete-operational (approximately between ages 7 and 10): The improvement of chance concept firstly began in this stage.

3. Stage: Formal-operational (begins at approximately age 11): The total comprehension of probability in children is in adolescence, in the third stage. Additionally, students are able to organize probability concepts in this stage.

According to the previous researches, the age is seen as a factor that influences probabilistic thinking of an individual. However, the effect of age has not been exactly straightened out. While Fischbein and Schnarch's study (1997) showed a reduction in the negative regency effect towards probability with age, a latest study conducted by Chiesi et al. (2007) found out that there is a negative regency effect on both young children and adults (as cited in Chiesi and Primi, 2008). Garfield and Ahlgren (1988) attributed why at any level students have difficulties to develop intuition about primary concepts of probability in at least three reasons. Firstly, majority of students have difficulties with prerequisite knowledge which are rational number concepts and proportional reasoning that are used in calculating, reporting and interpreting probabilities. Secondly, there is a conflict between students' experience, their perception of real word and probability concepts (Kapodia, 1985; as

cited in Garfield and Ahlgren, 1988). Thirdly, due to the exposure of probabilistic studies in an extremely abstract and formal method, students dislike probability.

Addition to studies examing probabilistic thinking in children, the importance of probability in real life is highlighted in the great majority of researches. For example, Bulut (2001) defined probability as an inevitable concept of daily life owing for making decisions in unsure situations and about random phenomena, in which individuals always make, requires probabilistic reasoning, knowledge, and experiences. Njenga (2010) indicates that probability has effects on how people comprehend the world surrounding and form their decisions at critical moments. Informal judgements about change in the field of health, finance, weather, sport games etc. are all familiar examples in which probabilistic reasoning is involved to make estimation (Njenga, 2010). Furthermore, the significance role of probability in the society is admitted by various influential organizations, such as National Council of supervisors of Mathematics in 1978, UNESCO in 1972 and the Cambridge Conference on School Mathematics in 1963 (Hope and Kelly, 1983; as cited in Mut, 2003).

Even though researches emphasize the significance of probability, concepts of probability cannot be learned well due to various reasons in our country as well as in many foreign countries (Gürbüz, 2006). There are various reasons of that insufficiency in probability teaching. Memnun (2008), in the light of literature review, grouped the reasons for not learning the concepts of the probability under six categories. Student's readiness level, age of students, lack of student’s reasoning skill, teacher, misconceptions and negative attitudes towards probability of students are among these categories. The readiness level of students is related with insufficiency in the prerequisite subject matters such as fraction, percentage, decimal numbers (Garfield and Ahlgren, 1988; Memnun, 2008) and the concept of cluster (Memnun, 2008). Memnun (2008) indicated that even age is one of the most important factors in learning the concept of probability, it cannot be said that the literature demonstrate the effect of age adequately. Teachers can also affect students learning of the concept of probability from different perspectives; however, instruction methods and materials teachers use considerably important factor in the

instruction of probability. Teacher-centered classroom environment (Gürbüz, 2006) and lack of appropriate teaching materials (Aksu, 1990; as cited in Gürbüz, 2006) are among the factors prevent the effective teaching and learning of the subject. Students' misconceptions towards probability is related with students understanding the probability concepts intuitively (Memnun, 2008). Memnun (2008) stated that researches proved that majority of students' intuitively understood probability concepts are misleading and it is difficult to correct these misconceptions later.

In view of difficulties in learning and teaching probability, some researchers recommend the use of different materials in probability instruction. For example, Lappan and Winter, as Yağcı (2010) indicated, concrete experiments provides more hope for students' probability achievements. Gürbüz (2008) claimed that traditional teaching methods are inadequate to overcome the difficulties in probability teaching and claimed that usage of computer aided material including animations and simulations is the best approach in dealing with these difficulties.

Moreover, Garfield and Ahlgren (1988) advised some recommendations for teachers to overcome difficulties faced in probability instruction, as following;

- Using simulations and activities, not abstract issues in the instruction of probabilistic subjects.
- Trying to encourage students to notice that probability is connected with reality and it is not just comprised of symbols, rules and conventions.
- Using visual instances, drawing attention to explorative data methods.
- Improving students' rational number concepts before probability instruction.
- Being aware of students' common mistakes in probabilistic thinking.
- Establishing positions conduces probabilistic reasoning that matched with students' world views.

Related literature demonstrates that there are many difficulties in learning and teaching probability concepts. One of the reasons is explaining probability concepts with an abstract instruction. Moreover, students cannot interrelate the subjects with the real life conditions. Many researchers give recommendations about how to overcome these difficulties, and how to provide an effective instruction of

probability. Based on these recommendations, the present study takes into consideration of using CAI method in the instruction of probability.

2.6.2 Research Studies on CAI Method in Probability Instruction

In the literature, there are some research studies conducted to examine the effectiveness of CAI methods on students' probability achievement. The related studies are summarized below:

In one of these studies, Andiç (2012) carried out a study to investigate the effects of CAI on the eighth grade students' permutation and combination achievement and attitudes. The related material was prepared by using Adobe Flash CS+ program. There were 34 students from the same class; 17 students in experimental group and the other 17 students in control group. The students in experimental group received instruction through CAI, while students in control group received traditional instruction. Mathematics Achievement Test and Scale of Attitudes towards Mathematics were applied to both experimental and control group. According to the result of the study, there was a statistically significant mean difference between experimental and control groups in favor of experimental group with respect to the posttest scores they obtained from the students' achievement test. Otherwise, there was no statistically significant mean difference between experimental and control groups with respect to the posttest scores they obtained from the Scale of Attitudes towards Mathematics.

In another study carried out by Fırat (2011), the effect of mathematics teaching performed through educational computer games on conceptual learning regarding some probabilistic concepts on the sixth grade students' probability achievement was investigated. The participants were 90 sixth grade students studying at a primary school located in Souteastern Region of Turkey. That study was carried out through quasi-experimental model. "Conceptual Development Test" consisted of 14 questions was the data collection tool and the related materials were designed in Java programming language by NetBeans editor to perform teaching process. There were two groups as control and experimental groups. The experimental group received instruction through educational computer games and control group received traditional instruction. Conceptual Development Test was applied to both

experimental and control group as pre-test and post-test. According to results of the study, teaching through educational computer games contributed students' conceptual learnings on some probabilistic concepts. Moreover, both groups had improvements in terms of conceptual learning but improvement in experimental group was more than in control group. In the light of these results, teaching through educational computer games was significantly more effective than traditional instruction for students' conceptual learnings on some probabilistic concepts.

In another study, Öztürk (2005) conducted a study to design a CAI of permutation and probability unit at the eighth grade in primary school. Both traditional instructional design and development session of CAI software were examined to design instructional material to be used in the study. The requirement literature review was executed in the analysis step about misconceptions and errors in permutation and probability and the instruction methods of permutation and probability. After examining objectives according to Primary School Mathematics Curriculum, determination of absent points and elimination of misconceptions; the scenario were written on the cards and software of unit was programmed. Authorware 7.0 produced by Macromedia Company was used for designing software program. Also; Photoshop, Flash, Paint and Sothink Glanda were used as a supportive programs. The software has the properties of tutorial, drill-practice and simulation. The software was implemented a group of 8th grade students to determine whether the software is effective for permutation and probability instruction by observing during the implementation process. According to the result of the observations, recommendations related to CAI in the primary school mathematics courses were made.

Similarly, Gürbüz (2008) presented a computer-assisted material designed for teaching probability topic at primary school. A test was developed to determine whether there was a need to develop CAI Material (CAIM) on probability instruction, and the evaluation of the results showed the necessity of implementation of CAIM. After clinical interviews with five mathematics teachers in the elementary class of the test was applied, the needs to develop CAI material gained strength. In the light of the studying, CAIM including simulations and animations, were

developed through the instrument of Dreamweaver MX 2004 and Flash MX 2004, and transformation to an HTML was supplied. Four groups were formed from seven students in the eighth grade from the Eastern Black Sea Region; all of these three group was in doubles and one group was just comprised of one student. After these students were informed about the usage of computer assisted material, the implementation phase was carried out in guidance of the researcher. Sections which students had difficulties to understand were observed during the application and the required notes were taken by talking with students about this part of the section. The final version of the material was received in accordance with the observations and notes. At the end of the study, it is suggested that these CAIM would be effective in teaching and learning of probability topic.

In another study, Ferreira et al. (2014) discussed aspects of high school students' learning of probability in a context where they were supported by the statistical software R. According to the result of the study, students' learning of basic concepts, such as: random experiment, estimation of probabilities, and calculation of probabilities using a tree diagram were improved with the instruction supported with R. The usage of R let students to develop their reasoning compared to traditional paper and pencil approaches due to providing opportunity to work with a large number of simulations and to exceed the standard equiprobability assumption in coin tosses.

In a study carried out by Braun et al. (2013), it was investigated how to introduce young students the ideas of randomness and uncertainty by using statistical program R in elementary schools. The study was conducted with approximately 20 fifth- and sixth-grade students in a 40 minute class where R was used in a sequence of simulation activities to illustrate basic probabilistic and statistical concepts in an engaging manner. According to results of the study, it was concluded that the students were observant and active throughout the session by posing good questions and responding quickly when they were asked questions. Moreover, it was concluded that the use of simulation to demonstrate activities which were appropriate and of direct interest to the children occurred to be a satisfactory way of simplifying learning about the concepts of randomness and uncertainty.

In another study, Koparan and Yılmaz (2015) conducted a study to investigate the effects of simulation-based probability teaching on the prospective teachers' inference skills. The design, implementation and efficiency of a learning environment for experimental probability concept were aimed to examine in line with this purpose. The quasi-experimental research method was used in the study. The participants were 55 prospective teachers who attended the statistics classes in Bülent Ecevit University. For the assessment of the efficiency of the designed learning environment, a test with 5 open-end questions was developed with regard to the experimental probability. It was implemented as pre- and posttests and the obtained data were supported by semi-structured interviews and observations. The comparison of the answers given by prospective teachers using papers and pencils and the answers given by means of simulations were used to determine the efficiency of the simulation-based learning. The results of the study showed that simulation-based probability teaching increased the prediction and related inference skills of the prospective teachers, and by implication, the success of the students would be influenced in a positive way.

In the study of Nikiforidou and Pange (2010), software testing children's abilities to make estimations and judgments based on probabilities was evaluated by preschool teachers. The participants were 45 service teachers from Greece. Educators had personal interaction with the software and filled in a questionnaire according to their opinions. Additional analysis was conducted to distinguish the criteria of significance that contain software as developmentally appropriate. The findings revealed that 88.8% of in-service teachers considered this sort of software useful in educational practices. According to the result of the study; the content, the process and the purpose of preschool software should be taken into consideration in addition to design for the implementation of software in preschool education.

Çelik and Çevik (2011) conducted a study to investigate the effect of computer-assisted instruction on teaching the unit of "probability and statistics" to seventh grade primary school students. An experimental model with pre-test and post-test group was used in the study. The participants were a group of 56 seventh grade students in Siirt Sancaklar Primary School, Turkey. While the experimental group

was consisted of 27 students, the control group was consisted of 29 students. Students in the experimental group were instructed within the framework of the plans based on the CAI activities while those in control group were instructed according to course plans prepared appropriate to traditional teaching method. Mathematics achievement test was developed by researchers as data gathering tool and applied as pre-test and post-test in both experimental and control groups. Results of the study revealed that the CAI is more effective in increasing student achievement compared to the traditional instruction at the seventh grade mathematics class.

In this section some research studies which examined the effects of CAI methods on students' probability achievement and research studies which design CAI material for probability teaching were presented. In the light of the researches; it was found that CAI was more effective than traditional instruction for teaching probability concepts and CAI materials would be effective in teaching and learning of probability topics. In the present study, a CAIM including a sequence of animation and simulation activities to illustrate basic probabilistic concepts, was improved by using statistical program R. It aims to investigate the effect of CAI method compared to traditional instructional method on students' probability achievement. In addition, unlike the other studies, this study also examines how the socio-economic and cultural factors affect the achievement.

CHAPTER 3

METHODOLOGY

The purpose of the present study is to investigate the effects of CAI to mathematical achievement and attitude of students when we have a large number of highly correlated categorical explanatory variables about socio-economic and cultural status of the students. For this purpose, we first employ a categorical principal components analysis (CATPCA) to deal with multicollinearity problem among categorical explanatory variables, and then use uncorrelated components instead of original correlated variables to regress the response variable with multiple linear regression (MLR).

3.1 Categorical Principal Components Analysis

In the study, there is a large number of categorical variables, which we wish to reduce to a small number of dimension with as little loss of information as possible. Principal component analysis (PCA) or factor analysis are considered to be appropriate ways to be executed in such a data reduction process. The aim of PCA or factor analysis is to reduce the number of m variables to smaller number of p uncorrelated linear combinations of these variables, called principal components, while maximizing the amount of variance in the data as much as possible (Everitt and Hothorn, 2011). However, traditional PCA is not a suitable method of data reduction for categorical variables, since variables in PCA are assumed to be scaled at numeric level (interval or ratio level of measurement) and also linear relationship among variables are required. Alternative to traditional PCA, categorical (also

known as nonlinear) principal components analysis (CATPCA/ NLPCA), which overcomes limitations of PCA, is used in this study.

3.1.1 Definition of CATPCA

CATPCA, is an alternative data reduction technique to PCA, concerned with identifying fundamental components of a set of variables while maximizing the amount of variance accounted for (VAF) by the principal components, for the variables which are categorical (e.g. nominal, ordinal and even numeric). The purpose of CATPCA is equivalent to that of PCA, namely to reduce a data set consists of many correlated variables to a smaller number of uncorrelated summary variable (principal components) that represent the observed data as closely as possible. The main difference between the methods is that, while PCA detect a linear relationship between variables, CATPCA can also detect nonlinear relationships by quantifying categorical or nonlinearly related variables in an optimal way to achieve the PCA goal (Linting, Groenen and Van der Kooji, 2007). It is important to underline the fact that when all variables in the data set are continuous and the linearity assumption between the variables are satisfied, CATPCA and PCA give exactly the same solutions.

Gifi (1990), as cited in Mair and Leeuw (2010), proposes a wide collection of nonlinear multivariate methods based on *optimal quantification*. NLPCA/CATPCA uses *optimal quantification* (also known as optimal scaling, or optimal scoring) approach to assign numeric values to categories of variables (Linting et al., 2007). Optimal quantification is a process which converts the category labels into category quantifications by maximizing the VAF among the quantified variables (Linting et al., 2007). A 0-1 dummy matrix based on the data consists of categorical variables is the starting point of the highlighted analysis. Afterward, a loss function comprising the (unknown) object and category scores is constituted. These variables are stretched during the iterations and category scores are computed in such way that they are optimal in terms of a minimal loss function. In the Gifi model, the transformations compared to that of regression such as exponential, logarithmic or square root transformations are unknown: The categories are quantified according to a certain criterion. In the given approach an objective function is selected and then

examined how the target function alters over all possible transformations of the variables, and eventually quantify the categories accordingly (Mair and Leeuw, 2010).

Let's work on a multivariate dataset with m variables. The aspect defined on the correlational matrix $R(X)$, ϕ defines the criterion to be optimized and $X = (x_1, x_2, \dots, x_m)$ with x_j as the vector of category scores to be computed. Broadly, the optimization problem can be formulated as

$$\phi\big(R(X)\big) \rightarrow \text{max!} \tag{1}$$

That is to say: The observed variables (categories) are scaled in such a way that the correlation matrix, based on these scores, is maximized (Mair and Leeuw, 2010).

At this point, we specify *Eigenvalue aspects* based on $R(X)$. It means to maximize the largest eigenvalue λ of R. In brief, the aim of the optimal quantification is to optimize the first p eigenvalues of the correlation matrix of the quantified variables, where p represents the number of components defined in the analysis.

As mentioned above, we emphasize optimal quantification of categorical variables. Suppose we have measurement of n objects or individuals on m variables collected in an $n \times m$ observed score matrix **H** where each variable is denoted by X_j, $j = 1,2, \dots, m$ that is the jth column of **H.** If the variables X_j are nominal or ordinal, then a nonlinear transformation, namely optimal quantification is required to transform observed scores into category quantification given by:

$$q_j = \varphi_j\big(X_j\big), \tag{2}$$

where $\boldsymbol{Q}$ is the matrix of category quantification.

Let **S** be the $n \times p$ matrix of object scores, which are the scores of the individuals on the principal components, obtained by CATPCA. The object scores are multiplied by a set of optimal weights, named component loadings.

Let **A** be $m \times p$ matrix of the component loadings where the jth column is denoted by a_j. Then the loss function for minimization of difference between original data and principal components are given as follows:

$$L(\boldsymbol{Q}, \boldsymbol{A}, \boldsymbol{S}) = n^{-1} \sum_{j=1}^{m} tr(q_j a_j^T - S)^T (q_j a_j^T - S), \quad (3)$$

where tr is the trace function, i.e. for any matrix **A**, $\mathrm{tr}(\mathrm{A}^T\mathrm{A}) = \sum_i \sum_j a_{ij}^2$.

As a result, the CATPCA is carried out by minimizing the least-squares loss function given in the equation (3) in which the matrix is replaced by the matrix **Q.** The loss function is exposed to some restrictions. Firstly, $q_j^T q_j = n$, that is transformed variables are standardized to solve the indeterminancy between q_j and a_j . This standartization indicates that q_j contains $z-$ scores and yields that the component loadings in a_j are correlations among transformed variables and principal components. The object scores are restricted by $S^T S = nI$, where **I** is the identity matrix, to avoid the trivial solution. However, the object scores are centered, i.e. $1^T S = 0$,where 1 is a vector of ones. Linting et. al. (2007) states that these restrictions imply the columns of **S** to be orthogonal z-scores (as cited in Kemalbay and Korkmazoğlu, 2014). Gifi (1990), as cited in Kemalbay and Korkmazoğlu (2014), the minimization of restricted loss function given in (3) is get by means of an Alternating Least Squares (ALS) algorithm.

Consequently, CATPCA converts categories into numeric values as mentioned above. The most important issues to be considered in this regard is that, the correlation matrix in CATPCA is not fixed as opposed to the correlation matrix in PCA; rather, *analysis level*, that is chosen for each of the variables in the active CATPCA process determines the type of quantification. The specified analysis level also decides the amounting freedom permitted in converting category values to category quantifications (Linting and Kooji, 2012).

3.1.2 Analysis Levels

The measurement levels of the variable (e.g. nominal, ordinal or numeric) do not determine the analysis level of a variable in CATPCA. Description of the properties of each analysis level of the variables is given below.

Nominal Analysis Level

Nominal analysis level is appropriate if the researcher concerns with potential nonmonotonic nonlinear relationship between the variable at hand and the other variables in the data. When a specific nonlinear pattern is present in the data, it is much more obvious to interpret the nominal quantifications compared to quantifications obtained by other analysis levels. In the case of nominal analysis level, it is required that individuals or objects who get the same category on the original variable, should also receive the same quantified value.

Ordinal Analysis Level

Ordinal analysis level is appropriate if the researcher concerns about the nonlinearity of relationships, but desires to keep the category order in the quantifications with the ordering of the original categories. It is advisable to use an ordinal analysis level when the number of categories is small compared to the number of individuals.

Numeric Analysis Level

Numeric analysis level is appropriate if the researcher does not concern about the nonlinear relationships between variables. If all variables are at a numeric analysis level, optimal quantification is not needed. Consequently, CATPCA will give the same output as the traditional PCA.

Spline Nominal and Ordinal Analysis Level

When the variables (such as continuous) have many categories and the researcher concerns about the nonlinear relationships between that variable and other variables, nominal and ordinal analysis levels might get very irregular category quantifications. This situation causes the researcher to have lack of understanding and consistency in the analysis level process. A more restrictive spline ordinal or spline nominal can be specified alternative to nominal and ordinal analysis level. However, a spline analysis level is more restrictive and thus lead to lower (VAF).

It is stated that specified analysis level determines the amount of freedom in category quantification. When a nominal analysis level is specified, CATPCA has the most freedom in quantifying a variable, and the most restricted when a numeric analysis

level is specified. As a result, the method obtains the highest VAF when all variables are specified nominally, and the lowest VAF when all variables are specified numerically.

3.1.3 Discretizing

CATPCA method requires categorical variables with (positive) integer valued. This requirement is just related with technical issues, not the property of the method nonlinear PCA. Before we run the program, variables that do not have integer values must be discretized. That means that the values of continuous variables should be transform to integers. CATPCA provides multiple discretizing options. The discretizing option *Multiplying* is advisable when continuous variables are analyzed numerically. The option *Ranking* is advisable for continuous variables that will be treated ordinally or nominally. The Grouping option is advisable if the researcher wants to decrease the number of categories of a variable before CATPCA.

3.1.4 Analysis Levels and nonlinear relationships between variables

After the variable is selected and the number of components are determined, we can evaluate the choice of analysis levels for the variables by examining *transformation plots*. The transformation plot shows the relation between the observed variable and its quantification. So, assume that a variable with three categories (1, 2 and 3), the transformation plot shows the first and the last category obtain a lower quantification than the middle category, and the first is slightly lower than the last. Then, this means that the transformed variable reordered the observed values (1, 3, 2) and changed the distances between the values in order to optimize the correlation between this variable and the set of other variables so to optimize the VAF by the principal components. The *category plot* shows how the quantification are placed on a vector, where categories 1 and 3 will be placed close together on the lower end of the vector, and category 2 will be on the higher end. To correctly interpret the relations between variables and see which variables are highly associated and which are not, *component loadings plot* is needed. When the variable from the example is close together with some other variables in the data set, category 2 will be most associated with the higher quantified values on these other variables, and categories 1 and 3 will be associated with lower values (Linting, by mail).

3.2 CATPCA Output

3.2.1 Model Summary of CATPCA

Variance Accounted For (VAF)

VAF is the amount of information retained when the variables are represented in a lower dimension. It is calculated by dividing the sum of the eigenvalues of the principal components to the total number of variables. When data set contains a large amount of variables, it is an appropriate way to exclude variables with bad fit from the analysis to provide a clear interpretation of the output (Linting et al., 2007). Since, variables with bad fits do not provide so much to the solution of the analysis, removing them will slightly influence the total fit of the solution (Linting and Kooji, 2012). VAF is considered as the main criterion in variable selection, since it is the most important indicator of fit for the principal components, and for the quantified variable. In the analysis process, the dimensions whose contribution is very little to the VAF is ignored.

Eigenvalue

The eigenvalues are comprehensive summary measures that denote the VAF by each component. In other words, each principal component is a composite variable combining the original variables and the eigenvalue is the indicator of how accomplished this summary is. The principal components are ordered with respect to their eigenvalues. The first component/dimension is linked with the largest eigenvalue, and so explains most of the variance; the following explains as much as possible of the remained variance, and so on. The summation of the eigenvalues through all feasible components is the same with the number of variables *m*. In the analysis process, principal components with corresponding eigenvalues that are greater than 1 are preferred.

3.2.2 Quantification Tables

Quantification tables show the frequency, the quantification value assigned after optimal scaling, the centroid coordinates, and the vector coordinates of each response category for each item. The centroid coordinates are the mean of the all individuals' object scores for a specific category on each dimension. The vector coordinates mean

to the coordinates for each response category when the categories are reproduced by a straight line between dimensions.

3.2.3 Variance Accounted for Table

VAF table does not reveal the variance accounted for as well as its name. However, it shows the coordinates for each variable on each dimension in relation to the centroid (0, 0) and when all variables are presented by a straight line between dimensions (Herrington and Starkweather, 2016). Variables with very small mean coordinates; close to or below 0.100, show that these are not contributing considerably to the principal components. Therefore, those variables are seen suspected to be excluded from the analysis.

3.2.4 Correlations between Transformed Variables

After optimal scaling, correlations between transformed variables are used as a matrix for the PCA. The bottom row of the correlations between transformed variables table gives the eigenvalues for all possible components, based on a solution with the number of components you specified. A scree plot can be constructed using the values from the bottom row of the table with correlations between transformed variables.

3.2.5 Component loadings

Component loadings state Pearson correlations between the principal components and the quantified variables. Therefore, the range of component loadings is between -1 and 1. Component loadings table shows the value of each variable on each dimension.

3.2.6 Object Scores

Object scores are the coordinates associated with each case on each of the dimensions. Objects score table shows the value of each individual on each dimension. The object scores corresponding to each individuals on the components can be used in further analysis.

3.3 Multiple Linear Regression Model

3.3.1 Definition of the Model

MLR is a statistical technique for examining and modeling the relationship between explanatory variables and a response variable (Montgomery, Peck and Vining, 2012). In MLR model, the response variables change around their mean values that leads to the following MLR mean function:

$$E(Y/X) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \ , \tag{4}$$

where β_0 is called the intercept and the β_k are called slopes or regression coefficients.

In general, MLR has the form

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \varepsilon, \tag{5}$$

which is equivalent to writing conditional mean function as above equation (1). This equation shows a MLR model with k regressors, where $\beta_j,\ j = 1, \ldots, k$ are regression coefficients. β_j symbolizes the expected change in the response variable y for per unit change in explanatory variables X_j when all the remaining regression variables are hold constant.

The MLR model can also be represented in matrix form as below:

Design matrix **X**:

$$X = \begin{bmatrix} 1 & X_{11} & \ldots & X_{1k} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & X_{n1} & \ldots & X_{nk} \end{bmatrix}_{n \times k+1}$$ shows the levels of the regressors.

Coefficient matrix β:

$$\beta = \begin{bmatrix} \beta_0 \\ \vdots \\ \beta_k \end{bmatrix}_{k+1}$$ is the regression coefficients vectors.

Error vector ϵ:

$$\epsilon = \begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_n \end{bmatrix}_{nx1}$$ is the vector of random errors.

As a result, the MLR model in matrix notation is equivalent to $Y = X\beta + \varepsilon$.

3.3.2 The Use of Dummy Variables in Multiple Linear Regression Analysis

The most important application of regression analysis is the inclusion of both qualitative and quantitative factors into regression model at the same time (Tunalı and Batmaz, 2003). Qualitative factors describes the categories, classes or levels of the observation. The categories of qualitative factor are indicated by the indicator variable also known as dummy variable that takes only zero and one value in the regression model (Tunalı and Batmaz, 2003). A second-order linear model containing quantitative factors as well as qualitative factors can be constructed by adding new terms to a second-order model containing only k quantitative factors (x):

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i \, x_i + \sum_{i \leq j} \beta_i \, x_i x_j + \varepsilon. \tag{6}$$

In the model (6), only one equation is used to symbolize the responses of all levels. That means that there is no any difference between the qualitative factor levels in relation to the quantitative factors. The following model is acquired by adding the main effect terms (τ) for the q incidator variables (z) to (6):

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i \, x_i + \sum_{i \leq j} \beta_i \, x_i x_j + \sum_{i}^{q} \tau_i z_i + \varepsilon. \tag{7}$$

To symbolize the interaction between the levels of qualitative factors and the quantitative factors, extra terms are added to the model (7). The related new model is given by:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i\, x_i + \sum_{i \le j} \beta_i\, x_i x_j + \sum_{i}^{q} \tau_i z_i + \sum_{i} \sum_{j} \varphi_{ij}\, x_i z_j + \sum_{l} \sum_{i<j} l_{ijl}\, x_i x_j z_j +$$

$$\sum_l \sum_i \eta_{il} x^2 z_l + \varepsilon. \qquad (8)$$

These three models can be written in matrix notation as $\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{\varepsilon}$**.** Here, **X** represents the design matrix, $\boldsymbol{\beta}$ coefficient matrix and $\boldsymbol{\varepsilon}$ is the error vector.

The indicator function (z) in (7) and (8) is determined for the different levels (j) of a qualitative factor (i) as below:

$$z_{ij} = \begin{cases} 1, & \text{if the jth level of the qualitative factor i is used,} \\ 0, & \text{otherwise,} \end{cases} \qquad (9)$$

where $i = 1, \ldots, n$ and $j = 1, \ldots, n_i$. In that case, the number of indicator variables is equal to the number of levels (categories) in that variable minus one.

3.3.3 Multiple Linear Regression Model Adequacy Checking

In the process of MLR, certain assumptions should be satisfied. The important assumptions made in regression analysis are presented as follows (Montgomery et al., 2012) :

- The relationship between the response variable y and the explanatory variables is approximately linear.
- Error term ε has zero mean, i.e. $E(\varepsilon) = 0$.
- Error term ε has a constant variance, i.e. $Var(\varepsilon) = \sigma^2$.
- Errors are almost normally distributed.
- Errors are uncorrelated, i.e. $Cov(\varepsilon_i, \varepsilon_j) = 0$, for $i \neq j$.

While uncorrelated error term and constant variance assumptions insure the best linear unbiased estimators, the normality assumption is required just for the test of significance and confidence intervals estimation (Tunalı and Batmaz, 2000).

3.3.4 Analysis of residuals

Assumptions related with error term are checked via analysis of residuals. Analysis of residuals is very beneficial to comprehend the appropriateness of the fitted values into regression model (Neter et al., 1990). In the analysis of residuals, both graphical and analytical methods are used (Neter et al., 1990). The following plots should be gathered to check the assumptions related with error term:

- Plot of residuals versus fitted values,
- Normal probability plot of residuals,
- Histogram of residuals,
- Plot of residuals versus order.

The residuals should occur in each plot as a random variation about zero in the case of the model is accurate and the assumptions are met (Tunalı and Batmaz, 2000). The properties of ordinary residuals, $e = Y - \hat{Y}$ are $E(e) = 0$ and $\mathrm{Var}(e) = \sigma^2\ (\mathrm{I} - \mathrm{H})$ where $\mathrm{H} = \mathrm{X}(X'X)^{-1}X'$. The points are outside of the band containing the most of the residuals are described as outlier (Tunalı and Batmaz, 2000).

Heterogeneity of variance

Violation of constant variance assumption, i.e. heterogeneity of variance causes the loss of accuracy in the parameter estimations (Tunalı and Batmaz, 2000). If the residuals are in a horizontal band in the plot of residuals versus fitted value, constant variance assumption is satisfied (Montgomery et al., 2012). However, in case of funnel-shaped pattern in the plot represents the existence of heterogeneity of variance (Tunalı and Batmaz, 2000). Various tests are present to test variance homogeneity assumption such as F, Bartlett, Box-Anderson, Levens, Box, Moses and Jacknife tests (Hall, 1972). Bartlett test is a multipurpose test and can be used for each sample sizes that equal or unequal (Tunalı and Batmaz, 2000).

Applying the transformation on the response variable or to use the method of Weighted Least Squares (WLS) are two remedial treatment in the case of heterogeneity of variance (Tunalı and Batmaz, 2000).

Normality

Normal plot of residuals plays an important role in determining whether normality assumption is satisfied or not. Data points are scattered on the straight line points out that normality assumption is satisfied. Substantial departures from the straight line implies that normality assumption is violated. Shapiro-Wilk W statistics, Kolmogorov-Simirnov, Cramer-Von Mises and Studentized range are formal tests to check normality assumption (Tunalı and Batmaz, 2000).

Uncorrelated errors

Error terms should be uncorrelated to fit regression models. Data gathered in time sequence and lack of randomization may result in errors to be correlated (Tunalı and Batmaz, 2000). Correlated errors on the method causes the loss of accuracy in the estimates, which violates the test of significance (Tunalı and Batmaz, 2000). Durbin-Watson test or runs test are used to detect existing of serial correlation in the residuals (Özdamar, 2011). The Durbin-Watson test statistic (Tunalı and Batmaz, 2000) is calculated as below;

$d = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t=1}^{n} {e_t}^2}$, where n is the observation number. (10)

The plot of residuals versus order is useful in detecting uncorrelated errors. It is expected this plot to resemble a horizontal band (Montgomery et al., 2012). If error at one time period is correlated with those at another time, autocorrelation is occurred (Montgomery et al., 2012). Remedial approach to deal with correlated errors is to benefit a model that conceives the correlation construct in the data (Tunalı and Batmaz, 2000).

Outliers

Measurement error, miscalculation, recording mistake, failure of assumptions may cause outliers (Tunalı and Batmaz, 2000). In case of one observation identified as an outlier, R-statistics for that observation can be utilized to conduct t-test with regarding critical values $t_{\alpha,n-p-1}$, where p is the parameter number in the model (Tunalı and Batmaz, 2000). Instead of conducting t-tests for each residuals at the same time that causes significance level larger than α, comparison of R-statistic for each observation with α/n 100% point of the $t_{\alpha,n-p-1}$ distribution is much more

convenient (Myers, 1990 as cited in Tunalı and Batmaz, 2000). Bonferroni inequality can gives more conservative critical values for R-statistic (Cook and Weisberg, 1982 as cited in Tunalı and Batmaz, 2000). Besides, normal probability of residuals also gives information about potential outliers.

3.3.5 Diagnostic check and remedies

If the assumptions mentioned above are not satisfied, the regression model can be omitted or a new model can be constructed. Or else, appropriate transformation can be applied on the response variable or WLS method can be used to estimate model parameters (Tunalı and Batmaz, 2000).

Transformations

In the violation of normality and homogeneity of variance assumptions, power transformation on y, y^{λ} where λ is the parameter to be decided, can be applied to remedy nonnormality and nonhomogenous error variance (Montgomery et al., 2012). Box-Cox transformation is a power transformation using maximum likelihood method to estimate both the parameters of the regression model and λ (Montgomery et al., 2012). The procedure is as below:

$$y^{\lambda} = \begin{cases} y^{\lambda} - 1/\lambda \dot{y}^{\lambda-1}, & \lambda \neq 0 \\ \dot{y}\ \ln y\,, & \lambda = 0 \end{cases} \tag{11}$$

where $\dot{y} = ln^{-1}[1/n \sum lny_i]$ is the geometric mean of the observations. And then, the model to fit is $y^{\lambda} = X\beta + \varepsilon$.

Box-Cox Transformation has the advantage of eliminating the requirement of high-order terms in the model so that simplier models are used in estimating the response (Tunalı and Batmaz, 2000). However, alternative fitting methods can be preferred to transformation in the case of destruction of the other assumptions while providing homogenous error variance (Tunalı and Batmaz, 2000).

CHAPTER 4

APPLICATION

The purpose of this study is to examine the impact of CAI with the simulation-animation activities prepared in R programme on eighth grade students' achievement and attitudes towards CAI. This chapter presents the methodology of the study. Firstly, research design of the study is presented, and this is followed by the description of the sample and variables of the study, and data collection instruments. Then, data collection and analysis procedures are explained. Finally, limitations of the study are discussed.

4.1 Research Design of the Study

In this study quasi-experimental research design is used in order to investigate the impacts of the simulation-animation activities prepared in R programme on the eighth grade students' achievement and attitudes on CAI. A quasi-experimental research design is utilized because the experiment involves nonrandom two groups of subjects, an experimental group and a control group. The experimental group received a treatment, a new teaching method named CAI, while the control group received no treatment.

Specifically, the Quasi-Experimental Posttest-Only Design was used in the study. This design is also a quasi-experimental design involves two groups, both of which are created by nonrandom assignment. While experimental group receives the treatment, the control group does not, and then, both groups are post tested on the dependent variable (Creswell, 2012). In the analysis, type of instruction, namely computer assisted or traditional instruction, is treated as an independent variable, and

the dependent variables are achievement and attitudes toward CAI in learning permutation-combination and probability subjects.

During the study, in the experimental group CAI based on animation-simulation prepared in R programme was used as a supplementary teaching tool. On the other hand, the control group was instructed through traditional teaching method during the study.

The experiment was set in two state elementary schools and two private schools, one located in Mardin and the other located in Ankara. These schools were chosen according to convenience sampling method, which is sample of a group of individuals who conveniently are available for the study (Fraenkel et al., 2011). In order to eliminate the bias of convenience sample, demographic information of the students and other characteristics of the sample were included in the study. 8th grade students (N=74) were the participants of this study throughout the spring semester of the 2015-2016 academic year.

Table 4. 1 *Quasi-Experimental Posttest-Only Design*

Select Control Group	Traditional Instruction	Posttest
Select Experimental Group	Computer-assisted Instruction	Posttest

As seen in Table 4.1, the experimental and control groups were conveniently selected and the experimental group received CAI in the unit of permutation-combination and probability, while the control group received traditional instruction in other word using paper-pen without using any information technology. After the treatment, the achievement and attitude posttest were implemented to investigate the effectiveness of the CAI with the simulation-animation activities prepared in R programme on eighth grade permutation-combination and probability subjects.

4.2. Participants of the Study

The subjects of this study were (N=74) eighth grade students from four distinct schools in two different regions of Turkey in the spring semester of the academic year 2015-2016. One of the school was a state, village elementary school "Dereyanı Ortaokulu" in Mardin, the other was a state, village elementary school "Şehit Öğretmen Fasih Söğüt" in Mardin, the third one was a private elementary school "Bahçeşehir College" in Mardin, and the last one was the private elementary school "Ihsan Doğramacı Foundation Bilkent College" in Ankara. "Dereyanı" elementary state school had one class of eighth grade students which consisted of 19 students in total, 11 of them girls and 8 were boys. "Şehit Öğretmen Fasih Söğüt" elementary state school had one class of eighth grade students which consisted of 19 students in total, 5 of them girls and 14 were boys. While a class, which was conveniently selected from Bahçeşehir College, consisted of 22 students in total, 8 of them were girls and rest was boys, a class conveniently selected from Bilkent College consisted of 14 students in total, including 8 girls and 6 boys. All of 74 the students were about the ages 13-14. While the socioeconomic statues of the students in private elementary schools Bahçeşehir $(\mathrm{Mean}_{\mathrm{income}} \approx 5001 - 7000)$ and Bilkent $(\mathrm{Mean}_{\mathrm{income}} \approx 7001 - 10000)$ were high, the socioeconomic statues of the students in village-state elementary schools Dereyanı $(\mathrm{Mean}_{\mathrm{income}} \approx 0 - 1500)$ and Şehit Öğretmen Fasih Söğüt $(\mathrm{Mean}_{\mathrm{income}} \approx 0 - 1500)$ were low. In addition to different demographic characteristics of the sample, technological equipment and environment varied according to the schools. While private elementary schools located both in Mardin and Ankara were better equipped technologically, state elementary schools located in the village of Mardin were under the standard.

The researcher was the instructor of the students in four distinct schools, and treatments had been performed by the researcher. In order to investigate the effectiveness of the CAI material including a sequence of simulation-animation activities to illustrate basic probabilistic concepts, improved by the researcher by using statistical program R, Dereyanı Elementary State School was conveniently assigned to experimental group while Şehit Öğretmen Fasih Söğüt Elementary State School assigned to control group. Due to the fact that both experimental and control groups consisted of schools located in village, it was difficult to determine the

effectiveness of CAI material, because these two schools had no enough technological equipment, and the students were not familiar with technology. Despite the possible deviations that may occur, two private schools, Bahçeşehir and Bilkent College, were included in the study to examine the cultural impact. Only CAI was given to both of these private elementary schools to identify potential cultural impact.

4.3 Description of Variables

There are five variables in this study. Three of them are independent variables, and two of them are dependent variables. These variables are as follows:

Independent variables: Treatment (Instructional Method): CAI with *R programme*, students' demographics characteristics such as gender, income, parents' education level, sibling number, city live in, type of the computer equipment used at home, computer/internet usage time per a day, purpose of computer/technology use; and schools' technological equipment such as type of technological equipment in class, school environment in terms of technology and attitude of school administrator towards CAI.

Dependent variables*:* (a) Achievement in permutation-combination and probability subjects, (b) Computer assisted learning attitude.

4.4 Preparation of Animations

4.4.1 R Project for Statistical Computing

R is a programming language and software environment for statistical computing and graphics. It is one of the most preferred programme in United States and Europe due to the advantage of being free and having non-commercial purposes (Ilk, 2015). R can be used for a variety of purposes from basic operations to data analysis, statistical models and so on. Due to the fact that many researchers write the code in R program when a new model or method is proposed, the first access to these new methods can be provided via R library (Ilk, 2015). R programme and C++ are very similar software in terms of writing codes.

In order to create animations in the study, ‘animation’ package of R was used. This package provides functions for animation in statistics, covering topics like probability theory, mathematical statistics, multivariate statistics, and nonparametric statistics, sampling survey, linear models, time series, computational statistics, data mining and machine learning. These functions are advised in teaching statistics and data analysis.

4.4.2 Animations

For the implementation of the animations, the R programme was loaded to computers in class. The R programme was introduced to the students briefly before the implementation. In CAI the subjects were taught via animations prepared in R programme by the directions of the instructor. The researcher was the runner of the animations because using R software program required expertise. Students were the active audience of the animations and active listener of the teacher.

As a first step, packages in R programme should be updated by the researcher to run the programme. Secondly, related packages should be installed to run the R codes (see Appendix I).

First animation was related with the basic rules of counting, namely addition rule and multiplication rule. It was aimed to show students how to calculate the number of occurrences of events by using the addition and multiplication rule. In order to run the R codes, the “jpeg” package was installed by the researcher, and then the written R codes (see Appendix I) were copied in the new script. Finally, the researcher run the codes, and representative figure is shown in the Figure 4.1.

Figure 4. 1. *Animation result for “Addition Rule” R codes*

The same procedure was applied for the written R codes (Appendix I) for multiplication rule. The representative figure is shown in the Figure 4.2.

Figure 4. 2. *Animation result for "Multiplication Rule" R codes*

Second animation was related with permutation and combination. In order to run the R codes, again "jpeg" package was required. It was aimed students to gain the objective that combination is a selection process and while order is important in permutation, it does not matter in combination. The same procedure was executed, and representative figures are shown in the Figure 4.3 and 4.4. respectively. Note that the R codes are provided at the Appendix I.

Figure 4. 3. *Animation result for "Combination" R codes*

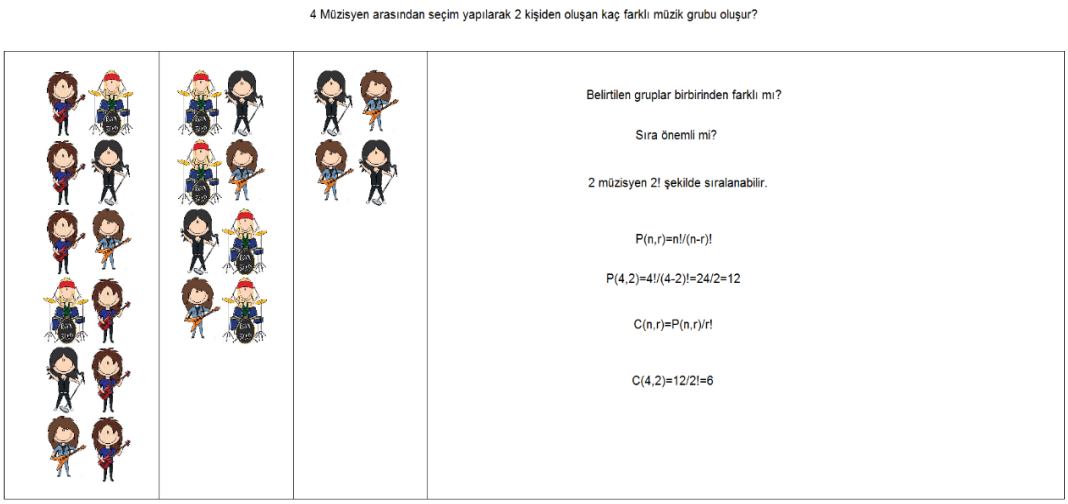


Figure 4. 4. *Animation result for "Two Combination" R codes*

The other animation was related with the type of probability: experimental, theoretical and subjective probability. In order to run the R codes (see Appendix I), "animation" package maintained by Yihui Xie was installed. We run the programme for different values of experiments to imply that the greater the number of experiments, the closer the experimental probability value to the theoretical probability value. The representative figure is shown in Figure 4.5.

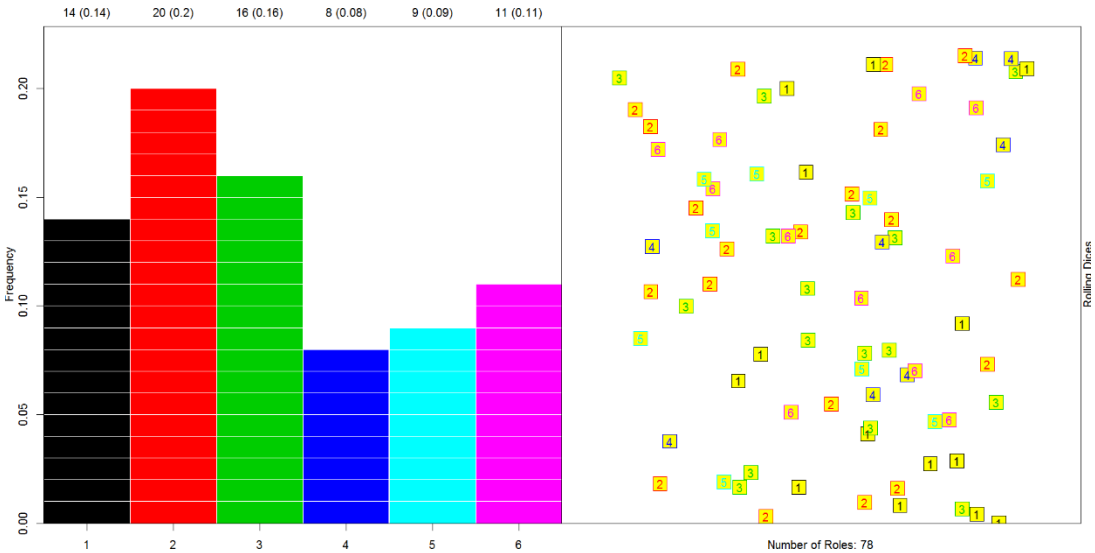


Figure 4. 5. *Animation result for "rolling dice" R codes*

The last animation was about dependent and independent events. In order to run the R codes, “plotrix” package was installed and loaded. Due to the requirement of other programs in addition to the R such as java and html, the last animation could just help us to teach the basic probability of events (see Appendix I for the R codes). Related result is shown in the Figure 4.6 as below.

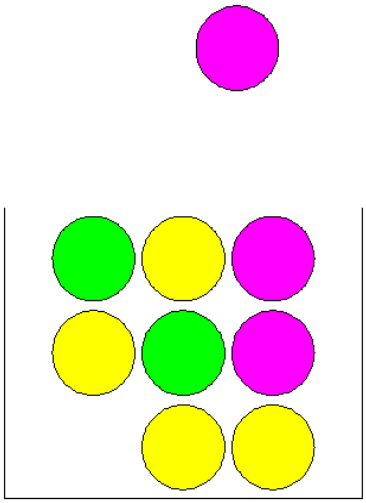


Figure 4. 6. *Animation result for “drawing ball” R codes*

4.5 Data Collection Instruments

In the present study, the following measuring instruments were used to test the hypotheses,

- Objective Comprehension Tests: post-tests (OCT1 and OCT2).
- Computer Assisted Learning Attitude Scale (CALAS)
- Demographic Survey
- School Technology Equipment Survey

4.5.1 Objective Comprehension Tests

Students’ achievement in permutation-combination and probability subjects was measured by the utilization of Objective Comprehension Tests that were prepared by General Manager of Measurement, Assessment and Exam Services of MoNE for the support and training courses. The objective comprehension tests were related with

the units of permutation, combination, probability and event types. The OCT1 post-test (see Appendix A) included the sub-learning area, namely identifying possible cases, of Probability and Statistics learning area of 8th grade mathematics curriculum. The objectives of the content were (1) explain and calculate the concept of combination, (2) explain the difference between permutations and combinations. Addition and multiplication rule of probability and the permutation subjects were the prerequisite subjects which must be given in prior classes of mathematics. The OCT1 consisted of 12 questions of the sub-learning area of identifying possible cases, specifically the questions were about identifying and calculating combination-permutation in the problems and applying addition or multiplication rule of probability to the related questions. The OCT2 post-test (see Appendix B) included the sub-learning area, namely probability and event types, of Probability and Statistics learning area of 8th grade mathematics curriculum. The objectives of the content of event types were (1) explain dependent and independent events, (2) calculate the probability of dependent and independent events. The objective of the content of probability types is to explain experimental, theoretical and subjective probability. The OCT2 consisted of 12 questions related with probability and event types. Specifically the questions were about identifying dependent and independent events and type of probability: experimental, theoretical and subjective probability.

Objective Comprehension Tests covered all the learning outcomes of the corresponding learning area, namely Probability and Statistics except the statistics part, as the statistics part was out of this study. Content validity and reliability of the Objective Comprehension Tests were applied by the General Manager of Measurement, Assessment and Exam Services of MoNE.

4.5.2 Computer Assisted Learning Attitude Scale

CALAS was used to investigate students' attitude towards the use of CAI in mathematics lessons**.**

In order to integrate the technology into mathematics teaching, students' attitudes and beliefs towards CAI should also be considered. To measure the eighth grade students' attitudes toward CAI, an attitude scale "CALAS" which was developed by Kenar and Balcı (2013) was conducted (see Appendix C).

Kenar and Balcı (2013) developed this scale in a study where it is aimed at developing an attitude scale to measure the attitudes of primary education fourth and fifth grade students towards technology use during classes. The CALAS consisted of a five-point Likert-type scale: “Completely agree”, “Agree”, “Neutral”, “Disagree” and “Completely Disagree.” The CALAS comprised of 20 items that were included in three factors. The first factor was related to the concern and worry about the use of technology in the lectures. Items 13, 9, 16, 10, 18, 6 and 12 were related to the first factor in the scale. The second factor was related to the satisfaction, interest and confidence for the use of technology in the lectures. Items 1, 2, 3, 4 and 8 were about the second factor in the scale. The third factor represented the impact of the technology used in the lecture on the success of the students. Item 5, 20 and 14 were about the third factor in the scale. After the implementation of the scale in the 144 primary education fourth and fifth grade students in the central of Kütahya, Turkey by randomized sampling method, the scale is decreased to 15 items. The revised CALAS consisted of eight positive (1, 2, 3, 4, 5, 8, 14 and 20) and seven negative items (6, 9, 10, 12, 13, 16 and 18). Therefore, the total score of CALAS was between 15 and 75.

Kaiser-Meyer-Olkin (KMO) value for the purpose of structural validity was found to be 0.85 and Bartlett’s test significance value was found as nearly 0.00. The factor loads of the scale items were consisted of three factors ranging between 0.40-0.83, and 57.00 % of the variance was explained by the three factors. In order to test reliability analysis of the scale, the inner consistency coefficient (Cronbach’s alpha) value was estimated and found as $\alpha = 0.86$. As a result of these findings, the scale had a valid and reliable structure and for that reason it was used in the present study.

4.5.3 Demographic Survey

The factors effecting quality of the performance of learners are a very curious subject among educators, trainers, and researchers (Farooq et al., 2011). These factors are categorized as inside and outside of school that influence students’ quality of academic achievement (Farooq et al., 2011). Crosnoe et al. (2004), as Farooq et al. (2011) indicated, students’ factors, family factors, school factors and peer factors are among these variables. In addition to these factors mentioned, Farooq et al. (2011)

specified other factors generally as age, gender, geographical belongingness, ethnicity, marital status, socioeconomic status, parents' education level, parental profession, language, income and religious affiliations.

According to Jabbar et al. (2011), demographic features are very fundamental in the completion of learner's performance. For example, the mental level of parents has a collaborative factor in the performance achievement of the students (Jabbar et al., 2011). According to Sirin (2005), as Blevins (2009) indicated, parental income has an important impact on student academic performance because of the fact that economic resources provide individuals to implement more academic components. Furthermore, Sirin (2005) sees the resources available at home as an indicator for the relationship between socioeconomic status and academic performance.

Jackson et al. (2006) indicated that National Center for Educational Statistics (2000) shows that the presence of educational resources in the home is a significant predictor of academic success in mathematics and science. For example having a computer at home has been correlated with higher test scores in reading, even after the family income and other factors related to test scores have been controlled.

Demographic survey used in this study was designed to investigate the effect of demographic factors and technology ownership of the students on the achievement of elementary school mathematics achievement (see Appendix D). The survey also included factors (gender: male/female, city live in, settlement: village/town/state/city, mother education level: illiterate/literate/primary school/elementary school/high school/bachelor/master/doctorate, father education level, number of siblings, number of siblings training, monthly family income, type of the computer equipment used at home: no use of computer/notebooks/desktop computer/tablet/smart phone/other, places to connect to the internet: home/work/school/dormitory/cafe/other, computer/internet usage time per a day: no use/less than one hour/1-3 hours/4-6 hours/7-9 hours/10 hours and more, purpose of computer/technology use: for fun/academic/routine things/office programs/other). The mentioned factors to analyze demography of the sample were determined in the light of the literature. An expert opinion was consulted in the process of forming the survey.

4.5.4 School Technology Equipment Survey

The use of technology has a positive effect on students' academic achievement due to creating self-esteem and worthiness on students and creating positive and successful learning environment (Blevins, 2009). Page (2002), as Blevins (2009) indicated, reported that the growth of interest in technology also brings the success together in the students' academic performance. A study conducted by the Educational Testing Service indicated that usage of computers to occupy higher order thinking skills is associated with better school performance in mathematics by fourth and eighth grades (Wenglinsky, 1998; as cited in Jackson et al., 2006).

School Technology Equipment Survey was conducted to investigate the effect of school environment and technological equipment on the eighth grade students' learning permutation-combination and probability subjects via simulation-animation activities prepared in R programme (see Appendix E). The survey consists of 8 multiple questions in total. The survey was prepared to be applied to school administrators. The survey included factors (the city in which the school is located, settlement of the school: village/town/state/city, type of school: state/private, technological equipment in school: computer lab/internet access in computer lab/projection/smart board/tablet/other, computer and technology education teacher: Yes/No, number of technological equipment used in the class: desktop computer/ notebook/tablet/smart phone/projection/other, items related to school environment in terms of technology, attitude of school administrator towards CAI: positive/negative/neutral/other.) . An expert opinion was consulted in the process of forming the survey.

4.6 Data Collection Procedures

Quantitative data collection methods were used in this study. The data for the research was collected from the eighth grade students in "Mardin Dereyanı" elementary school, "Mardin Şehit Öğretmen Fasih Söğüt" elementary school, "Mardin Bahçeşehir College" and "Ankara Ihsan Doğramacı Foundation Bilkent College" over a period from March 2016 to June 2016. Convenient sampling method

was used in order to determine the experimental and control groups. While Dereyanı Elementary State School was conveniently assigned to experimental group, Şehit Öğretmen Fasih Söğüt Elementary State School is assigned to control group. In the process of assigning experimental and control groups, similar environments of the schools were taken into consideration. Both "Dereyanı" and "Şehit Öğretmen Fasih Söğüt" elementary state schools were in the village of Mardin, the ethnicity, demographic characteristics of the students, school environment and school construction, student capacity and academic success of the students were considerably similar. First term mathematics average and general average grades of the students were taken into account when determining the similarity of students' academic performance. The information that these students had never been instructed by computer assisted teaching methods before, was gathered after the interviews with teachers of the schools. As a result of that information, it was concluded that these students were neutral about CAI. Due to the fact that both experimental and control groups consisted of schools located in village, it was difficult to determine the effectiveness of CAI material prepared in R programme, owing to the fact that both of the schools had not enough technological equipment, and the students were not familiar with technology. Despite the possible deviations that may occur, two private schools; Mardin Bahçeşehir College and Ankara Bilkent College were also included in the study to examine the cultural impact. CAI was also given to both of these private elementary schools to identify potential cultural impact on the students' achievement.

The consent for permissions to conduct the research and to use computer equipment during the treatment were received from the appropriate authorities (see Appendix F). For the treatment group, the R programme was loaded to computers in class. Due to requirement of internet connection for downloading and running R programme and the village schools had no internet connection, the researcher used portable internet in the village school where the treatment would be applied. The R programme was introduced to the students briefly before the implementation.

During the intervention period, two groups were taught by using the same sub-learning area of Probability and Statistics subjects, namely permutation-combination

and probability, and the same books, which were taken from the 8th grade elementary school curriculum that was prepared by the Director of Talim-Terbiye, Ministry Education of Turkey. Two different teaching methods were used through the study, CAI and traditional instruction.

In CAI the subjects were taught via animations prepared in R programme by the directions of the instructor. These animation programs were prepared by the researcher via using R programme. The researcher was the runner of the animations because using R software program required expertise. Students were the active audience of the animations and active listener of the teacher. In CAI, students received compatible activity sheets with the animations prepared by the researcher (see Appendix G). Due to the limitation of computer equipment in schools, it was not possible to assign a computer to every student. Therefore, the related animation activities were presented to students as hard copy. While the researcher was teaching the subjects via R animations, students firstly participated in the lecture by watching the animations, then they completed these activity sheets. The instruction of permutation-combination and probability subjects has been determined as a total of nine hours in the curriculum by the MoNE. The four hours of that time was for the instruction of permutation and combination, while the five hours was for probability subjects. The four hours instruction consisted of the sub-learning area, namely identifying possible cases, of Probability and Statistics learning area of eighth grade mathematics curriculum. The objectives of the content were (1) explain and calculate the concept of combination, (2) explain the difference between permutations and combinations. According to the objectives of the content, the animations were conducted. For the permutation and combination subjects, the animations of “What to wear today” and “Create your music group” were developed. The activity sheets related to the animations were distributed to students before the animations were run. The researcher was active at all times during the instruction, presented the animations and provided directions to individual students as needed. Students were required to follow the animations with *R* software to do activity sheets by solving the exercises related to the treatment units. For instance, if the researcher presented the animation about permutation and combination, “Create your music group”, then the

students in the experimental group were required to complete the activity sheets related to the animation during the instruction.

As mentioned experimental group received CAI with animations prepared in R software as a supplementary teaching method. On the other hand, the students in the control group received the eighth grade permutation-combination and probability content through regular mathematics instruction (e.g. direct instruction, questioning-answering, problem-solving, discussion, etc.) as recommended in the curriculum. Textbook, chalkboard, paper- pencil drills were used during the traditional teaching process. The researcher provided regular lecture instruction, wrote exercises on the board from the text-book and students were required to listen the instructor and solve these exercises. The instructor did not use any supplementary teaching material except the text-book. However, both experimental and control groups received the same content to reach exactly the same objectives during totally nine lecture hours.

The same procedure provided to experimental group at "Mardin Dereyanı Elementary School", was applied to both "Mardin Bahçeşehir College" and "Ankara Ihsan Doğramacı Foundation Bilkent College." Due to the limitation of time and appropriate conditions, it was impossible to cover all of the content of the learning area in these private schools. As a result of these circumstances, only the "Probability" topic was introduced via R software to the private schools. Owing to the fact that these private schools had advanced technological equipment, it was much easier to apply CAI in these schools.

The researcher was also the instructor of the related subjects during the study in the four distinct schools. This study assumed that the instructor was not biased during the treatment. It also was assumed the intervention process and tests were administered under standard conditions. Moreover, the study assumed that all students' participation and responses to the activity sheets were honest and accurate. And lastly, it was assumed that there was no interaction between the students in the experimental and control groups.

The role of the researcher/instructor was to present and facilitate learning by organizing and supervising students' learning process during the R software

animation programs and by traditional instruction. On the other hand, before the treatment process, the instructor and mathematics teachers of the schools came together and prepared the lesson plan, class hours, unit plans and the other regulations.

The continuance of the study was 8 weeks including administration of the treatment and posttests. The selection of subjects and forming the groups was completed at the beginning of the second semester of 2015-2016 academic year as presented earlier in this chapter.

According to the mathematics curriculum, the first unit of the "Probability and Statistics" learning area was "Permutation and Combination." Whenever the unit was presented, students in the experimental group carried on with the activity sheets related to "Permutation and Combination", meanwhile students in the control group carried on with the same unit by solving paper-and pencil based exercises. This procedure was carried on one week-4 class hours (each class hour was 40 minutes) of mathematics lessons until the researcher presented the unit 2 which was "Probability." Just after one week when the first unit was covered, OCT1 were administered to both groups. The instruction of the second unit "Probability" was presented in one week- five lecture hours with the same procedure with unit 1. Finally OCT2 were administered to both experimental and control groups. The same process was utilized just for the unit 2 that is "Probability" for private schools. And finally, the comprehension test 2 related with probability was applied to these privates schools.

After the treatment had been completed, CALAS were administrated as post-tests to both the experimental groups and the control group to assess the effects due to treatment; R animations on attitudes towards CAI. The demographic survey was implemented to all students participated to the study. And finally, School Technology Equipment Survey was implemented to the principal of the schools by the researcher.

4.7 Limitations

Before the results are presented and suggestions are made, it is better to underline some of the limitations the researcher confronted while carrying out this research. Briefly,

- This study is limited to eighth grade students in two state and one private elementary schools in Mardin and a private elementary school in Ankara, during the spring semester of the 2015-2016 academic year. Because the sample is limited with 74 students in total, it might not reflect the general population. Therefore, the results of the study cannot be generalized to other contexts.
- This study is limited to the sub-learning area of "Probability and Statistics" units of the eighth grade mathematics curriculum, namely permutation-combination and probability. Due to the fact that the researcher was also a teacher at one of the schools in Mardin, it was not possible to apply the CAI to all schools at the specified academic time because of time limitation.
- Due to the limitation of time and appropriate conditions, it was impossible to cover all contents of the sub-learning area, permutation-combination-probability in private schools as an example. As a result of these circumstances, only the "Probability" topic was introduced via R software to the private schools.
- Another limitation, since there was no adequate technological equipment in all schools and the cities where the schools located were far away from each others, the pilot study could not be conducted for the CAI material prepared in R programme. However, there was no problematic situation faced throughout the implementation in the actual study.

CHAPTER 5

ANALYSIS AND RESULTS

5.1 Data Description

The data of this study was collected from (N=74) eighth grade students from four distinct schools in two different regions of Turkey in the spring semester of the academic year 2015-2016. In this study, in addition to *teaching method variable* and *school* variable there were 44 categorical explanatory variables gathered via Demographic Survey and School Technology Equipment Survey. The Demographic Survey provides two types of information: *demographic factors and technology ownership of the students*. The explanatory variables in here are gender: male/female, city that is lived in, settlement: village/town/state/city, mother education level: illiterate/literate/primary school/elementary school/high school/bachelor/master/ doctorate, father education level, number of siblings, number of siblings training, monthly family income, type of the computer equipment used at home: no use of computer/notebooks/desktop computer/tablet/smart phone/other, places to connect to the internet: home/work/school/dormitory/cafe/other, computer/internet usage time per a day: no use/less than one hour/1-3 hours/4-6 hours/7-9 hours/10 hours and more, purpose of computer/technology use: for fun/academic/routine things/office programs/other. School Technology Equipment Survey provides two types of information: *technological equipment and environment of the school.* The explanatory variables in here: the city in which the school is located, settlement of the school: village/town/state/city, type of school: state/private, technological equipment in school: computer lab/internet access in computer lab/projection/smart board/tablet/other, computer and technology education teacher: Yes/No, number of technological equipment used in the class: desktop computer/ notebook/tablet/smart

phone/projection/other, items related to school environment in terms of technology, attitude of school administrator towards CAI: positive/negative/neutral/other.

As it is seen, there are excessive number of categorical explanatory variables in the data to build a MLR model. For this reason, we firstly made data reduction in two different ways. The first method was combining schools in pairs according to their similarities and differences. First, we combined two state schools in Mardin as state-village school, but the private schools remained as separate. Next, we exclude those variables giving information about demographic factors, technological equipment and environment of the school. Since, the combined schools already contains the information. The second method was using categorical PCA to construct a new set of variables, called principal components. Then, MLR model was fitted to investigate the effects of CAI on mathematical achievement and attitude of students towards CAI.

5.2 First Data Reduction Method

We firstly used descriptive statistics to summarize data. Since the data was categorical, crosstabs procedure was applied to describe the data. At first view; it was seen that private schools in the study showed same pattern according to school technological equipment and economic status, while the state-village schools showed same. And it was seen that schools located in Mardin showed similar properties according to social status, while Bilkent College in Ankara differed from them. To have a deeper understanding about which variables changed according to schools, the Chi-Square test of independence was used to determine if there was a significant dependency between the schools according to the categorical variables. Data can be displayed in an r*c contingency table, where r is the number of rows and c is the number of columns. For example, we wanted to examine the difference between schools (e.g. Bahçeşehir College and Bilkent College) and all other variables (e.g. mother education level) in this study. The test is applied when there are two categorical variables and used to determine whether there is a significant association between the two variables (Özdamar, 2011). If the null hypothesis is rejected the

implication would be that there is a relationship/dependency between variables. The test can be applied when the sampling method is simple random sampling, the variables are categorical and the expected frequency for each cell of the table in contingency table is at least 5. The last condition for this test was not satisfied in this study. Therefore, we used Fisher's Exact Test that overcome this deficiency. For example Table 5.1 shows the result of the analysis on whether there is independency between schools and the family income.

Table 5. 1. *Schools∗Income Test Result*

			income					
			1501-3000	3001-5000	5001-7000	7001-10000	10001 and more	Total
Schools	Bahçeşehir	Count	4	5	4	6	3	22
		Expected Count	3.1	4.3	3.1	6.7	4.9	22.0
	Bilkent	Count	1	2	1	5	5	14
		Expected Count	1.9	2.7	1.9	4.3	3.1	14.0
Total		Count	5	7	5	11	8	36
		Expected Count	5.0	7.0	5.0	11.0	8.0	36.0

Chi-Square Tests

	Value	Df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)	Point Probability
Pearson Chi-Square	3.891^a	4	.421	.462		
Continuity Correction						
Likelihood Ration	3.987	4	.408	.468		
Fisher's Exact Test	3.604			.506		
Linear-by-Linear Association	3.077^b	1	.079	.085	.051	.022
N of Valid Cases	36					

a. 9 cells (90%) have expected count less than 5. The minimum expected count is 1.94.
b. The standardized statistics is 1.754.

According to the explanation below Table 5.1., 9 cells have expected count less than 5. Therefore, Fisher Exact Chi Square result is used. The p-value corresponding to the Fisher's Exact Test (0.506) is higher than 0.05, so the null hypothesis is not

rejected. That means, we don't have enough evidence towards any difference between these schools with respect to family average monthly income. This result is rational, because both of the schools are private and the economic level of the families are high regardless of the location of the school. The pairwise comparisons of schools- totally six comparisons (Bahçeşehir-Bilkent, Bahçeşehir-Dereyanı, Bahçeşehir-Şehit Öğretmen, Bilkent-Dereyanı, Bilkent-Şehit Öğretmen, Şehit Öğretmen-Dereyanı) was applied, and it was found that Ankara Bilkent College-Mardin Bahçeşehir College were similar in terms of school technological equipment and economic status, and Dereyanı Elementary School and Şehit Öğretmen Fasih Söğüt Elementary School were similar in the same features. Moreover, it was found that schools located in Mardin, Dereyanı, Bahçeşehir and Şehit Öğretmen Fasih Söğüt, showed similar properties according to social status, while Bilkent College in Ankara differed from them. As a result, we combined two state-village schools according to their similarities in terms of technological equipment of those schools and social-economical statues of the family. However, the same procedure could not be applied for those privates schools. Although they showed similar properties in terms of school technological equipment and economic statues of the family, those schools completely differed from each other with respect to social properties. For example, the education level of the mothers of the students in Bahçeşehir College was lower compared to Bilkent College. Moreover, the number of siblings of the students was much higher in Bahçeşehir College (Mean≈4) compared to those in Bilkent college (Mean≈1.643). In conclusion, Dereyanı Elementary School and Şehit Öğretmen Fasih Söğüt Elementary School were accepted as a one school, named state schools, and the others remained same. After data reduction, we re-coded new variables with dummies as below.

- V: Schools (1: Dereyanı, 2: Şehit Öğretmen Fasih Söğüt, 3: Bahçeşehir, 4: Bilkent)
- V1: Gender (V1=1 Female, o.w 0)
- V2: State Schools (combined due to their similarities. V2=1 o.w 0 ⇒ Mardin state-village schools-Dereyanı and Şehit Öğretmen Fasih Söğüt Elemantary Schools.)

- V3: Mardin Bahçeşehir College (V3=1, o.w 0. If V2=0 and V3=0 ⇒ Bilkent College)
- V9: Use of computer/Internet for fun (V9=1 for fun, o.w 0)
- V10: Use of computer/Internet for academic staff (V10=1 for academic, o.w 0)
- V11: Use of computer/Internet for routine works (V11=1 for routine works, o.w 0)
- V12: Use of computer/Internet for office programs (V12=1 for office programs, o.w 0)
- V13: Use of computer/Internet for other things (If V10, V11, V12 equal to 0)
- V14: Instruction method (V14=1 means CAI, V14=0 means Traditional Instruction)
- V15: First term mathematics grades
- V16: First term GPA
- V17: Computer/Internet usage time in hours (1= no use, 2= less than one hour, 3= 1-3 hours, 4= 4-6 hours, 5= 7-9 hours and 6= 10 hours and more)

The one-way analysis of variance (ANOVA) was used to determine whether there were any statistically significant differences between the mentioned four schools in terms of scores obtained from OCT2. Since the assumption of homogeneity of variances was not satisfied, transformation was applied on the OCT2 score. The rounded lambda value was 0.50, so sqrt (OCT2) transformation was used and the transformed OCT2 variable was recoded as OCT2 TR. The analysis results shown in Table 5.2 are obtained.

Table 5. 2. *One way ANOVA Results: OCT2 TR vs School*

One-way ANOVA: OCT2 TR versus V

```
Source  DF      SS     MS      F      P
V        3   94.23  31.41  20.26  0.000
Error   70  108.54   1.55
Total   73  202.77

S = 1.245   R-Sq = 46.47%   R-Sq(adj) = 44.18%


                         Individual 95% CIs For Mean Based on
                         Pooled StDev
Level   N   Mean  StDev  ------+---------+---------+---------+---
1      17  6.044  1.529  (-----*-----)
2      21  5.961  0.775  (-----*----)
3      22  8.540  1.330                           (----*-----)
4      14  7.534  1.300                 (-----*------)
                         ------+---------+---------+---------+---
                             6.0       7.0       8.0       9.0

Pooled StDev = 1.245


Grouping Information Using Tukey Method

V   N   Mean  Grouping
3  22  8.540  A
4  14  7.534  A
1  17  6.044    B
2  21  5.961    B

Means that do not share a letter are significantly different.
Tukey 95% Simultaneous Confidence Intervals
All Pairwise Comparisons among Levels of V

Individual confidence level = 98.95%


V = 1 subtracted from:

V   Lower  Center  Upper  --------+---------+---------+---------+-
2  -1.151  -0.082  0.986             (-----*----)
3   1.439   2.496  3.554                          (----*-----)
4   0.308   1.490  2.672                      (----*-----)
                          --------+---------+---------+---------+-
                               -2.0       0.0       2.0       4.0
V = 2 subtracted from:

V  Lower  Center  Upper  --------+---------+---------+---------+-
3  1.579   2.579  3.578                          (----*----)
4  0.442   1.573  2.703                     (-----*-----)
                         --------+---------+---------+---------+-
                              -2.0       0.0       2.0       4.0


V = 3 subtracted from:

V   Lower  Center  Upper  --------+---------+---------+---------+-
4  -2.126  -1.006  0.114         (-----*-----)
                          --------+---------+---------+---------+-
                               -2.0       0.0       2.0       4.0
```

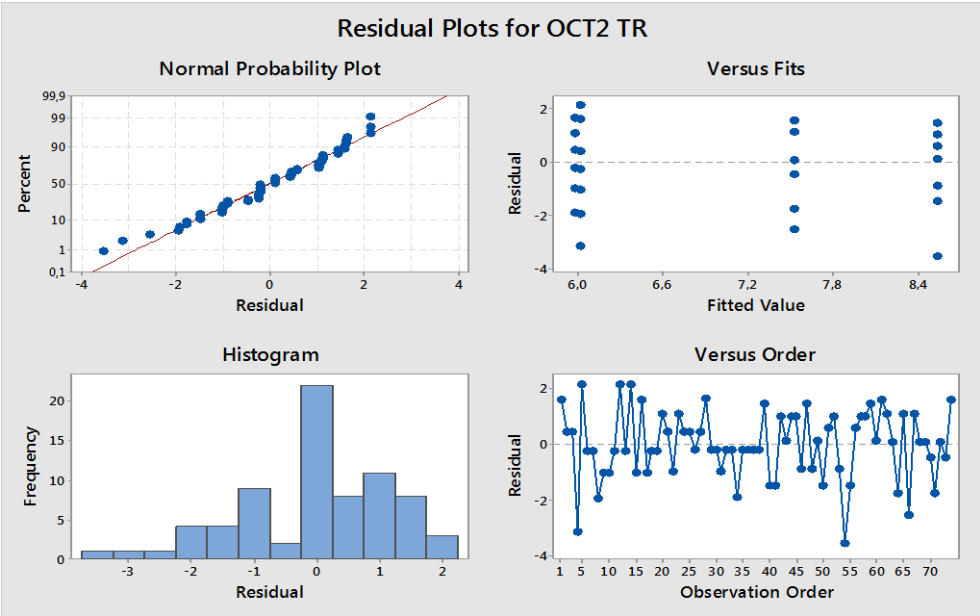


Figure 5. 1. *Residual Plots for OCT2 TR*

According to the results of One Way ANOVA, it was found that there was a statistically significant difference between the schools (1: Mardin Dereyanı Elementary school, 2: Mardin Şehit Öğretmen Fasih Söğüt Elementary School, 3: Mardin Bahçeşehir College, 4: Ankara Bilkent College) in terms of scores obtained from OCT2. The same procedure was applied to understand whether there was a difference in attitude based on schools. Before the ANOVA was applied, the assumptions were checked. It was seen that the dependent variable CALAS was not approximately normally distributed for each group of schools. Therefore, Box-Cox Transformation was applied on the CALAS variable and the rounded value was found to be as -3. $1/CALAS^3$ transformation was applied and the transformed variable was recoded as CALAS TR. After transformation was applied, all of the required assumptions for One-Way ANOVA were satisfied. Then analysis was repeated and related outputs and graphs are shown in Table 5.3 and Figure 5.2, respectively.

Table 5. 3. *One way ANOVA Results: CALAS TR vs School*

One-way ANOVA: CALAS TR versus V

```
Method

Null hypothesis         All means are equal
Alternative hypothesis  At least one mean is different
Significance level      α = 0.05

Equal variances were assumed for the analysis.


Factor Information

Factor  Levels  Values
V            4  1; 2; 3; 4


Analysis of Variance

Source  DF    Adj SS    Adj MS  F-Value  P-Value
V        3  0.000534  0.000178     1.62    0.192
Error   70  0.007690  0.000110
Total   73  0.008224


Model Summary

        S   R-sq  R-sq(adj)  R-sq(pred)
0.0104814  6.50%      2.49%       0.00%


Means

V   N     Mean    StDev        95% CI
1  19  0.04132  0.00847  (0.03652; 0.04611)
2  19  0.03554  0.01063  (0.03074; 0.04033)
3  22  0.04209  0.01310  (0.03763; 0.04654)
4  14  0.03814  0.00768  (0.03255; 0.04372)

Pooled StDev = 0.0104814
```

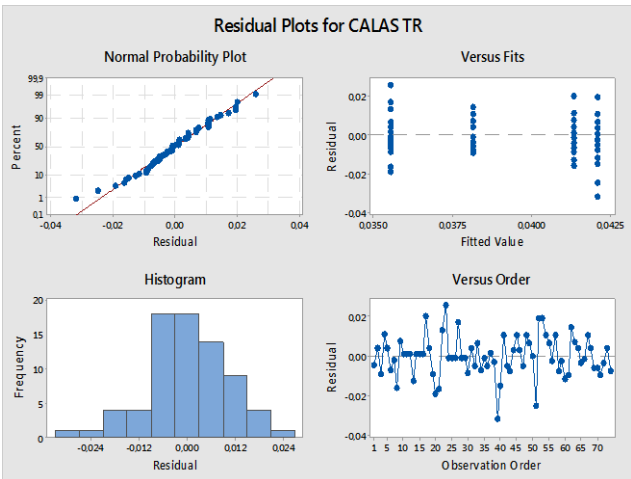


Figure 5. 2. *Residual Plots for CALAS TR*

According to the results of One Way ANOVA, it was found that there was no statistically significant difference between the schools in terms of attitudes towards CAI. After receiving the results that schools differed from each other based on mathematics achievement scores and did not differ in terms of attitudes towards CAI, regression analysis was applied to understand the effecting factors. Regression models were fitted separately to comprehend which factors were effective to explain mathematics achievement and attitudes towards CAI. In all stages, various diagnostic statistical tests such as normality test, variance homogeneity test, lack-of-fit test and etc. were carried out to make sure that the method of least squares was properly and efficiently applied.

Firstly, MLR model was fitted on OCT2 score with these variables; V1, V2, …, V17. All the explanatory variables except V15 (first term mathematics grade) were found to be insignificant. Therefore, a new model was constructed with only one independent variable V15. Since the model exhibited lack-of-fit, some improvements were made by including higher-order polynomial terms of V15 in the model. Next, due to multicollinearity in the estimated model, centering was applied. That is, instead of using V15 directly, CV15= (V15-mean (V15)), square of CV15 and CV15CB, the cube of CV15 were used. Since the square of CV15 was found insignificant, we dropped it not to cause an increase in the error variance. Although there was no lack-of-fit in the model, Breusch-Pagan test showed that there was heterogeneous variance in the data ($\rho = 0.03$). To deal with the heterogenous variance, transformation was applied and λ was found to be 0.52 (Figure 5.3).

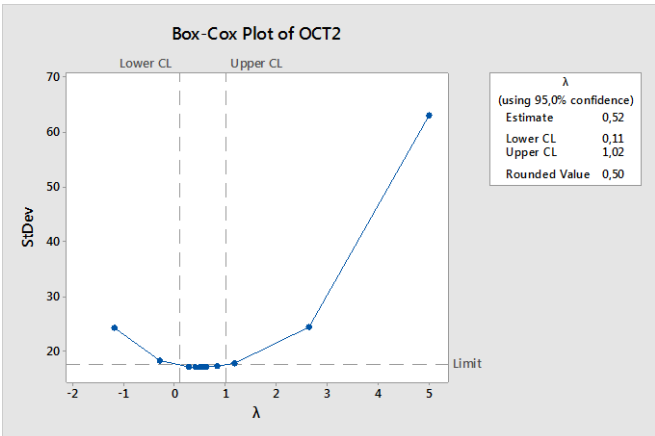


Figure 5. 3. *Box-Cox Plot of OCT2*

However, regression analysis on transformed observations showed that homogeneity of variance was still not satisfied. As an alternative remedial approach, we also used the method of WLS to deal with the heterogeneous variance by giving different weights to different genders in different schools (Figure 5.4).

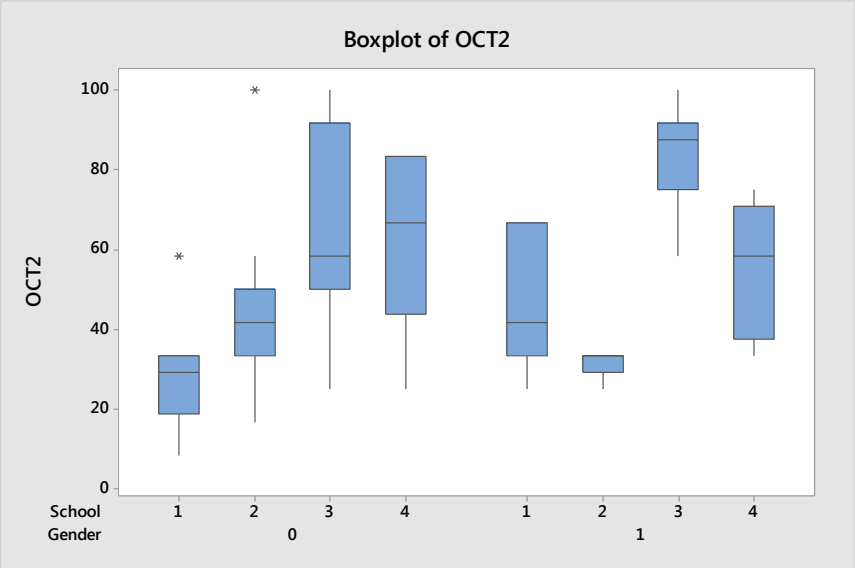


Figure 5. 4. *Boxplot of OCT2 for School and Gender*

Again, the homogeneity assumption was violated. Because the remedies suggested in literature were not successful for our problem, we adapted an alternative approach. The gender variable, V1, was included in the model even if it was found insignificant in the first regression model, because it was stated in the literature that gender is among the significant factors affecting students learning (Weissglass, 2002). Since statistically significant lack-of-fit was not detected (ρ =0.483), it was decided that the model was adequate in representing the relation between the mean response and independent variables. Based on a set of residual analysis plots given in Fig. 5.5, we could state that normality assumption was satisfied since the data points have scattered on the line and histogram of residuals has a symmetric shape. Also, Shapiro-Wilk normality test indicated that at this level of significance ($\alpha = 0.05$) the normality assumption was satisfied ($\rho = 0.165$). Based on the plot of residuals versus fitted values in Fig. 5.5, we stated that homogeneity of variance assumption might be satisfied. To make a formal decision on homoscedasticity assumption,

Breusch-Pagan test was conducted. The critical value at the 0.05 significance level for a Chi-square statistic with 3 degrees of freedom was 7.016. The p-value for this test was 0.071 which was greater than 0.05. Therefore, the test for checking the validity of the assumption resulted in homogeneous error variance. To check uncorrelated errors assumption, Durbin Watson test was conducted ($D = 2.588$). Corresponding critical values at 0.05 significance level are $d_L = 1.543$ and $d_U = 1.709$ according to D-W table. Since D-W statistic was larger than upper bound, it was stated that there was no autocorrelation. Multicollinearity assumption was assessed using variance inflation factors (VIF) values which suggested the absence of multicollinearity. Moreover, the overall regression F test was significant ($\rho = 0.0$) leading the acceptance of the model. Table 5.4 and Figure 5.5 shows the results of regression model.

Table 5. 4. *Regression Analysis: OCT2 vs First Term Mathematics Grade vs Gender*

Regression Analysis: OCT2 versus CV15; CV15CB; V1

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	31060,0	10353,3	70,61	0,000
CV15	1	25658,5	25658,5	174,98	0,000
CV15CB	1	5548,9	5548,9	37,84	0,000
V1	1	134,4	134,4	0,92	0,342
Error	70	10264,4	146,6		
Lack-of-Fit	48	7110,2	148,1	1,03	0,483
Pure Error	22	3154,2	143,4		
Total	73	41324,4			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
12,1093	75,16%	74,10%	72,37%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	38,69	2,84	13,62	0,000	
CV15	0,9821	0,0742	13,23	0,000	1,01
CV15CB	0,03446	0,00560	6,15	0,000	1,01
V1	2,74	2,86	0,96	0,342	1,02

Regression Equation

OCT2 = 38,69 + 0,9821 CV15 + 0,03446 CV15CB + 2,74 V1

Durbin-Watson Statistic

Durbin-Watson Statistic = 2,58865

The R^2 is 74.1 for the regression, which shows that the model explains 74.1% of the variation in the data.

The final model is as follows:

$$\mathrm{OCT2} = 38.69 + 0.982\ CV15 + 0.034\ CV15\mathrm{CB} \tag{12}$$

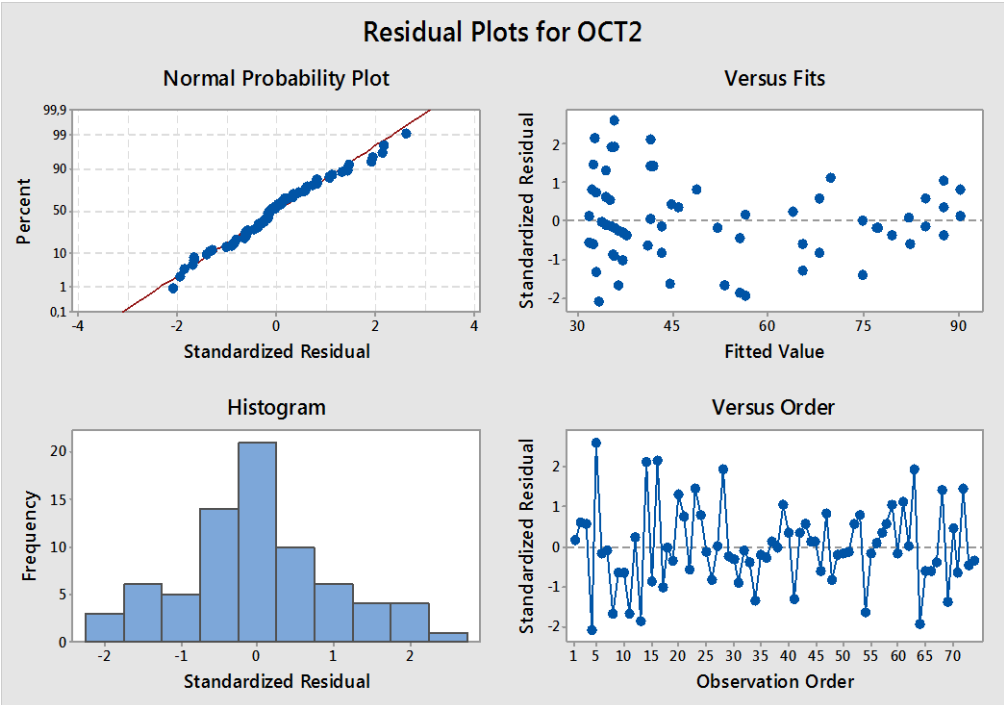


Figure 5. 5. *Residual Plots for OCT2*

Secondly, MLR model was fitted on CALAS score with these variables to identify the factors affecting students' attitude towards CAI. All the explanatory variables except V10 and V13 were found to be insignificant. Therefore, a new model was constructed with only two independent variables V10 and V13. Shapiro-Wilk test showed that the normality assumption was not satisfied ($p < 0.01$). Outliers were detected in the model, so firstly 39th observation was removed from the analysis. However, the normality assumption violation was not disappeared. Next, 20th, 21th and 51th observations were also removed from the analysis. After the observations had been excluded, the normality assumption was satisfied ($p > 0.1$). Since statistically significant lack-of-fit was not detected ($\rho = 0.675$), it was decided that the model was adequate in representing the relation between the mean response and

independent variables. Based on a set of residual analysis plots given in Fig. 5.6, we could also state that normality assumption was satisfied since the data points have scattered on the line. Based on the plot of residuals versus fitted values in Fig. 5.6, we might state that homogeneity of variance assumption satisfied. To make a formal decision on homoscedasticity assumption, Breusch-Pagan test was conducted. The critical value at the 0.05 significance level for a Chi-square statistic with 2 degrees of freedom was 1.822. The p-value for this test was 0.402 which was greater than 0.05. Therefore, the test for checking the validity of the assumption resulted in homogeneous error variance. To check uncorrelated errors assumption, D-W test was conducted ($D = 1.616$). Corresponding critical values at 0.05 significance level are $d_L = 1.554$ and $d_U = 1.672$ according to D-W table. Since D-W statistic value was between lower and upper bound, it was stated that the test was inconclusive. Multicollinearity assumption was assessed using VIF values which suggested the absence of multicollinearity. The related analysis results and graphs are shown in Table 5.5 and Figure 5.6, respectively.

Table 5. 5. *Regression Analysis: CALAS vs V10; V13*

Regression Analysis: CALAS versus V10; V13

```
Method

Rows unused  4


Analysis of Variance

Source         DF   Adj SS    Adj MS  F-Value  P-Value
Regression      2  0.20994  0.104972     2.31    0.107
  V10           1  0.05912  0.059117     1.30    0.258
  V13           1  0.16366  0.163658     3.61    0.062
Error          67  3.03837  0.045349
  Lack-of-Fit   1  0.00815  0.008146     0.18    0.675
  Pure Error   66  3.03023  0.045913
Total          69  3.24832

Model Summary

       S   R-sq  R-sq(adj)  R-sq(pred)
0.212953  6.46%      3.67%       0.32%

Coefficients

Term        Coef  SE Coef  T-Value  P-Value   VIF
Constant  2.8968   0.0367    78.91    0.000
V10       0.0583   0.0510     1.14    0.258  1.00
```

Tablo 5.5 *(Cont'd)*

```
V13    0.239     0.126      1.90      0.062      1.01
Regression Equation
CALAS =2.8968+0.0583 V10+0.239 V13
Durbin-Watson Statistic
Durbin-Watson Statistic= 1.61623
```

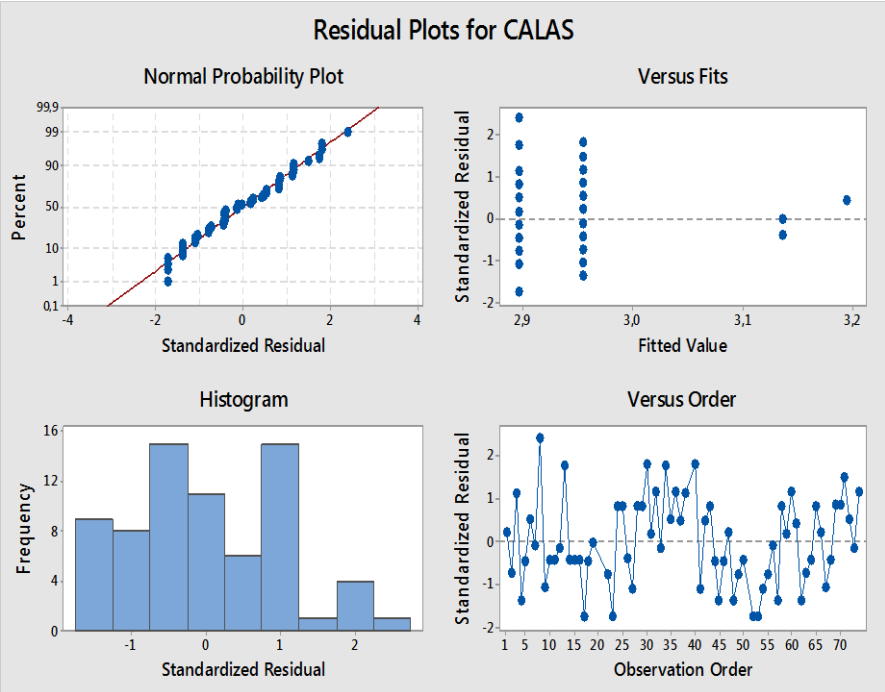


Figure 5. 6. *Residual Plots for CALAS*

All the assumptions were checked to make sure that the model was properly and efficiently applied. However, none of the explanatory variables were significant ($p > 0.1$). Considering the results of the regression model based on attitude towards CAI, it was concluded that there was no statistically significant relationship between the attitude and explanatory variables.

As a result of the regression models above, we concluded that just first term mathematics grade was significant for explaining achievement of students based on probability and event types objective, while the other relevant variables such as technological equipment, socio-economic statues had no effect. It was also found that none of the explanatory variables were significant for explaining attitude of the

students towards CAI. It can be concluded that there is no evidence that the animation programs prepared in R including the sub-learning area, namely probability and event types, of Probability and Statistics learning area of 8th grade mathematics curriculum effects students' achievements and attitudes.

Due to the limitation of time and other conditions mentioned in the application part of the study, CAI and respectively OCT1 were just applied to the state-village schools, namely Dereyanı Elementary School and Şehit Öğretmen Fasih Söğüt Elementary School located in Mardin ($N = 38$). Regression models were constructed separately to comprehend which factors were effective to explain mathematics achievement on OCT1 and attitudes towards CAI.

Firstly, regression was fitted on OCT1 scores and the related analysis results were shown in Table 5.6 and Figure 5.7. Since statistically significant lack-of-fit was not detected ($\rho = 0.07$), it was decided that the model was adequate in representing the relation between the mean response and independent variables. Based on a set of residual analysis plots given in Fig. 5.7, we could also state that normality assumption was satisfied since the data points have scattered on the line. Based on the plot of residuals versus fitted values in Fig. 5.7, we might state that homogeneity of variance assumption was satisfied. To make a formal decision on homoscedasticity assumption, Breusch-Pagan test was conducted. The critical value at the 0.05 significance level for a Chi-square statistic with 2 degrees of freedom was 2.450. The p-value for this test was 0.294 which was greater than 0.05. Therefore, the test for checking the validity of the assumption resulted in homogeneous error variance. To check uncorrelated errors assumption, D-W test was conducted ($D = 1.728$). Corresponding critical values at 0.05 significance level are $d_L = 1.391$ and $d_U = 1500$ according to D-W table. Since D-W statistic value was bigger than the upper bound, it was stated that no autocorrelation existed. Multicollinearity assumption was assessed using VIF values which suggested the absence of multicollinearity. Moreover, the overall regression F test was significant ($\rho = 0.02$) leading the acceptance of the model. The related analysis results and graphs are shown in Table 5.6 and Figure 5.7, respectively.

Table 5. 6. *Regression Analysis: OCT1 vs V13; V14*

Regression Analysis: OCT1 versus V13; V14

```
The regression equation is
OCT1 = 25.1 + 23.4 V13 + 11.4 V14


Predictor     Coef  SE Coef      T      P    VIF
Constant    25.086    2.825   8.88  0.000
V13         23.378    8.824   2.65  0.012  1.000
V14         11.403    3.941   2.89  0.007  1.000


S = 12.1460   R-Sq = 30.5%   R-Sq(adj) = 26.6%

PRESS = 7300.31   R-Sq(pred) = 1.80%


Analysis of Variance

Source          DF      SS      MS     F      P
Regression       2  2270.7  1135.4  7.70  0.002
Residual Error  35  5163.4   147.5
  Lack of Fit    1   483.5   483.5  3.51  0.070
  Pure Error    34  4679.8   137.6
Total           37  7434.1


 2 rows with no replicates



Durbin-Watson statistic = 1.72771

No evidence of lack of fit (P >= 0.1).
```

The final model is as follows:

$$OCT1 = 25.1 + 23.4\ V13 + 11.4\ V14. \quad (13)$$

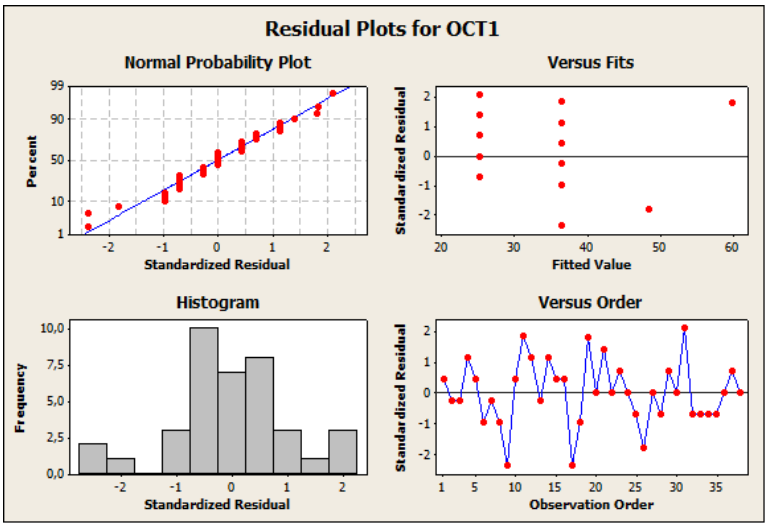


Figure 5. 7. *Residual Plots for OCT1*

According to the regression table above, we concluded that the use of computer and instruction method (CAI or traditional instruction) were significant for explaining mathematics achievement of the students on OCT1. Considering the results obtained, two sample t test was constructed to determine whether the means of OCT1 differed according to schools and to identify with which instruction type students obtained better results. According to results of the test shown in Table 5.7, it was obtained that OCT1 results differed between schools. Also, boxplot of OCT1 shown in Figure 5.8 displayed that the test results were different; Dereyanı Elementary School students had higher results than Şehit Öğretmen Fasih Söğüt Elementary School students.

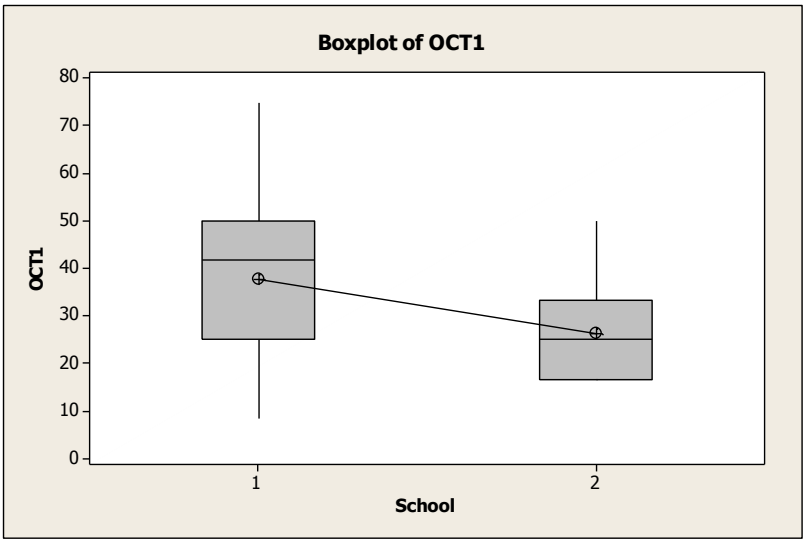
Table 5. 7. *Comparison of state-village schools*

Two-Sample T-Test and CI: OCT1; School

```
Two-sample T for OCT1

School   N   Mean  StDev  SE Mean
1       19   37.7   16.0      3.7
2       19  26.32   9.32      2.1

Difference = mu (1) - mu (2)
Estimate for difference:  11.40
95% CI for difference:  (2.68; 20.12)
T-Test of difference = 0 (vs not =): T-Value = 2.68  P-Value = 0.012  DF = 28
```



Note: 1. Dereyanı Elementary School, 2: Şehit Öğretmen Fasih Söğüt Elementary School

Figure 5. 8. *Boxplot of OCT1*

In the light of the analysis results, we concluded that instruction types affected students' learning. While students taught via CAI got higher results, the others taught via traditional instruction got lower on OCT1. As a result, we could indicate that the part of animation program including the sub-learning area, namely identifying possible cases, of Probability and Statistics learning area of 8th grade mathematics curriculum was an effective CAI material. In order to understand whether the same deduction would be obtained for OCT2 results, we constructed another regression model on OCT2 scores between those state schools. Based on a set of residual analysis plots given in Fig. 5.9, we could state that normality assumption was satisfied since the data points have scattered on the line. Also, Shapiro-Wilk normality test showed that the normality assumption was satisfied ($p = 0.213$). Based on the plot of residuals versus fitted values in Fig. 5.9, we might state that the homogeneity of variance assumption was satisfied. To make a formal decision on homoscedasticity assumption, Breusch-Pagan test was conducted. The critical value at the 0.05 significance level for a Chi-square statistic with 6 degrees of freedom was 3.007. The p-value for this test was 0.808 which was greater than 0.05. Therefore, the test for checking the validity of the assumption resulted in homogeneous error variance. To check uncorrelated errors assumption, D-W test was conducted ($D = 2.570$). Corresponding critical values at 0.05 significance level are d_L =1.175 and d_U =1.854 according to D-W table. Since D-W statistic value was bigger than the upper bound, it was stated that no autocorrelation existed. Multicollinearity assumption was assessed using VIF values which suggested the absence of multicollinearity. Table 5.8 and Figure 5.9 show the results of the regression model.

Table 5. 8. *Regression Analysis on OCT2 Scores between state schools*

Regression Analysis: OCT2 versus V1; V9; V10; V14; CV16; CV17

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	6	993.77	165.628	0.83	0.556
V1	1	53.98	53.976	0.27	0.607
V9	1	49.95	49.955	0.25	0.621
V10	1	164.25	164.245	0.82	0.372
V14	1	0.08	0.075	0.00	0.985
CV16	1	369.00	369.001	1.85	0.184
CV17	1	5.03	5.027	0.03	0.875
Error	31	6192.56	199.760		

Table 5.8 *(Cont'd)*

```
Total        37   7186.33


Model Summary

      S     R-sq  R-sq(adj)  R-sq(pred)
14.1336  13.83%      0.00%       0.00%


Coefficients

Term        Coef  SE Coef  T-Value  P-Value   VIF
Constant   43.79     8.27     5.30    0.000
V1          3.08     5.93     0.52    0.607  1.63
V9         -3.87     7.74    -0.50    0.621  2.85
V10        -6.10     6.73    -0.91    0.372  2.06
V14         0.11     5.72     0.02    0.985  1.56
CV16        0.294    0.216    1.36    0.184  1.35
CV17        0.56     3.50     0.16    0.875  1.41
Regression Equation

OCT2 = 43.79 + 3.08 V1 - 3.87 V9 - 6.10 V10 + 0.11 V14 + 0.294 CV16 + 0.56 CV17

Durbin-Watson statistic = 2.56995
```

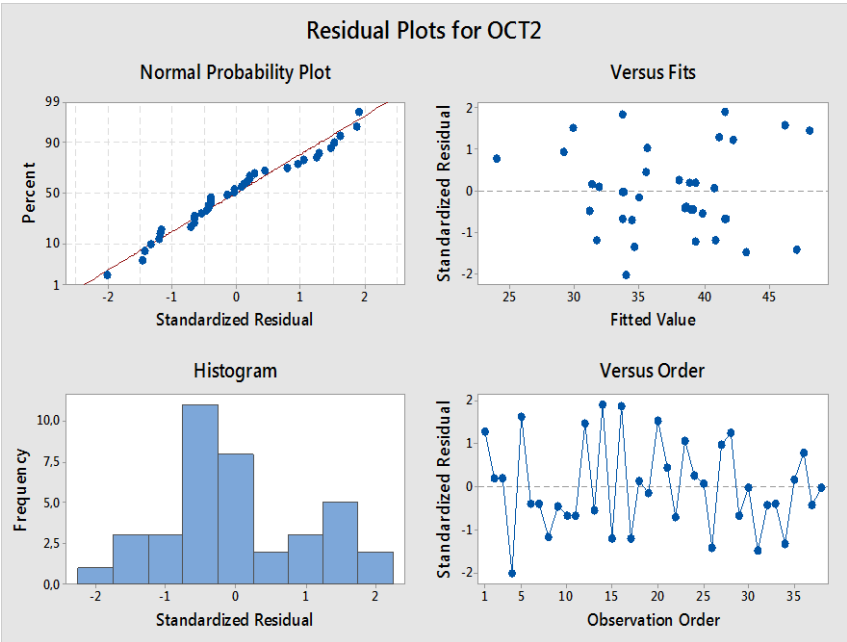


Figure 5. 9. *Residual Plots for OCT2*

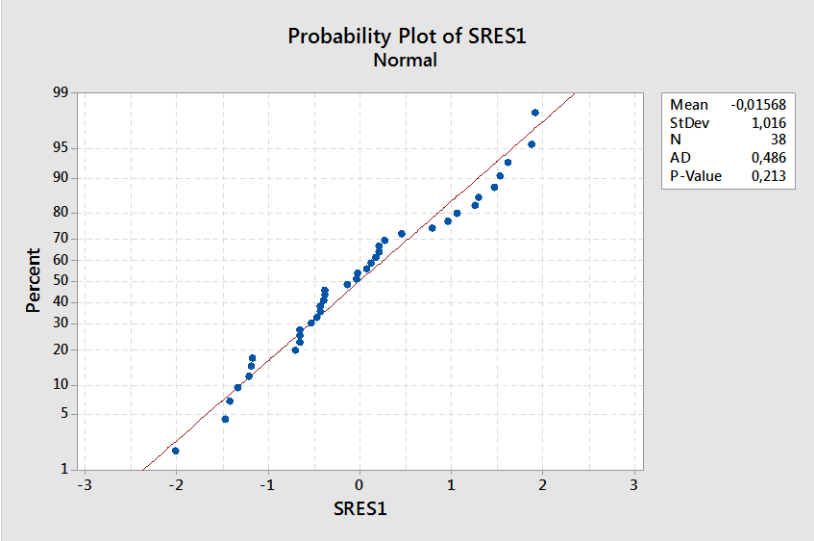


Figure 5. 10. *Probability Plot of OCT2*

According to the results of regression model on scores, none of the variables were significant. Therefore, we could conclude that just the part of animation program including the sub-learning area, namely identifying possible cases, of Probability and Statistics learning area of 8th grade mathematics curriculum was an effective CAI material.

Lastly, MLR model was fitted on CALAS score with explanatory variables to identify the factors affecting students' attitude towards CAI among state schools. All the explanatory variables except V9 and V13 were found to be insignificant. Therefore, a new model was constructed with only two independent variables V9 and V13. Since statistically significant lack-of-fit was not detected ($\rho > 0.1$), it was decided that the model was adequate in representing the relation between the mean response and independent variables. Shapiro-Wilk test showed that the normality assumption was not satisfied ($p = 0.019$). Outliers were detected in the model, so 20th and 21th observations were removed from the analysis. After the observations had been excluded, the normality assumption was satisfied ($p > 0.1$). Based on a set of residual analysis plots given in Fig. 5.11, we could also state that normality assumption was satisfied since the data points have scattered on the line, and also histogram of residuals has a symmetric shape. Based on the plot of residuals versus fitted values in Fig. 5.11, we might state that homogeneity of variance assumption

satisfied. To make a formal decision on homoscedasticity assumption, Breusch-Pagan test was conducted. The critical value at the 0.05 significance level for a Chi-square statistic with 2 degrees of freedom was 1.655. The p-value for this test was 0.437 which was greater than 0.05. Therefore, the test for checking the validity of the assumption resulted in homogeneous error variance. To check uncorrelated errors assumption, D-W test was conducted (D = 1.935). Corresponding critical values at 0.05 significance level are d_L =1.343 and d_U =1.584 according to D-W table. Since D-W statistic value was bigger than the upper bound, it was stated that no autocorrelation existed. Multicollinearity assumption was assessed using VIF values which suggested the absence of multicollinearity. The related analysis results and graphs shown in Table 5.9, Figure 5.11 and Figure 5.12 respectively.

Table 5. 9. *Regression Analysis on CALAS between state schools*

Regression Analysis: CALAS versus V9; V13

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	2	0.14118	0.07059	1.61	0.215
V9	1	0.10248	0.10248	2.34	0.136
V13	1	0.07018	0.07018	1.60	0.214
Error	33	1.44536	0.04380		
Total	35	1.58654			

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.209282	8.90%	3.38%	0.00%

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	2.9020	0.0508	57.17	0.000	
V9	0.1098	0.0718	1.53	0.136	1.06
V13	0.198	0.156	1.27	0.214	1.06

Regression Equation

CALAS = 2.9020 + 0.1098 V9 + 0.198 V13

Durbin-Watson Statistic

Durbin-Watson Statistic = 1,93464

No evidence of lack of fit (P >= 0.1).

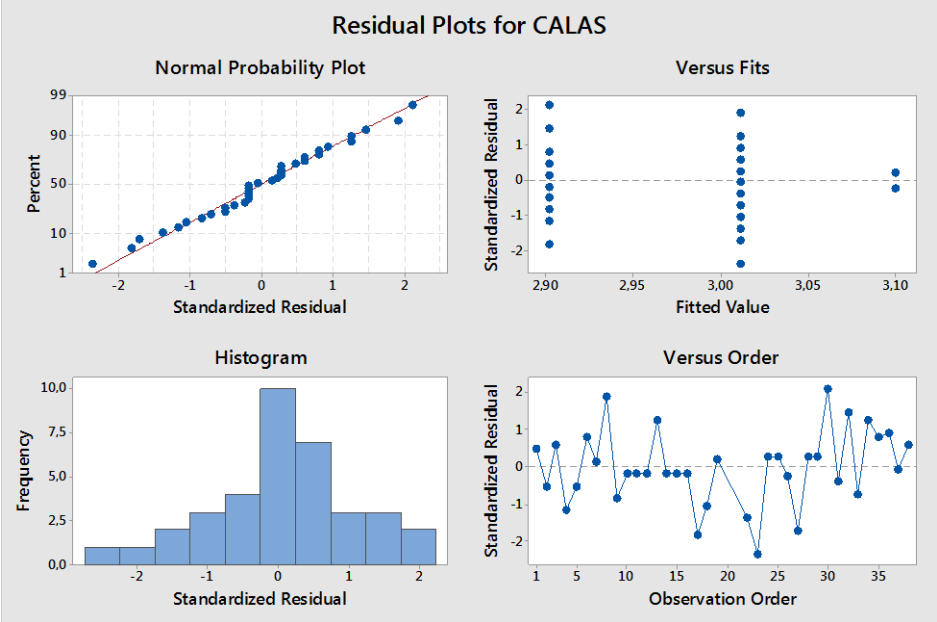


Figure 5. 11. *Residual Plots for CALAS*

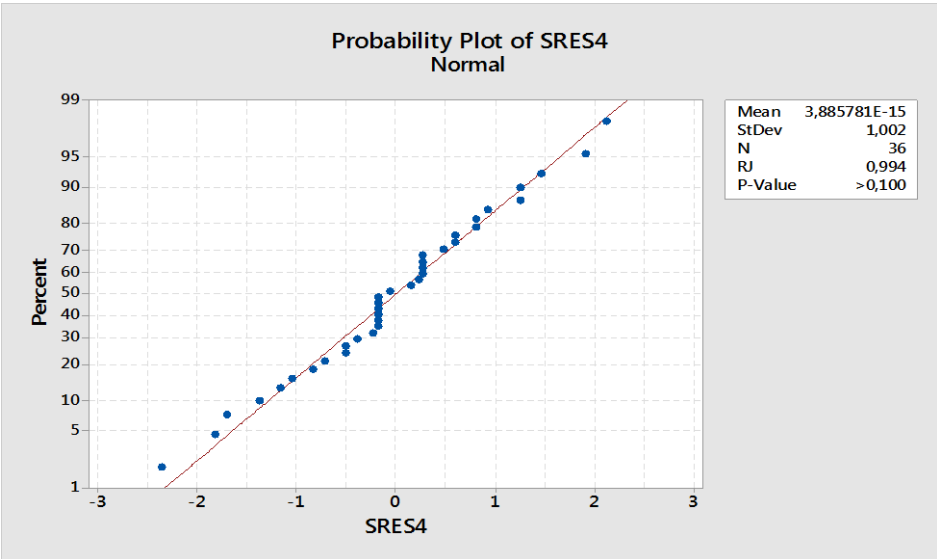


Figure 5. 12. *Probability Plot of CALAS*

All the assumptions were checked to make sure that the model was properly and efficiently applied. However, none of the explanatory variables were significant ($p > 0.05$). Considering the results of the regression model based on attitude

towards CAI among state schools, it was concluded that there was no statistically significant relationship between the attitude and explanatory variables.

To sum up, only first term mathematics grade (V15) significantly contributed to eight grade students' probability achievement. This result was also supported by the literature. Subject matters such as fraction, percentage, decimal numbers, the concept of cluster and proportional reasoning were stated in the literature as prerequisite knowledge enhancing success of learning probability subject. There was no cultural effect that determined success of eight grade students' permutation-combination and probability achievement. Comparing two state-village schools, CAI via R animation program was found more effective teaching method than traditional instruction for permutation-combination subjects on eight grade. However, the same deduction was not valid for probability subjects. The result might be due to the quality of the prepared animation program. Finally, it was concluded that animation in R programme had no effect on attitude toward CAI.

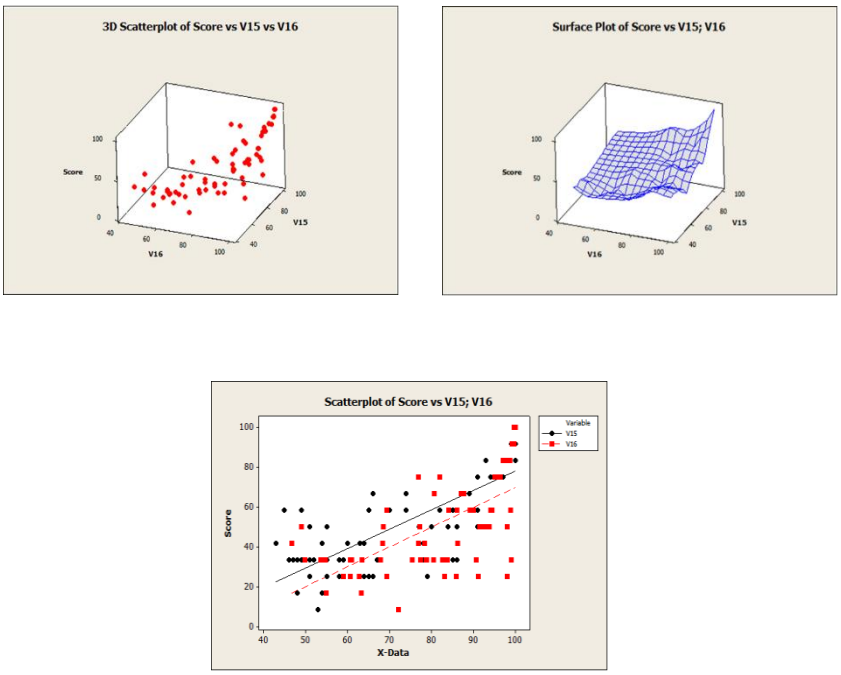


Figure 5. 13. *Scatterplot of score vs V15, V16 in different plots.*

According to the graphs shown in Figure 5.13, there are deviations from the surfaces and plot respectively. That means that model prediction quality is not sufficient. To improve model prediction quality, quantile regression model would be better. However, we do not aim to predict students' scores, but instead to find the factors affecting students' achievement in probability subjects and students' attitudes towards CAI. If someone wants to fit the response for the different quantiles, quantile regression model might be used. This improvement would increase the sufficiency of the regression model. However, predicting scores is out of purposes of that study, so quantile regression is not used in the study.

5.3 Second Data Reduction Method

Clearly, the number of explanatory variables is quite many to build a MLR model. Therefore, as a second data reduction method, we analyzed a mixed categorical data set by using categorical PCA to construct a new set of variables, called principal components. Then, MLR model was developed to investigate the effects of CAI to mathematical achievement and attitude of students.

Categorical Principal Components Analysis

In the study, data consist of 45 explanatory variables with different measurement levels (nominal, ordinal and numeric), which we wished to reduce to a small number of dimension with as little loss of information as possible. "Gender" and "City" factors obtained from surveys were not included in CATPCA, because they would be included in regression model directly. Therefore, a total of 43 variables obtained from surveys were used for CATPCA. The following variables have zero variance: *Projection School, Desktop Computer in Class, Smartphone in Class and Projection in Class,* so execution of CATPCA has stopped in SPSS. Therefore, those four variables that were rarely chosen were excluded from the analysis, 39 variables left.

In the following sections, we give a step by step description of the data reduction using the program CATPCA (SPSS). In the preliminary analysis, we include 43 variables described in Table 5.10.

Table 5. 10. *Description of the 43 variables in the analysis*

Variables: Name (Description)	
1. Settlement	25. Math Average Grade (over 100)
2. Mother Education Level	26. Overall GPA (over 100)
3. Father Education Level	27. Location of School
4. Sibling Number	28. School Type
5. Sibling Training (Yes/No)	29. Computer Lab in School
6. Income (Yes/No)	30. Net in Computer Lab
7. Computer Use (Yes/No) *(Yes/No)*	31. *Projection in School*
8. Laptop Use (Yes/No) (Yes/No)	32. Smart board in School
9. Desktop Use (Yes/No)	33. Tablet in School (Yes/No)
10. Tablet Use (Yes/No)	34. Computer Teacher in School
11. Smartphone (Yes/No)	35. Computer Lesson (Yes/No)
12. PS3 (Yes/No) *(Yes/No)*	36. *Desktop Computer in Class*
13. Internet Home (Yes/No)	37. Laptop in Class (Yes/No)
14. Internet Work (Yes/No)	38. Tablet in Class (Yes/No)
15. Internet School (Yes/No) *(Yes/No)*	39. *Smartphone in Class*
16. Internet Dormitory (Yes/No) *(Yes/No)*	40. *Projection in Class*
17. Internet Cafe (Yes/No)	41. School Environment
18. Internet Everywhere (Yes/No)	42. School Attitude (toward CAI)
19. Net Use Time	43. Schools (4 category)
20. Net for Fun (Yes/No)	
21. Net for Academic Affairs (Yes/No)	
22. Net for Routine Works (Yes/No)	
23. Net for Office Program (Yes/No)	
24. Net for PS3 (Yes/No)	

Note. Variables shown in italics were not selected for the analyses.

CATPCA Step 1: Determination of appropriateness of CATPCA

Bartlett's test of sphericity (BTS) and Kaiser-Meyer-Olkin (KMO) criteria are checked to determine appropriateness of traditional PCA. BTS is used to check whether the correlation matrix between variables is an identity matrix that means the

variables are uncorrelated. Rejecting the null hypothesis means there are dependent variables for PCA to group, and hence PCA is appropriate. KMO is the indicator of sample adequacy and measures the degree of correlation between variables. Small values of KMO indicates that correlations between variables cannot be explained accurately by other variables and therefore PCA may not be suitable. However, high values (between 0.5 – 1.0) indicate that PCA is useful as a means of data reduction. The same criteria to develop the traditional PCA can be used in the CATPCA (Mendes and Ganga, 2013). In the light of the information, we applied those methods for the implementation of CATPCA. We applied BTS and KMO to original data. However, SPSS did not provide the results of those methods, rather gave the error of "This matrix is not positive definite." It is likely the case that correlation matrix of the data is nonpositive definite, i.e., some of the eigenvalues of correlation matrix are nonpositive numbers. Eigenvalues might take negative values due to linear dependencies among variables. As a result of this analysis, we checked correlation between variables. Two things are significant with respect to correlation matrix: the variables have to be intercorrelated, but they cannot correlate too highly since this causes multicollinearity (Field, 2009). Therefore, we used Spearman Rank Correlation coefficients to determine which variables were highly correlated, and then used only one in the analysis. Spearman Rank Correlation was used since it is a nonparametric test to measure the degree of association between two variables and it does not require any assumption about the distribution of the data and it is appropriate for the variables with different measurement levels. A cut off for highly correlated variables was determined as 0.90 according to literature. Table 5.11 shows the correlation coefficients that are above 0.90.

Table 5. 11. *Highly correlated variables*

Corr(Settlement, Location school)= 0,945
Corr (Settlement, School Type)= 0,928
Corr(Settlement, Computer Lab) = −0.928
Corr(Settlement, Net Computer Lab)= −0,928
Corr(Settlement, Computer Teacher) = −0,928

Table 5. 11 *(cont'd)*

Corr(Settlement, Computer Lesson) = −0,928
Corr(Income, Location School= −0,913
Corr(Income, School Type) = 0,925
Corr(Income, Computer Lab) = −0,925
Corr(Income, Computer Teacher) = −0,925
Corr(Income, Computer Lesson) = −0,925
Corr(Location School, School Type) = 0,949
Corr(Location School, Computer Lab) = −0,949
Corr(Location School, Net Computer lab) = −0,949
Cor(Location School, Computer Teacher) = −0,949
Cor(Location School, Computer Lesson) = −0,949
Corr(School Type, Settlement) =0,928
Corr(School Type, Computer lab) = −1
Corr(School Type, Net Computer Lab) = −1
Corr(School Type, Computer Teacher) = −1
Corr(School Type, Computer Lesson) = −1
Corr(Computer Lab, Net Computer Lab) = −1
Corr(Computer Lab, Computer Teacher) = 1
Corr(Computer Lab, Computer Lesson) = 1
Corr(Net Computer, Computer Teacher) = 1
Corr(Location School, Schools) = 0,944
Corr(Net Computer, Computer Lesson)= 1
Corr(Net Computer, School Attitude) = 0,938
Corr(Computer Teacher, Computer Lesson)= 1
Corr(Computer Teacher, School Attitude) = 0,938
Corr(Computer Lesson, School Attitude) = 0,938
Corr(School Enviroment, School Attitude)= 0,955
Corr(Tablet School, Tablet Class) = 1
Corr(City, Smartboard) = 1

As shown in Table 5.11, some variables were highly correlated and even correlation coefficients between some of them was 1 or -1. Therefore, it was unnecessary to include those variables to analysis at the same time. As a result of the correlation coefficients shown in Table 5.11, “Location School”, “School Type”, “Computer Lab”, “Net Computer Lab”, “Computer Teacher”, “Computer Lesson”, “School Environment”, “Tablet School”, “Schools” and “Smardboard School” variables were excluded from the analysis due to linear dependency. After these 10 variables were excluded, remaining number of variables for CATPCA analysis was 29. We applied the BTS and KMO with remaining variables. Considering Table 5.12, KMO index is 0.786 that is between 0.5 and 1 and BTS rejected the existence of an identity matrix. Based on those results, the data sample with 29 variables was considered adequate for implementation of the CATPCA.

Table 5. 12. *KMO and Bartlett’s Test Result*

KMO and Bartlett’s Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.786
Bartlett’s Test of Sphericity	Approx. Chi-Square	1612.907
	Df	406
	p-value	<0.0001

CATPCA Step 2: Specifying analysis levels.

In the present data set, we did not wish to assume linearity and the number of the categories was small compared to the number of individuals. Therefore, we treated all variables ordinally. Since some of the variables like “Mother/Father Education Level” have numerous categories compared to the others, it might have been useful to apply a monotonic spline analysis level to those variables; however, a spline analysis level is more restrictive than ordinal analysis level and thus gives lower VAF. In summary, we specified an ordinal analysis level for the 29 variables.

CATPCA Step 3: Missing values

The number of missing values in the data were considerably small: Three students had missing values only in "Overall GPA" scores. Therefore, the missing values were treated passively, which is the default option for the treatment of missing data in CATPCA. That means, students with missing values were deleted only for those variables on which they had missing values. When the PASSIVE option is specified, missing values do not contribute to the solution. The benefit of using Passive option is that all existing data are used in the analysis without creating additional data (Linting and Kooji, 2012).

CATPCA Step 4: Discretizing

The theory of nonlinear PCA is based on categorical variables with integer values (Linting et al., 2007). Therefore, (positive) integer valued data is required in CATPCA. This is not the feature of CATPCA, but just a technical requirement in SPSS for the analysis. In the data we had two variables that were continuous; "Math Average Grade" and "Overall GPA." We had to discretize these variables for the analysis by CATPCA. Since sample is not very large, we wanted small number of categories of those variables to increase stability of results, so *Grouping option* was used as a discretizing option. When the number of categories were chosen as seven for both "Math Average Grade" and "Overall GPA", ties were seen for Overall GPA, so the number of categories for that variable was changed as six. Figure 5.14 shows the transformation plot after discretizing "Math Average Grade" and "Overall GPA" variables with grouping options.

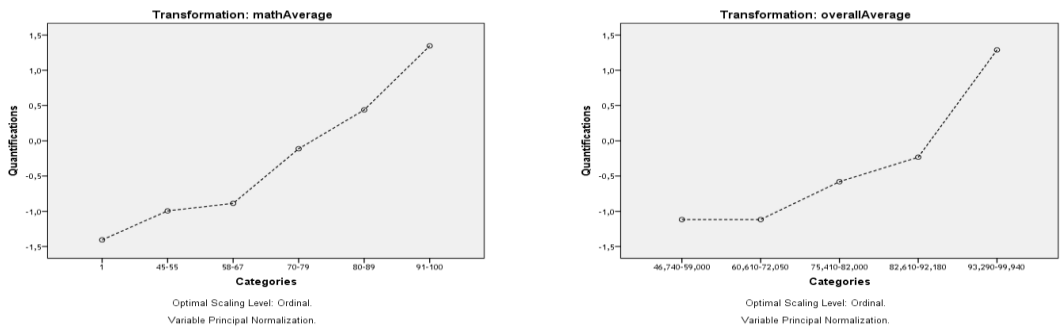


Figure 5. 14. *Transformation plot after discretizing variables "Math Average Grade" and "Overall GPA"*

CATPCA Step 5: Evaluating the Number of components

We had to determine the sufficient number of components/dimensions to retain in the analysis. The survey instruments measure socio-economic and cultural factors of students, in addition to technology ownership of the students, the purpose of using technology, technological equipment and environment of the school. Therefore, it seemed reasonable to assume that six components/dimensions were called for. Since CATPCA solutions are not nested, it is required to look at scree plots in different dimensions. So, we generated scree plots of the eigenvalues (of the correlation matrix of the quantified variables) in four-, five-, six-, and seven-dimensional solutions to check this assumption. Figure 5.15 shows scree plots for these four solutions.

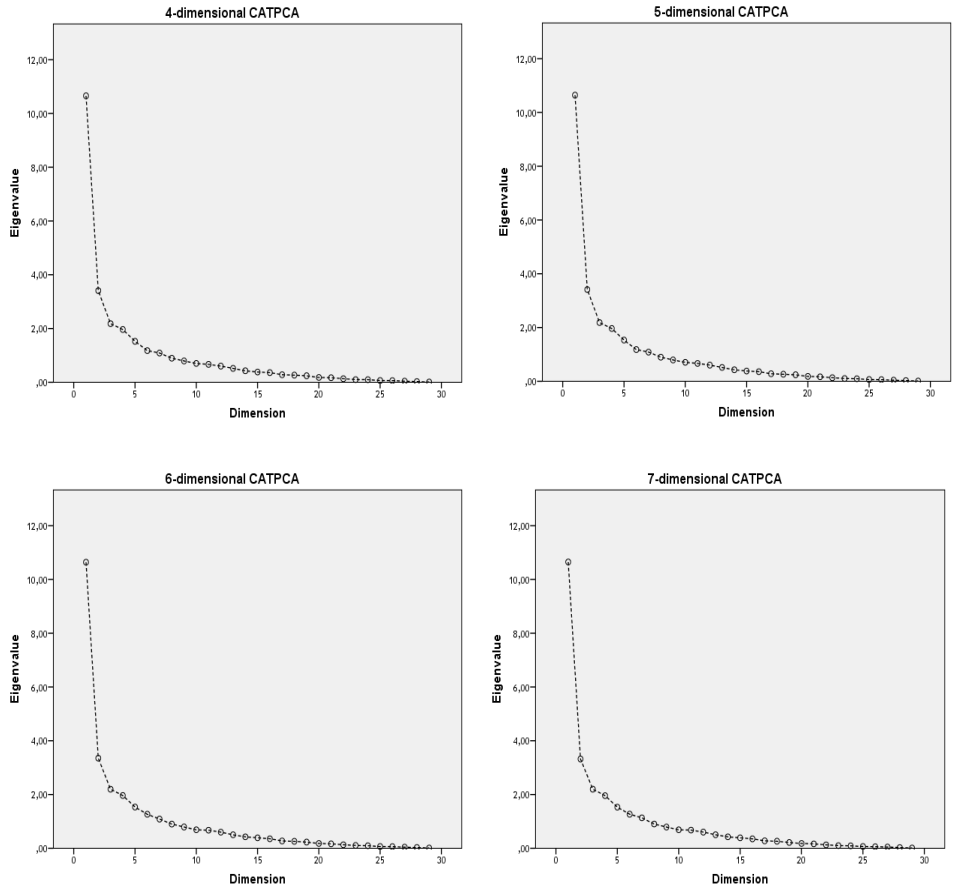


Figure 5. 15. *Scree plots with lines denoting the eigenvalues for a four-, five-, six-, and seven-dimensional CATPCA solutions on 29 variables analyzed at an ordinal analysis level.*

From these plots, presented in Fig. 5.15, we concluded that the elbow is located at the seventh dimension. Since CATPCA solutions are not nested, for instance a scree plot for a seven-dimensional solution that optimized the sum of the seven largest eigenvalue can be different from a scree plot for a six-dimensional solution, with the stand of the elbow going from seven to six dimensions. In the present analysis, four different dimensionalities constantly indicate elbow at the seventh dimension. Review of the seven-dimensional solution showed that this solution is not theoretically appreciable and therefore has a little value (Fabrigar et al., 1999; as cited in Linting et al., 2007). Due to the lack of interpretability of the seventh dimension, added with the information from the scree plot and it does not seem quite difference between the graph of dimension 7-6-5, we tried the six-dimensional and five-dimensional solution.

CATPCA Step 6: Preliminary Analysis

After selection of variables and deciding on the number of dimensions, we applied CATPCA.

Table 5. 13. *Model Summary of CATPCA for 6-dimensional solution with 29 variables.*

Dimension		**Variance Accounted For**	
	Cronbach's Alpha	Total (Eigenvalue)	% of Variance
1	0.938	10.590	36.517
2	0.734	3.435	11.845
3	0.564	2.196	7.572
4	0.508	1.963	6.769
5	0.369	1.554	5.359
6	0.218	1.266	4.365
Total	0.986(a)	21.005	72.431

a Total Cronbach's Alpha is based on the total Eigenvalue.

The percentage of VAF for each dimension and the total can be calculated by dividing the eigenvalue by the number of variables included in the analysis. For instance, the first dimension accounts for 36.517 % of the variance in the optimally

scaled matrix of 29 variables. As a result, all six dimensions account for a substantial percentage of 72.431% of the total variance in transformed variables. According to 6-dimensional CATPCA solution, “No Computer”, “Laptop Use”, “Desktop Use”, “Smartphone Use”, “PS3”, “Internet Work”, “Internet School”, “Internet Everywhere” and “Routine Works” variables have very small mean coordinate; very close to or below 0.1. Those variables were considered to be excluded from the analysis. Since we could not assign meaningful interpretations to dimensions with the result of this analysis, those variables were excluded from the analysis CATPCA with 6-dimensional solution was repeated with the remaining 20 variables.

Table 5. 14. *Variance Accounted For table for 6-dimensional solution with 29 variables.*

	Centroid Coordinates							Total (Vector Coordinates)						
	Dimension							Dimension						
	1	2	3	4	5	6	Mean	1	2	3	4	5	6	Total
Setlement	**.890**	**.447**	**.002**	**.007**	**.041**	**.032**	**.237**	**.885**	**.020**	**.001**	**.006**	**.001**	**.023**	**.936**
Mother Edu	**.765**	**.423**	**.044**	**.110**	**.311**	**.077**	**.288**	**.704**	**.139**	**.001**	**.001**	**.013**	**.020**	**.878**
Father Edu	**.758**	**.180**	**.043**	**.049**	**.116**	**.028**	**.196**	**.754**	**.003**	**.011**	**.008**	**.010**	**.007**	**.793**
Sibling Number	**.622**	**.376**	**.066**	**.049**	**.058**	**.032**	**.201**	**.574**	**.265**	**.000**	**.006**	**.001**	**.010**	**.857**
Sibling Training	**.260**	**.400**	**.048**	**.098**	**.081**	**.027**	**.152**	**.219**	**.371**	**.012**	**.003**	**.000**	**.012**	**.616**
Income	**.897**	**.162**	**.064**	**.023**	**.039**	**.081**	**.211**	**.891**	**.038**	**.002**	**.008**	**.000**	**.006**	**.944**
No Computer	**.189**	**.032**	**.000**	**.024**	**.005**	**.261**	**.085**	**.189**	**.032**	**.000**	**.024**	**.005**	**.261**	**.512**
Laptop Use	**.347**	**.027**	**.004**	**.048**	**.020**	**.026**	**.079**	**.347**	**.027**	**.004**	**.048**	**.020**	**.026**	**.472**
Desktop Use	**.243**	**.019**	**.019**	**.013**	**.105**	**.101**	**.083**	**.243**	**.019**	**.019**	**.013**	**.105**	**.101**	**.500**
Tablet Use	**.428**	**.012**	**.009**	**.012**	**.073**	**.160**	**.115**	**.42**	**.012**	**.009**	**.012**	**.073**	**.160**	**.693**
Smart Phone Use	**.402**	**.019**	**.002**	**.071**	**.003**	**.072**	**.095**	**.402**	**.019**	**.002**	**.071**	**.003**	**.072**	**.569**
Ps3	**.134**	**.155**	**.003**	**.017**	**.199**	**.016**	**.087**	**.134**	**.155**	**.003**	**.017**	**.199**	**.016**	**.522**
Iternet Home	**.324**	**.059**	**.104**	**.187**	**.038**	**.029**	**.124**	**.324**	**.059**	**.104**	**.187**	**.038**	**.029**	**.741**
Internet Work	**.061**	**.073**	**.276**	**.050**	**.013**	**.105**	**.096**	**.061**	**.073**	**.276**	**.050**	**.013**	**.105**	**.578**
Internet school	**.467**	**.001**	**.091**	**.022**	**.019**	**.008**	**.101**	**.467**	**.001**	**.091**	**.022**	**.019**	**.008**	**.608**
Internet Dormitory	**.002**	**.009**	**.239**	**.556**	**.012**	**.004**	**.137**	**.002**	**.009**	**.239**	**.556**	**.012**	**.004**	**.822**

Table 5.14. *(Cont'd)*

Internet Café	**.000**	**.347**	**.290**	**.021**	**.188**	**.012**	**.143**	**.000**	**.347**	**.290**	**.021**	**.188**	**.012**	**.858**
Internet Everywhere	**.090**	**.008**	**.071**	**.008**	**.407**	**.005**	**.098**	**.090**	**.008**	**.071**	**.008**	**.407**	**.00**	**.588**
Net Use Time	**.504**	**.158**	**.162**	**.103**	**.026**	**.284**	**.206**	**.483**	**.023**	**.105**	**.000**	**.003**	**.174**	**.786**
Fun	**.199**	**.005**	**.222**	**.321**	**.048**	**.027**	**.137**	**.199**	**.005**	**.222**	**.321**	**.048**	**.027**	**.823**
Academic	**.089**	**.098**	**.317**	**.037**	**.152**	**.048**	**.124**	**.089**	**.098**	**.317**	**.037**	**.152**	**.048**	**.741**
Routine Works	**.367**	**.062**	**.037**	**.008**	**.029**	**.097**	**.100**	**.367**	**.062**	**.037**	**.008**	**.029**	**.097**	**.601**
Office Prog	**.270**	**.363**	**.023**	**.000**	**.059**	**.004**	**.120**	**.270**	**.363**	**.023**	**.000**	**.059**	**.004**	**.718**
Net For Ps3	**.001**	**.021**	**.039**	**.490**	**.116**	**.007**	**.112**	**.001**	**.021**	**.039**	**.490**	**.116**	**.007**	**.674**
Math Avarege	**.488**	**.314**	**.065**	**.076**	**.024**	**.040**	**.168**	**.478**	**.293**	**.002**	**.006**	**.003**	**.000**	**.783**
Overall Average	**.559**	**.203**	**.012**	**.052**	**.097**	**.016**	**.157**	**.551**	**.193**	**.000**	**.000**	**.028**	**.012**	**.784**
Laptop_Class	**.337**	**.093**	**.289**	**.031**	**.004**	**.001**	**.132**	**.377**	**.093**	**.289**	**.031**	**.004**	**.001**	**.795**
Tablet_Class	**.201**	**.611**	**.012**	**.009**	**.003**	**.014**	**.142**	**.201**	**.611**	**.012**	**.009**	**.003**	**.014**	**.850**
School_attitude	**.877**	**.099**	**.470**	**.078**	**.004**	**.010**	**.256**	**.860**	**.078**	**.016**	**.000**	**.001**	**.007**	**.962**
Active Total	**10.812**	**4.774**	**3.021**	**2.570**	**2.291**	**1.622**	**4.182**	**10.590**	**3.435**	**2.196**	**1.963**	**1.554**	**1.266**	**21.005**

The second 6-dimensional CATPCA included only the 20 retained variables, and the related model summary is shown in Table 5.15.

Table 5. 15. *Model Summary of CATPCA for 6-dimensional solution with 20 variables.*

Dimension		**Variance Accounted For**	
	Cronbach's Alpha	Total (Eigenvalue)	% of Variance
1	0.929	8.539	42.695
2	0.709	3.066	15.330
3	0.512	1.948	9.740
4	0.436	1.707	8.535
5	0.012	1.011	5.055
6	-0,211	0.833	4.165
Total	0.991(a)	17.104	85.520

a Total Cronbach's Alpha is based on the total Eigenvalue.

We can see in the model summary table that the internal consistency coefficient increased from 0.986 with all 29 variables to 0.991 with only 20 variables. When we calculated the VAF, we came up with 85.52% of the VAF in our 20 variables. So, there were fewer variables, but we were accounting for more of the variance with those 20 items than the amount of VAF by the 29 variables. However, the eigenvalue for the six dimension decreased below 1. Therefore, we also applied CATPCA with 5-dimensions and later decided which one to use in data reduction. It is worth pointing out in this point that Cronbach's Alpha value for six dimension is negative. This might be due to small sample size or the correlation between variables are very weak. Table 5.16 shows that there is no value with mean coordinate close to or below 0.1.

After deciding on the number of dimensions and the number of variables in 6-dimensional solution, we checked if we could simplify the structure of the solution by rotating the results. Rotation options are not available within CATPCA in SPSS. However, rotation can be performed by saving the transformed variables and applying them in a linear PCA (Linting and Kooji, 2012). There are various types of rotation including orthogonal rotations such as varimax and quartimax, and oblique rotations such as promax and direct oblimin. First of all, we had to decide on the type of rotation; orthogonal or oblique rotation. In orthogonal rotation, there should not be correlation between the extracted factors, while it should be in oblique rotation (Alpar, 2013). It is suggested that we look at the factor correlation matrix to decide on which type of rotation is more reasonable. Values around .32 and above means there is 10% even more overlap among factors, and then oblique rotation should be used (Brown, 2009). Considering Table 5.17, there are no variables with correlation above .32, so orthogonal rotation seems reasonable. Moreover, since we would apply regression model after data reduction with CATPCA, there should not be collinearity between dimensions. Therefore, it was much more suitable to apply orthogonal rotation. As a result, we used VARIMAX rotation as an orthogonal rotation within traditional PCA in SPSS to rotate the transformed variables.

Table 5. 16. *Variance Ae for 6-dimensional solution with 20 variables.*

	Centroid Coordinates							Total (Vector Coordinates)						
	Dimension							Dimension						
	1	2	3	4	5	6	Mean	1	2	3	4	5	6	Total
Settlement	**.909**	**.410**	**.011**	**.004**	**.058**	**.032**	**.237**	**.907**	**.006**	**.009**	**.002**	**.014**	**.016**	**.953**
Mother Edu	**.765**	**.394**	**.031**	**.157**	**.174**	**.107**	**.271**	**.724**	**.133**	**.000**	**.001**	**.005**	**.005**	**.868**
Father Edu	**.809**	**.156**	**.036**	**.032**	**.038**	**.057**	**.188**	**.805**	**.012**	**.000**	**.003**	**.001**	**.009**	**.830**
Sibling Number	**.581**	**.451**	**.071**	**.044**	**.054**	**.088**	**.215**	**.505**	**.360**	**.001**	**.013**	**.006**	**.006**	**.892**
Sibling Training	**.246**	**.463**	**.061**	**.082**	**.092**	**.110**	**.176**	**.201**	**.429**	**.010**	**.020**	**.014**	**.008**	**.683**
Income	**.922**	**.117**	**.050**	**.007**	**.077**	**.096**	**.212**	**.919**	**.014**	**.011**	**.001**	**.003**	**.005**	**.953**
Tablet Use	**.417**	**.032**	**.001**	**.042**	**.316**	**.007**	**.136**	**.417**	**.032**	**.001**	**.042**	**.316**	**.007**	**.815**
Internet Home	**.334**	**.051**	**.247**	**.040**	**.101**	**.068**	**.140**	**.334**	**.051**	**.247**	**.040**	**.101**	**.068**	**.842**
Internet Dormitory	**.007**	**.016**	**.000**	**.818**	**.006**	**.013**	**.143**	**.007**	**.016**	**.000**	**.818**	**.006**	**.013**	**.860**
Internet Cafe	**.004**	**.438**	**.166**	**.001**	**.082**	**.187**	**.146**	**.004**	**.438**	**.161**	**.001**	**.082**	**.187**	**.879**
Net Use Time	**.463**	**.182**	**.166**	**.112**	**.101**	**.126**	**.192**	**.456**	**.066**	**.086**	**.063**	**.075**	**.089**	**.835**
Fun	**.210**	**.000**	**.589**	**.023**	**.014**	**.045**	**.147**	**.210**	**.000**	**.589**	**.023**	**.014**	**.045**	**.881**
Academic	**.085**	**.085**	**.426**	**.040**	**.014**	**.206**	**.143**	**.085**	**.085**	**.426**	**.040**	**.014**	**.206**	**.856**
Office Prog	**.234**	**.357**	**.015**	**.003**	**.115**	**.017**	**.123**	**.234**	**.357**	**.015**	**.003**	**.115**	**.017**	**.741**
Net For Ps3	**.001**	**.023**	**.020**	**.603**	**.221**	**.000**	**.145**	**.001**	**.023**	**.020**	**.603**	**.221**	**.000**	**.870**
Math Average	**.550**	**.258**	**.064**	**.115**	**.017**	**.026**	**.172**	**.541**	**.220**	**.008**	**.017**	**.000**	**.014**	**.801**
Overall Average	**.605**	**.185**	**.051**	**.045**	**.099**	**.037**	**.170**	**.598**	**.174**	**.009**	**.009**	**.019**	**.025**	**.833**
Laptop_Class	**.410**	**.085**	**.303**	**.007**	**.000**	**.051**	**.143**	**.410**	**.085**	**.303**	**.007**	**.000**	**.051**	**.857**
Tablet_Class	**.261**	**.527**	**.044**	**.000**	**.000**	**.058**	**.149**	**.261**	**.527**	**.044**	**.000**	**.000**	**.058**	**.891**
School_Attitude	**.920**	**.086**	**.566**	**.008**	**.007**	**.132**	**.286**	**.919**	**.038**	**.000**	**.002**	**.005**	**.002**	**.966**
Active Total	**8.735**	**4.318**	**2.919**	**2.182**	**1.587**	**1.465**	**3.534**	**8.539**	**3.066**	**1.948**	**1.707**	**1.011**	**.833**	**17.104**

Table 5. 17. *Correlation between dimensions in 6-dimensional CATPCA with 20 variables.*

Component Correlation Matrix						
Component	1	2	3	4	5	6
1	**1**	**-.006**	**.000**	**.001**	**-.001**	**.000**
2	**-.006**	**1**	**-.001**	**-.001**	**.001**	**-.001**
3	**.000**	**-.001**	**1**	**.000**	**.000**	**.000**
4	**.001**	**-,001**	**.000**	**1**	**.000**	**.000**
5	**-.001**	**.001**	**.000**	**.000**	**1**	**.000**
6	**.000**	**-,001**	**.000**	**.000**	**.000**	**1**

Table 5.18 shows the rotated component loadings from a 6-dimensional CATPCA on 20 variables. Stevens (1992; as cited in Field, 2009) advices using only the factor loadings with an absolute value greater than 0.40. Field recommends suppression of factor loadings with absolute values less than 0.50 when the sample is not very large. Because we have a small sample, we defined cut off for component loadings as 0.50. According to Table 5.18, Dimension-1 includes the variables: Overall GPA, Math Average Grade, Father Education Level, Income, Settlement, School Attitude and Tablet Use in class. We named this factor as "The general success of the students and basic socio-economic and technological factors affecting this situation." Dimension-2 includes the variables: Sibling Number, Sibling Training, Mother Education Level, and Use of Office Program. This dimension was named as "the secondary social situation of the family." Net Use Time and Tablet Use Variables are involved in dimension-3, while Internet Cafe, Internet Home, Laptop Class constitute dimension-4. Dimension-5 includes the variables: Net for PS3 and Internet Dormitory. Lastly, Dimension-6 includes the variables of use of technology for Academic and Fun. As it is seen, dimension-3 through dimension-6 are related with internet ownership and use, so named like that. In summary, those 6 dimensions, obtained by the result of CATPCA with 20 variables, account for a substantial percentage of 85.52 % of the total variance in the data.

Table 5. 18. *Rotated component loadings from a 6-dimensional CATPCA on 20 variables, with all variables analyzed ordinally.*

	Component					
	1	2	3	4	5	6
Overall GPA	.886					
Tablet Use in Class	-.873					
Settlement	.868					
Income	.865					
School Attitude	-.865					
Mathematic Average Grade	.858					
Father Education Level	.706					
Sibling Number		.858				
Use of Office Program		.842				
Sibling Training		.796				
Mother Education Level	.559	-.662				
Tablet Use			.819			
Net Use Time			-.671			
Internet Cafe				.880		
Laptop Class				-.711		
Internet Home			.528	-.615		
Net For Ps3					.898	
Internet Dormitory					.855	
Academic						.852
Fun						-.730

Extraction Method: PCA.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 6 iterations.

Note. Loadings lower than .50 are excluded.

Since 6-dimensional solution with 20 variables involve an eigenvalue smaller than 1, 5-dimensional CATPCA was also applied to determine the final analysis. The same

procedure was applied. VAF 5-dimensional CATPCA with all 29 variables was founded as 68.237 %. The variables "No Computer, Laptop Use, Desktop Use, Tablet Use, Smartphone Use, PS3, Internet Work, Routine Works" whose mean coordinates were around or below 0.1 were excluded from the analysis, and then CATPCA was repeated with the remaining variables. The model summary for 5-dimensional CATPCA with 21 variables was shown in Table 5.19.

Table 5. 19. *Model Summary of CATPCA for 5-dimensional solution with 21 variables.*

Dimension		**Variance Accounted For**	
	Cronbach's Alpha	Total (Eigenvalue)	% of Variance
1	0.928	8.618	41.038
2	0.712	3.111	14.814
3	0.512	1.952	9.295
4	0.449	1.748	8.324
5	0.261	1.330	6.333
Total	0.987(a)	16.758	79.800

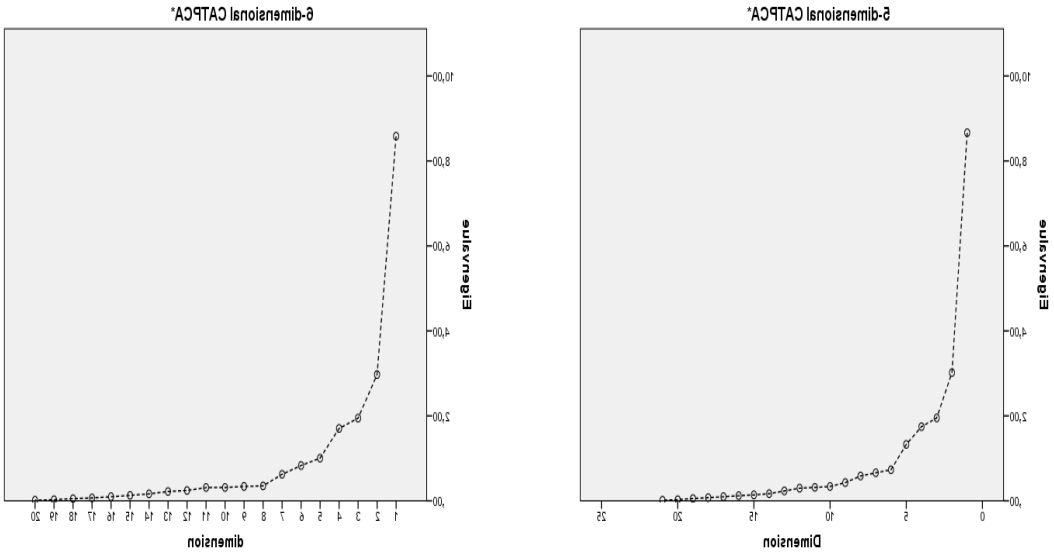
a Total Cronbach's Alpha is based on the total Eigenvalue.

As seen on the model summary table above, the model with 5 dimensions accounts for 79.80% of the total variance in the optimally scaled variables.

CATPCA Step 7: Final Analysis and Interpretation

In order to decide which dimensional solution to use in the categorical data reduction, we compared 6-dimensional and 5-dimensional solutions with respect to VAF. 6-dimensional solution accounted for 85.52% of the total variance, while 5-dimensional solution accounted for 79.80% of the total variance. Although the eigenvalue of the sixth dimension in the first solution was below 1, the total variance explained in that model was higher compared to 5-dimensional solution. Extracting too many factors may cause undesired error variance, so selecting the most suitable

criterion for study when deciding the number of factors to extract is very important (Young and Pearce, 2013). The eigenvalue and scree plot are two determination technique to decide on how many factors to retain. To define a cut off for eigenvalue, Kaiser's criterion or Jolliffe's criterion can be used. *Kaiser's criterion* is the most known technique in traditional PCA, and it recommends retaining all factors with eigenvalue above 1. The Kaiser's criterion is reliable when the sample size is above 250 (Field, 2009). Another criterion is Joliffe's criterion which suggests retaining factors with eigenvalues above 0.70 (Jolliffe, 1986). Jolliffe (2002) argues that a cut off value of 1 for eigenvalue retains too few variables. It is recommended to look at scree plots in addition to eigenvalues to determine the number of factors to retain (Costello and Osborne, 2005; Field, 2009). In the light of the information above and the corresponding scree plots shown in Figure 5.16, Joliffe's criterion was used in this study.



a. 6-dimensional CATPCA b. 5-dimensional CATPCA

Figure 5. 16. *Scree plots*

a. 6-dimensional solution on 20 variables, with all variables analyzed ordinally.

b. 5-dimensional solution on 21 variables, with all variables analyzed ordinally.

In conclusion, we decided to use 6-dimensional CATPCA solution on 20 variables, with all variables analyzed ordinally. The total VAF across the 6 dimensions is 85.52%, with clearly dominant first dimension (VAF: Dimension 1= 42.69%, Dimension 2= 15.33%, Dimension 3= 9.74%, Dimension 4= 8.53%, Dimension 5= 5.05%, Dimension 6=4.16%). That implies that the six selected dimensions/components explain about 86% of the variance in the 20 ordinally quantified variables, which indicates a good fit.

5.3.2 Multiple Linear Regression Model

The method of this thesis is focused on narrowing down large amounts of variables in order to see relevant patterns and relationships between variables. Therefore, we reduced the dimension of the covariates in the MLR model to avoid multicollinearity. Six principal components were achieved as explanatory variables for this MLR model after categorical PCA - CATPCA. The data for regression model consist of 74 observations of the following variables: gender, city, instruction method and six principal components- PC1, PC2, PC3, PC4, PC5 and PC6. The observations are mainly from the four distinct schools during the spring semester of the 2015-2016 academic year.

The method used to determine significant factors contributing students' mathematical achievement (measured by OCT1 and OCT2) and students' attitude toward CAI (measured by CALAS) is the multiple regression model. There are certain assumptions that have to be met in order for the regression to be valid. The related regression model and these assumptions were examined with the statistical tool Minitab and SPSS in the study. Firstly, MLR model was fitted on OCT2 score with these variables; gender, city, instruction method and six principal components. Before making any comments on the model fit, assumptions for the regression to be valid were examined. To check the assumption of errors to be normally distributed, Shapiro-Wilk Normality test result was obtained. The p-value was larger than 0.1 (α). Thus, we fail to reject the null hypothesis and conclude that at this level of significance the errors did not depart from a normal distribution. After normality assumption was validated, homoscedasticity assumption was checked by Breusch-Pagan test. The critical value at the 0.05 significance level for a Chi-square statistic

with 9 degrees of freedom was 6.682. The p-value for this test was 0.6701 which was greater than 0.05. Therefore, it was concluded that at this significance level, the errors had constant variance. To check uncorrelated errors assumption, D-W test was conducted, and the statistic was found as 2.382. Corresponding critical values at 0.05 significance level are $d_L = 1.369$ and $d_U = 1.901$ according to D-W table. Since D-W statistic was larger than upper bound, no autocorrelation existed at this significance level. Multicollinearity assumption was assessed using VIF values which were not over 10 suggesting the absence of multicollinearity. The p-value of the test (ANOVA) was approximately zero, which was smaller than α, so there was a statistically significant relationship between the OCT2 score and the explanatory variables. PC1 and PC2 are found significant and a new model was constructed with only these two independent variables, PC1 and PC2. The new regression model exhibited lack-of-fit, so it failed to adequately describe the functional relationship between PC1, PC2 and the response variable-OCT2. Therefore, interaction term was added to the model to obtain reliable results and final regression was fitted. The results of the regression are displayed in Table 5.20.

Table 5. 20. *Regression Output with PC1, PC2 and PC1∗PC2 variables*

Regression Analysis: OCT2 versus PC1; PC2; PC1*PC2

```
Regression Equation

OCT2 = 52.37 + 17.97 PC1 + 3.32 PC2 + 6.41 PC1*PC2

Coefficients
Term        Coef  SE Coef  T-Value  P-Value   VIF
Constant   52.37     1.83    28.69    0.000
PC1        17.97     2.10     8.57    0.000  1.33
PC2         3.32     2.71     1.22    0.226  2.23
PC1*PC2     6.41     2.67     2.40    0.019  2.56

Model Summary

      S    R-sq  R-sq(adj)  R-sq(pred)
15.6998  58.25%     56.46%      53.57%

Analysis of Variance

Source      DF   Adj SS   Adj MS  F-Value  P-Value
Regression   3  24070.6   8023.5    32.55    0.000
  PC1        1  18095.8  18095.8    73.42    0.000
  PC2        1    367.8    367.8     1.49    0.226
  PC1*PC2    1   1424.0   1424.0     5.78    0.019
Error       70  17253.8    246.5
Total       73  41324.4
Durbin-Watson statistic = 2.31253

No evidence of lack of fit (P >= 0.1).
```

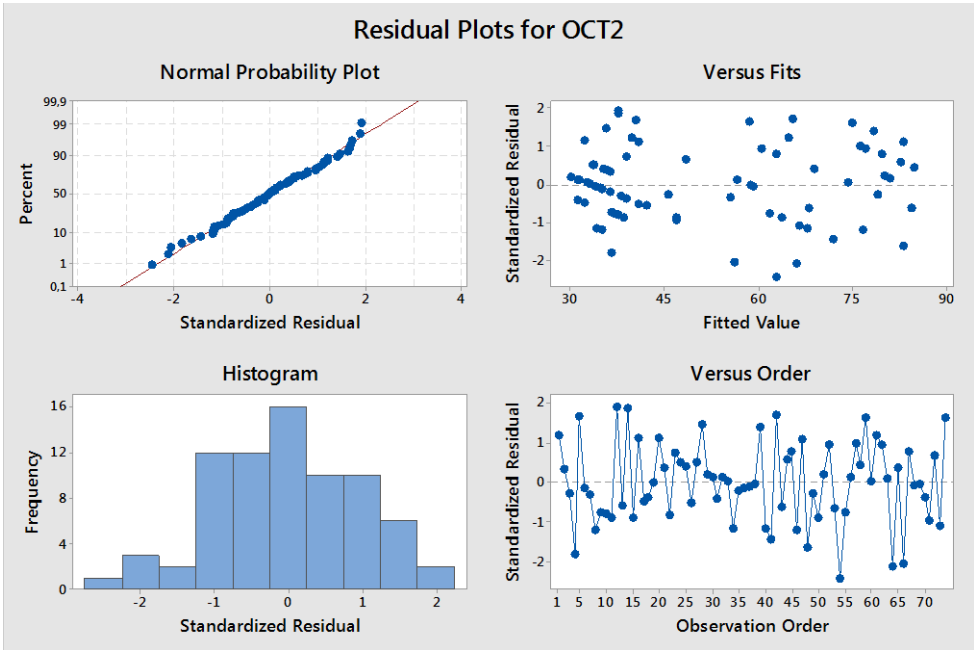


Figure 5. 17. *Residuals Plots for OCT2*

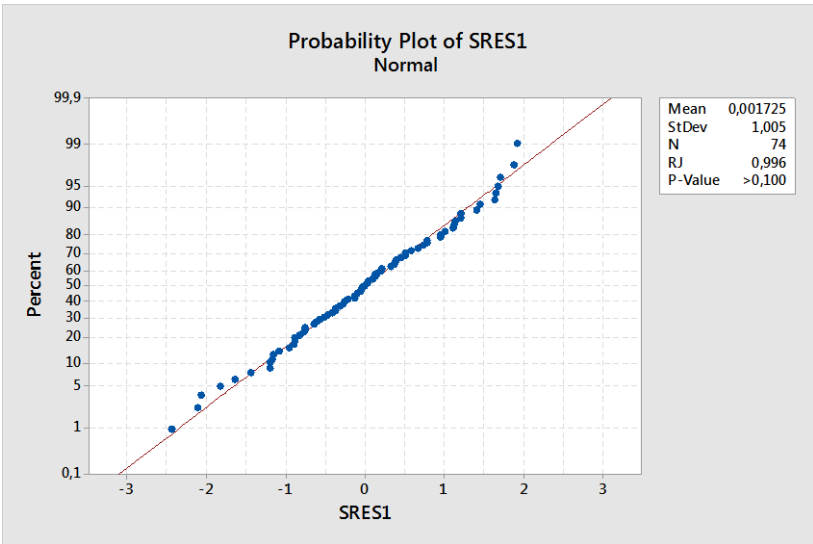


Figure 5. 18. *Normal probability plot of residuals*

After making improvements on the model by adding interaction term, statistically significant lack-of-fit was not detected ($p > 0.1$). Therefore, it was concluded that the model accurately fitted the data. Based on a set of residual analysis plots given in Fig. 5.17, we could state that normality assumption was satisfied since the data

points have scattered on the line and histogram of residuals has a symmetric shape. Also, Shapiro-Wilk normality test indicated that at this level of significance ($\alpha = 0.05$) the normality assumption was satisfied ($\rho > 0.1$). The plot of residuals versus fitted values does not show any pattern which indicates nonconstant variance. To make a formal decision on homoscedasticity assumption, Breusch-Pagan test was conducted. The critical value at the 0.05 significance level for a Chi-square statistic with 3 degrees of freedom was 6.682. The p-value for this test was 0.083 which was greater than 0.05. Therefore, the test for checking the validity of the assumption resulted in homogeneous error variance. VIF values has showed that multicollinearity has not existed in the regression analysis. Durbin-Watson test statistic was found as 2.313. According to the D-W table, corresponding critical values at 0.05 significance level are $d_L = 1.543$ and $d_U = 1.709$. Since, D-W statistic was higher than upper bound, it was stated that there was no autocorrelation. Moreover, the overall regression F test was significant ($\rho = 0.0$) leading the acceptance of the model. The R^2 was 56.46 for the regression, which shows that the model explains 56.46% of the variation in the data.

The final model is as follows:

$$\mathrm{OCT2} = 52.37 + 17.97\ \mathrm{PC1} + 3.32\ \mathrm{PC2} + 6.41\ \mathrm{PC1} * \mathrm{PC2} \tag{14}$$

Secondly, MLR model was fitted on OCT1 scores with these variables; gender, instruction method and six principal components. OCT1 scores were obtained just for the students having education in Mardin. Therefore, city variable was essentially constant in the model, and has been removed from the equation. According to normal probability plot of (standardized) residuals and Shapiro-Wilk Normality test ($p>0.1$), the normality assumption was satisfied. However, the constant variance assumption of errors was not satisfied according to residuals versus fitted values plot since the residuals increased with the fitted values in a pattern. Therefore, Box-Cox Transformation was applied on the response variable OCT1. But confidence interval included 1, so transformation was not seem applicable. Even so, transformation was applied. The estimated lambda value was 0.50, so square root (OCT1) transformation was used and the transformed OCT1 variable was recoded as OCT1tr. As a result of the analysis, it was seen that transformation did not work. Due to lack of theory

about selection of significant variables for the model and to interactively explore which variables provided a good fit to the model, we used stepwise regression. Stepwise regression is an approach used to improve model's prediction performance by selecting a subset of effects for a regression model. Forward selection is a procedure in stepwise regression which choose the independent variable that maximizes the squared partial-correlation coefficient with the dependent variable until the sample partial correlation is found nonsignificant by the standard F test (Bendel and Afifi, 1977). Therefore, forward stepwise selection was used on the independent variables whereby the variable with largest absolute correlation with OCT1 was chosen as an explanatory variable. As a result of the forward stepwise regression output shown in Table 5.21, only instructional method among explanatory variables was found significant. Therefore, instructional method was included in the model as the only major factor explaining success in OCT1.

Table 5. 21. *Stepwise Regression*

Stepwise Regression: OCT1 versus Gender; Ins. Mth.; PC1; PC2; PC3; PC4; PC5; PC6

```
Alpha-to-Enter: 0.15  Alpha-to-Remove: 0.15


Response is OCT1 on 8 predictors. with N = 38


Step            1
Constant    26.32

Ins. Mth.    11.4
T-Value      2.68
P-Value     0.011

S            13.1
R-Sq        16.62
R-Sq(adj)   14.30
Mallows Cp    4.6
```

After stepwise regression analysis, the same procedure was followed as before in MLR. Again the assumptions of the regression were not satisfied even though essential transformation was made with respect to Box-Cox control chart. Therefore, instead of transformation, three observations- 9., 17. and 19. - stated in OCT1 vs Instruction method regression model were excluded from the analysis. Then, the

regression procedure was repeated. The related outputs and graphs are shown in Table 5.22 and Figure 5.19, respectively.

Table 5. 22. *Regression analysis OCT1 vs Instruction Method*

Regression Analysis: OCT1 versus Ins. Mth.

```
Analysis of Variance

Source        DF  Adj SS   Adj MS  F-Value  P-Value
Regression     1    1411  1411.13    15.25    0.000
  Ins. Mth.    1    1411  1411.13    15.25    0.000
Error         33    3053    92.51
Total         34    4464


Model Summary

      S    R-sq  R-sq(adj)  R-sq(pred)
9.61798  31.61%     29.54%      23.02%


Coefficients

Term        Coef  SE Coef  T-Value  P-Value   VIF
Constant   26.32     2.21    11.93    0.000
Ins. Mth.  12.75     3.26     3.91    0.000  1.00


Regression Equation

OCT1 = 26.32 + 12.75 Ins. Mth.

Durbin-Watson statistic = 1.96389

No evidence of lack of fit (P >= 0.1).
```

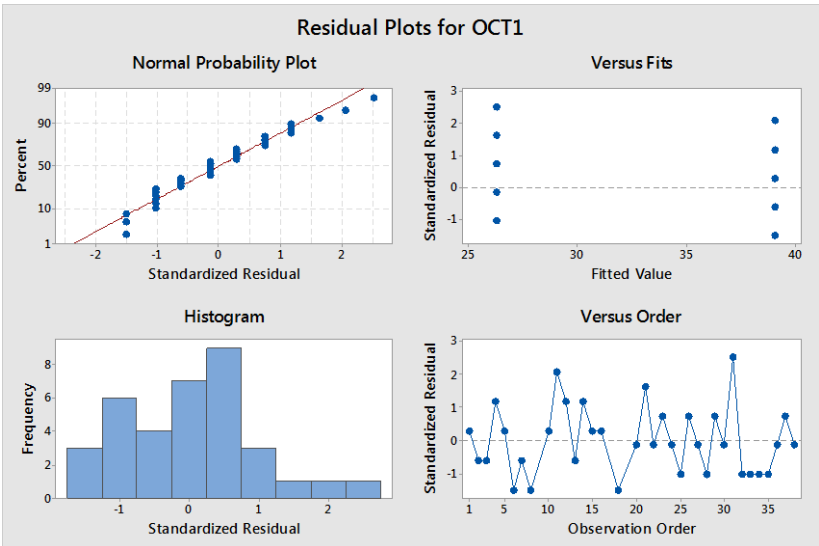


Figure 5. 19. *Residuals Plots for OCT1*

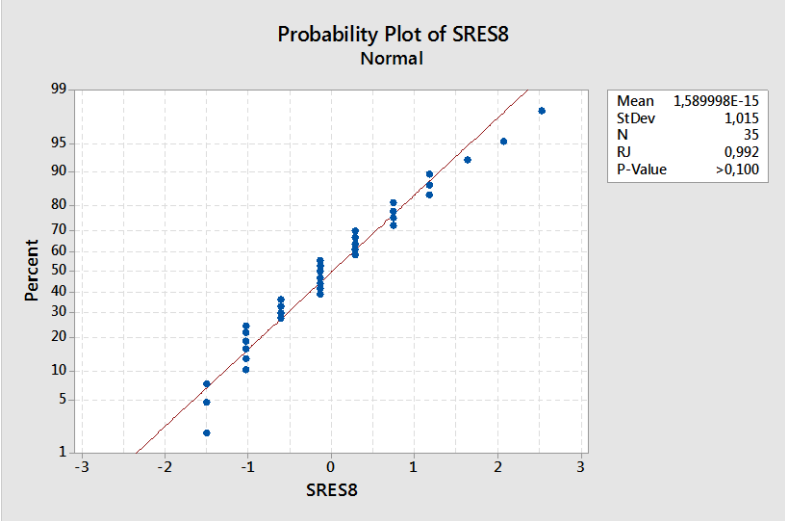


Figure 5. 20. *Normal probability plot of residuals*

Before making any comments on the model fit, the assumptions were checked. Since statistically significant lack-of-fit was not detected ($\rho > 0.1$), it was decided that the model was adequate in representing the relation between the mean response and independent variables. Based on a set of residual analysis plots given in Fig. 5.19, we could state that normality assumption was satisfied since the data points have scattered on the line. Also, Shapiro-Wilk normality test indicated that at this level of significance the normality assumption was satisfied ($\rho > 0.1$). After normality assumption was validated, homoscedasticity assumption was checked by Breusch Pagan test. The critical value at the 0.05 significance level for a Chi-square statistic with 1 degree of freedom is 0.066. The p-value for this test was 0.797, which was greater than 0.05. Therefore, the test for checking the validity of the assumption resulted in homogeneous error variance. Moreover, the plot of residuals versus fitted value does not show any pattern which also indicates constant variance. To check uncorrelated errors assumption, D-W test was conducted. Corresponding critical values at 0.05 significance level are d_L=1.402 and d_U=1.519 according to D-W table. Since, D-W statistic was 1.964 which was greater than the upper bound, it was concluded that errors are uncorrelated. VIF value was 1 indicating the absence of multicollinearity. The p-value of the test (ANOVA) was approximately 0 which was

smaller than α, so there is a statistically significant relationship between the OCT1 score and the instruction method.

The final model is as follows:

$$\text{OCT1} = 26.32 + 12.75 \text{ Instruction Method} \tag{15}$$

Lastly, MLR model was fitted on CALAS score with these variables; gender, city, instruction method and six principal components to understand which factors contributed students' attitude towards CAI. According to the normal probability plot, there were deviations from a straight line and also the plotted points bent down to the right of the normal line indicating a long tail to the left. That might indicate that the errors came from a non-normal distribution. Also, histogram of the residuals was not normally distributed, on the contrary the distribution of the residuals was quite skewed. To make a formal decision on normality assumption, Shapiro-Wilk normality test was conducted ($\rho < 0.1$). The test for checking the validity of the assumption resulted in nonnormality. To deal with nonnormality, we performed Box-Cox Transformation to the response variable CALAS as a model diagnostics. Since the estimated value for lambda was found -3, $1/\text{CALAS}^3$ transformation was applied and the transformed variable was recoded as CALAS^*. Then, the regression procedure was repeated. The related outputs and graphs are shown in Table 5.23, Figure 5.21 and Figure 5.22, respectively.

Table 5. 23. *Regression analysis* $\boldsymbol{CALAS^*}$ *vs Gender, City,...*

Regression Analysis: CALAS* versus Gender; City; Ins. Mth.; PC1; PC2; PC3; PC4; PC5; PC6

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	9	0.000917	0.000102	0.89	0.537
Gender	1	0.000043	0.000043	0.38	0.542
City	1	0.000021	0.000021	0.19	0.668
Ins. Mth.	1	0.000001	0.000001	0.00	0.946
PC1	1	0.000027	0.000027	0.24	0.627
PC2	1	0.000014	0.000014	0.12	0.732
PC3	1	0.000057	0.000057	0.50	0.484
PC4	1	0.000030	0.000030	0.27	0.607

Table 5.23 *(Cont'd)*

```
   PC5          1  0.000257  0.000257     2.25    0.138
   PC6          1  0.000105  0.000105     0.92    0.342
Error          64  0.007307  0.000114
Total          73  0.008224


Model Summary

        S    R-sq  R-sq(adj)  R-sq(pred)
0.0106853  11.15%      0.00%       0.00%


Coefficients

Term           Coef   SE Coef  T-Value  P-Value   VIF
Constant    0.03658   0.00947     3.86    0.000
Gender     -0.00186   0.00304    -0.61    0.542  1.47
City       0.000084  0.000194     0.43    0.668  6.29
Ins. Mth.   0.00053   0.00792     0.07    0.946  7.77
PC1         0.00165   0.00337     0.49    0.627  7.41
PC2         0.00085   0.00246     0.34    0.732  3.94
PC3         0.00178   0.00253     0.70    0.484  4.15
PC4         0.00068   0.00131     0.52    0.607  1.12
PC5        -0.00201   0.00134    -1.50    0.138  1.16
PC6         0.00152   0.00158     0.96    0.342  1.63


Regression Equation

CALAS* = 0.03658 - 0.00186 Gender + 0.000084 City + 0.00053 Ins. Mth.
+ 0.00165 PC1
         + 0.00085 PC2 + 0.00178 PC3 + 0.00068 PC4 - 0.00201 PC5 + 0.00152 PC6

Fits and Diagnostics for Unusual Observations
Obs   CALAS*      Fit     Resid  Std Resid
 17  0.06151  0.03830   0.02321       2.35  R
 23  0.06151  0.03775   0.02376       2.36  R
 26  0.03467  0.03290   0.00178       0.45  X
 39  0.01027  0.04036  -0.03009      -2.93  R
 51  0.01730  0.04301  -0.02572      -2.50  R
 52  0.06151  0.04043   0.02107       2.05  R

R  Large residual
X  Unusual X


Durbin-Watson Statistic

Durbin-Watson Statistic =  1.81638


No evidence of lack of fit (P >= 0.1).
```

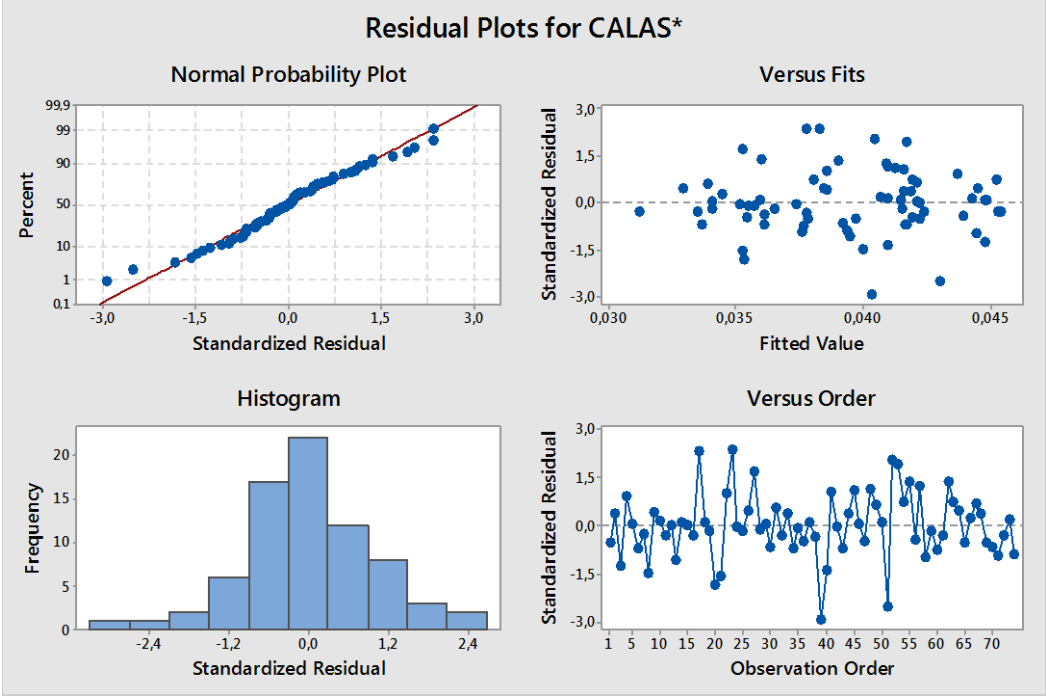


Figure 5. 21. *Residuals Plots for* ***CALAS****

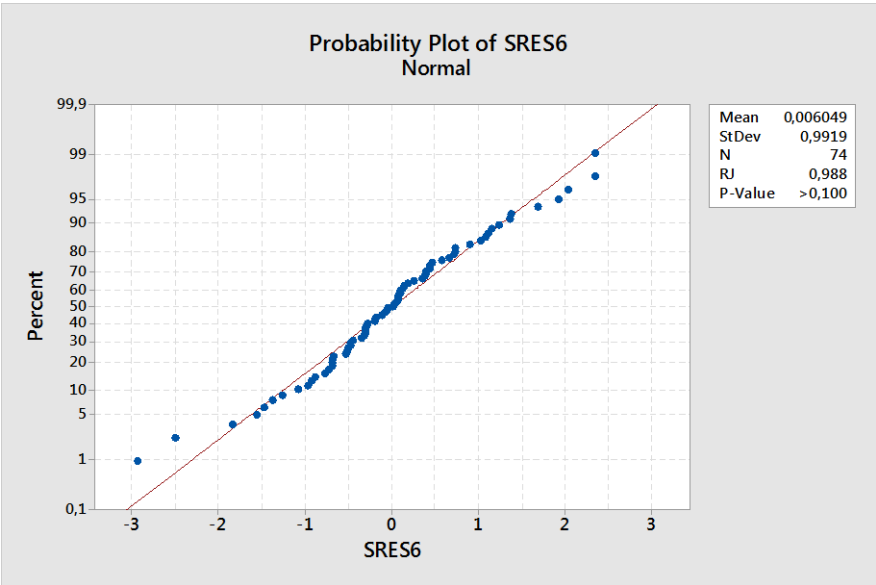


Figure 5. 22. *Normal probability plot of residuals*

After the transformation, the normality assumption was satisfied ($p > 0.1$). Based on a set of residual analysis plots given in Fig. 5.21, we could also state that normality

assumption was satisfied since the data points have scattered on the line and histogram of residuals has a symmetric shape. Since statistically significant lack-of-fit was not detected ($\rho > 0.1$), it was decided that the model was adequate in representing the relation between the mean response and independent variables. Based on the plot of residuals versus fitted values in Fig. 5.21, we might state that homogeneity of variance assumption was satisfied. To make a formal decision on homoscedasticity assumption, Breusch-Pagan test was conducted. The critical value at the 0.05 significance level for a Chi-square statistic with 9 degrees of freedom is found as 13.219. The p-value for this test was 0.153 which was larger than 0.05. Therefore, the test for checking the validity of the assumption resulted in homogeneous error variance. To check uncorrelated errors assumption, D-W test was conducted. Corresponding critical values at 0.05 significance level are d_L=1.369 and d_U=1.901 according to D-W table. The statistic was 1.816 which was between the lower and upper bound. Since D-W statistic value was between lower and upper bound, it was stated that the test was inconclusive. Multicollinearity assumption was assessed using VIF values which suggested the absence of multicollinearity. According to the regression outputs and related graphs shown in Table 5.23, Fig. 5.21 and Fig. 5.22, all of the model assumption were satisfied. However, as seen in the output, none of the explanatory variables are significant. As a result of the analysis, those independent variables does not explain the response variable.

CHAPTER 6

CONCLUSION

The purpose of this study was to examine the impact of CAI with the simulation-animation activities prepared in R programme on eighth grade students' achievement on probability subjects and attitudes towards CAI while demographic factors, technology ownership of the students, technological equipment and environment of the school factors taken into consideration. By taking the research questions into consideration, this chapter provides the main conclusions of the study. The first section of this chapter presents the findings from first data reduction method. The second section presents the findings from the second data reduction method, namely CATPCA. The chapter ends with limitations and implications of the study.

6.1 Results Concerning First Data Reduction Method

As aforementioned in the analysis section, two state-village schools were combined according to their similarities in terms of technological equipment of those schools and social-economical statues of the families. Therefore, Dereyanı Elementary School and Şehit Öğretmen Fasih Elementary School were accepted as one school, named as state schools, while Bahçeşehir College and Bilkent College were included in the analysis directly. This method provided to exclude those variables that the combined school variable already contains.

6.1.1 Results of OCT2 Scores

According to the results of One-Way ANOVA, there was a significant mean difference on OCT2 scores between schools. While the mean of OCT2 was 8.540 for Bahçeşehir College, means of OCT2 was 7.534 for Bilkent College, 6.044 for

Dereyanı Elementary School and 5.961 for Şehit Öğretmen Fasih Söğüt Elementary School. According to the mean comparisons with respect to the OCT2 scores, achievement level is higher in Bahçeşehir College educated with CAI, while it is lower in Şehit Öğretmen Fasih Söğüt Elementary School educated with traditional instruction method as shown in Table 6.1.

Table 6. 1. *Grouping Information Using the Tukey Method and 95% Confidence*

V	N	Mean	Grouping
3	22	8.540	A
4	14	7.534	A
1	17	6.044	B
2	21	5.961	B

Means that do not share a letter are significantly different.

Multiple regression analysis was used to test which explanatory variable was significant factor in explaining students' achievement on OCT2 score. The results of the regression indicated that the first term mathematics grade was a significant factor and explained 74.10% of the variance ($R^2 = 75.16\%$ and $R^2_{adj} = 74.10\%$, F-value=70.61, p<0.05).

In accordance with the regression analysis result, it could be concluded that just the first term mathematics grade was significant for explaining probability achievement of the students. The teaching method was founded as insignificant. That shows that we don't have enough evidence towards the effectiveness of the animation programs including the sub-learning area, namely probability and event types, of Probability and Statistics learning area of 8th grade mathematics curriculum. Also, all the relevant variables containing the information of technological equipment of schools, socio-economic statues of the students were found as insignificant; that means those variables did not explain the success of students. As a result, we could conclude that

if the students in the study had a good pioneer mathematics knowledge, s/he might be successful in the probability subject too regardless of other explanatory variables mentioned in the study.

6.1.2 Results of CALAS Scores

According to the results of One-Way ANOVA, there was not a significant mean difference on CALAS scores between schools, F-value = 1.62, p =0.192. First-, second-, third-, and fourth-school students did not differ on the CALAS (see Table 6.2 for means).

Table 6. 2. *Mean for CALAS Score*

Means

V	N	Mean	StDev	95% CI
1	19	0.04132	0.00847	(0.03652; 0.04611)
2	19	0.03554	0.01063	(0.03074; 0.04033)
3	22	0.04209	0.01310	(0.03763; 0.04654)
4	14	0.03814	0.00768	(0.03255; 0.04372)

MLR model was fitted on CALAS score to identify the factors affecting students' attitude towards CAI. According to the results of the regression model based on attitude towards CAI, there was no significant relationship between the attitude towards CAI and explanatory variables. It was concluded that our data do not support any evidence on the effect of the animation programs on students' attitudes towards CAI.

6.1.3 Results of OCT1 Scores

OCT1 were only applied to the state-village schools, namely Dereyanı Elementary School and Şehit Öğretmen Fasih Söğüt Elementary School located in Mardin. Multiple regression analysis was used to test the effects of instruction method and other factors on OCT1 score. The results of the regression indicated the two predictors explained 30.5% of the variance ($R^2 = 30.5\%$ and $R^2_{adj} = 26.6\%$, F-

value =7.70, $p<0.05$). It was found that V13: Use of computer/internet for other things as PS3 (β = 23.378, $p<.005$) and V14: Instruction method (CAI and Traditional Instruction) (β =11.403, $p<.005$) have a significant effect on OCT1 scores. Considering the results obtained, two sample t test was conducted to determine whether the means of OCT1 differed according to schools and to identify with which instruction type students obtained better results. Dereyanı Elementary School students (Mean = 37.7, SD =16) reported significantly higher scores on OCT1 than Şehit Öğretmen Fasih Söğüt Elementary School students (Mean = 26.32, SD = 9.32), (t-value = 2.68, $p<0.05$). In the light of the analysis results, we concluded that instruction types affected students' learning. While students taught via CAI got higher results, the others taught via traditional instruction got lower scores on OCT1. As a result, we could indicate that the part of animation program including the sub-learning area, namely identifying possible cases, of Probability and Statistics learning area of 8th grade mathematics curriculum was an effective CAI material. In order to understand whether the same deduction would be obtained for OCT2 results, we built another regression model on OCT2- scores between those state schools. According to the results of regression model on scores, none of the variables were significant. Therefore, we could conclude that only the part of animation program including the sub-learning area, namely identifying possible cases, of Probability and Statistics learning area of 8th grade mathematics curriculum was an effective CAI material.

To sum up, only first term mathematics grade (V15) significantly contributed to eight grade students' probability achievement- OCT2. This result was also supported by the literature. Subject matters such as fraction, percentage, decimal numbers (Garfield and Ahlgren, 1988; Memnun, 2008), the concept of cluster and proportional reasoning (Memnun, 2008) were stated in the literature as prerequisite knowledge enhancing success of learning probability subject. Demographic factors, cultural effect, technology ownership of the students, technological equipment and environment of the school factors did not determine success of eight grade students' permutation-combination and probability achievement. Comparing two state-village schools, CAI via R animation program was found to be a more effective teaching method than traditional instruction for permutation-combination subjects on eight

grade. However, the same deduction was not valid for probability subjects. The result might be due to the quality of the prepared animation program. Finally, it was concluded that animation in R programme had no significant effect on attitude toward CAI.

6.2 Results Concerning Second Data Reduction Method-CATPCA

The number of explanatory variables was too many to fit a MLR model. Therefore, CATPCA- nonlinear PCA was used to reduce the data. As a result of the CATPCA analysis, six principal components obtained by 6-dimensional CATPCA solution on 20 variables were decided to be used in the regression analysis. Principal component-1 (PC1) is "The general success of the students and basic socio-economic and technological factors affecting this situation." Principal component-2 (PC2) is "the secondary social situation of the family." Principal components 3 through 6 (PC3-PC6) are related with internet ownership and use. MLR model including those six principal components, gender, city and instruction method was fitted to investigate the effects of CAI to mathematical achievement and attitude of students towards CAI.

6.2.1 Results of OCT2 Scores

Multiple regression analysis was fitted to explain the relationship between OCT2 scores and the explanatory variables; six principal components, gender, city and instruction method. The results of the regression indicated that two predictors explained 58.25% of the variance ($R^2 = 58.25\%$ and $R^2_{adj} = 56.46\%$, F-value=32.55, $p<0.05$). It was found that PC1 (β = 17.9, $p<.005$) and interaction between PC1 and PC2 (β = 6.41, $p<.005$) have significant effects on OCT2 scores. PC1 includes the variables: Overall GPA, Math Average Grade, Father's and Mother's Education Levels, Income, Settlement, School Attitude and Tablet Use in class. According to the Overall GPA, Math Average Grade variables included in PC1, we can conclude that the general success of the students is an important predictor of achievement in probability subject. In addition, socioeconomic factors such as family income and father's and mother's education levels seem to

significantly influence a student's ability to succeed. Also, technological factors present in schools have positive impact on student's success. Factors related with the secondary social situation of the family, such as number of siblings, is not significantly related with student performance; but the interaction between these factors with PC1 seem to significantly influence a student's ability to succeed. Lastly, it is also concluded that gender, city and instructional method do not have a significant effect in students' probability performance.

6.2.2 Results of CALAS Scores

MLR model was fitted on CALAS score with these variables; gender, city, instruction method and six principal components to understand which factors contributed students' attitude towards CAI. The results of the regression model indicated that none of the explanatory variables significantly explained students' attitude towards CAI.

6.2.3 Results of OCT1 Scores

Since OCT1 scores were obtained only for the students having education in Mardin, city variable has been removed from the equation. Then, MLR model was fitted on OCT1 score with these variables; gender, instruction method and six principal components. The results of the regression indicated that instruction method explained 31.65% of the variance ($R^2 = 31.61\%$ and $R^2_{adj} = 29.54\%$, F-value=15.25, $p<0.05$). It was found that instruction method (β =12.75, $p<.005$) has a significant effect on OCT1 scores. Although, general success of the students and basic socio-economic and technological factors affecting this situation and interaction of those factors with the secondary social situation of the family has a significant effect on OCT2 score, all those factors do not contribute to the results of OCT1 score.

In the light of the findings obtained by the statistical analyses, the results could be summarized as follows:

1. Instruction method is an insignificant factor in explaining students' achievement in OCT2 including the sub-learning area, namely probability and event types, of Probability and Statistics learning area of eighth grade mathematics curriculum. According to the first data reduction method, just the first term mathematics grade significantly contributes to students'

achievement on OCT2, while all the relevant variables containing the information of technological equipment of schools, socio-economic statues of the students do not. However, in addition to the first term mathematics grade, socio-economic and technological factors significantly influence a student's ability to succeed with respect to second data reduction method-CATPCA. The advantage of CATPCA in the analysis is that correlated variables are included in principal components, thereby all the relevant factors are included in the analysis.

2. According to the results obtained by two data reduction methods, none of the variables included in the analysis contributes students' attitude towards CAI. Therefore, it is concluded that CAI material prepared in R programme does not significantly affect students' attitude towards CAI.
3. Instruction method is a significant factor in explaining students' achievement in OCT1 including the sub-learning area, namely identifying possible cases, of Probability and Statistics learning area of eight grade mathematics curriculum with respect to the result of the two data reduction methods. In the light of the analysis results, we concluded that instruction types affected students' learning.

6.3 Limitations of the study

- This study is limited to eighth grade students in two state and one private elementary schools in Mardin and a private elementary school in Ankara, during the spring semester of the 2015-2016 academic year. Because the sample is limited with 74 students in total, it might not reflect the general population. Therefore, the results of the study cannot be generalized to other contexts.
- This study is limited to the sub-learning area of "Probability and Statistics" units of the eighth grade mathematics curriculum, namely permutation-combination and probability. Due to the fact that the researcher was also a teacher at one of the schools in Mardin, it was not possible to apply the CAI to all schools at the specified academic time because of time limitation.

- Due to the limitation of time and appropriate conditions, it was impossible to cover all contents of the sub-learning area, permutation-combination-probability in private schools as an example. As a result of these circumstances, only the “Probability” topic was introduced via R software to the private schools.
- Another limitation, since there was no adequate technological equipment in all schools and the cities where the schools located were far away from each others, the pilot study could not be conducted for the CAI material prepared in R programme. However, there was no problematic situation faced throughout the implementation in the actual study.
- Content validity and reliability of the Objective Comprehension Tests was not analyzed by the researcher. It was assumed to be applied by the General Manager of Measurement, Assessment and Exam Services of MoNE.
- Due to the requirement of other programs in addition to the R such as java and html, the last animation could not be completed effectively in R.

6.4 Implications of the study

The first significance of this study is related to education area. In the light of literature review, it is stated that concepts of probability cannot be learned due to various reasons in our country as well as in many foreign countries (Gürbüz, 2006). Related literature demonstrates that there are many difficulties in learning and teaching probability concepts. One of the reasons is explaining probability concepts with an abstract instruction and lack of suitable instructional material about probability subject (Aksu, 1990; Gürbüz, 2006). This study aims to eliminate the lack of suitable instructional material in probability teaching by using computer and educational software. The study is supposed to encourage the administrators, principals and educators to concentrate the use of CAI in every field of education. The second significance of this study is related to statistics area. In the behavioral and social sciences, researchers have to deal with a huge number of variables, which they want to reduce to a less number of principals by losing as little information as possible (Linting, Groenen and Kooji, 2007). Traditional PCA might be thought as

an appropriate method to apply such a data reduction. However, traditional PCA is not a suitable method of data reduction for categorical variables, since variables in PCA are assumed to be scaled at numeric level (interval or ratio level of measurement) and also linear relationship among variables are required. Alternative to traditional PCA, CATPCA/ NLPCA overcomes the limitations of PCA. Although there are excessive number of examples on the use of PCA, there are limited resources about the application of CATPCA. This study aims to be an example of the use of CATPCA in the education area which is also a social science.

REFERENCES

Alpar, R. (2013). *Çok değişkenli istatistiksel yöntemler.* Ankara: Detay.

Akinsola, M. K., and Animasahun, I. A. (2007). The effect of simulation-games environment on students achievement and attitudes to mathematics in secondary schools. *The Turkish Online Journal of Educational Technology, 6*(3), 113-119.

Aksu, M. (1990). Problem areas related to statistics in training teachers of mathematics in Turkey training teachers to teach statistics. Proceedings of the International Statistical Institution. (pp. 127-137). Voorburg, Holland.

Aksu, H. H. (2008). Öğretmen adaylarının matematik öğretimine yönelik öz-yeterlilik inançları. *Education journal of Abant İzzet Baysal University, 8*(2), 161-170.

Alakoç, Z. (2003). Matematik öğretiminde teknolojik modern öğretim yaklaşımları. *The Turkish Online Journal of Educational Technology, 2*(1), 43-49.

Andiç, T. (2012). İlköğretim 8. Sınıf matematik dersi permütasyon kombinasyon konusunun bilgisiyar destekli öğretiminin öğrenci erişi düzeylerine ve tutumlarına etkisi. (Master's thesis, Yeditepe University, İstanbul, Türkiye).

Anthony, G., and Walshaw, M. (2009). Characteristics of effective teaching of mathematics: A view from the West. *Journal of Mathematics Education, 2*(2), 147-164.

Aqda, M. F., Hamidi, F. and Rahimi, M. (2011). The comparative effect of computer-aided instruction and traditional teaching on student's creativity in math classes. *Procedia Computer Science, 3*, 266–270.

Arslan, A. (2008). Web destekli öğretimin ve öğretimsel materyal kullanımının öğrencilerin matematik kaygısına , tutumuna ve başarısına etkisi, (Dissertation, Marmara University, İstanbul, Türkiye).

Aydın, E. (2005). The use of computers in mathematics education: A paradigm shift from "computer assisted instruction" towards "student programming. The Turkish Online Journal of Educational Technology, *4*(2), 27-34.

Baki, A., Çatlıoğlu H., Coştu, S., and Birgin, O. (2009). Conceptions of high school students about mathematical connections to the real-life. *Procedia Social and Behavioral Sciences, 1*, 1402–1407.

Batanero, C., Biehler, R., Maxara, C., Engel, J., and Vogel, M. (2005). Using simulation to bridge teachers´ content and pedagogical knowledge in probability. *Proceedings of the 15th ICMI Study Conference: The Professional Education and Development of Teachers of Mathematics*, 1-6. January 2005-Águas de Lindóia, Brazil.

Bayturan, S. (2012). The effect of computer-assisted instruction on the achievement and attitudes towards mathematics of students in mathematics education. *International Journal of Global Education –IJGE, 1*(2), 50-57.

Bendel, R. B., and Afifi, A. A. (1977). Comparison of stopping rules in forward "stepwise" regression. *Journal of the American Statistical Association, 72*(357), 46-53.

Blevins, B. M. (2009). *Effects of socioeconomic status on academic performance in Missouri Public Schools.* (Dissertation, University of Lindenwood, Kingshighway St, St Charles, USA).

Birgin, O., Çatlıoğlu, H., Çoçtu, S., and Aydın, S. (2009). The investigation of the views of student mathematics teachers towards computer-assisted mathematics instruction. *Procedia Social and Behavioral Sciences, 1,* 676–680.

Borovcnik, M. G., and Kapadia, R. (2010). Research and developments in probability education internationally. In *Proceedings of the British Congress for Mathematics Education.* (pp. 41-48).

Braun, W. J., White, B. J., Craig, G. (2013). R tricks for kids. *Teaching Statistics Trust, 36*(1), 7-12.

Brown, J. D. (2009). Choosing the right type of rotation in PCA and EFA. *Shiken: JALT Testing & Evaluation SIG Newsletter, 13*(3), 20-25.

Bull, G. (2009). Tutor, tool, tutee: A vision revisited. *Contemporary Issues in Technology and Teacher Education, 9*(2), 89-94.

Bulut, S. (2001). Investigation of performances of prospective mathematics teachers on probability. *Educational Journal of Hacettepe University,* 20, 33 -39.

Burrill, G. (2002). *Simulation as a tool to develop statistical understanding*. Paper presented at the Sixth International Conference on Teaching Statistics, Cape Town, South Africa.

Butler, R. W. (1982). Bounds on the significance attained by the best-fitting regressor variable. *Journal of the Royal Statistical Society. Series C (Applied Statistics), 31*(3), 290-292.

Can, R. (2010). Cabri geometri ile hazırlanan bir ders tasarımının öğretmen adaylarının gelişmelerine etkisinin incelenmesi, (Master's thesis, Marmara University, İstanbul, Türkiye).

Chernoff, E. J. and Sriraman, B. (2014). *Probabilistic thinking.* New York: Springer.

Chiesi, F. and Primi, C. (2008). Primary school children's and college students' recency effects in a gaming situation. 11th International Congress on Mathematics Education. (pp. 1-8). Monterrey, Mexico.

Cingi, C. C. (2013). Computer aided education. *Social and Behavioral Sciences, 103*(1), 220-229.

Creswell, J.W. (2012). Educational research: Planning, conducting, and evaluating quantitative and qualitative research. Lincoln: Pearson.

Çelik, H. C. and Çevik, M. N. (2011, September). The effect of computer-assisted instruction on teaching the unit of "probability and statistics" to 7th grade primary school students. 5th International Computer & Instructional Technologies Symposium, Fırat University, Elazığ, Türkiye.

Çelikler, D., Aksan, Z. (2011). The effect of computer assisted instruction in teaching ionic compounds on pre-service elementary science teacher's academic achievement and permanent learning environment. *Social and Behavioral Sciences, 28*(1), 547-552.

Ersoy, Y. (2003). Teknoloji destekli matematik öğretimi-2: Hesap makinesinin matematik etkinliklerinde kullanılması. *Elementary Online Journal, 2*(2), 35-60.

Dementiev, Y., Burulko, L. and Suvorkova, E. (2015). Pedagogical aspects of applied software packages and computer technologies use in student's education. *Social and Behavioral Sciences, 206*(1), 289-294

Dollard, C. (2011). Preservice elementary teachers and the fundamentals of probability. *Statistics Education Research Journal, 10*(2), 27-47.

Dudeney, G. (2000). *The internet and the language classroom a practical guide for teachers.* Cambridge University Press.

Earle, R.S. (2002). The Integration of instructional technology into public education: Promises and challenges. *Educational Technology Magazine, 42*(1), 5-13.

Ely, D. P., and Plomp, T. (1986). The promises of educational technology: A reassessment. *International Review of Education, 32*(3), 231-249.

Everitt, B. and Hothorn, T. (2011). *An introduction to applied multivariate analysis with R.* New York: Springer.

Farooq, M. S., Chaudhry, A. H., Shafig, M., Berhanu, G. (2011). Factors affecting students' quality of academic performance: A case of secondary school level. *Journal of Quality and Technology Management, 7*(2), 01-14.

Ferreira, R. D. S., Kataoka, V. Y., and Karrer, M. (2014). Teaching probability with the support of the R statistical software. *Statistics Education Research Journal, 13*(2), 132-147.

Fırat, S. (2011). *Bilgisayar destekli eğitsel oyunlarla gerçekleştirilen matematik öğretiminin kavramsal öğrenmeye etkisi.* (Master's thesis, Adıyaman

University, Adıyaman, Türkiye).Field, A. (2009). *Discovering statistics using SPSS for windows*. London– Thousand Oaks –New Delhi: Sage publications.

Fraenkel, J. R., Wallen, N. E. and Hyun, H. H. (2011). *How to design and evaluate research in education.* New York: McGraw-Hill.

Gal, I. (2005). Towards 'probability literacy' for all citizens. In G. Jones (ed.), *Exploring probability in school: Challenges for teaching and learning* (pp. 43-71). Kluwer Academic Publishers.

Garfield, J., Ahlgren, A. (1988). Difficulties in learning basic concepts in probability and statistics: Implications for research. *Journal for Research in Mathematics Education, 19*(1), 44-63.

Gürbüz, R. (2006). Olasılık kavramlarının öğretimi için örnek çalışma yapraklarının geliştirilmesi. *Educational Journal of Çukurova University, 31*(1), 111-123.

Gürbüz, R. (2006). Olasılık kavramlarıyla ilgili geliştirilen öğretim materyallerinin öğrencilerin kavramsal gelişimine etkisi. *Educational Journal of Dokuz Eylül University,* 20, 59-68.

Gürbüz, R. (2008). Olasılık konusunun öğretiminde kullanılabilecek bilgisayar destekli bir materyal. Educational Journal of *Mehmet Akif Ersoy University, 8*(15), 41-52.

Hall, I.J. (1972). Some comparisons of tests of equality of variances. *Journal of Statistical and Computational Simulation, 1,*183-194.

Han, O. B., Halim, N. D. B. A., Shariffuddin, R. S. B., and Abdullah, Z. B (2013). Computer based courseware in learning mathematics: potentials and constrains. *Procedia - Social and Behavioral Sciences, 103,* 238 – 244.

HodnikČadež, T., Škrbec, M. (2011). Understanding the concepts in probability of pre-school and early school children. *Eurasia Journal of Mathematics, Science and Technology Education, 7*(4), 263-279.

Işık, A., Konyalıoğlu, A. (2005). Visualization approach in mathematics education. *Educational Journal of Kazım Karabekir University,* (11), 463-471.

Ilk, O. (2015). *R yazılımına giriş, 2. baski.* Ankara: Odtü Yayıncılık.

Jabbar, M., Aziz, M. A., Zeb, S. (2011). A study on effect of demographic factors on the achievement of secondary school students in the Punjab, Pakistan. *International Journal of Academic Research in Business and Social Sciences, 1*(1), 63-76.

Jackson, L. A., Eye, A. V., Biocca, F. A., Barbatsis, G., Zhao, Y., Fitzgerald, H. E. (2006). Does home internet use influence the academic performance of low-income children?. *American Psychological Association, 42*(3), 429-435.

Jolliffe, I. T. (2002). *Principal components analysis* (2nd Ed.). New York: Springer.

Jones, S. and Tanner, H. (2002). Teachers' interpretations of effective whole-class interactive teaching in secondary mathematics classrooms. *Educational Studies, 28*(3), 265-274.

Karamustafaoğlu, O., Aydın, M., and Özmen, H. (2005). Bilgisayar destekli fizik etkinliklerinin öğrenci kazanımlarına etkisi: basit harmonik hareket örneği. *The Turkish Online Journal of Educational Technology, 4*(4), 67-81.

Keeler, C., Steinhorst, K. (2001). A new approach to learning probability in the first statistics course. *Online Journal of Statistics Education, 9*(3). (http://www.amstat.org/ publications /jse/v9n3/keeler.html)

Kemalbay, G., Korkmazoğlu, Ö. B. (2014). Categorical principal component logistic regression: a case study for housing loan approval. *Procedia- Social and Behavioral Sciences,* 19, 730-736.

Kenar, İ., Balcı, M. (2013). Öğrencilerin derslerde teknoloji ürünü kullanımına yönelik tutumu: bir ölçek geliştirme çalışması, *Mustafa Kemal University Journal of Social Sciences Institute, 10*(22), 249-262.

Kırılmazkaya, G., Keçeci G., and Zengin, F. (2014). The effect of computer assisted instruction in science and technology course to teachers and students' attitudes and achievements. *International Journal of Social Science, 30*, 453-466.

Kibar, Z. (2006). *İlköğretim düzeyi fen bilgisi öğretiminde yüksek etkileşimli bdö yazılımlarının öğrenci başarısına etkisi.* (Master's thesis, University of Dokuz Eylül, İzmir, Türkiye).

Koparan, T. and Yılmaz, G. K. (2015). The effect of simulation-based learning on prospective teachers' inference skills in teaching probability. *Universal Journal of Educational Research, 3*(11), 775-786.

Köse, S., Ayas, A. and Taş, G.E. (2003). Bilgisayar destekli öğretimin kavram yanılgıları üzerine etkisi: fotosentez. *Pamukkale University Education Faculty Journal, 14*(2), 106-112.

Köse, N. Y. (2008). İlköğretim 5. Sınıf Öğrencilerinin dinamik geometri yazılımı cabri geometriyle simetriyi anlamlandırmalarının belirlenmesi: Bir eylem araştırması, (Dissertation, Anadolu University, Eskişehir, Türkiye).

Kulik, J. A., Kulik, C. C. and Drowns, R. L. B. (1985). Effectiveness of computer-based education in elementary schools. *Computers in Human Behavior, 1*, 59-74.

Linting, M., Meulman, J. J., Groenen, P. J. F., and Van der Kooij, J. J. (2007). Nonlinear principal components analysis: introduction and application. *Psychological Methods,* 12, 336-358.

Linting, M., and Van der Kooij, A. (2012). Nonlinear principal components analysis with CATPCA: a tutorial. *Journal of Personality Assessments, 94*(1), 12-25.

Lopes, C. A. E., Moura, A. R. L. (2002, July). *Probability and statistics in elementary school: a research of teachers' training1.* Paper presented at International Association for Statistical Education: ICOTS6, Cape Town, South Africa.

Mair, P., de Leeuw, J. (2010). A general framework for multivariate analysis with optimal scaling: The R package aspect. *Journal of statistical software, 32*(9), 1-23.

Meifeng, L., Jinjiao, L. and Cui, K. (2010). Educational technology in China. *Journal of Educational Technology, 41*(4), 541-548. Doi:10.1111/j.1467-8535.2010.01094.x

Mendes, G. H. de S., Ganga, G. M. D. (2013). Predicting success in product development: The application of principal component analysis to categorical data and binomial logistic regression. *Journal of technology management & innovation, 8*(3), 83-97.

Memnun, D. S. (2008). Difficulties of learning probability concepts, the reasons why these concepts cannot be learned and suggestions for solution. *Educational Journal of İnönü University, 9*(15), 89-101.

Milli Eğitim Bakanlığı, (2005). *Ortaöğretim matematik (9-12. sınıflar) dersi öğretim programı.* Ankara: Milli Eğitim Bakanlığı Talim Terbiye Kurulu Başkanlığı.

Ministry of National Education. (2009b). *İlköğretim Matematik Dersi 6-8. Sınıflar Öğretim Programı.* Retrieved May 21, 2016 from http://ttkb.meb.gov.tr/

Ministry of National Education (MoNE). (2013). *İlköğretim Matematik Dersi 6-8. Sınıflar Öğretim Programı.* Retrieved May 21, 2016 from http://ttkb.meb.gov.tr/www/guncellenen-ogretim-programlari/icerik/151

Montgomery, D.C., Peck, E.A. and Vining, G.G. (2012). *Introduction to linear regression analysis, 5th edition.* New York: John Wiley.

Mut, A. İ. (2003). *Investigation of Students' probabilistic misconceptions.* (Master's thesis, Middle East Technical University, Ankara, Türkiye).

National Council of Teachers of Mathematics (2000). *Principles and standards for school mathematics*. Reston, Va.: Author.

Neter, J., Wasserman, W., and Kutner, W. (1990). *Applied linear statistical models,* Boston: PWS-Kent.

Nikiforidou, Z. and Pange, J. (2010). Teachers' evaluation of preschool educational software: the case of probabilistic thinking. *Procedia Social and Behavioral Sciences, 9,* 537-541.

Njenga, D. N. (2010). *Seventh-grade curriculum in probability (a guide for teachers).* (Master's thesis, Louisiana State University, Baton Rouge, USA).

Özdamar, K. (2011). *Paket programlar ile istatistiksel veri analizi.* Eskişehir: Kaan.

Öztürk, G. (2005). *İlköğretim 8. Sınıf düzeyinde permütasyon ve olasılık ünitesinin bilgisayar destekli öğretim tasarımı.* (Master's thesis, Balıkesir University, Balıkesir, Türkiye).

Pilli, O. (2008). *The effects of computer-assisted instruction on the achievement, attitudes and retention of fourth grade mathematics course.* (Dissertation, Middle East Technical University, Ankara, Türkiye).

Salout, S. S., Behzadi, M. H., Shahvarani A., and Manuchehri, M. (2013). Students' conception about the relation of mathematics to real-life. *Mathematics Education Trends and Research, 1*, 1-7.

Serin, O. (2011). The effects of the computer-based instruction on the achievement and problem solving skills of the science and technology students. *TOJET: The Turkish Online Journal of Educational Technology, 10*(1), 183-201.

Souza, L. O. (2015). Collaborative training for teaching probability and statistics: Empirical approaches and simulation with elementary school students. *Proceedings of the Satellite conference of the International Association for Statistical Education (IASE)*, 2-6: July 2015- Rio de Janeiro, Brazil.

Stohl, H. (2005). Probability in teacher education and development. In G. A. Jones (Ed.), *Exploring probability in school: Challenges for teaching and learning* (pp. 297-324). New York: Springer.

Sulaiman, T., Abdurahman A. R. and Rahim, S. S. A. (2010). Teaching strategies based on multiple intelligences theory among science and mathematics secondary school teachers. *Procedia Social and Behavioral Sciences, 8*(1), 512–518.Şahin, T., Yıldırım, S. (1999). *Öğretim teknolojileri ve materyal geliştirme*. Ankara: Anı.

TIMSS, (1999). International Mathematics Report: Retrieved May 20, 2016, from http://timss.bc.edu/timss1999i/pdf/T99i_Math_All.pdf

TIMMS, (2015). International Mathematics Report: Retrieved January 5, 2017, from https://nces.ed.gov/pubs2017/2017002_timss_2015_results.pdf

Toros, S., and Yeşiltaş, E. (2015). The effect on overcoming misconceptions of computer assisted instruction in teaching social studies. *International Journal of Social Science, 39(1)*, 157-172.

Tsakiridou, H., Vavyla, E. (2015). Probability concepts in primary school. *American Journal of Educational Research, 3*(4), 535-540.

Tunalı, S. and Batmaz I. (2000). Dealing with the least squares regression assumptions in simulation metamodeling. *International Journal of Computers and Industrial Engineering, 38,* 307-320.

Tunalı, S. and Batmaz I. (2003). A metamodeling methodology involving both qualitative and quantitative input factors. *European Journal of Operational Research, 150,* 437-450.

Tutkun, Ö. F., Öztürk B. and Demirtaş, Z., (2011, April). Software in mathematics teaching and their impact. *2nd international conference on new trends in education and their implications.* (pp. 691-698). Antalya, Turkey.

Uşun, S. (2000). *Dünyada ve Türkiye'de bilgisayar destekli öğretim*. Ankara: PegamA.

Van de Walle, J. A. (2004). *Elementary and middle school mathematics: Teaching developmentally.* Virginia: Pearson.

Weissglass, J. (2002). Inequity in Mathematics Education: Questions for Educators. *The Mathematics Educator, 12*(2), 34-39.

Yağcı, F. (2010). *The effect of instruction with concrete models on eighth grade students' probability achievement and attitudes toward probability.* (Master's thesis, Middle East Technical University, Ankara, Türkiye.)

Yenilmez, K., Uysal, E. (2007). The primary school students' level of the ability of establishing relation the mathematical expression and symbols wıth daily life. *Educational Journal of Ondokuz Mayıs University,* (24), 89-98.

Young, A. G., Pearce, S. (2013). A beginner's guide to factor analysis: Focusing on exploratory factor analysis. *Tutorials in quantitative methods for psychology, 9*(2), 79-94.

Yushau, B., Mji, A., and Wessels, D. C. J. (2005). The role of technology in fostering creativity in the teaching and learning of mathematics. *Pythagoras, 62,* 1-22.

Zieffler, A., and Garfield, J. B. (2007). Studying the role of simulation in developing students' statistical reasoning. In *Proceedings of the 56*th *Session of the International Statistical Institute*, Lisboa, 22–29 August 2007. Voorburg, The Netherlands: International Statistical Institute.

APPENDIX A

OBJECTIVE COMPREHENSION TEST 1- OCT1

1. $C(n, 2) = 15$ olduğuna göre n kaçtır?

A) 4 B) 5
C) 6 D) 7

2. Düzlemdeki 10 noktadan 5 tanesi doğrusaldır. Köşeleri bu 10 noktadan herhangi üçü olan <u>en çok</u> kaç üçgen çizilebilir?

A) 50 B) 100
C) 110 D) 120

3. 9 öğrenci arasından 4 kişilik bir ekip, bu ekip içerisinden de bir başkan seçilecektir. Bu seçimin kaç farklı şekilde yapılabileceği aşağıdakilerden hangisi ile hesaplanabilir?

A) $C(9,4).C(4,1)$
B) $P(9,4).P(4,1)$
C) $C(9,4)+C(4,1)$
D) $P(9,4)+C(4,1)$

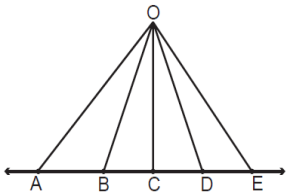
4. $C(12,2)+C(12,10)$ işleminin sonucu kaçtır?

A) 66 B) 132
C) 198 D) 264

5. $C(n,r) = 84$ ve $P(n,r) = 504$ olduğuna göre r kaçtır?

A) 3 B) 4
C) 5 D) 6

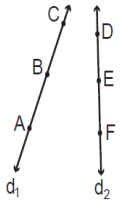
6.



Yukarıda verilen A, B, C, D ve E noktaları doğrusal olduğuna göre şekilde <u>en fazla</u> kaç farklı üçgen vardır?

A) 4 B) 5
C) 8 D) 10

7.



Yukarıda A, B, C noktaları d_1 ve D, E, F noktaları d_2 doğrusu üzerinedir. Köşeleri bu noktalardan herhangi üçü olan <u>en fazla</u> kaç farklı üçgen oluşturulur?

A) 9 B) 12
C) 18 D) 20

8. I. 20.19
II. $C(20,2)$
III. $P(20,2)$

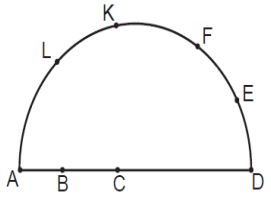
20 kişilik bir sınıftan bir başkan ve bir başkan yardımcısı seçilecektir. Bu seçimin <u>en fazla</u> kaç farklı biçimde yapılabileceği yukarıdaki ifadelerden hangisi ya da hangileri ile hesaplanabilir?

A) Yalnız I B) Yalnız II
C) I ve II D) I ve III

9. Bir topluluktaki kişilerle oluşturulacak 4 kişilik farklı grupların sayısı aynı topluluktan oluşturulacak 5 kişilik farklı grupların sayısına eşittir. Buna göre bu topluluktan 2 kişilik <u>en fazla</u> kaç farklı grup oluşturulur?

A) 48 B) 36
C) 24 D) 18

10.



Yukarıda verilen [AD] çaplı yarım çember üzerindeki 8 nokta kullanılarak <u>en çok</u> kaç farklı doğru çizilebilir?

A) 23 B) 26
C) 28 D) 29

11. Birbirinden farklı 2 türkçe, 3 matematik ve 3 tarih kitabı bir rafa aynı tür kitaplar bir arada olmak şartıyla yan yana <u>en fazla</u> kaç farklı şekilde yerleştirilir?

A) 54 B) 72
C) 216 D) 432

12. 6 çeşit çorba ve 8 çeşit yemek arasından bir çeşit çorba ve iki çeşit yemek <u>en fazla</u> kaç farklı şekilde seçilir?

A) 34 B) 96
C) 168 D) 366

APPENDIX B

OBJECTIVE COMPREHENSION TEST 2- OCT2

8. SINIF MATEMATİK — KAZANIM KAVRAMA TESTİ — TEST 23

Olasılık ve Olay Çeşitleri

1. I. Bir zar atıldığında üst yüzüne 3 gelme olasılığının $\frac{1}{6}$ olması

II. Burak'ın deprem olma olasılığının %70 olduğunu söylemesi

III. 100 kere atılan bir madeni paranın 48'inin tura geldiğini gören Sinem'in paranın 101. kez atıldığında tura gelme olasılığını hesaplaması

Yukarıda verilen ifadelerde sırasıyla hangi olasılık çeşitleri vardır?

A) Teorik - Öznel - Deneysel
B) Teorik - Deneysel - Öznel
C) Deneysel - Öznel - Teorik
D) Öznel - Teorik - Deneysel

2. Zeynep bir madeni parayı 60 kez havaya atıyor. Paranın üst yüzüne 35 kez tura, 25 kez yazı geliyor. Zeynep'in 61. atışında madeni paranın üst yüzüne yazı gelme olasılığı nedir?

A) $\frac{5}{7}$ B) $\frac{7}{12}$
C) $\frac{5}{12}$ D) $\frac{25}{61}$

3. Nur yağmur yağma olasılığını % 25, Ece ise % 40 olarak tahmin ediyor. Bu tahminlerde hangi olasılık çeşidi kullanılmıştır?

A) Öznel Olasılık B) Deneysel Olasılık
C) Kesin Olasılık D) Teorik Olasılık

4. Dört öğrenci bir zarı atarak üst yüzüne 1 gelme olasılığını hesaplamak istiyor. Ece zarı 10 kere atıyor ve 3 kere 1 geliyor. Poyraz zarı 25 kere atıyor ve 12 kere 1 geliyor. Mert zarı 50 kere atıyor ve 29 kere 1 geliyor. Burcu zarı 100 kere atıyor ve 41 kere 1 geliyor. Buna göre bu dört öğrencinin deneylerindeki 1 gelme olasılıkları hesaplandığında hangi öğrencinin sonucu teorik olarak 1 gelme olasılığına daha yakındır?

A) Ece B) Poyraz
C) Mert D) Burcu

5. Renkleri dışında tüm özellikleri aynı olan 3 mor, 7 pembe, 5 mavi bilye bir torbaya konuluyor. Torbaya geri atılmamak şartıyla rastgele çekilen iki bilyeden birincinin mor ikincinin mavi olma olasılığı nedir?

A) $\frac{1}{15}$ B) $\frac{1}{14}$
C) $\frac{1}{10}$ D) $\frac{1}{8}$

6. Bir hesap makinesinin 0'dan 9'a kadar olan tuşlarına art arda rastgele 4 kez basılarak bir sayı üretiliyor. Bu sayının 9070 olma olasılığı nedir?

A) $\frac{24}{5040}$ B) $\frac{24}{10\,000}$
C) $\frac{1}{5040}$ D) $\frac{1}{10\,000}$

7. $A = \{1, 2, 3\}$ kümesinin elemanları ile yazılabilecek iki basamaklı sayılar eşit büyüklükteki kartlara yazılarak bir torbaya atılıyor. Bu torbadan geri atılmamak şartıyla rastgele iki kart çekiliyor. Çekilen kartlardan birincisinin üzerinde çift sayı ikincisinin üzerinde asal sayı yazıyor olma olasılığı nedir?

A) $\frac{1}{9}$ B) $\frac{2}{9}$

C) $\frac{1}{6}$ D) $\frac{5}{6}$

8. 12 kız, 10 erkek öğrenci arasından art arda ve rastgele seçilen 3 öğrencinin üçününde kız olma olasılığı nedir?

A) $\frac{15}{121}$ B) $\frac{3}{22}$

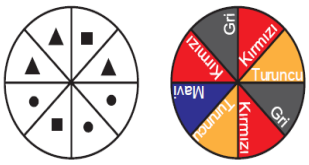
C) $\frac{1}{7}$ D) $\frac{1}{4}$

9. Bir kutuda 8'i bozuk 15 tane eş büyüklükte yumurta vardır. Bu kutudan geri koymamak şartıyla rastgele iki yumurta seçiliyor. Seçilen yumurtalardan birincisinin bozuk ikincisinin sağlam olma olasılığı nedir?

A) $\frac{1}{56}$ B) $\frac{4}{15}$

C) $\frac{15}{56}$ D) $\frac{15}{29}$

10.



1.Dart 2.Dart

Verilen daire biçimindeki dartlar eşit büyüklükteki dilimlerden oluşmaktadır. Bu dartlara fırlatılan iki oktan birisi 1. darta diğeri 2. darta saplanıyor. Saplanan okların kare ve kırmızı rengin olduğu dilimler üzerine gelme olasılığı nedir?

A) $\frac{1}{6}$ B) $\frac{5}{36}$

C) $\frac{1}{9}$ D) $\frac{3}{32}$

11. Bir şekerlikte renkleri dışında tüm özellikleri aynı olan eşit sayıda sarı, yeşil ve mor şekerler vardır. Şekerlikten geri atılmamak şartıyla rastgele çekilen iki şekerden ikisinin de sarı olma olasılığı $\frac{3}{29}$'tür. Buna göre şekerlikte kaç şeker vardır?

A) 27 B) 30

C) 33 D) 36

12. 18 öğrencinin bulunduğu bir sınıfta erkek öğrencilerin sayısı kız öğrencilerin sayısının 2 katıdır. Bu sınıftan art arda rastgele iki öğrenci seçiliyor. Seçilen öğrencilerden ilkinin kız ikincinin erkek olma olasılığı nedir?

A) $\frac{1}{72}$ B) $\frac{2}{9}$

C) $\frac{4}{17}$ D) $\frac{1}{4}$

APPENDIX C

COMPUTER ASSISTED LEARNING ATTITUDE SCALE (CALAS)

ADI:

SOYADI:

Teknoloji Tutum Ölçeği	Kesinlikle Katılıyorum	Katılıyorum	Kararsızım	Katılmıyorum	Kesinlikle katılmıyorum
1. Matematik dersinde kullanılan teknoloji benim bilimsel becerilerimi arttırır.					
2. Matematik dersinde teknoloji kullanılması, konuları daha iyi öğrenmeme yardımcı olur.					
3. Matematik dersinde teknolojinin kullanılmasından hoşlanırım.					
4. Matematik dersinde teknolojiyi verimli bir şekilde kullanabilirim.					
5. Matematik dersinde teknolojinin kullanılması ders başarımı arttırır.					
6. Matematik dersinde teknolojinin kullanılması, dikkatimin dağılmasına sebep olur.					
7. Matematik dersinin teknoloji ile daha sık işlenilmesini isterim.					
8. Matematik dersinde teknoloji kullanırken kendimi yetersiz hissederim.					
9. Matematik dersinde teknoloji kullanmak, öğrenmemi zorlaştırır.					
10. Matematik dersinde teknoloji kullanılmasının başarıma olumlu bir katkısı yoktur.					
11. Matematik dersinde teknoloji kullanılması beni endişelendirir.					
12. Matematik dersinde teknoloji kullanımında kendime güvenirim.					
13. Matematik dersinde teknoloji kullanırken kendimi çaresiz hissederim.					
14. Matematik dersinde teknolojiyi başarılı bir şekilde kullanamam.					
15. Teknoloji ile güncel hayattan örnekler verilmesi matematik dersine yönelik ilgimi arttırır .					

APPENDIX D

DEMOGRAPHIC SURVEY

Değerli Öğretmenim,

Bu anket Orta Doğu Teknik Üniversitesi'nde yürütülen bir yüksek lisans tez çalışması kapsamında veri toplamak amacıyla hazırlanmıştır. Anketin amacı, ortaokul 8.sınıf öğrencilerinin matematik öğrenme başarısını belirlemek amacıyla okulunuzun teknolojik (bilgisayar, internet vb.) sahipliğini ve donanımı hakkında bilgi toplamaktadır. Bu ankete katılım, tamamen gönüllülük esasına dayanmaktadır. Anketteki sorulara vereceğiniz yanıtlar sadece bu çalışma için kullanılacaktır.

Vereceğiniz samimi cevaplarınız gerçeği yansıtması açısından önemlidir.

Yardımınız ve katılımınız için şimdiden çok teşekkür ederiz.

Tuğba KAPUCU- Prof. Dr. İnci BATMAZ
Orta Doğu Teknik Üniversitesi, Fen Bilimleri Enstitüsü
İstatistik Anabilim Dalı

1. **Cevaplayanın Cinsiyeti** *

   a-) Kadın [1]

   b-) Erkek [2

2. **Yaşadığınız İl***

   [ ]

3. **Yaşadığınız Yerleşim Yeri** *

   a-) Köy [1]

   b-) Kasaba [2]

   c-) İlçe [3]

   d-) İl [4]

4. **Annenizin Eğitim Durumu** *

   a-) Okuma Yazması Yok [1]

   b-) Okur-Yazar [2]

   c-) İlkokul Mezun [3]

d-) Ortaokul Mezunu [4]

e-) Lise Mezunu [5]

f-) Lisans Mezunu [6]

g-) Yüksek Lisans Mezunu [7]

h-) Doktora Mezunu [8]

ı-) Diğer: ...<u>.....</u> [ ]

(Belirtiniz)

5. Babanızın Eğitim Durumu *

a-) Okuma Yazması Yok [1]

b-) Okur-Yazar [2]

c-) İlkokul Mezunu [3]

d-) Ortaokul Mezunu [4]

e-) Lise Mezunu [5]

f-) Lisans Mezunu [6]

g-) Yüksek Lisans Mezunu [7]

h-) Doktora Mezunu [8]

ı-) Diğer: ...<u>.....</u> [ ]

(Belirtiniz)

6. Kardeş Sayısı (Siz Dahil) *

a-) Tek Çoçuk [1]

b-) 2 [2]

c-) 3 [3]

d-) 4 [4]

e-) 5 [5]

f-) 6 ve daha fazla [6]

7. Eğitim Gören Kardeş Sayısı (Siz Dahil) *

a-) 1 [1]

b-) 2 [2]

c-) 3 [3]

d-) 4 [4]

e-) 5 [5]

f-) 6 ve daha fazla [6]

8. Ailenizin Aylık Ortalama Geliri *

a-) 0-1500 ₺ [1]

b-) 1501-3000 ₺ [2]

c-) 3001- 5000 ₺ [3]

d-) 5001- 7000 ₺ [4]

e-) 7001-10000 ₺ [5]

f-) 10001 ₺ ve üstü [6]

9. Size ait veya evde kullandığınız bilgisayarın türü (Lütfen size uygun olan bütün seçenekleri işaretleyiniz.) *

a-) Herhangi bir bilgisayar kullanmıyorum [1]

b-) Dizüstü bilgisayar (Notebook, netbook gibi) [2]

c-) Masaüstü bilgisayar [3]

d-) Tablet [4]

e-) Akıllı Telefon [5]

f-) Diğer: ...<u>.....</u> (Belirtiniz) [ ]

10. İnternete bağlandığınız yer (Lütfen size uygun olan bütün seçenekleri işaretleyiniz.) *

a-) Ev [1]

b-) İşyeri [2]

c-) Okul [3]

d-) Yurt [4]

e-) Kafe [5]

f-) Diğer: ...<u>.....</u> [ ]

(Belirtiniz)

11. Günde kaç saat bilgisayar/internet kullanıyorsunuz? *

a-) Hiç kullanmıyorum [1]

b-) 1 saatten az [2]

c-) 1-3 saat [3]

d-) 4-6 saat [4]

e-) 7-9 saat [5]

f-) 10 saat ve üzeri [6]

12. Bilgisayar ve İnterneti hangi amaçlar için kullanıyorsunuz? (Lütfen size uygun olan bütün seçenekleri işaretleyiniz.) *

a-) Eğlence (Oyun oynamak, müzik dinlemek, sosyal ağlara (facebook, twitter vb.) girmek) [1]

b-) Akademik (Ödev araştırma, bir konuyla ilgili bilgi edinme vb.) [2]

c-) Günlük İşler (İletişim, sohbet, gazete okuma, alışveriş vb.) [3]

d-) Ofis Programları Kullanmak (Word, Excel, Power Point vb.) [4]

e-) Diğer: ...<u>.....</u> [ ]

(Belirtiniz)

Anketimiz burada sona ermiştir. Katıldığınız için çok teşekkür ederiz.

APPENDIX E

SCHOOL TECHNOLOGY EQUIPMENT SURVEY

Değerli Öğretmenim,

Bu anket Orta Doğu Teknik Üniversitesi'nde yürütülen bir yüksek lisans tez çalışması kapsamında veri toplamak amacıyla hazırlanmıştır. Anketin amacı, ortaokul 8.sınıf öğrencilerinin matematik öğrenme başarısını belirlemek amacıyla okulunuzun teknolojik (bilgisayar, internet vb.) sahipliğini ve donanımı hakkında bilgi toplamaktadır. Bu ankete katılım, tamamen gönüllülük esasına dayanmaktadır. Anketteki sorulara vereceğiniz yanıtlar sadece bu çalışma için kullanılacaktır.

Yardımınız ve katılımınız için şimdiden çok teşekkür ederiz.

Vereceğiniz samimi cevaplarınız gerçeği yansıtması açısından önemlidir.

Tuğba KAPUCU- Prof. Dr. İnci BATMAZ
Orta Doğu Teknik Üniversitesi, Fen Bilimleri Enstitüsü
İstatistik Anabilim Dalı

* Gerekli

1. **Okulun Bulunduğu İl** *

   [ ]

2. **Okulun Bulunduğu Yerleşim Yeri** *

   a-) Köy [1]

   b-) Kasaba [2]

   c-) İlçe [3]

   d-) İl [4]

3. **Okul Türü***

   a-) Devlet Okulu [1]

   b-) Özel Okul [2]

4. **Okulunuzda var olan teknolojik alt yapıları işaretleyiniz. (Lütfen size uygun olan bütün seçenekleri işaretleyiniz.)** *

a-) Bilgisayar laboratuvarı [1]

b-) Bilgisayar laboratuvarında internet erişimi [2]

c-) Projeksiyon cihazı [3]

d-) Akıllı tahta [4]

e-) Tablet [5]

f-) Diğer: ..... [ ]

(Belirtiniz)

5. **Okulunuzda Bilgisayar ve Eğitim Teknolojileri Öğretmeni var mı? (Cevabınız "EVET" ise lütfen sayı belirtiniz.)***

a-) Evet [1]

b-) Hayır [2]

6. **Okulunuzda ders programı içinde veya özel olarak bilgisayar kullanımı dersi veriliyor mu?**

a-) Evet [1]

7. **Sınıflarda kullanılan her bilgisayar cihazı için yaklaşık bir sayı giriniz.** *

a-) Masaüstü bilgisayar [1]

b-) Dizüstü bilgisayar (Notebook, netbook gibi) [2]

c-) Tablet [3]

d-) Akıllı Telefon [4]

e-) Projeksiyon [5]

f-) Diğer: ..... [ ]

(Belirtiniz)

8. **Okul ortamınızı anlamamıza yardımcı olmak için, okulunuzu sınıflandırınız. (Lütfen size uygun olan sadece bir seçeneği işaretleyiniz.)***

a-) Öğrencilerimizin okuldaki bir bilgisayar cihazını evde, okulda ya da herhangi bir yerde kullanmaya hakkı vardır. [1]

b-) Öğrencilerimizin okuldaki bir bilgisayar cihazını sadece okulda kullanma hakkı vardır. [2]

c-) Her öğrenciye atanmış bir bilgisayar yok, ancak öğrencilerimiz okul ağına ve internete bilgisayar cihazındaki öğrenci profili ile gün boyunca erişim sağlayabilir. [3]

d-) Öğrencilerimizin okuldaki bir bilgisayar cihazını ders dışında kullanma hakkı yoktur. [4]

e-) Öğrencilerimizin okuldaki bir bilgisayar cihazını sadece derslerde ve öğretmen gözetiminde kullanma hakkı vardır. [5]

f-) Öğrencilerimizin okuldaki bir bilgisayar cihazını hiçbir şekilde kullanma hakkı yoktur. [6]

g-) Diğer: ..... [ ]

(Belirtiniz)

9. Okul Yönetiminin derslerde yeni teknolojilerin kullanılmasına karşı tutumu*

a-) Olumlu [1]

b-) Olumsuz [2]

c-) Kayıtsız [3]

d-) Diğer: ..... [ ]

(Belirtiniz)

Anketimiz burada sona ermiştir. Katıldığınız için çok teşekkür ederiz.

APPENDIX F

THE CONSEST FOR PERMISSIONS

UYGULAMALI ETİK ARAŞTIRMA MERKEZİ
APPLIED ETHICS RESEARCH CENTER

ORTA DOĞU TEKNİK ÜNİVERSİTESİ
MIDDLE EAST TECHNICAL UNIVERSITY

DUMLUPINAR BULVARI 06800
ÇANKAYA ANKARA/TURKEY
T: +90 312 210 22 91
F: +90 312 210 79 59
ueam@metu.edu.tr
www.ueam.metu.edu.tr

14 HAZİRAN 2016

Sayı: 28620816 / 286

Konu: Etik Onay

Gönderilen: Prof.Dr. İnci BATMAZ

İstatistik Böl

Gönderen: Prof. Dr. Canan SÜMER

İnsan Araştırmaları Etik Kurulu Başkanı

İlgi: Etik Onayı

Sayın Prof.Dr. İnci BATMAZ'ın danışmanlığını yaptığı yüksek lisans öğrencisi Tuğba KAPUCU'nun "İlköğretim 8. Sınıf Matematik Dersi Permütasyon Kombinasyon ve Olasılık Konusunun Bilgisayar Destekli Öğretiminin Öğrenci Erişi Düzeylerine ve Tutumlarına Etkisi" başlıklı araştırması İnsan Araştırmaları Etik Kurulu tarafından uygun görülerek gerekli onay **2016-EGT-101** protokol numarası ile **10.06.2016-17.11.2016** tarihleri arasında geçerli olmak üzere verilmiştir.

Bilgilerinize saygılarımla sunarım.

Prof. Dr. Canan SÜMER

İnsan Araştırmaları Etik Kurulu Başkanı

Prof. Dr. Meliha ALTUNIŞIK

İAEK Üyesi

Prof. Dr. Ayhan SOL

İAEK Üyesi

Prof. Dr. Mehmet UTKU

İAEK Üyesi

Prof. Dr. Ayhan Gürbüz DEMİR

İAEK Üyesi

Yrd .Doç .Dr. Pınar KAYGAN

İAEK Üyesi

Yrd. Doç. Dr. Emre SELÇUK

İAEK Üyesi

BU BÖLÜM, İLGİLİ BÖLÜMLERİ TEMSİL EDEN İNSAN ARAŞTIRMALARI ETİK ALT KURULU TARAFINDAN DOLDURULACAKTIR.

Protokol No: 2016-EGT101

İAEK DEĞERLENDİRME SONUCU

Sayın Hakem,

Aşağıda yer alan üç seçenekten birini işaretleyerek değerlendirmenizi tamamlayınız. Lütfen "Revizyon Gereklidir" ve "Ret" değerlendirmeleri için gerekli açıklamaları yapınız.

Değerlendirme Tarihi: 14.06.2016

Ad Soyad:

☑ **Herhangi bir değişikliğe gerek yoktur. Veri toplama/uygulama başlatılabilir.**

☐ **Revizyon gereklidir**

- ☐ Gönüllü Katılım Formu yoktur.
- ☐ Gönüllü Katılım Formu eksiktir.

  Gerekçenizi ayrıntılı olarak açıklayınız:
- ☐ Katılım Sonrası Bilgilendirme Formu yoktur.
- ☐ Katılım Sonrası Bilgilendirme Formu eksiktir.

  Gerekçenizi ayrıntılı olarak açıklayınız:
- ☐ Rahatsızlık kaynağı olabilecek sorular/maddeler ya da prosedürler içerilmektedir.

  Gerekçenizi ayrıntılı olarak açıklayınız:
- ☐ Diğer.

  Gerekçenizi ayrıntılı olarak açıklayınız:

☐ **Ret**

Ret gerekçenizi ayrıntılı olarak açıklayınız:

APPENDIX G

ACTIVITY SHEETS

BENİM ŞANSIM NE?

Şans Oyunu olasılık konusunu anlamanı sağlayacak bir oyun.

Her şans oyununda, en sık tekrarlayacak sonucu tahmin etmen

gerekiyor. Daha sonra bu deneyi 10 kez tekrarlayacaksın. Her denemede, bulduğun sonucu "Sonuç" satırına kaydedeceksin.

1. **DENEY:** Bir madeni parayı havaya atma
   Sık tekrarlayan sonuç için tahmin: YAZI TURA

SONUÇ										
TAHMİN										

- Elde ettiğiniz sonuçları sütun grafiğinde gösteriniz. "YAZI" çıktısını belirtmek için siyah, "TURA" çıktısını belirtmek için kırmızı renk kullanınız.

2. **DENEY:** Bir zarı havaya atma
   Sık tekrarlayan sonuç için tahmin: 1 2 3 4 5 6

SONUÇ										
TAHMİN										

- Elde ettiğiniz sonuçları sütun grafiğinde gösteriniz.

3. Aşağıdaki tabloyu yukarıdaki deneylerde elde ettiğiniz sonuçlara göre doldurunuz.

ŞANS OYUNU	OLAY	DENEYSEL OLASILIK	TEORİK OLASILIK
PARA ATMA	YAZI		
PARA ATMA	TURA		
ZAR ATMA	1		
ZAR ATMA	2		
ZAR ATMA	3		
ZAR ATMA	4		
ZAR ATMA	5		
ZAR ATMA	6		

- Her bir şans oyunu için deneysel ve teorik olasılıkları karşılaştırınız.

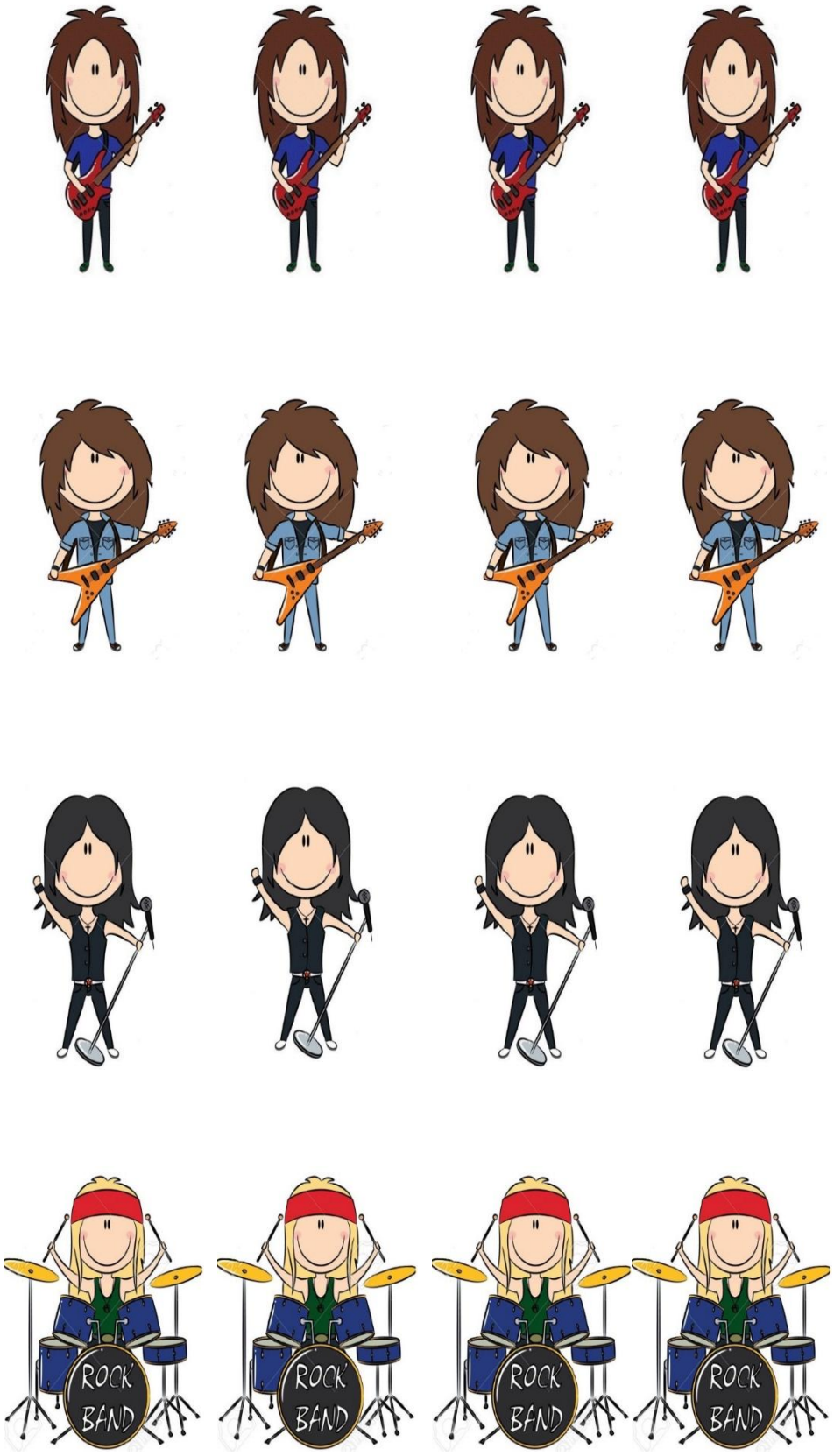
4. Sonuç ile eşleşen bir olayın olasılığını bulmak için bütün sınıfın bulduğu verileri toplayınız. Doğru tahmini denemelerin sayısını ve her birinin deneysel olasılığını kaydediniz. Her grup , her bir şans oyunu için 10 deneme yaptığı için, deneme sayısı 10×grup sayısıdır.

ŞANS OYUNU	OLAY	DENEYSEL OLASILIK	TEORİK OLASILIK
PARA ATMA	YAZI		
PARA ATMA	TURA		
ZAR ATMA	1		
ZAR ATMA	2		
ZAR ATMA	3		
ZAR ATMA	4		
ZAR ATMA	5		
ZAR ATMA	6		

- 4. ve 5. sorulardaki deneysel olasılıklar birbirinden farklı mı? Neden evet ya da hayır?

- Son durumda deneysel olasılık ile teorik olasılık arasında nasıl bir değişim oldu? Daha fazla deneme yapılırsa sonuç nasıl değişir, açıklayınız.

AKTİVİTE KAĞIDI: Müzik Grubu Kuralım☺



Karşınızda birbirinden yetenekli 4 müzisyen... Onlar partilerin, şenliklerin, gösterilerin vazgeçilmezleri... Bu müzisyenler 2'li olarak sahne aldıkları gibi 3'lü ve 4'lü olarak da performans sergiliyorlar. Bu etkinlikte bir müzik grubu kurmak için, müzisyenleri farklı şekilde gruplandıracaksınız.

Kaç farklı kombinasyon olduğunu bulmak için verilen tabloyu kullanınız. Bulmuş olduğunuz tüm olası kombinasyonların listesini yapınız. Sonuca nasıl ulaştığınızı resimlerle ve hesaplamalarla gösteriniz.

- 4 müzisyen arasından seçim yapılarak 2 kişiden oluşan kaç farklı müzik grubu oluşturulabilir?

1. Müzisyen	2. Müzisyen

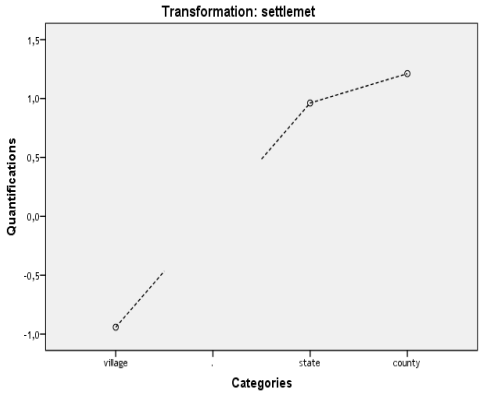
- 4 müzisyen arasından seçim yapılarak 3 kişiden oluşan kaç farklı müzik grubu oluşturulabilir?

1.Müzisyen	2.Müzisyen	3.Müzisyen

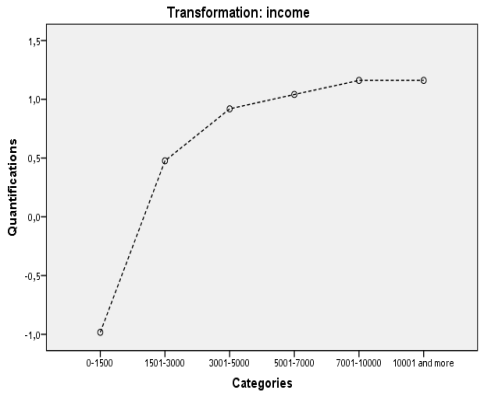
- 4 müzisyen arasından seçim yapılarak 4 kişiden oluşan kaç farklı müzik grubu oluşturulabilir?

APPENDIX H

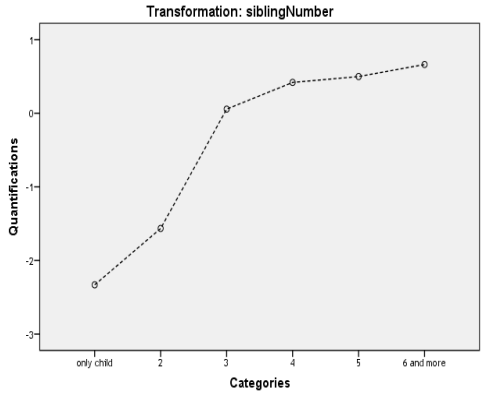
TRANSFORMATION PLOTS OF THE 20 VARIABLES TREATED AT AN ORDINAL SCALING LEVEL IN CATPCA



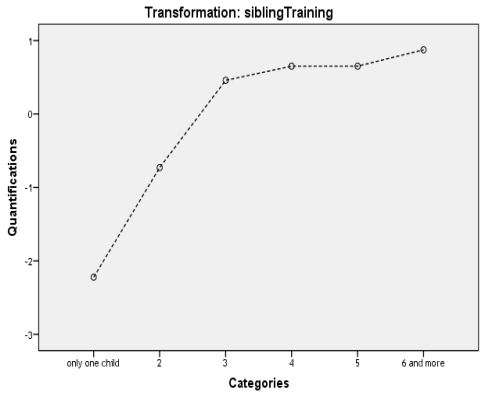
Optimal Scaling Level: Ordinal.
Variable Principal Normalization.



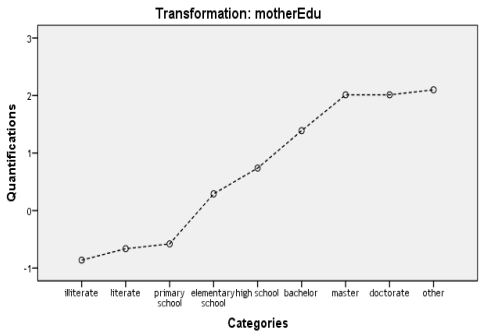
Optimal Scaling Level: Ordinal.
Variable Principal Normalization.



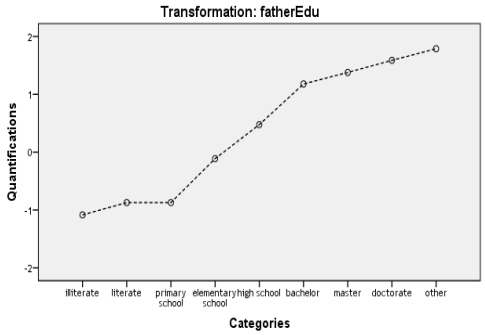
Optimal Scaling Level: Ordinal.
Variable Principal Normalization.



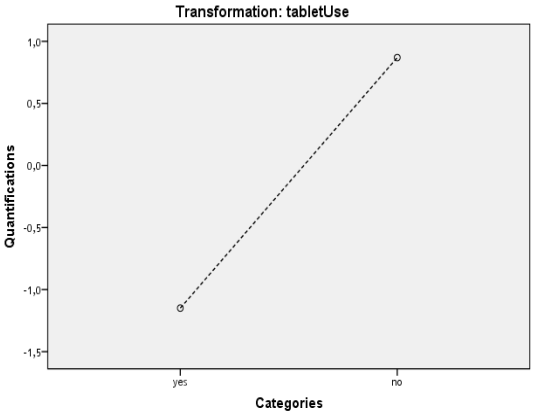
Optimal Scaling Level: Ordinal.
Variable Principal Normalization.



Optimal Scaling Level: Ordinal.
Variable Principal Normalization.

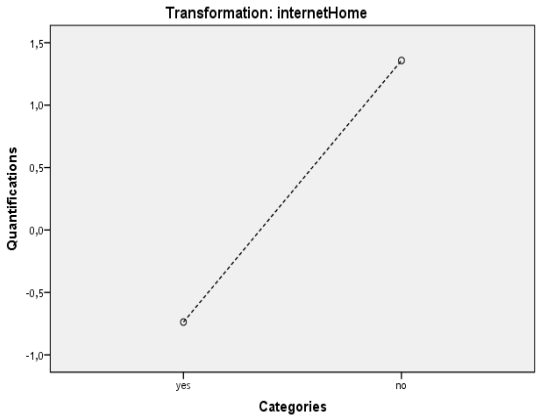


Optimal Scaling Level: Ordinal.
Variable Principal Normalization.



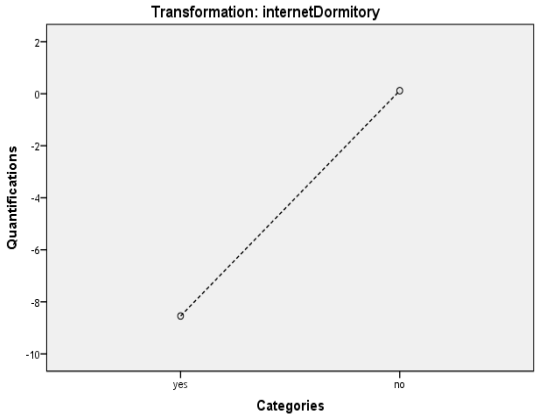
Optimal Scaling Level: Ordinal.

Variable Principal Normalization.



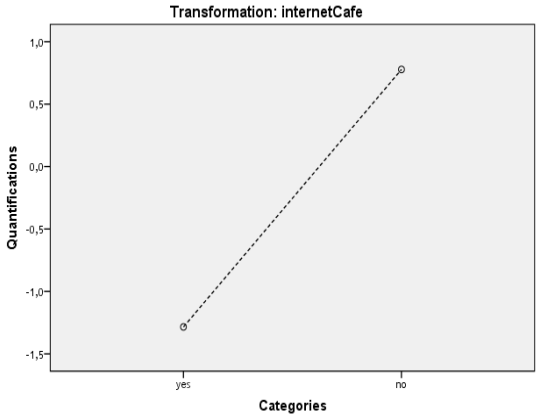
Optimal Scaling Level: Ordinal.

Variable Principal Normalization.



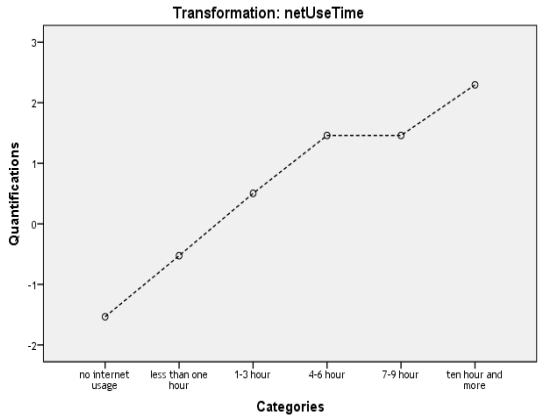
Optimal Scaling Level: Ordinal.

Variable Principal Normalization.



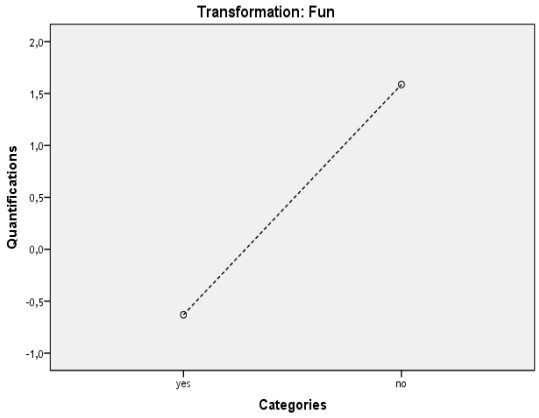
Optimal Scaling Level: Ordinal.

Variable Principal Normalization.



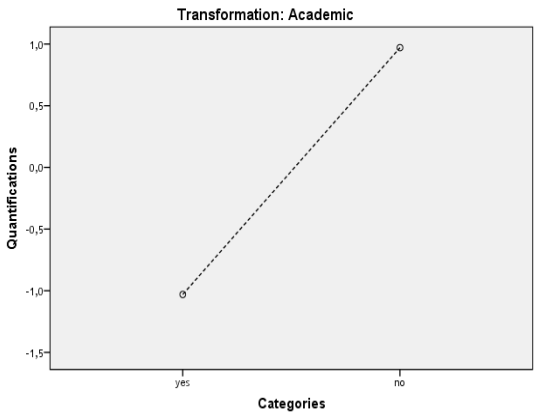
Optimal Scaling Level: Ordinal.

Variable Principal Normalization.

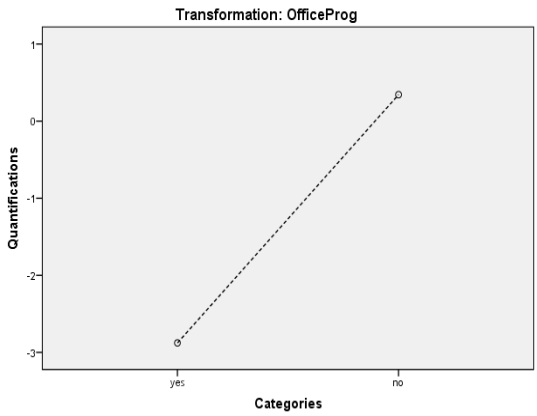


Optimal Scaling Level: Ordinal.

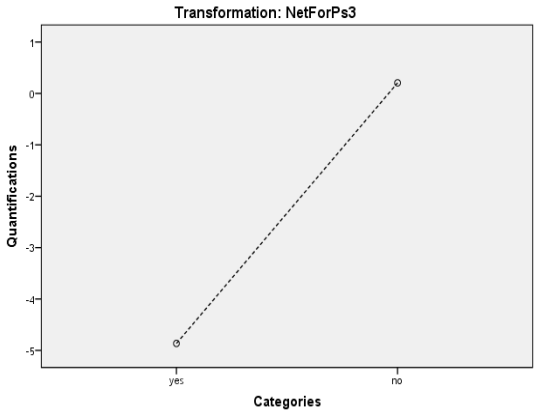
Variable Principal Normalization.



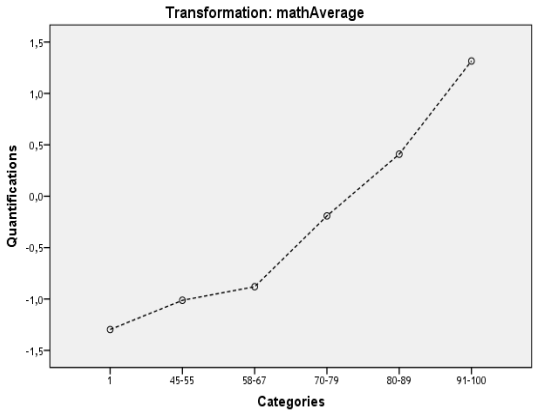
Optimal Scaling Level: Ordinal.
Variable Principal Normalization.



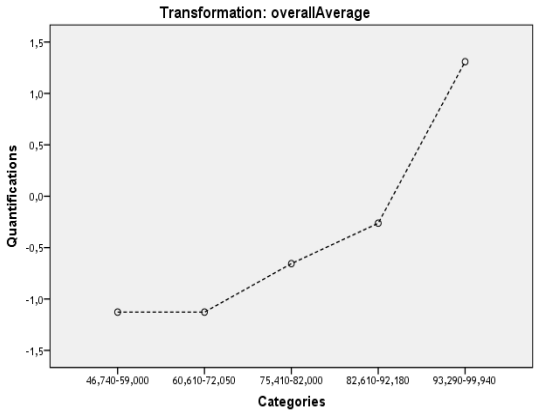
Optimal Scaling Level: Ordinal.
Variable Principal Normalization.



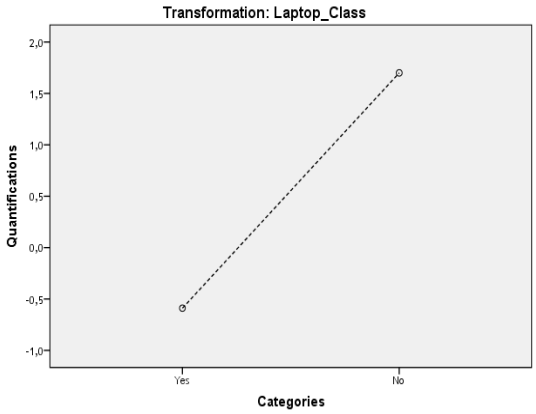
Optimal Scaling Level: Ordinal.
Variable Principal Normalization.



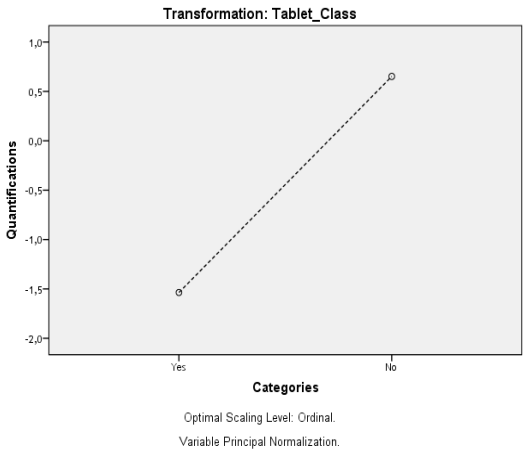
Optimal Scaling Level: Ordinal.
Variable Principal Normalization.

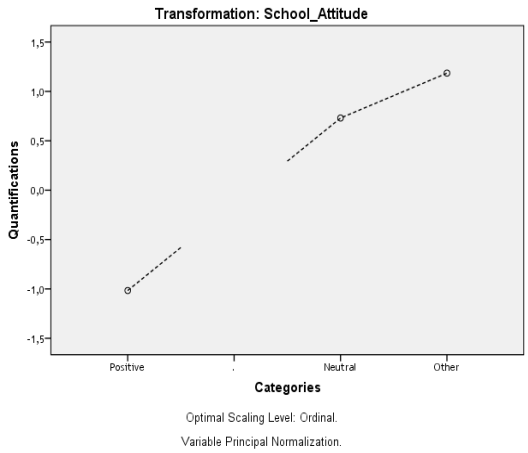


Optimal Scaling Level: Ordinal.
Variable Principal Normalization.



Optimal Scaling Level: Ordinal.
Variable Principal Normalization.





Tablo H. 1. *Unrotated component loadings of the 6-dimensional CATPCA solution on the 20 variables, with all variables analyzed ordinally.*

	Dimension					
	1	2	3	4	5	6
Settlemet	.952	.079	-.092	.041	.119	-.127
MotherEdu	.851	-.365	.007	-.032	.070	-.074
FatherEdu	.897	-.108	.006	.054	.030	-.097
SiblingNumber	-.711	.600	-.037	-.114	-.077	-.077
SiblingTraining	-.448	.655	-.102	-.142	-.118	-.088
Income	.959	.120	-.107	.030	.053	-.068
TabletUse	-.646	.179	.035	.204	.562	-.086
InternetHome	-.578	-.226	-.497	.200	.318	-.262
InternetDormitory	.083	.128	.009	.904	.078	.115
InternetCafe	.066	.662	.407	.037	.286	.432
NetUseTime	.675	-.256	-.294	-.250	-.274	.298
Fun	-.459	.004	.768	-.150	-.116	-.213
Academic	-.292	.292	-.653	-.201	.116	.453
OfficeProg	-.484	.597	-.122	-.050	-.339	-.131
NetForPs3	.038	.153	-.142	.777	-.470	.020
MathAverage	.736	.469	-.091	-.130	-.017	-.120
OverallAverage	.773	.417	-.095	-.093	.137	-.157
Laptop_Class	-.640	-.292	-.551	-.086	-.021	-.225
Tablet_Class	-.511	-.726	210	.013	-.013	.241
School_Attitude	-.958	-.194	-.017	-.044	-.072	.046

Tablo H. 2. *Rotated component loadings from a 5-dimensional CATPCA on 21 variables, with all variables analyzed ordinally.*

	Component				
	1	2	3	4	5
School Attitude	-.907				
Mathematic Average	.902				
Income	.887				
Overall GPA Average	.884				
Settlement	.862				
Tablet Class	-.854				
Father Education	.693	-.547			
Laptop Class	-.618		.520		
Internet School	-.556				
Sibling Number		.883			
Office Prog		.804			
Sibling Training		.797			
Mother Education	.517	-.745			
Net Use Time					
Fun			-.760		
Academic			.737		
Internet Home	-.583		.587		
Internet Dormitory				.895	
Net For Ps3				.828	
Internet Everywhere					.784
Internet Cafe					-.764

Extraction Method: PCA.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 6 iteration

APPENDIX I

R CODES FOR ANIMATIONS

```
#For addition rule


plot(1, type="n", xlim=c(100, 210), ylim=c(300, 350), xaxt='n', yaxt='n', axes =
TRUE, ann = FALSE)
mtext('Bugün Ne Giysem?', side = 3, line = 2)
abline(v=140)
Sys.sleep(1)
pantolon<- readJPEG(system.file("img", "pantolon.jpg", package="jpeg"))
etek<- readJPEG(system.file("img", "etek.jpg", package="jpeg"))
rasterImage(pantolon,100, 300, 125, 320, interpolate = FALSE)
Sys.sleep(1)
rasterImage(etek,100, 330, 125, 350, interpolate = FALSE)

gomlek <- readJPEG(system.file("img", "gomlek (2).jpg", package="jpeg"))
kazak<- readJPEG(system.file("img", "kazak.jpg", package="jpeg"))
kısakol<- readJPEG(system.file("img", "kısakol.jpg", package="jpeg"))
rasterImage(gomlek,155, 330, 170, 350, interpolate = FALSE)
Sys.sleep(1)
rasterImage(kazak,185, 330, 195, 350, interpolate = FALSE)
Sys.sleep(1)
rasterImage(kısakol,165, 300, 180, 320, interpolate = FALSE)
text(locator(1),"üs giyim")
text(locator(1),"alt giyim")




#For multiplication rule


plot(1, type="n", xlim=c(100, 210), ylim=c(300, 350), xaxt='n', yaxt='n', axes =
TRUE, ann = FALSE)
mtext('Bugün Ne Giysem?', side = 3, line = 2)
abline(h=325)
pantolon<- readJPEG(system.file("img", "pantolon.jpg", package="jpeg"))
gomlek <- readJPEG(system.file("img", "gomlek (2).jpg", package="jpeg"))
rasterImage(pantolon,100, 300, 110, 320, interpolate = FALSE)
Sys.sleep(2)
rasterImage(gomlek,100, 330, 110, 350, interpolate = FALSE)
```

```
Sys.sleep(1)
abline(v=115)
Sys.sleep(1)
pantolon<- readJPEG(system.file("img", "pantolon.jpg", package="jpeg"))
kazak<- readJPEG(system.file("img", "kazak.jpg", package="jpeg"))
rasterImage(pantolon,120, 300, 130, 320, interpolate = FALSE)
Sys.sleep(2)
rasterImage(kazak,120, 330, 130, 350, interpolate = FALSE)
Sys.sleep(1)
abline(v=135)
Sys.sleep(1)
pantolon<- readJPEG(system.file("img", "pantolon.jpg", package="jpeg"))
kısakol<- readJPEG(system.file("img", "kısakol.jpg", package="jpeg"))
rasterImage(pantolon,140, 300, 150, 320, interpolate = FALSE)
Sys.sleep(2)
rasterImage(kısakol,140, 330, 150, 350, interpolate = FALSE)
abline(v=155)
Sys.sleep(1)


etek<- readJPEG(system.file("img", "etek.jpg", package="jpeg"))
gomlek <- readJPEG(system.file("img", "gomlek (2).jpg", package="jpeg"))
rasterImage(etek,160, 300, 170, 320, interpolate = FALSE)
Sys.sleep(2)
rasterImage(gomlek,160, 330, 170, 350, interpolate = FALSE)
Sys.sleep(1)
abline(v=175)
Sys.sleep(1)


etek<- readJPEG(system.file("img", "etek.jpg", package="jpeg"))
kazak<- readJPEG(system.file("img", "kazak.jpg", package="jpeg"))
rasterImage(etek,180, 300, 190, 320, interpolate = FALSE)
Sys.sleep(2)
rasterImage(kazak,180, 330, 190, 350, interpolate = FALSE)
Sys.sleep(1)
abline(v=195)
Sys.sleep(1)

etek<- readJPEG(system.file("img", "etek.jpg", package="jpeg"))
kısakol<- readJPEG(system.file("img", "kısakol.jpg", package="jpeg"))
rasterImage(etek,200, 300, 210, 320, interpolate = FALSE)
Sys.sleep(2)
rasterImage(kısakol,200, 330, 210, 350, interpolate = FALSE)


test1 <- readJPEG(system.file("img", "pantolon.jpg", package="jpeg"))
test2 <- readJPEG(system.file("img", "gomlek (2).jpg", package="jpeg"))
```

```
plot(1, type="n", xlim=c(100, 150), ylim=c(300, 350))
mtext('Combinations of Clothing', side = 3, line = 2)
abline(h=325)
rasterImage(test1,100, 300, 120, 320, interpolate = FALSE)
Sys.sleep(2)
rasterImage(test2,100, 330, 120, 350, interpolate = FALSE)
abline(v=125)
test1<- readJPEG(system.file("img", "pantolon.jpg", package="jpeg"))
test3<- readJPEG(system.file("img", "kazak.jpg", package="jpeg"))
rasterImage(test1,130, 300, 145, 320, interpolate = FALSE)
Sys.sleep(3)
rasterImage(test3,130, 330, 145, 350, interpolate = FALSE)


pantolon<- readJPEG(system.file("img", "pantolon.jpg", package="jpeg"))
gomlek <- readJPEG(system.file("img", "gomlek (2).jpg", package="jpeg"))
plot(1, type="n", xlim=c(100, 180), ylim=c(300, 350))
mtext('Bugün Ne Giysem?', side = 3, line = 2)
abline(h=325)
rasterImage(pantolon,100, 300, 120, 320, interpolate = FALSE)
Sys.sleep(2)
rasterImage(gomlek,100, 330, 120, 350, interpolate = FALSE)
abline(v=125)

pantolon<- readJPEG(system.file("img", "pantolon.jpg", package="jpeg"))
kazak<- readJPEG(system.file("img", "kazak.jpg", package="jpeg"))
rasterImage(pantolon,130, 300, 150, 320, interpolate = FALSE)
Sys.sleep(2)
rasterImage(kazak,130, 330, 150, 350, interpolate = FALSE)
pantolon<- readJPEG(system.file("img", "pantolon.jpg", package="jpeg"))
t-shırt<- readJPEG(system.file("img", "t-shırt.jpg", package="jpeg"))
rasterImage(pantolon,160, 300, 180, 320, interpolate = FALSE)
Sys.sleep(2)
rasterImage(t-shırt,160, 330, 180, 350, interpolate = FALSE)




#For combination

plot(1, type="n", xlim=c(100, 210), ylim=c(300, 350), xaxt='n', yaxt='n', axes =
TRUE, ann = FALSE)
mtext('MÜZİK GRUBU KURALIM:)))', col.mtext="red", side = 3, line = 2)
Sys.sleep(1)
gitar<- readJPEG(system.file("img", "gitar.jpg", package="jpeg"))
davul<- readJPEG(system.file("img", "davul.jpg", package="jpeg"))
rasterImage(gitar,100, 315, 120, 340, interpolate = FALSE)
```

```
Sys.sleep(1)
rasterImage(davul,130, 315, 150, 340, interpolate = FALSE)

DJ<- readJPEG(system.file("img", "DJ.jpg", package="jpeg"))
elektro<- readJPEG(system.file("img", "elektro.jpg", package="jpeg"))
rasterImage(DJ,160, 315, 180, 340, interpolate = FALSE)
Sys.sleep(1)
rasterImage(elektro,190, 315, 210, 340, interpolate = FALSE)
Sys.sleep(1)
text(locator(1),"Gitar")
text(locator(1),"Davul")
text(locator(1),"Solist")
text(locator(1),"Elektro Gitar")
text(locator(1),"Bir müzik grubu kurmak için müzisyenleri kaç farklı şekilde
gruplandırabiliriz?")
text(locator(1),"4 müzisyen arasından kaç kişilik müzik grubu kurulabilir?")
Sys.sleep(6)




#For two combination


plot(1, type="n", xlim=c(100, 210), ylim=c(300, 360),, xaxt='n', yaxt='n', axes =
TRUE, ann = FALSE)
mtext('4 Müzisyen arasından seçim yapılarak 2 kişiden oluşan kaç farklı müzik
grubu oluşur?', side = 3, line = 2)

gitar<- readJPEG(system.file("img", "gitar.jpg", package="jpeg"))
davul<- readJPEG(system.file("img", "davul.jpg", package="jpeg"))

rasterImage(gitar,100, 350, 105, 360, interpolate = FALSE)
Sys.sleep(2)
rasterImage(davul,105, 350, 110, 360, interpolate = FALSE)
Sys.sleep(1)


gitar<- readJPEG(system.file("img", "gitar.jpg", package="jpeg"))
DJ<- readJPEG(system.file("img", "DJ.jpg", package="jpeg"))

rasterImage(gitar,100, 340, 105, 350, interpolate = FALSE)
Sys.sleep(2)
rasterImage(DJ,105, 340, 110, 350, interpolate = FALSE)
Sys.sleep(1)
```

```
gitar<- readJPEG(system.file("img", "gitar.jpg", package="jpeg"))
elektro<- readJPEG(system.file("img", "elektro.jpg", package="jpeg"))

rasterImage(gitar,100, 330, 105, 340, interpolate = FALSE)
Sys.sleep(2)
rasterImage(elektro,105, 330, 110, 340, interpolate = FALSE)

Sys.sleep(1)

gitar<- readJPEG(system.file("img", "gitar.jpg", package="jpeg"))
davul<- readJPEG(system.file("img", "davul.jpg", package="jpeg"))
rasterImage(davul,100, 320, 105, 330, interpolate = FALSE)
Sys.sleep(2)
rasterImage(gitar,105, 320, 110, 330, interpolate = FALSE)
Sys.sleep(1)

gitar<- readJPEG(system.file("img", "gitar.jpg", package="jpeg"))
DJ<- readJPEG(system.file("img", "DJ.jpg", package="jpeg"))
rasterImage(DJ,100, 310, 105, 320, interpolate = FALSE)
Sys.sleep(2)
rasterImage(gitar,105, 310, 110, 320, interpolate = FALSE)

Sys.sleep(1)

gitar<- readJPEG(system.file("img", "gitar.jpg", package="jpeg"))
elektro<- readJPEG(system.file("img", "elektro.jpg", package="jpeg"))
rasterImage(elektro,100, 300, 105, 310, interpolate = FALSE)
Sys.sleep(2)
rasterImage(gitar,105, 300, 110, 310, interpolate = FALSE)
abline(v=113)
Sys.sleep(1)


davul<- readJPEG(system.file("img", "davul.jpg", package="jpeg"))
DJ<- readJPEG(system.file("img", "DJ.jpg", package="jpeg"))

rasterImage(davul,115, 350, 120, 360, interpolate = FALSE)
Sys.sleep(2)
rasterImage(DJ,120, 350, 125, 360, interpolate = FALSE)
Sys.sleep(1)

davul<- readJPEG(system.file("img", "davul.jpg", package="jpeg"))
elektro<- readJPEG(system.file("img", "elektro.jpg", package="jpeg"))

rasterImage(davul,115, 340, 120, 350, interpolate = FALSE)
Sys.sleep(2)
rasterImage(elektro,120, 340, 125, 350, interpolate = FALSE)
Sys.sleep(1)
```

```
DJ<- readJPEG(system.file("img", "DJ.jpg", package="jpeg"))
davul<- readJPEG(system.file("img", "davul.jpg", package="jpeg"))
rasterImage(DJ,115, 330, 120, 340, interpolate = FALSE)
Sys.sleep(2)
rasterImage(davul,120, 330, 125, 340, interpolate = FALSE)
Sys.sleep(1)

elektro<- readJPEG(system.file("img", "elektro.jpg", package="jpeg"))
davul<- readJPEG(system.file("img", "davul.jpg", package="jpeg"))
rasterImage(elektro,115, 320, 120, 330, interpolate = FALSE)
Sys.sleep(2)
rasterImage(davul,120, 320, 125, 330, interpolate = FALSE)
Sys.sleep(1)

abline(v=128)

DJ<- readJPEG(system.file("img", "DJ.jpg", package="jpeg"))
elektro<- readJPEG(system.file("img", "elektro.jpg", package="jpeg"))
rasterImage(DJ,130, 350, 135, 360, interpolate = FALSE)
Sys.sleep(2)
rasterImage(elektro,135, 350, 140, 360, interpolate = FALSE)
Sys.sleep(1)

elektro<- readJPEG(system.file("img", "elektro.jpg", package="jpeg"))
DJ<- readJPEG(system.file("img", "DJ.jpg", package="jpeg"))
rasterImage(elektro,130, 340, 135, 350, interpolate = FALSE)
Sys.sleep(2)
rasterImage(DJ,135, 340, 140, 350, interpolate = FALSE)
Sys.sleep(1)

abline(v=143)
text(locator(1),"Belirtilen gruplar birbirinden farklı mı?")

text(locator(1),"Sıra önemli mi?")

text(locator(1),"2 müzisyen 2! şekilde sıralanabilir.")

abline(v=143)
Sys.sleep(1)
text(locator(1),"P(n,r)=n!/(n-r)!")
Sys.sleep(1)
text(locator(1),"P(4,2)=4!/(4-2)!=24/2=12")

Sys.sleep(1)
text(locator(1),"C(n,r)=P(n,r)/r!")
text(locator(1),"C(4,2)=12/2!=6")
```

```
#Rolling dice

role.dice = function(
  faces = 6, prob = NULL, border = 'white', grid = 'white', col = 1:6, type = 'p',
  pch = 22, bg = 'transparent', digits = 3
) {
  nmax = ani.options('nmax')
  if (length(faces) == 1) {
    faces = as.factor(seq(faces))
  }
  else {
    faces = as.factor(faces)
  }
  if (length(faces) < 6)
    stop("'faces' must be at least 6")
  lv = levels(faces)
  n = length(lv)
  res = sample(faces, nmax, replace = TRUE, prob = prob)
  frq = table(res)/nmax
  ylm = max(frq)
  x = runif(nmax, 1.1, 1.9)
  y = runif(nmax, 0, ylm)
  col = rep(col, length = n)
  y0 = numeric(n)
  s = seq(0, ylm, 1/nmax)
  for (i in 1:nmax) {
    dev.hold()
    plot(1, xlim = c(0, 2), ylim = c(0, ylm * 1.04), type = 'n', axes = FALSE,
        xlab = '', ylab = '', xaxs = 'i', yaxs = 'i')
    abline(v = 1)
    axis(1, (1:n - 0.5)/n, lv)
    axis(2)
    mtext('Frequency', side = 2, line = 2)
    mtext('Rolling Dices', side = 4)
    k = as.integer(res[1:i])
    points(x[1:i], y[1:i], cex = 3, col = col[k], type = type, pch = pch, bg = bg)
    text(x[1:i], y[1:i], res[1:i], col = col[k])
    y0[k[i]] = y0[k[i]] + 1
    rect(seq(n)/n - 1/n, 0, seq(n)/n, y0/nmax, border = border, col = col)
    segments(0, s, 1, s, col = grid)
    abline(v = 1)
    axis(3, (1:n - 0.5)/n,
        paste(y0, ' (', round(y0/nmax, digits = digits), ')', sep = ''),
        tcl = 0, mgp = c(0, 0.5, 0))
    axis(1, 1.5, paste('Number of Roles:', i), tcl = 0)
    box()
    ani.pause()
  }
```

```
  invisible(list(freq = as.matrix(frq)[, 1], nmax = i))
}



#Drawing ball

plot.new
plot(1:5,seq(1,10,length=5),type="n",xlab="",ylab="",main="circles")
x = c(2,2,4,4)
y = c(6,2,2,6)
lines(x, y)
axis(1)
axis(2)
a=draw.circle(2.5,2.7,0.23,border="black",
col=c("#ff00ff","#ff77ff","#ffccff"),lty=1,lwd=1)
b=draw.circle(3.5,2.7,0.23,border="black",col="yellow")
c=draw.circle(3,2.7,0.23,border="black",col="yellow")
d=draw.circle(2.5,4,0.23,border="black",col="yellow")
e=draw.circle(3,4,0.23,border="black",col="green")
f=draw.circle(3.5,4,0.23,border="black",col=c("#ff00ff","#ff77ff","#ffccff"),lty=1,lw
d=1)
g=draw.circle(2.5,5.3,0.23,border="black",col="green")
h=draw.circle(3,5.3,0.23,border="black",col="yellow")
ı=draw.circle(3.5,5.3,0.23,border="black",col=c("#ff00ff","#ff77ff","#ffccff"),lty=1,l
wd=1)

Sys.sleep(5)

xx=seq(2.7,7,0.1)
yy=xx
#yy=rep(2.5,44)
zz=seq(1,44)

for(i in zz)
{
dev.hold()
plot(1:5,seq(1,10,length=5),type="n",xlab="",ylab="",main="circles")
x = c(2,2,4,4)
y = c(6,2,2,6)
lines(x, y)
axis(1)
axis(2)

draw.circle(yy[i],xx[i]+0.1*i^2,0.23,border="black",
col=c("#ff00ff","#ff77ff","#ffccff"),lty=1,lwd=1)
b=draw.circle(3.5,2.7,0.23,border="black",col="yellow")
c=draw.circle(3,2.7,0.23,border="black",col="yellow")
```

```
d=draw.circle(2.5,4,0.23,border="black",col="yellow")
e=draw.circle(3,4,0.23,border="black",col="green")
f=draw.circle(3.5,4,0.23,border="black",col=c("#ff00ff","#ff77ff","#ffccff"),lty=1,lw
d=1)
g=draw.circle(2.5,5.3,0.23,border="black",col="green")
h=draw.circle(3,5.3,0.23,border="black",col="yellow")
ı=draw.circle(3.5,5.3,0.23,border="black",col=c("#ff00ff","#ff77ff","#ffccff"),lty=1,l
wd=1)

dev.flush()
Sys.sleep(0.1)
plot.new()
}
```