EVALUATING E-LEARNING ENVIRONMENT BY USING DATA MINING TECHNIQUES

YASEMİN AYDOĞDU

BOĞAZİÇİ UNIVERSITY

2011

EVALUATING E-LEARNING ENVIRONMENT
by
USING DATA MINING TECHNIQUES

Thesis submitted to the

Institute for Graduate Studies in the Social Sciences

in partial fulfillment of the requirements for the degree of

Master of Arts

in

Management Information Systems

by
Yasemin Aydoğdu

Boğaziçi University

2011

Evaluating E-Learning Environment

by

Using Data Mining Techniques

The thesis of Yasemin Aydoğdu

has been approved by

Assoc. Prof. Dr. Zuhal Tanrıkulu ______________________

(Thesis advisor)

Prof. Dr. Meltem Özturan ______________________

Assoc. Prof. Dr. Sevinç Gülseçen ______________________

March 2011

Thesis Abstract

Yasemin Aydoğdu, "Evaluating E-Learning Environment by Using Data Mining Techniques"

Learning is an inevitable life-long process for human beings and today, the concept of continuous learning gets much more acceptance. The demanding nature of today's life conditions force people and corporations to invest in life-long education. It is important to make this continuous learning process more affordable and accessible to larger groups of people. At this point, online learning seems to be an attractive solution.

This fact brings about the core research question guiding this study as: what are the most significant factors influencing e-learning effectiveness? The goal of this study is to develop e-learning effectiveness models and to understand main contributors of e-learning systems.

Corporate e-learning programs are studied in the scope of this study. Learner achievement, learner's course program completion duration, completion or withdrawal decision are selected as key measures of e-learning effectiveness. The effect of learner demographics, learner's e-learning experience, course characteristics and perceived usefulness factors is analyzed via appropriate data mining methods using SPSS 17.0 (Statistical Package for the Social Sciences) tool.

Most of the independent factors (demographics, experience, course program) are discovered to have power at different levels for explaining variance in e-learning effectiveness. Course program characteristics like content, existence of certification are explored having a strong influence on the success of e-learning process.

Tez Özeti

Yasemin Aydoğdu, "Elektronik Öğrenme Ortamlarının Veri Madenciliği Teknikleri ile Değerlendirilmesi"

Öğrenme, yaşam boyu süren vazgeçilemez bir süreçtir ve günümüzde sürekli öğrenme kavramı daha çok kabul görmeye başlamıştır. Talepkar ve dinamik yaşam koşulları, bireyleri ve kurumları yaşam boyu eğitime yatırım yapmaya zorlamaktadır. Önemli olan sürekli eğitimi mümkün olduğu kadar çok kişi için erişilebilir hale getirmektir. Bu nokta da elektronik öğrenme önemli bir çözüm olarak görülmektedir.

Bu olgu, bu çalışmaya yön veren temel araştırma sorusunu ortaya çıkarmıştır: Kurumsal elektronik öğrenmenin verimliliğini ve başarısını etkileyen en önemli faktörler nelerdir? Bu çalışmanin amacı; elektronik öğrenme modelleri geliştirmek ve elektronik öğrenme sistemlerinin verimliliğine katkı sağlayan temel başarı faktörlerini anlamaktır.

Bu çalışma kapsamında kurumsal elektronik öğrenme programları çalışılmıştır. Öğrencinin başarısı, elektronik öğrenme programını bitirip bitiremediği, programı bitirme süresi ve öğrenci memnuniyeti elektronik öğrenme verimliliğinin anahtar göstergeleri olarak seçilmiştir. Çalışmada öğrencinin demografik özelliklerinin, öğrencinin elektonik öğrenme tecrübesinin, elektronik dersin özelliklerinin ve algılanan faydaya ilişkin faktörlerin etkisi uygun veri madenciliği methotları ile SPSS aracı kullanılarak analiz edilmiştir.

Bağımsız faktörlerin birçoğunun başarıdaki varyansı farklı seviyelerde açıklayabildiği sonucu çıkarılmıştır. Elektronik dersin içeriği, sertifikalı olup olmama gibi özelliklerin elektronik öğrenme başarısına daha güçlü etkisi olduğu görülmüştür.

ACKNOWLEDGEMENTS

I would like to express the deepest appreciation to my thesis supervisor Assoc. Prof. Dr. Zuhal Tanrıkulu whose encouragement, guidance and support from the initial to the final level enabled me to complete my thesis. Without his guidance and persistent help this dissertation would not have been possible. I would also like to thank my committee members, Prof. Dr. Meltem Özturan and Assoc. Prof. Dr. Sevinç Gülseçen who devoted their valuable time and energy to this study.

This research was realized at the Information Systems Research and Application Center of Boğaziçi University. It is also a pleasure to thank enocta® for their support.

Lastly, I would like to show my gratitude to my husband, Göktuğ Ataç. This thesis would not have been a real fulfillment without his support and his understanding attitude.

CONTENTS

CHAPTER I: INTRODUCTION

Why is it so important to increase e-learning effectiveness? Learning is an inevitable life-long process for human beings. The conditions in private life, work life and social life force people being faster and less costly in learning activities as in every aspect of life. At this point, online learning seems to be an attractive solution by its current and potential benefits which increase by the advancements in the technology especially in recent years. It seems that with the advantages of online learning, it is possible to enrich the learning experience of human beings and make life-long learning a part of our lives. Indeed, increasing the participation in life-long learning and making 15% of adults participate in lifelong learning programs is aimed to be achieved by European Commission by 2020 (Eurostat, n.d.).

To be able to increase the contribution of e-learning to the overall learning experience, it should be made sure that whether these online activities are really effective and whether there are some influencers on effectiveness or not. It is obvious that some statistical analysis and results may serve for providing insights on the nature of e-learning. For this reason, this study aims to derive some statistical results on e-learning effectiveness and to be able to give e-learning stakeholders some useful directions and recommendations on how to treat to some important e-learning related factors and ultimately, on how to enhance e-learning systems further and make them much more contributive for the learner.

E-Learning Trends

E-Learning has a parallel evolution with the letter “e” which stands for the word “electronic”. As the electronic world offers new concepts, methods and tools, learning in the electronic environment adapts to those trends, simultaneously.

Statistical research has proven that e-learning market has been growing day by day all around the world. In 1999, the USA spent $646 million on education and e-learning's share was $17.2 million and represented a relatively small piece of overall training and education marketplace (Sachs, 2000). In the beginning of 2000s, the USA Federal Government's National Center for Educational Statistics (NCES) reported that 91% of two-year and four-year public universities planned to establish web based courses. NCES indicated that online learning and teaching programs would be 31% of all course registries through 2010. As the statistical outcomes support the fact that e-learning is becoming the most dynamic and popular sector of educational systems. Relatedly, according to the surveys, online learning systems' users have an interest in those new learning opportunities and are satisfied with the current systems at a significant level (Alexander, 2001).

Garrett (2009) reports the e-learning market in the USA in 2008. In the report for-profit, private-non profit and public organizations are compared with respect to their online learning market share. They have market shares as about 30%, 12% and 58% respectively. It is highlighted that interestingly for-profit organizations have a higher share in e-learning compared to their higher education share in general which is 7%.

The overall online enrollments are about 11% of all enrollments in 2008 and it is expected to increase to 20% by 2014. Importantly, even if the ratio is decreased from 69%, 55% of US degree-granting institutions are reported as not offering fully online courses. According to the report, 24% of adults who are over the age 25 take online programs and this ratio is predicted to increase to 35-40% by 2014 (Garrett, 2009).

In his report, Garrett (2009) presents the market share figures with respect to educational level in 2008. Online students with bachelor level make up the largest portion with 46,5%. Associate level is reported as relatively weak in online learning environment due to less number of online programs and less academic experience at this level. Online students with associate level consist up 22.2% of online market. When graduate (master) and doctoral levels are compared, graduate level seems to have strength in the market due to short programs and higher level of academic experience. The market share of graduate and doctoral level is 28.3% and 3% respectively.

The 2010 State of the Industry report on learning market in the USA by the American Society for Training and Development presents figures on e-learning market. It is stated that while formal learning hours which are available online were 23% of all formal learning hours in 2008, it increased to 27,7% in 2009. Moreover, electronic technology was used in 37% of all training hours in 2009 (E-Learning Market Update December 2010, n.d.).

A research study by Learning Light Company reports the situation of UK e-learning market in 2009 and presents the predictions for the following years (Broadhead, Jung, and Patterson, 2009):

- It is reported that e-learning market was not mature in 2009 and has a potential to grow by the acceptance of learning technologies.
- The most significant e-learning demand comes from marketing and communication departments. Industries like automotive and financial services which are affected by the recession also have an increasing demand.
- There are 200 Learning Management Systems (LMS) and 70 Virtual Learning Environments (VLE).
- It is investigated whether advancing technology like open source systems, Web 2.0 and social networking is an opportunity or threat for the companies providing LMS and VLE. It is explored that e-learning companies do not see new technology as a concern. They consider adapting to new technologies and using if appropriate.
- It is explored that new applications of technologies will be increasingly

used. Mobile learning, learning through gaming, TV quality production of learning is among most popular trends. Moreover, the use of e-books, e-reference, e-passports including Smartcards, e-portfolio is reported as becoming a part of e-learning. However, it is highlighted as a concern that there is no cooperation between video games industry and learning technologies industry.

- It is highlighted that more companies will create environmental benefits to the market.
- It is forecasted that increasing number of medium sized companies will adopt e-learning as a result of new rapid tools and Web 2.0. Moreover, pricing models like 'softare as a service' will enable medium sized companies access to larger e-learning applications.
- It is predicted that 47.5% of organizations would use e-learning in 2009.
- It is predicted that the percentage of e-learning expenditure over total training expenditure to be 13% in 2009.
- Total e-learning market revenue is forecasted to be £313 million in 2009.
- Market growth rate is forecasted to decrease, but still a positive trend in growth is predicted with a ratio of 6.7% in 2009.
- UK is compared with other European countries. Scandinavia along with UK is predicted to be the most developed markets with 8% growth rate. Scandinavia market size is forecasted to be £1 billion. French market is reported to be the second biggest market with 15% growth rate and a market size between £300- £350. It is highlighted that UK, Scandinavia and France together make up 80% of the whole European e-learning market.

Learning Light Company conducts the same research study in 2010. In this report, the situation of UK e-learning market in 2010 and the predictions for the following years are presented: (Broadhead, Halton, Jung, and Patterson, 2010)

- It is stated that the e-learning demand may be decreased due to the economic downturn and reductions in the Government expenditures.
- It is predicted that market growth rate will not be greater than 4,76%
- Total e-learning market revenue is forecasted to be £472 million.

Lööf and Seybert (2010) present the figures of the Internet usage for learning in Euperan Union in 2010 based on Eurostat data. Among all Internet users, about 45% of users consult the Internet for learning, 32% searches information on courses and 7% participates in e-learning course. Eurostat data also provides Internet for learning statistics by education level, by age and by employment status. According to 2010 figures, users between 16 and 24 ages benefit from the Internet with highest percent.

It is seen that as age increases, use of the Internet for learning decreases. While about 61% of people between 16 and 24 consult the Internet for learning, it is about 35% for people between 55 and 74. Similarly, the ratio decreases for e-learning course participation. While 9% of people between 16 and 24 participate in e-learning courses, only 3% of older people take e-learning courses. In their report, Lööf and Seybert (2010) make a comparison of the Internet for learning statistics between low, medium and high education levels. Based on the Eurostat data, it is presented that people with high education level take e-learning course with the highest ratio as 10%. Data on employment status shows that unemployed people benefit from the Internet for learning more than employed people.

Further figures on online learning in Europe are provided by Chartered Institute of Personnel and Development (CIPD) which is Europe's largest HR and development professional organization. CIPD carries out annual survey and publish reports on learning and development of organizations. The following figures are retrieved from 2008, 2009 and 2010 annual reports of CIPD.

- Organizations e-learning usage level increased between 2004 and 2008 from 30% to 57%. It is reported that 82% of public sector companies use e-learning, while the ratio is 42% for private sector organizations (Chartered Institute of Personnel and Development [CIPD], 2008).
- Annual Learning and Development survey of CIPD (2009) which was held in UK reports that only 7% of survey respondents consider e-learning as an effective learning method, while it is reported as 12% in Learning and Talent Development survey of CIPD (2010). There is also an increase in the use of e-learning in the organizations. While 42% of organizations report actually using e-learning for their learning activities in 2009 (CIPD, 2009), in 2010, it is highlighted that the most significant increase is explored in e-learning practice compared to other learning activities and it is reported that 49% of companies use e-learning for their learning and talent development activities. 62% of companies mention using e-learning more than in 2009 (CIPD, 2010).
- In annual survey of CIPD (2010), it is highlighted that even if there is an increase in the use of e-learning, it is not rated high for its effectiveness.
- In the report by CIPD (2009), learning specialists are reported to spend only 8% of their time on designing technology-enabled learning environment which was reported as 7% in 2008 (CIPD, 2008).

Not just in the USA or in UK, in most of the European countries, in Asia, all around the world, popularity of e-learning increases and it becomes a part of educational systems. To exemplify, in 1994, a project started in order to increase the number of online learners of Assumption University of Thailand, in Thailand. The project was successful and in 2002, the number of online learners increased from 3000 to 100000 per year (Charmonman, and Chorpothong, 2004)

Kopf (2007) states that the e-learning market in the world would reach to a size of $52.6 billion by 2010, based on the research of Global Industry Analysts, Inc.. It is also reported that e-learning systems are now the second choice of the corporations for the corporate learning and development concerns. The USA is reported as the world’s market leader with a more than 60% corporate e-learning market share. The Europe has the second-largest share with a less than 15%. According to the report by Global Industry Analysts, Inc., Asian e-learning market is predicted to grow at a faster rate and to have a compound annual growth rate between 25% and 30% through 2010. Globalization is considered as an important factor for those high growth rates in Asia. The worldwide growth rate is predicted to become between 15% and 30% through 2010. Besides those best estimate growth rates, an important barrier for the growth is pointed as the non-existence of interoperability standards in the market.

Forecasts on e-learning around the world by 2015 and an analysis of the market for self-paced e-learning products and services are presented in the market analysis report by Adkins (2011). It is reported that the market of e-learning products and services was worth $18,2 billion in the US in 2010 and it is forecasted to reach $24,2 billion by 2015 with a five-year annual compound growth rate as 5,9%. The growth rates between 2010 and 2015 by regions are presented in the report. Asia has the largest growth rate as about 30%. The growth rates of Eastern Europe, Latin America and Africa are about 25%, 18% and 17% respectively. Middle East, Western Europe and North America have relatively lower growth rates as about 8%, 6% and %5 respectively. As a result of these growth rates, North America will have the largest share on self-paced e-learning product expenditures by 2015. While Western Europe had the second largest share in 2010, Asia will have the second largest share after North America by 2015 (Adkins, 2011).

According to the statistics published by TUIK (n.d.), there are 23 million students in formal education in 2009 and 2010 school term, in Turkey. It does not include associate, bachelor and graduate degree students. According to TUIK statistics, in order to provide education for each student, in average, a teacher should be responsible for 29 students and there should be 41 students in each classroom.

It seems that online learning can contribute to formal educational processes by decreasing the number of students in classrooms. Also, according to TUIK (n.d.) statistics, there are nearly 1.5 million students who apply for studying in the universities in 2010. However, the capacity of universities may not meet this demand not just because there are not enough physical locations, but also there is not sufficient academic and administrative staff. Moreover, this limited capacity affects the quality of education. At this point, e-learning is considered as a good solution for Turkey.

However; the culture, the need to train technical staff, students' educational background and habits are highlighted as key issues to be taken into consideration (Altıkardeş, 2004).

There are some reasons of rapid growth of e-learning market. It is obvious that increasing investment in e-learning is directly related to availability of advanced technology. New technologies eliminate inabilities of e-learning significantly, so that crucial characteristics of traditional learning can be provided through online learning to some extent. Face-to-face meetings can be managed via video-conferencing tools, for instance (Galusha, 1997). Use of advanced technology in learning provides some major benefits compared to traditional learning. All learners have access to a large variety of courses. Technology-based systems provide scalability which means learning activities are provided for larger number of people at lower costs. Moreover, intelligent systems have the ability to match learner needs. These systems offer timely update content and provide more effective delivery (Gudanescu, 2010). Odabası's study highlights that computers make the education process smoother with their functions like the Internet, multimedia, audio and visual content. These functions make learners and teachers much more effective throughout the learning and teaching process (as cited in Akdağ and Tok, 2008).

Technology enables learning at a distance and e-learning becomes an effective alternative for individual life-long education. As a result of technology, there are no time and place boundaries in e-learning. This nature of e-learning enables individuals learn at any time and at anywhere (Arbak, Özmen, and Saatçioğlu, 2004). Importantly, its high degree of flexibility in terms of time and place provides equal educational opportunity for students in varying localities. This opportunity is crucial, especially, when high increasing rates in student population are considered (Galusha, 1997).

As mentioned in a study by Alkan, insufficient number of teachers together with increasing number of students, information complexity as a result of the need to transfer much more information to the students, increasing demand for education and higher personal expectations to be able to benefit from educational services also makes e-learning an attractive alternative (as cited in Akdağ and Tok, 2008).

On the other hand, it is sure that change in the nature of the economy has a strong effect in increasing demand of e-learning, as well. As the knowledge-based economy takes the place of product-based economy, knowledge-workers gain value. They can contribute to the organization in a more smart and practical way, with less time and effort. Knowledge gains value and training and education becomes much more valuable and inevitable. Here, the main concerns are time, place and cost-effectiveness and efficiency in order to create benefits for the organization (Gudanescu, 2010; Chao and Chen, 2009) Organizations can decrease internal training costs in the long run and class learning can be supplemented and improved by online self-training (Chao and Chen, 2009). Improved organizational learning supported by e-learning systems leads for establishing good infrastructure for strengthening and expanding the capabilities of the individuals to be able to collaborate and communicate and use specialized knowledge and expertise of others (Galusha, 1997).

Moreover, e-learning creates economies of scale. High quality e-learning material can be duplicated as electronic media and can be made use of over and over again. Learners can access synchronously published material through the Internet anytime, anywhere. This advantage is considered as an opportunity especially for developing countries in which high quality education is limited (Ağaoğlu, and Kırlıdoğ, 2004).

Learning and teaching transformation from teacher-based to leaner-based, in which learners will have the opportunity to discover and learn more on its own is considered as a valuable change. E-learning is considered as a medium for this transformation (Ağaoğlu, and Kırlıdoğ, 2004). It enriches the learning process and makes it more effective by some major benefits provided for the learner. The major advantages are listed as being learner centered, self-paced, active, proactive, constructive, accommodating individual learning styles, collaborative, interactive and so on (Baltaş, Baltaş, Dedehayır, and Sakar, 2004). It provides learners a problem-based learning and makes learners take responsibility and experience a self-directed learning process. E-learning also increases motivation by good design which decreases user concerns about their insufficient technical skills. Importantly, it provides a reflective approach, since there is no class time constraint and all the information is achieved in online environment. Moreover, it supports individual learning styles and experiential learning. It turns the learning experience into both a private and social activity. Lastly, it provides deep and detailed information cycles and enables learners experience a spiral learning rather than a linear study (Hamid, 2002). Moreover, enhanced coordination and team-work, communication, improvement in critical thinking skills, opportunity for supplementary exercises are listed among outstanding benefits of e-learning (Arıkan and Khezerlou, 2010).

In a study by Uşun, it is mentioned that computers help learners reach their educational objectives fast and easier and it is presented that computer mediated learning decrease the learning duration by 20% - 40% compared to traditional learning. Alan's study reports the differences between traditional and computer-supported education in terms of learners' success and reports that success level increases as the learning is supported by technological tools (as cited in Akdağ and Tok, 2008).

Besides the advantages of e-learning, some insufficiencies are also reported. In a study by Şahin and Yıldırım, it is mentioned that socio-psychological development of learners may be limited in a computer-based educational system. Furthermore, the need for computer skills to be able to benefit from technological services and the fact that the computer-mediated environment may not always support the education syllabus is listed as outstanding disabilities (as cited in Akdağ and Tok, 2008). Some further challenges are presented by Gudanescu (2010). Digital divide, social loafing, accommodation for individuals with disabilities, compatibility, development costs and lack of credibility is listed as main difficulties to be coped with to make e-learning more effective. It is stated that there is a digital divide where all the people do not have equal chance for using technologies and it makes technology implementation more difficult. Social loafing is considered to increase by technology based learning, since people begin reducing effort thinking that it will not cause to negative social effects. Providing technology for people with disabilities and providing compatible technology is also challenge. Additionally, development costs are higher, since investments are made for significant programs. When there are not a sufficient number of students to register in those programs, it may not be possible to afford those high development costs. Lastly, credibility level of e-learning programs is not yet the same with traditional programs.

Even though there are some challenges and inabilities, the growth of e-learning as a result of advancements in the technology and its crucial benefits seems to go on. The research by the Gartner Group reveals nine important trends which will affect the direction of e-learning in the corporations, schools and governments (E-Learning Trends, 2010).

As a result of standardization in the e-learning processes, organizations which plan to construct an e-learning environment can prefer turnkey e-learning systems which will result in lower costs, lower research and development expenses and faster deployment. Some examples of these systems can be listed as IBM ELearning Systems, Knowledge Anywhere Corporate Solutions, Moodle Hosting Providers and etc.

- As e-learning content has a more modular nature, organizations have the chance to integrate e-learning into the overall company infrastructure. Different functions of the organization can make use of the same e-learning tools.
- There is a rapid increase in the number of new job descriptions and higher need for qualified personnel in the highly competitive markets. By the use of e-learning systems, companies will easily train its staff for new skills and for key improvements without a need for classroom training which consumes more time.
- High quality content will be available at lower costs by the use of advancements in the technology and the Internet for schools, businesses, governments and etc.
- Instead of physically, travelling to learning centers in different regions of the world, corporations will have the opportunity to take the same quality content at a distance. Moreover, this high-level information will be available not just for companies with huge budgets but also for relatively smaller businesses. Additionally, students from both rural and urban areas will take the same benefits without time and place boundaries, as far as the technology in those areas enables.
- Video game technologies which enable fun, engaging, effective simulations will help the workers learn in a simulated environment. For some sophisticated tasks, the workers will learn the content without taking risk of injury or decrease in product quality. For some soft skills and best practices, workers will have an enjoyable learning time.
- Governments will also take advantage of e-learning systems. The problem about the lack of sophisticated teachers in the rural areas can be compensated through e-learning programs. Universities can get access to some international specialized programs and provide better quality education for their students.
- Partners and collaborators can understand the objectives and standards of each other, mutually through the online learning programs.
- Wireless technology enables the researchers' access to any rural areas, deserts, farms and rainforests. Radio, satellite and Wi-Fi signals allow two ways information flows and provide learning opportunities at any distance.

Taken all above into consideration, technology usage and maintenance for learning and creating an online learning environment seems to be a critical concern for many parties, government, corporations, educational institutions and learners, as well. Corporations as important stakeholders can make use of e-learning systems in order to adapt to the knowledge economy and train the personnel as knowledge workers. Advantages of technology based learning can create a great value if applied properly. On the other hand, the disabilities and challenges should not be ignored in order to make it more contributive for all parties.

E-Learning Content

Especially, in recent years, e-learning seems to be very attractive alternative with its potential advantages. Computer technology makes the education process smoother with their functions like the Internet and multimedia. These functions make learners and teachers more effective throughout the learning and teaching process. Audio-visual content makes online computer learning even more attractive (Akdağ and Tok, 2008). Moreover, enhanced motivation, coordination and team-work, communication, improvement in critical thinking skills, opportunity for supplementary exercises are listed among outstanding benefits of e-learning (Arıkan and Khezerlou, 2010).

Hamid (2002) presents how e-learning and traditional learning differs from each other in terms of content. Information architecture, user interface design and content strategy are the key elements of online learning. Information architecture of e-learning means designing a system which provides a good organization of information and capabilities like navigation and searching. User interface design is another differentiating element which gives the user control power. Content strategy is based on not reading but scanning. The content design should enable scanning and should be in a pyramid form beginning with important information going into details.

Availability and accessibility of e-learning systems increases day by day with the advancements in the technology. The technology enables required tools and methods to distribute educational content to the learners. In their study, Heindel, Smith, and Torres-Ayala (2008) demonstrate that on-campus courses from various academic disciplines can be delivered online at an increasing rate. Their research study held at a major university in the south eastern United States presents the result that the number of distance courses is increased from 327 to 505 between 2002 and 2007. The distribution of online courses between 2002 and 2007 is also studied. In the study, Biglan's taxonomy of academic disciplines is used which classifies the courses based on two dimensions as hard versus soft and pure versus applied. According to the taxonomy, courses are classified as hard-pure (HP), hard-applied (HA), soft-pure (SP) or soft-applied (SA). Mathematics, physics, chemistry is regarded as hard-pure courses, while engineering, applied mathematics is classified as hard-applied courses. On the other hand, social sciences, humanity, sociology is listed as soft-pure disciplines, whereas nursing, education is considered among soft-applied disciplines. According to the study results, in 2002, soft-pure courses make up 5%, hard-pure courses make up 8%, hard-applied courses make up 38% and soft-applied courses make up the largest proportion with 54% among all online courses. In 2007, the ratio of soft-pure courses increases to 15%, while soft-applied courses make up a smaller proportion (44%) compared to 2002. The ratios of hard-applied and hard-pure courses also change slightly with 35% and 6%, respectively. These results show that mostly, content for applied sciences are delivered through e-learning environment.

Artificial intelligence is highlighted as a method for creating more intelligent content rather than a solid content. It is mentioned that the key point is to understand each learner's background, knowledge level and current needs and then to offer some alternative learning paths. Based on the information about the learner and his behavior during the course, connection with existing course contents can be established and the learner can be directed to related contents. It is claimed that this integrated process can increase the quality of information presented to the learner and can increase the effectiveness of e-learning (Aslan, İnceoğlu, and Uğur, 2004). Educational data mining is mentioned as a promising area for contributing to e-learning processes. It makes use of data in the systems, produces specific recommendations for learners and educators and provides adaptive and intelligent e-learning environments. E-learning recommendation agents and semantic web mining is among educational data mining tools (Romero, and Ventura, 2007).

Personalized e-learning systems which have the ability to make recommendations with respect to both learner capability and difficulty of course program increase learning efficiency. These customized proposed genetic-based personalized e-learning systems are explored to be much more contributive to online learning compared to freely browsing learning mode (Chen, 2008).

E-Learning Tools and Technologies

Hullet and Mitra (1997) highlight the beginning of technology-aided instruction popularity in 1990s. In those years, the instructors of three different courses have made use of different technologies to be able to deliver maximum benefit. For a plant biology course, a videotape player, a computer and a projection is used and some graphics and animations of biological processes have been demonstrated via those tools. In a course of history of architecture, students had access to the computer tutorials. They could go through hyper-text interfaces and get related images sound clips and textual material. The instructor of a psychology course also made use of some technological tools. Students were encouraged to use a computer-aided system in order to do some experiments. Students answered some questions including images and text and at the end, based on the answers, a data set had been produced by the computer for the students to analyze the results.

As can be seen in the examples above, the use of technology in different disciplines can be observed in 1990s, as well. The technologies were basic and simpler in those years and still, they stand for the major tools today. However, the changes and advancements in the technology give a direction to distance learning, and today, many new tools, systems and platforms are available to deliver online education.

Rapid improvements in technology make technology based learning a part of life-long learning process. In different levels of education, technology becomes a crucial player. Similarly, knowledge based economy requires much more training of work forces and leads technology-based learning to take place in corporate learning processes. In order to deliver learning and manage the learning process with the use of technology, many different software and hardware tools and different kind of delivery methods are made use of by e-learning system designers (Gudanecsu, 2010).

In the following part, basic tools and technologies in online learning environment from simplest to the most complex ones are presented.

Web Browsers

Web browsers are regarded as the most basic and most important tools for accessing e-learning content. It displays the graphical user interface of the Internet. The information is available all around the world through web browsers. People request and display pages and images on the web based user interfaces. Through web browsers, learners also display forms, run programs, download files, upload files. Since there are many advances with related to security concerns, secure information transformation is now available through the Internet and learners can pay for their course credit online, for instance, which makes the process easier. Internet Explorer, Firefox, Netscape navigator, Mozilla, Amaya, Opera are the most well-known web browsers. Furthermore, web pages can be displayed on television screens by the use of MSN TV and Palm OS and Pocket PC OS is generated for handheld devices with wireless connections and content can be displayed in smaller screens (Horton, K and Horton, W., 2004).

Media Players and Viewers

These are the tools which let the learners play dynamic media like audio and video which cannot be played directly by the web browser. Additionally, another content of media players are used for some proprietary file formats which include both media and rich interactivity. Quicktime player, Windows media player, realone player, winamp player as audio and video players, and flash player, acrobat reader as viewers are some well-known examples of media players (Horton, K and Horton, W., 2004).

Collaboration Tools

People at a distance can communicate and work with each other via collaboration tools. Those tools are crucial for collaborative online learning, online mentoring and knowledge management activities. People can share their ideas, share the information, give feedback, and learn from each other in a collaborative environment provided by such tools. There are simple and complex, synchronous and asynchronous collaboration tools. Synchronous tools enable real time information exchange, while in asynchronous communications, users can send the information at a point in time and receivers can take the message and respond anytime later (Horton, K and Horton, W., 2004).

Email is the most basic and most widely used collaboration tool enabling asynchronous communication. It provides simple and inexpensive message exchange. In e-learning process, email is used both by the instructor and the learner. Instructors make use of e-mail in order to give assignments or communicate some announcements. Learners can ask questions and submit assignments to the instructor via e-mail, and can also communicate with other learners via e-mail groups. This method of e-learning has a connection and shows similarity with the postal correspondence courses in the nineteenth and twentieth centuries. Today, instead of postal exchange, electronic environment is made use of as a way of communication between instructor and learner (Horton, K and Horton, W., 2004). E-mail is a method both for instructors and learners. Instructors can send assignments, can publish course grades. Learners can ask questions, participate in discussions. It can provide feedback for both parties (Goffe and Sosin, 2005).

Online discussion via newsgroups, net news, discussion groups, discussion forums, computer bulletin boards is another method of asynchronous communication. Users ask questions or share ideas via threading. Online discussions can be easily and effectively used for brainstorming, teamwork, group-critiquing and etc. (Horton, K and Horton, W., 2004). Blogging is similar technology which enables people discuss on a specific issue and share ideas and comments. People directly publish their ideas by journal type blogs or they can link to another Web content by filter-style type blogging. There are three primary uses of blogs over the Internet as student blogs, group blogs or academic keeping blogs (Mason, Pegler and Weller, 2005).

On the other hand, for real time information exchange, chat and instant messaging can be preferred as the simplest synchronous communication method. People set their status as busy or available, can send and receive message in real time. The advantage over e-mail is that users know whether their message is read or not by the receiver (Mason et al., 2005).

Online voting (virtual response pads) is used for e-learning activities, especially for soft-skills training. It enables the learners think about a presented issue and express their act on that issue. Online voting can provide hints about general tendencies, point of views and attitudes of the learners (Horton, K and Horton, W., 2004).

Whiteboards enable real time communication via online drawing. They are similar to dry-erase boards, differently run in electronic environment. Whiteboards can be used in early education (Solvie, 2004). Also, more complex visual subjects such as engineering, architecture or design can make use of these tools (Horton, K and Horton, W., 2004). However, they require computer skills of the instructor and are relatively expensive and require financial resource. A recently proposed electronic board is EduBoard. It has some more powerful features than the existing ones: requires less maintenance concerns, less technical skills, less power, provide higher quality learning materials with graphics and displays content in sub-second time (Belle, 2004).

Another tool for e-learning purposes is electronic paper. It is very thin, flexible plastic sheet. Its content can be changed just like memory cards. Electrophoretic displays, bi-chromal bead technologies are some contents of electronic papers (Belle, 2004).

Application sharing is an effective method for computer program training.

The instructor demonstrates the program on real time and then, shares the control with the learner and expect him repeat the steps. The learner has the chance to experience the program without a need of having the program on his own computer. Application sharing is useful especially for sales representative trainings (Horton, K and Horton, W., 2004).

Presentations are the content sources for reuse over the Internet. There are one-way or two-way flows in presentations. If the information comes from just one source and the learners just watch or listen, this is a presentation with one-way flow. If the learner can also ask questions and share his ideas, this is a presentation with two-way flow (Horton, K and Horton, W., 2004).

Learners and instructors can talk to each other via the Internet by setting a conference call. This way of communication is called audio conferencing. Audio conferencing is synchronous and effective in smaller groups. It enables only one person's talk (Mason et al., 2005).

Video conferencing allow people in different locations to communicate each other via video through the Internet. People can share their knowledge, questions or expertise even across different countries (Jones, Dean and Hui-Chan, 2010). WebSCoRe (Web Based Synchronous Colloboration Review) tool enable users (students or instructors) to review online documents synchronously. Users can make comments on the document and get immediate feedback from each other. It enables high participation and mutual discussion. However, limited size of the group, speed of the communication, lack of facial mimics and limited size of discussion is highlighted as the drawbacks of the tool (Demirors, and Serce, 2004).

LMS (Learning Management Systems)

Learning management systems are web-based learning systems which enable sharing information and enable interactions among students, instructor and content. To manage the interaction between those parties, it provides some specific tools with various functions. Syllabus, course readings, slides and other course content is managed in materials management module and this module coordinates the interaction between the student and course content. Interaction between the instructor and students is provided by interactive teaching module. The instructor can give assignments and quizzes or send notifications. Peer learning manages interactions between students. They can make group projects or peer reviews (Lonn and Teasley, 2009).

The major function of LMS is to manage learners and to follow up their situation in all kind of learning processes (Süral, 2010). LMS ease teaching and learning process by providing content sharing, group working and learner and instructor interaction through the Internet. Documents, blogs, forums, media can be disseminated through LMS. LMS systems can be integrated with different e-learning technologies like semantics and ontologies. An integrated LMS system can make knowledge distribution process easier and more robust (Cuéllar, Delgado and Pegalajar, 2011)

LCMS (Learning Content Management System)

Different than LMS, major goal of LCMS is to administer the content and other learning objects rather than the learners. LCMS serves for delivering the content to the learner who needs it at the correct time (Süral, 2010).

LCMS are the online learning platforms which enable learners share information and communicate with others and enable instructors provide most of the traditional learning activities in online environment such as publishing a variety of course contents, assignments and tests, communicating with students and encouraging collaborative learning via forums, chats, file storage areas, etc. There are both commercial and free learning content management systems. Blackboard, Virtual-U, WebCT, TopClass, etc. are the examples of commercial LCMS and Moodle, Ilias, Claroline, aTutor, etc. are the examples of free ones. These systems store large log data about the students' activities. All the students' activities such as reading, taking tests, participating in forums, communicating with peers, etc. and also all the systems information such as personal information, academic results is stored in large databases (Romero, and Ventura, 2007)

Virtual School Systems

As a hybrid collection of LMS, LCMS and collaboration tools, virtual-school systems support e-learning activities as a whole. Tools are gathered together as a complete package of features within the virtual school systems to maintain all e-learning processes like organizing, delivering and managing e-learning courses. Course content authors, system administrators, instructors and learners make use of those tools in consistent with each other. Course content authors organize related contents and compose courses. Moreover, they can organize the courses into programs. Instructors manage courses by easily maintaining the sub tasks like giving homework, grading, making announcements, establishing online discussions with the learners and etc. Learners can also benefit from such systems to get course content and other sources, to submit homework, to communicate with instructors and other learners, to track progress and etc. Lastly, administration tasks like registration, keeping track of information about learners and courses, retrieving some reports can be effectively managed within virtual-school systems.

Based on the needs and preferences, virtual school systems can be enriched by some additional functions and properties such as more visual or interactional page content, more audio, video or animations, more complex assessing or testing tools and etc. Some popular virtual school systems are Aspen Virtual Classroom Server, Blackboard, Convene, eCollege Campus, e-education, Enhanced Distance Learning Environment, FirstClass, Integrated Virtual Learning Environment, WebCT Campus Edition, Lotus Learning Space and etc.

Semantic Web Technologies and Multi-Agent Systems

Semantic web technologies enable the web content which is defined and linked to be used by other applications and increases efficiency. It provides great value for e-learning activities, because it provides reusability of the content and quickness. Course materials can be tagged to be used later for other courses and learners can easily reach to desired content which is tagged before. Another technology which is beneficial for e-learning is multi-agent systems. An agent has the ability to decide on its own about what it needs to do in order to meet its design goals. It should have functions as reactivity, pro-activeness and social interaction. E-learning agents serve for providing the right content to the right student at the right time. It provides a personalized guidance for the learners. Moreover, since it learns about the learner, it decides for the learner and keeps the learner away from unnecessary and time-consuming operations (Fernandez-Breis, Garcia-Sanchez, Gladun, Martinez-Bejar, and Rogushina, 2009).

(AIWBES) Adaptive and Intelligent Web-Based Educational Systems

AIWBES is a more adaptive system which builds a model of the goals, preferences and knowledge of each individual student and makes use of this model for satisfying the specific needs and demands of that student. These systems can be regarded as a joint evolution of intelligent tutoring systems (ITS) and adaptive hypermedia systems (AHS). The AIWBES provide richer data and enables more deeper analysis than the traditional web based learning systems. As a result of continuous student interaction with the system, information is augmented and a new student interaction model for each student should be produced by applying data mining to this augmented information (Romero, and Ventura, 2007).

Brusilovsky and Peylo (2007) present the components of adaptive and intelligent web-based educational systems. The study explains the goals of each technology in detail. By the use of curriculum sequencing, the learners are provided a customized learning plan in which learning topics and tasks are organized based on the learner's needs. Intelligent solution analysis help the learners deeply understand the solutions of the problems. Other than just telling the answer is correct or not, the intelligent solution analysis system guides the learner about incorrect parts of the solution, it makes connection between the solution and required knowledge and directs the learner about missing knowledge. Interactive problem solving support aims to guide the learner in each problem solving step. Adaptive presentation technology provides dynamic content based on the information about learner. The pages are adaptively generated for each user. Adaptive navigation support technology makes navigation easier and simpler. It dynamically changes the visibility of links on the page and makes the learner choose the next link easier.

E-Learning Success Factors

Increasing the quality of learning and making education available for everyone is an important focus. Moreover, some financial concerns also make e-learning programs important. E-learning seems to be attractive by providing cost-effective educational systems as a result of technology usage.

To develop effective e-learning systems and ultimately, to make use of its benefits and to increase satisfaction of the learners, researchers have identified critical e-learning success factors. Selim (2007) states that identifying and focusing on e-learning critical success factors is among the most important issues of e-learning systems. It should be studied to give directions and assistance to decision makers to improve e-learning systems.

Study results on e-learning success factors can be reviewed in five major categories. Instructor related, learner related, course related, e-learning system related factors and other external factors.

- Instructor has an effect on the e-learning success (Macher, Maier, and Paechter, 2010; Koseler and Ozkan, 2009; Chen, Finger, Sun, Tsai and Yeh, 2008; Selim, 2007; Levy, 2006). Instructor's attitude, teaching methods and guidance is considered as important factors for an effective e-learning process.
- E-learning success also depends upon some learner-related factors. Learner's demographics (Koseler and Ozkan, 2009; Levy, 2006; Lai and Ong, 2004; Erorta, Mutlu, and Yılmaz, 2004; Hullet and Mitra, 1997; Galusha, 1997), IT skills (Selim, 2007; Kerr, M. C., Kerr, M. S., and Rynearson, 2006, Alexander, 2001), time management skills (Selim, 2007; Kerr et al., 2006), learning and academic skills (Kerr et al., 2006), metacognitive skills (Baltaş et al., 2004) have influence on e-learning process. Leaners' success in

traditional formal education is also a determinant (Cavanaugh, 2001). Moreover, frequency of e-learning usage (Selim, 2007; Erorta et al., 2004; Cavanaugh, 2001) and previous e-learning experience (Selim, 2007; Erorta et al., 2004; Galusha, 1997) is important determinants for success or failure. Previous knowledge of the learner is also explored to be a key success factor (Coleman and Furnborough, 2010). Another key factor is learner's attitude towards using technology (Hullet and Mitra, 1997). Computer anxiety is discovered as a significant factor for learner satisfaction (Chen et al., 2008). Moreover, learner's perceived effectiveness (Koseler and Ozkan, 2009), perceived usefulness and perceived ease of use (Chen et al., 2008), motivation (Macher et al., 2010; Kerr, et al., 2006; Baltaş et al., 2004; Galusha, 1997), satisfaction (Shee, Wang, H. and Wang, Y., 2007; DeLone and McLean, 2003; Wang, 2003) and learner's achievement goals (Macher et al., 2010) should be taken into consideration for better learning outcomes. Available time allocation by the learners effects whether the learner completes or withdraws the program (Alexander, 2001). Lastly, communication and collaboration among learners and instructors increases the quality of e-learning process (Macher et al., 2010; Levy, 2008; Alexander, 2001).

- E-learning course is a crucial part of learning process. Course content, design and quality (Macher et al., 2010; Chao and Chen, 2009; Koseler and Ozkan, 2009; Chen et al., 2008; Shee et al., 2007; Levy, 2006; Baltaş et al., 2004; DeLone and McLean, 2003; Cavanaugh, 2001; Galusha, 1997) should be taken into consideration to make learners experience a useful learning program. Cohesion between the online program and assessment is crucial for increasing the participation (Alexander, 2001). Similarly, diversity in assessment is a significant determinant for learner satisfaction (Chen et al., 2008). Enjoyment and usefulness of course program (Koseler and Ozkan, 2009); the use of different teaching strategies like simulations, case studies, animations and multiple representations (Alexander, 2001) should not be ignored while designing course programs.

- E-learning system - related factors are also explored for improving e-learning experience. Technology, system design and quality (Chao and Chen, 2009, Koseler and Ozkan, 2009; Levy, 2006; Selim, 2007; Shee et al., 2007; Baltaş et al., 2004; DeLone and McLean, 2003) effect the learner's performance and learning program's effectiveness. Some specific system related factors are also studied. Accessibility, performance, security and standard compliance are listed as important factors for evaluating e-learning system effectiveness (Kor and Tanrıkulu, 2008). Usability, interaction, functionality, reusability, evaluation, appropriateness, design, interoperability, and accessibility of the system are presented as key factors in the study by Tanrikulu, Tugcu and Yilmaz, in 2010. Furthermore, availability for individual learning process (Chao and Chen, 2009; Macher et al., 2010) and existence of synchronous learning (Chao and Chen, 2009; Khalifa and Shen, 2004) is proposed as important characteristics of the system. Importantly, the existence of grading and monitoring system is a key factor for correct evaluations and feedback (Chao and Chen, 2009, Alexander, 2001). Additionally, non-existence of technical support is considered as a factor for e-learning failure (Selim, 2007, Alexander, 2001). Learning method and environment is stated as another success factor. Success increases in distributive interactive learning environment compared to passive distance learning environment (Khalifa and Shen, 2004). Similarly, collaborative and interactive learning environment is highlighted (Baltaş et al., 2004)

- Environmental factors like ethical, legal and environmental issues and trends (Koseler and Ozkan, 2009), the responsibility of human resources and the effect of top management (Baltaş et al., 2004), organization support (Galusha, 1997) are presented as having influence on e-learning process.

CHAPTER II: PROBLEM

Dynamic and demanding nature of today's life conditions force human beings to invest in their self-development, continuously. The need for life-long education is realized by higher number of people and corporations. Corporations aim to invest in creating knowledge workers in their organizations for long-term success. Especially, in recent years, other than in-classroom educational programs, establishment of online learning programs is also considered as a part of life-long education. To make use of online learning environment effectively, it has been a crucial concern to explore and improve the process of online learning.

People spend time for e-learning while also fulfilling daily responsibilities. Similarly, corporations spend time and budget for building required technical infrastructure and for restructuring some organizational processes, accordingly. While both people and corporations are spending resources for this learning activity, it is crucial to understand whether e-learning process really adds value. To get the return on all investments, the critical point here is to determine and to improve the factors related with e-learning effectiveness.

CHAPTER III: RESEARCH QUESTIONS

The core research question guiding this study is what the most significant factors influencing corporate e-learning effectiveness are. As mentioned in previous sections, many studies on key success factors present some key factors and measures for effectiveness. The most outstanding measures of effectiveness are stated as learner achievement and learner satisfaction (Macher et al., 2010). In this study, learner performance, learner satisfaction and learner perceived usefulness is selected as three distinct key indicators of e-learning effectiveness. Importantly, in this study, the focus is corporate e-learning and it is aimed to understand online learning experience of corporate users who participate in corporate e-learning programs. Online learning programs which are included in this study are mostly related to banking sector. These programs aims to train the personnel of a Turkish bank which has been operating for more than half and a century on some areas of specialization like budgeting, consumer loaning, corporate loaning, capital market committee, fraud in banking, published banking notices, time deposit modules and so on. Furthermore, some skill development educational programs are included in the study. These programs aim personal development of the bank personnel and focus on social relationships, communication, and team-work and so on.

Core research questions of this study focus on:

1. Identifying the factors influencing learner performance
    a. What are the learner demographics-related significant factors for learner success, learner's course program completion duration and whether learner completes or withdraw?
    b. What are the learner previous e-learning performance-related

significant factors for learner success, learner's course program completion duration and whether learner completes or withdraw?

c. What are the course program-related significant factors for learner success, learner's course program completion duration and whether learner completes or withdraw?

d. What is the effect of perceived usefulness on learner success?

In order to derive conclusions on the core research question, some specific research questions are as follows:

- Are there any learner groups with some similarities with the same success level and what kind of similarities are there among those learner groups?
- What are the learner-related significant factors for learner success?
    - Is there a relationship between learner success and learners' demographics (age, gender, education level, functional and hierarchical occupation, region, work experience)?
    - Does formal education success of the learner influence his/her e-learning success?
    - Is there a relationship between learner's success and his/her completion duration of that course program?
- Is the learner's previous e-learning performance is determinant for his/her success for other course-packages?
    - Is previous e-learning experience important for e-learning success?
    - Does number of e-learning course programs previously taken by the learner influence learner's success in other course-packages?
    - Does a learner who is successful in average in online learning make better scores in other online courses?

    - Is there a relationship between learner's average course completion duration and his/her success?
- What are the course program-related significant factors for learner success?
    - Does the content of course program, whether it has a vocational or skill development content influence the learner's success? (Programs with vocational content aim to train the users on an area of specialization related to banking sector such as fraud management, loaning and budgeting. Programs with skill development content aim to contribute to the personal development of the users such as team work, communication and collaboration and stress management)
    - Does learner's success change, if the duration of course program is changed?
    - Is there a relationship between learner's success and whether course program is certificated or not?
- What is the effect of learner's perceived usefulness level?
    - Does learner's perceived usefulness have an influence on e-learning success?
- What are the learner-related significant factors which have influence on whether the learner will complete or withdraw the course program?
    - Do learner's demographics as age, gender, hierarchical and functional occupation, region, work experience and education level influence whether learner will complete or withdraw the course program?
    - Does formal education success of the learner influence his/her e-learning success?
- Is the learner's previous e-learning performance is determinant for his/her

success for other course-packages?

    - Does number of online course programs previously taken influence whether the learner will complete current course program or not?
    - Is there a relationship between learner’s average success in e-learning and his/her course program completion decision? (Learner’s scores on course programs in which he/she participated are used and for each learner, an average score is calculated. This average score is treated as learner’s average success in e-learning.)

- What are the course program-related significant factors which have influence on whether the learner will complete or withdraw the course program?
    - Is there a relationship between the content of course program and decision to complete or to withdraw?
    - Does the certification of course program, that is, whether a certificate will be given at the end of the course program or not, influence the learner’s decision to complete or to withdraw the course program?
    - Is there a relationship between the duration of course program determined by the system and whether the learner will complete or withdraw the course program?
- What are the learner-related significant factors for learner’s course program completion duration?
    - Do the learner’s demographics as age, gender, hierarchical and functional occupation, region, and work experience and education level influence his/her completion duration of a course program?
    - Does formal education success of the learner influence his/her e-learning success?

- Is the learner’s previous e-learning performance is determinant for his/her success for other course-packages?
    - Does number of online learning programs influence the completion duration?
    - Is there a relationship between learner’s average success and his/her course program completion duration?
- What are the course program-related significant factors for learner’s course program completion duration?
    - Is there a relationship between the content of course program and completion duration?
    - Does the certification, that is, whether a certificate will be given at the end of the course program or not, influence the learner’s completion duration?
    - If duration of course program determined by the system changes, does the course program’s completion duration change? Do learners have a tendency to prolong the course program, if allowed duration is longer?

It is aimed to gain a deeper understanding on e-learning effectiveness by giving answers to those questions. The study evaluates the e-learning effectiveness in three distinct terms: learner success, course program completion or withdrawal and course program completion duration. The results can be turned into a great value. E-learning stakeholders- students, designers, decision makers- can make use of the answers to those research questions to improve the e-learning systems and as a result, to make e-learning experience more valuable in terms of learner performance.

CHAPTER IV: OBJECTIVES

The goal of this study is to develop e-learning effectiveness models and to understand the main contributors to the effectiveness of e-learning systems in corporations. It is aimed to answer whether demographics, course program characteristics, previous e-learning performance and learner's perceived usefulness of e-learning system are strong indicators of e-learning performance. It is aimed to provide important insights and useful directions for the decision makers of e-learning systems on how to treat to important e-learning related factors and ultimately, on how to enhance e-learning systems further and on how to make them much more contributive for the learner.

CHAPTER V: HYPOTHESES

In order to derive concrete results, hypotheses are produced related with the research questions. Some statistical tests are applied and results are analyzed for each hypothesis.

Learner Success

In the following section, hypotheses for learner success are presented in four groups: Learner’s demograhics, previous e-learning experience, course program-related factors and perceived usefulness.

Learner’s Demographics vs. Learner’s Success

- HA0: There is a statistically significant association between learner’s success and learner’s age.
- HA1: There is a statistically significant association between learner’s success and learner’s gender.
- HA2: There is a statistically significant association between learner’s success and learner’s education level.
- HA3: There is a statistically significant association between learner’s success and learner’s functional occupation.
- HA4: There is a statistically significant association between learner’s success and learner’s hiearchical occupation.
- HA5: There is a statistically significant association between learner’s success and learner’s region.

- HA6: There is a statistically significant association between learner's success and learner's current work experience.
- HA7: There is a statistically significant association between learner's success and formal education success of the learner.

Learner's Previous E-Learning Performance vs. Learner Success

- HB0: There is a statistically significant association between learner's success and number of online course programs previously taken by the learner.
- HB1: There is a statistically significant association between learner's success and learner's average success in e-learning.
- HB2: There is a statistically significant association between learner's success and learner's average course program completion duration.

Course Program-Related Factors vs. Learner's Success

- HC0: There is a statistically significant association between learner's success and the content of course program, that is, whether it has a vocational or skill development content.
- HC1: There is a statistically significant association between learner's success and duration of course program.
- HC2: There is a statistically significant association between learner's success and whether course program is certificated or not.
- HC3: There is a statistically significant association between learner's success and learner's course program completion duration.

Learner Success vs. Perceived Usefulness

- HD0: There is a statistically significant association between learner's success and perceived usefulness of course program.
- HD1: There is a statistically significant association between learner's success and information usefulness of course program.
- HD2: There is a statistically significant association between learner's success and sample practices in the course program.
- HD3: There is a statistically significant association between learner's success and content quality of course program.
- HD4: There is a statistically significant association between learner's success and permitted duration of course program.
- HD5: There is a statistically significant association between learner's success and visual and interactional content of course program.
- HD6: There is a statistically significant association between learner's success and fluency of course program.
- HD7: There is a statistically significant association between learner's success and cohesion of content and exam in the course program.

Course Program Completion

In the following section, hypotheses for course program completion are presented in three groups: Learner's demograhics, previous e-learning experience and course program-related factors.

Learner’s Demographics vs. Course Program Completion

- HE0: Learner’s age significantly influence whether the learner completes or withdraw the course program.
- HE1: Learner’s gender significantly influence whether the learner completes or withdraw the course program.
- HE2: Learner’s hierarchical occupation significantly influence whether the learner completes or withdraw the course program.
- HE3: Learner’s functional occupation significantly influence whether the learner completes or withdraw the course program.
- HE4: Learner’s region significantly influence whether the learner completes or withdraw the course program.
- HE5: Learner’s work experience significantly influence whether the learner completes or withdraw the course program.
- HE6: Learner’s education level significantly influence whether the learner completes or withdraw the course program.

Learner’s Previous E-Learning Performance vs. Course Program Completion

- HF0: Number of online learning course programs previously taken significantly influence whether the learner completes or withdraw the course program.
- HF1: Learner’s average success in e-learning significantly influence whether the learner completes or withdraw the course program.

Course Program-Related Factors vs. Course Program Completion

- HG0: Course program content significantly influence whether the learner completes or withdraw the course program.
- HG1: Whether the course program is certificated or not significantly influence whether the learner completes or withdraw the course program.
- HG2: Course program duration assigned by the system significantly influence whether the learner completes or withdraw the course program.

Course Program Completion Duration

In the following section, hypotheses for course program completion duration are presented in three groups: Learner's demograhics, previous e-learning experience and course program-related factors.

Learner's Demographics vs. Course Program Completion Duration

- HH0: There is a statistically significant association between learner's course program completion duration and learner's age.
- HH1: There is a statistically significant association between learner's course program completion duration and learner's gender.
- HH2: There is a statistically significant association between learner's course program completion duration and learner's education level.
- HH3: There is a statistically significant association between learner's course program completion duration and learner's functional occupation.
- HH4: There is a statistically significant association between learner's course program completion duration and learner's hiearchical occupation.

- HH5: There is a statistically significant association between learner's course program completion duration and learner's region.
- HH6: There is a statistically significant association between learner's course program completion duration and learner's current work experience.
- HH7: There is a statistically significant association between learner's course program completion duration and learner's formal education success.

<u>Learner's Previous E-Learning Performance vs. Course Program Completion Duration</u>

- HI0: There is a statistically significant association between learner's course program completion duration and number of e-learning course programs previously taken by the learner.
- HI1: There is a statistically significant association between learner's course program completion duration and learner's average success in e-learning.

<u>Course Program-Related Factors vs. Course Program Completion Duration</u>

- HJ0: There is a statistically significant association between learner's course program completion duration and learning course program content.
- HJ1: There is a statistically significant association between learner's course program completion duration and whether the course program is certificated or not.
- HJ2: There is a statistically significant association between learner's course program completion duration and course program duration assigned by the system.

CHAPTER VI: METHODOLOGY

Research Design

The process of knowledge discovery in databases is applied and data mining methods are used to explore the significant factors on e-learning effectiveness. Statistical correlational tests, chi-square tests, factor analysis as a part of exploratory analysis, k-means clustering analysis as a descriptive method, decision tree by CHAID growing method and logistic regression models as predictive classification methods are selected as the basic statistical techniques to explore the patterns in data sets and to develop e-learning effectiveness models. Learner's course score, learner's course program completion duration and whether learner completes the program or not is key indicators of effectiveness. The variance in these dependent variables is measured based on learner related and course program related factors. Age, gender, education, geographical region, occupation in terms of functional group and hierarchical level and work experience is introduced as main demographics of learners. Learner average success, average course program completion duration and previous e-learning experience which are measured by the number of previous e-learning programs are used as indicators for leaners' e-learning history. Course program content, duration and certification is included as course program characteristics. Furthermore, the influence of learner's perceived usefulness on learner success and learner's course program completion duration is analyzed. Some factors revealing the quality of the course program according to learners' perspectives and indicating the learner's perceived usefulness are used to explain the variance. These factors are the content, usefulness of the information, sample practices or case studies, visual and interactional representations, fluency, and cohesion of content and assessment and meeting expectations. The content means the explanatory information about the subject of interest. Usefulness of information measures whether the learners acquire worthwhile information from the content. Availability of sample practices is a factor measuring to what extent the subject is illustrated with case studies or samples. Using visual and interactional representations factor shows the use of different media to present the content. Fluency factor measures whether the whole program is organized in a smooth style. Cohesion of content and assessment is used for measuring whether the assessment method is suitable for the content or not. Lastly, statistically significant factors influencing the variance in learner's satisfaction level is explored. Lastly, statistically significant factors influencing the variance in learner's satisfaction level is explored.

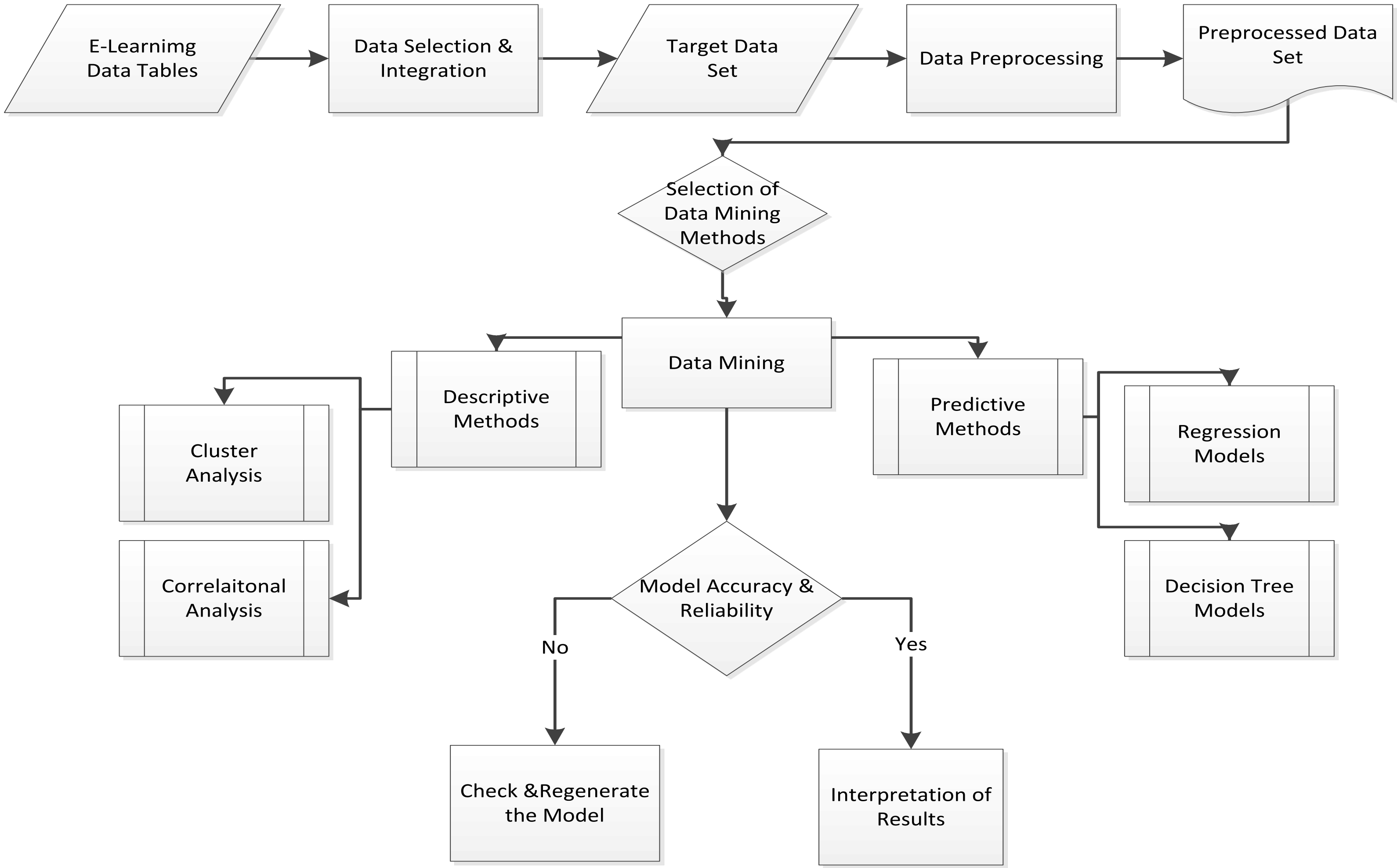

Fig. 1 Methodology

Sample

This research study is based on the database provided by BSUYGAR (Information Systems Research and Application Center). It consists of real data about online educational programs applied to the personnel of a private bank of Turkey. It includes data about learners, course programs, educations, exams and education evaluations. The database contains information about 5484 learners, 94 educations, 90 exams and 218 course programs. The data set contains about 45322 records before data preprocessing tasks. In the data set, data on vocational courses like budgeting, consumer loaning, capital market committee and skill development courses like social relationships, communication, and team-work is stored.

Sample Distribution and Reliability

Kolmogorov-Smirnov test shows that there is no normal distribution in the data set ($p=0,000<0.05$), so that it is more meaningful and reliable to apply non-parametric tests. The reliability of data set is measured by the ratio of Cronbach's alpha. It shows the level of inner consistency in the data set. Alpha is measured as 0,702 and is acceptable for applying statistical test, since it is greater than the threshold ratio $\alpha \geq 0,70$ (Nunnally, 1974).

Data Analyses

In this study, knowledge discovery in databases (KDD) process is applied. Knowledge discovery or data mining process in e-learning aims retrieving useful knowledge from data. It contains four major steps as data collection, preprocessing, applying data mining methods, evaluating and interpreting results. Data mining models and tests are used in the study, since it seems not to be possible to analyze huge amounts of data with informal monitoring or similar methods. Data mining enables to explore hidden and important data patterns in huge data sets (Garcia, Romero, and Ventura, 2008). Outcomes of data mining analysis are important for continuous improvement of e-learning systems. Not only academic responsible and administrators, but also learners and educators can make use of explored information as a feedback (Romero, and Ventura, 2007).

As mentioned, KDD process and data mining methods are used in the study. Why is data mining used in the study? Currently, web based learning materials seem to be much more static and do not take the diversification of the learners, context and other factors into account. However; similar to many other service industries, customization is inevitable in online learning environment, as well. In order to offer more customized and personalized services to each learner and to improve e-learning systems, the hidden and implicit data patterns should be acquired and processed. At that point, feedback from learners to instructors is a critical consideration for improvement. Different from traditional learning, face-to-face evaluation or comments are not available in the online environment. Dependent on the nature of the learning environment, data can be collected through web based learning systems in various forms. Learner's portfolio which includes the learning path, preferred learning course, grade of course, and learning time can be recorded. Similarly, log files about learner's actions on the web sites can be collected. Moreover, collected data can be combined with user profiles, informal information and other metadata extracted from e-learning environment (Romero, and Ventura, 2007).

As a result of data collection via different methods, huge amounts of data sets are generated. Induction is the core problem in such big data sets. Search space gets bigger as a result of high dimensionality of data (Maimon and Rokach, 2008). Informal monitoring of such kind of data does not seem to be possible. Knowledge discovery process (KDD) which includes data mining process comes to the forward at this point and proposed for the automated analysis of this large amount of data. Data mining methods are considered to be very effective for e-learning systems which make a large volume of data available. By the use of proper techniques such as clustering, classification, outlier association, pattern matching and text mining, it is possible to process, explore, visualize and analyze data (Romero and Ventura, 2007).

The major characteristics of data mining which differentiates it from other traditional methods for data extraction are its scalability. It can be applied to very large data sets with various types of data. It can overcome high number of dimensionality, high number of classes or heterogeneousness of data (Maimon and Rokach, 2008). Eventually, data mining serves to improve the e-learning programs. E-learning decision makers can derive useful information patterns, trace the student's progress and learn more about them, get correct feedback and make more personalized recommendations and develop strategies, accordingly. All in all, KDM process helps understand how students and instructors interact with the system and ultimately, discover the useful information in formative evaluation and guide instructors for establishing a pedagogical basis while designing an effective e-learning model.

Romero and Ventura (2007) mentions that both instructors and learners are stakeholders of e-learning systems. The instructors plan, design, establish and maintain the educational systems and the learners use and interact with those systems. So that, rich information on learners, courses, usage and interaction can be collected through the systems and different data mining techniques in KDM process can be applied to discover useful data patterns which can be oriented to different stakeholders of e-learning from instructors to students. At the end, stakeholders can make use of significant outcomes to make improvements in their online learning process. Learners may get corrective recommendations about their activities, resources and learning tasks. Instructors can get more objective feedback for their instruction process and can evaluate the course and learner effectively. Moreover, administrators or designers can get recommendations about how to enhance e-learning site efficiency.

Romero and Ventura (2007) points out that data can be collected from both traditional and distance education systems for data mining analysis. It is stated that data mining can be applied to understand student enrollment, to understand whether syllabus changes affect students, to offer remedial courses for unsuccessful students or to acquire information about general characteristics and similarities of students.

The most outstanding academic and commercial data mining tools which provide mining techniques, modeling and visualization are listed as Clementine, DBMiner, Intelligent Miner, and Weka. It is also mentioned that these tools are general mining tools and not used just for the learning systems. It is highlighted that all these tools cannot be made use of efficiently by the academic responsible or instructors who do not have much expertise on data mining tools and techniques, so that in the article, specific educational data mining tools are exemplified as MultiStar, Data Analysis Center, KAON, TADA-ED, GISMO/CourseVis and so on (Romero, and Ventura, 2007).

Application of KDD Process

In this study, knowledge discovery in databases (KDD) process has been applied. The process contains some major steps in which core aim is to retrieve the useful knowledge from data. The following figure presents the overall picture of the KDD process (Maimon and Rocah, 2008; Fayyad and Stolorz, 1997). Steps can be listed as:

- Goal identification
- Selection and creation of target data set-data collection
- Data Integration
- Data preprocessing
  - Data cleaning
  - Data transformation
  - Data reduction
  - Data discretization and categorization
- Data mining (Selection of appropriate models and application)
- Presentation and evaluation
- Taking action

Data Collection

After setting the objectives of the study, the first phase is selection and organization of the data. In order to make useful analysis on any subject and to derive meaningful results, collection of sufficient and reliable data is crucial. Giudici (2004) mentions that collecting data from internal resources costs less and this internal data is usually more reliable. It is stated that if a business problem of a company is aimed to be studied, then company data warehouse is a good alternative. It keeps the experiences of the company, as well. Historical data which is not subject to change anymore is also a good source for mining.

In traditional learning, just student attendance, course information, course schedule and similar information can be kept track of. On the other hand, e-learning systems can store user information, course information, academic records and users' interaction information. Furthermore, all the student activities can be accumulated within the systems: Reading, taking tests, participating in forums, chatting with peers and so on. Web-based or computer based learning systems provides much more information than the traditional learning environments. All in all, e-learning systems make vast amount of crucial data available (Garcia, Romero, and Ventura, 2008).

The aim of this study is analyzing e-learning effectiveness on a learner-course program basis. Collection of data about learner, online course programs and the interaction between the learner and course program is critical. Data from different dimensions is required to be collected in this study. Accordingly, historical data on e-learning activities is provided from BSUYGAR. Educational platform from which historical data is extracted aims to meet educational needs through a single central platform and to enable central management of educational processes. System managers, administrative managers, education managers, educators and learners are the major stakeholders of the platform.

Raw Data Set Information

The database contains large amount of data and stores valuable information about the components of e-learning process. However, it is a large, but a dispersed database, which makes the analysis process more difficult. There are 48 tables in the database.

The main tables are learner, course program, education, exam, education evaluation and survey. The Microsoft Access database contains information about 5484 learners, 94 educations, 90 exams and 218 course programs. Mostly, online learning programs for banking sector are included in this study. These programs are applied to the personnel of a bank which has been operating for more than half a century. It is aimed to train the personnel on some areas of specialization like budgeting, consumer loaning, corporate loaning, capital market committee, fraud in banking, published banking notices, time deposit modules and so on. Other than the data on vocational programs, data which is related to some personal development training programs are also included in the database. These skill development educations focus on social relationships, communication, and team-work and so on.

In order to perform meaningful analysis on the e-learning effectiveness, firstly, it is required to retrieve the useful data set from the database. As mentioned, the main problem about the database is its disorganization. The relationships among tables are not established which makes it hard to understand the general data structure and to use the data. To eliminate the problem and to get a thorough understanding about the data, an interview with a program manager in education platform is conducted. As a result, following information about the database content is obtained:

- Learner: People, who participate in online learning course programs, evaluate the educations and are assessed by online exams. Data such as demographical information, course program information, some performance indicators like total score, course program completion duration, and course program completion ratio and so on is stored.
- Education: regarded as an education unit and presents an organized content on a subject. There are some small exams within the education content. The

exam score and learner's education completion time is used for the learner's assessment. Learner gets an average score for each education.

- Exam: regarded as an education unit and includes online course program assessment material which is applied to learners at the end of education and an exam score is assigned to the learner. Data such as exam content, content, number of questions, number of correct-wrong answers is stored.
- Course program: An online course program includes one or more units. Units are either educations or exams. A course program contains one or more educations and zero or more exams. Learner has a total score for each course program. The score for course program is composed from the average of the learner's scores for all educations in the course program and separate exam scores taken from the exams included in the course programs.
- Evaluation: each online education is evaluated by learners after it is completed. Mainly, it aims to evaluate perceived usefulness of education (content quality, fluency, content usefulness, existence of sample practices, assigned duration and assessment of education and so on).
- Survey: questions on various educations and course programs.
- Major relationships:
    - Each education is related with zero or more course programs.
    - Each exam is related with zero or more course programs.
    - Each course program is related with one or more educations and zero or more exams.
    - There is no direct relationship with education and exam in the database. The relationship can be guessed by checking whether they are in the same course program or not.

- Evaluation form is related with each education.
- There is no relationship between evaluation form and exam.

Data Integration and Creation of Summarization Tables

The aim of this study is to analyze the e-learning effectiveness on a learner basis. To do that, lot of tables should be integrated and useless ones should be eliminated, so that a meaningful data set can be generated. Two different data sets which make various analyses available are identified to be able to be retrieved from the database:

1. Learner-course program: each record includes one learner's characteristics and characteristics of one course program in which the learner participated and leaner's score if the learner completed the course program.
2. Learner-course program-evaluation: each record includes one learner's characteristics, characteristics of course program which the learner completed, leaner's score at the end of this course program and additionally, average evaluation results of that course program. Normally, only the educations are evaluated by the learners, not the course programs. However, it is possible to derive average evaluation scores for each course program by calculating the average of evaluation scores of all the educations which are included in this course program. This data set is generated by using this method. Also it is proposed that one overall average evaluation score can be used as an indicator of course program perceived usefulness.

To be able to generate these summarization tables, first of all, the data is transferred to the Microsoft SQL server. Then, the relationships among tables are established dependent on the information driven from the interview. Via SQL make table queries, all related tables are merged in single tables and these distinct data sets are generated.

Data Set Attributes

After data integration is completed and new data sets bringing all related data together are generated within MS SQL database, these raw data sets are exported to Microsoft Excel 2007. The Excel data files are imported into SPSS Statistics 17.0. All the data mining steps are handled within this tool.

Database contains about 45322 records before data preprocessing tasks. Three summary tables are produced. First and second table is generated from a larger table: learner-course program. Last table is generated from data about learners' course program evaluation results.

1. Learner-course program completed: includes 18963 records. All course programs are completed in this data set. It is used to analyze the factors influencing the course program completion duration.
2. Learner-course program completion or withdrawal: includes 29017 records. There are records of incomplete course programs. It is used analyze the factors influencing whether the learner completes the learning program or not.
3. Learner perceived usefulness: includes 8683 records. It contains learners' program evaluation survey results.

It seems to be useful to have a general overview on the raw data set attributes. It should be noted that the following table provides a list of filtered attributes, that is, some redundant and irrelevant attributes are excluded during data integration process. Table 1 provides information about meanings of final attributes in learner-course program data set before data preprocessing.

Table 1. Raw Data Attributes

Attribute name	Description	Used in analysis?
User Related		
User code	a code assigned by the system	No
User active?	whether user is active or passive	Yes
User region	where the user lives	Yes
User date of birth	when the user was born	Yes
User gender	male or female	Yes
User current work start date	when the user started to work	Yes
User occupation	user occupation	Yes
User education level	user’s graduation level	Yes
User education branch	user’s area of specialization	Yes
User type	normal or personnel	No
User status	whether user is active or passive	No
Course Program Related		
Course program code	a code assigned by the system	No
Course program name	name of the course program	Yes
Course program status	whether course program is active, passive or deleted	No
Course program-package code	package in which the course program is included	No
Course program certification	Whether course program is certificated or not	Yes
Course program start date	Course program opening date	Yes
Course program end date	Course program closing date	Yes
User- Course Program Related		
User’s course program status	whether user is active in the course program or not	No
User’s completion status	whether user completed the course program or not	Yes
Course program assign date	when course program is open for the user	Yes
Course program completion date	when the user completes the course program	Yes
User’s course program success	success of user in this course program	No
User’s course program score	Total score of user in this course program	Yes
User’s first course program?	whether course program is the first one for the user	Yes
E-Learning Program Evaluation-Related		
InformationUsefulness	whether the content has rich information	Yes
Overall Satisfaction	Whether the program provides learner satisfaction	Yes
SamplePractices	Whether the program include practices	Yes
Content	Whether the content is well-prepared	Yes
PermittedActiviyDuration	Whether the duration is sufficient	Yes
VisualInteractionalContent	Whether the program includes visual and interactional content	Yes
Fluency	Whether the program is fluent	Yes
CohesionofContentExam	whether there is a cohesion between content and exam	Yes
PerceivedUsefulness(Generated)	The level of learner’s perceived usefulness	Yes

Data Preprocessing

According to Giudicci (2003), data preprocessing is an important phase for detecting and eliminating problems with data quality and also, for transforming all the data in a standardized form by putting all the attributes into the same measurement unit. Larose (2005) states that most of the times, the raw data within the large databases is not in a suitable form to be mined and needs to be preprocessed. It is stated preprocessing is required, since the database may include redundant data, missing values or outliers. The data may be inconsistent with the common sense or may be irrelevant for data mining analysis. Hellerstein (2008) mentions that these corruptions in the raw data may be resulted from data entry errors, data integration errors, measurement or distillation errors. Larose (2005) highlights that preprocessing step makes up 60% of all data mining process.

In alignment with the facts which Larose (2005) states, the data set is not organized in a very systematic way. There are many tables and many fields. Some fields in the tables are repeated, that is, there is redundancy. There is no standard representation of the data. Data in some fields which has the same meaning is stored differently. There may be misclassifications of data. For example, in one record, the region is stored as ‘Ege’, in another the same meaning is represented as ‘Ege Bölgesi’. There are many missing, incomplete or dirty values for some attributes.

All in all, the database contains huge amount of data, but the complexity, noise and incompleteness of the raw data set forces to clean, to shape and to put the data in a more meaningful form. For that reason, data preprocessing is a core step in this study.

Data cleaning and data transformation is considered as the two major steps in data preprocessing (Larose, 2005) In order to explore the data and to make an initial evaluation, exploratory data analysis is made use of. This preliminary analysis provides information on whether transformation of original variables is required, whether data is redundant or insufficient. Understanding the data set also gives direction about which data mining or statistical tests to be chosen (Giudici, 2003). For this reason, exploratory analysis is applied by using the SPSS Statistics tool and basic properties of raw data set is tired to be discovered. However, in order to explore and correct some errors in the data more effectively, human involvement and data visualizations are considered as a necessity (Hellerstein, 2008). For example, data entry errors or different data representations can mostly be corrected by human involvement.

Data Cleaning

There are several reasons of why data cleaning is required. Missing values, redundancy, outliers, and irrelevant data can be listed as some of them. There are some methods for handling each of these problems with the data.

Missing Values

Giudicci (2003) points out two methods for dealing with missing values in the data set: deleting or replacing it by using the remaining data. Deleting directly the missing rows or deleting the field which contains a lot of missing values is a common method to cope with missing values in the data set. These methods result in data loss. So instead of wiping out the missing values, replacing those missing values is proposed by some researchers. Several replacement methods are listed as:

1. Replacing missing values with a constant by the use of domain knowledge
2. Replacing missing values with mean for quantitative data and with mode for

qualitative data.

3. Replacing missing values with random values generated from the variable distribution.

Table 2 summarizes the missing value analysis. There are some missing values in the raw data set.

Table 2. Missing Values and Outliers

	N	Missing		No. of Extremes[a]	
		Count	Percent	Low	High
U_DateofBirth	42252	3070	6.7	1518	26
U_WorkStartDate	45034	288	.6	0	2576
CP_StartDate	45322	0	.0	0	0
CP_EndDate	45322	0	.0	31	0
CP_U_AssignDate	34866	10456	23	2815	0
CP_U_CompletionDate	34102	11220	24.7	1023	0
CPScore	45322	0	.0	2111	0
CP_U_CompletionStatus	45322	0	.0		
Gender	45127	195	.4		
U_OccCat	45322	0	.0		
Reg	41908	3414	7,5		
U_FirstCourse program	34970	10352	22.8		
U_CP_Status	45322	0	.0		
U_Success	45322	0	.0		
Educ	44998	324	.7		
U_Status	45322	0	.0		
U_Type	45322	0	.0		
CPCont	45322	0	.0		
CP_Status	45322	0	.0		
CPCer	45322	0	.0		
CP_Completed	45322	0	.0		

- Date of birth, work start date, gender, region, first course program and education attributes contain some missing values. To prevent data loss, firstly, replacing the missing value with the series mean value for date of birth (in terms of age) and for work start date (in terms of work experience) is tried. For the remaining missing values, replacement with the mode is performed. However, after cleaning these missing values, a reliability analysis (cronbach’s alpha) is conducted and reliability decrease is observed. For this reason, instead of replacing, rows with missing values are deleted.

- Missing values in course program-user assign date attribute is replaced with an assumption. It is assumed that assign date equals to course program start date, if the assign date is missing, so that all the missing values in assign date are replaced with the corresponding course program start date.
- Furthermore, many missing values are observed in course program completion date. However, this situation should not be considered as an error in the data set. There is another variable as completion status keeping information about whether the user completed the course program or not. If the user does not even complete the course program, then, it is normal not to have a record in course program completion date. For this reason, missing values in course program completion date are not cleared. Instead, the data set is split into two different sets to be able prevent data loss and to be able to use the data set for the prediction analysis of course program completion or withdrawal.
- Instead of deleting the variable or records, missing values are filled with series mean for the branch score. Other replacement methods like linear trend at a point or mean of nearby points are applied, but since the reliability is higher with series mean method, this method is preferred.
- Outliers in total score are discovered and cleared by comparing z-scores. Values with z-scores lower than -2 and greater than +2 are excluded from the data set.

Irrelevant Attributes

User code, user content, user status, course program code, course program status, course program-package code, user's course program status, user's course program success attributes are excluded from the data set. Code attributes are not required for the analysis and status attributes are not meaningful for the analysis, since they contain constant values after rows with missing values are deleted.

Outliers

Outliers are the extreme values within the data set and they are very different and distant from the remaining data values. Outliers may be resulted from data entry errors or may not be. Even in two cases, the identification of outlier is important, since they may affect the performance and the results of statistical tests (Dang, and Serfling, 2010). In learning-course program data set, some outliers in total point, completion date, and assign date, date of birth and work start date attributes are observed.

Some graphical visualization can also be used to identify the outliers. Histograms, P-P Plots, Steam-and-Leaf plots or scatter plots can be used for visual presentation and discovery of outliers (Larose, 2005). To exemplify, the following stem - leaf plot graphs show the distribution of course program completion date and the outliers in this attribute.

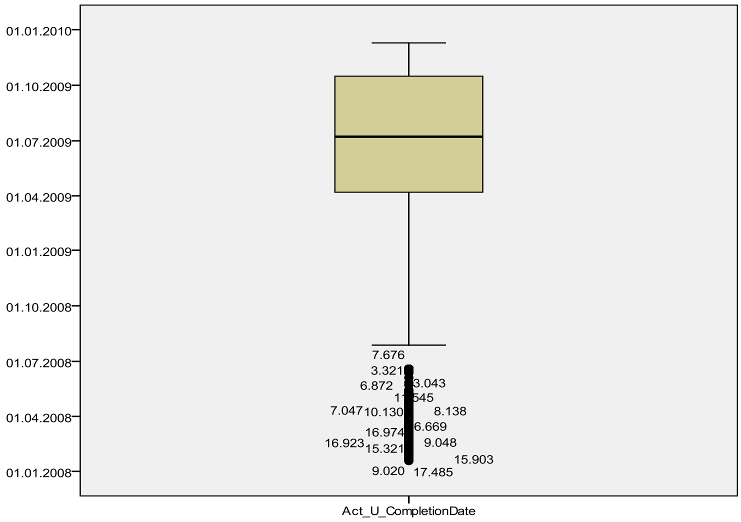

Fig. 2 Outliers in completion date

Outliers may be sometimes resulted from errors in data entry. When the outlier values in course program end date are examined within this data set, it is seen that there are wrong data entries. A date before the course program start date is entered into the database as the course program end date, so that these outliers are removed. Moreover, some outliers in total score are discovered and cleared by comparing z-scores. Values with z-scores lower than -2 are excluded from the data set.

However, it is observed that outlier values in some attributes are not a result of wrong data entries or similar errors. To exemplify, when the completion date is observed, it can be said that one user may have complete very early and the other may have complete very late. When the age is observed, it is seen that it ranges between 20 and 52. However, the outlier analysis shows that some age values are outliers. It seems that in order to decide whether to include or exclude the outlier, the root cause of outlier should be understood by human interpretation. If the outliers are not considered as affecting the overall statistical results, then they should be remained in the data set.

Misclassifications and Data Entry Errors

Other than missing values, outliers and irrelevant attributes, some other errors are also detected in data set. As mentioned above in outliers section, some of the attributes contain data entry errors. For example, in some records, activity completion date is smaller than the course program assign date. Since a course program cannot be completed before it is assigned, this entry can be considered as an entry error. By the use of outlier analysis, such entry errors are detected and cleared.

Misclassification of data is another issue which should be identified and corrected usually by human interpretation and involvement. In the data set, such errors are encountered so often. For example, in region attribute, while one record contains 'Marmara', the other record includes 'Marmara Region'. In another case, a record has a value of 'Ankara' and most of the others have the value of 'İç Anadolu'. In this case, if this region data will be categorized into regions as Marmara, Ege, İç Anadolu and so on, then, Ankara should be included in İç Anadolu region. Such cases are carefully investigated and misclassifications are eliminated.

Data Classification and Discretization

Another step in data preprocessing is data classification and discretization. In order to make use of the data more effectively and efficiently, decreasing the number of discrete number and grouping them together is an important process. For this reason, categorical variables can be put in predetermined groups and continuous variables can be discretized into groups.

Data Classification in Ordinal and Categorical Variables

In the learning-course program data set, there are some categorical (nominal) and ordinal variables. In order to be able to use in data mining analysis, all these variables should be put in a suitable and consistent form. For this reason, all the data values in all attributes are analyzed and it is identified what kind of groups to be established for each variable.

Occupation: In the data set, it is exported that this attribute takes 94 distinct values. To exemplify, division head, region head, corporate selling representative, lawyer, asistant, security guard and 88 other titles. It is considered that occupation variable can be grouped based on two different perpectives as functional and hierarchical. It is aimed to explore the effect of occupation on e-learning effectiveness with respect to two different points of views.

- Functional occupations are represented by the values as follows:

  1= Marketing and Selling

  2= IT

  3= Business Support

- Hierarchical occupations are represented by the values as follows:

  1= Operational Level

  2= Supporting Level

  3= Low-level decision making level

  4= High-level decision making level

- Region: Six distinct regions are explored in the data set. The values assigned for each region are as follows:

  1= Marmara

  2= İç Anadolu

  3= Ege

  4= Karadeniz

5= Güneydoğu Anadolu

6= Doğu Anadolu

- Education: Based on the education information of learners, four education levels are generated as high school, associate degree, bachelor degree, grad degree.

  1= high school

  2= associate degree

  3= bachelor degree

  4= grad degree

- Gender: 0= female and 1= male
- Certification: 0= not certificated and 1= certificated
- Course program completion: 0= not completed and 1= completed
- Course program content: 1= vocational and 2= skill development

Data Discretization in Continuous Variables

Continuous variables like age, work experience, course program total duration, completion duration, formal education score, average e-learning success, number of previous e-learning course programs, total score and evaluation attributes are transformed into categories. Except for evaluation attributes, all other attributes are binned by equi-depth method.

- Age: variable age computed from date of birth and transformed into three categories as younger(<=29), middle age(between 29 and 35), older(>35)
- Work experience (years): variable current work experience computed from work start date and transformed into three categories as low experience(<=2), experienced(between 2 and 7) and very experienced(>7)
- Course program duration (days): variable course program duration computed

from course program start-end date and transformed into three groups as short(<=14), medium(between 14 and 99) and long(>99)

- Course program completion duration (days): variable course program duration computed from course program assign –complete date and transformed into three groups as short(<=3), medium(between 3 and 14) and long(>14)
- Branch Score: variable branch score computed by using ‘OSS’ (Ögrenci Seçme Sınavı) scores of each branch to analyze the effect of formal education success on online course program and transformed into three groups as low(<=310), medium(between 310 and 320) and high(>320)
- Number of course programs: it is computed by counting the course programs a learner participated via SQL queries and transformed into three categories as low(<=10), medium(between 10 and 14) and high(>14)
- Average course program completion duration: it is computed by taking the average of all course program completion durations a learner via SQL queries and transformed into three categories as low(<=20), medium(between 20 and 36) and high(>36)
- Learner average success: it is computed via SQL queries by taking the average of all course program scores of a learner and transformed into three categories as low(<=77), medium(between 77 and 84) and high(>84)
- Total Score: total score of learners is grouped into three categories as unsuccessful (<=64), medium success (between 64 and 90) and successful (>90).
- Evaluation criteria: Evaluation criteria is divided into three categories as unsatisfactory (>0 and <=0.55), relatively satisfactory (>0.55 and <=0.7) and satisfactory (>0.7 and <=1).

Data Transformation

For clustering analysis, all attributes are transformed into 0-1 interval. Different methods are used for different types of variables. Scale, ordinal, nominal and binary variable transformation is performed as follows:

Z-score, mean-standardized transformation and max value transformation is some of proposed methods for scale variable transformation. Age, work experience, course program duration, course program completion duration and total score are scale variables in this study. In order to put the values into a range of 0 -1, max value transformation is applied.

v_new=((v_original-min_original)/(max_original-min_original))*
(max_new-min_new)+min_new

In this method, all the values are divided by the maximum value of the selected variable and at the end, the max value is 1 and the min value is 0 for that variable.

- Age: All the values are divided by 62 which is the oldest age.
- Work experience: All the values are divided by 35 which is the longest work experience.
- Course program duration: All the values are divided by 513 which is the longest duration.
- Course program completion duration: All the values are divided by 502 which is the longest duration.
- Number of course programs: All the values are divided by 38 which is the highest number of course programs.

- Total score: All the values are divided by 100 which is the highest score.

Ordinal variables can be transformed into a range of 0-1 as follows:

$$r_{if} \in \{1,...,M_f\} \qquad z_{if} = \frac{r_{if} - 1}{M_f - 1}$$

In the equation, f is the variable and r_{if} is the i'th object in the data set. In order to protect the ordinality, the value is divided by maximum ordinal value minus 1 (Yang, Yu, Wang, H., and Wang, W., 2002; Ganti, Gehrke, and Ramakrishan, 1999; Gibson, Kleinberg, and Raghavan, 1998)

Another proposed method is to create a new binary variable for each ordinal value. For example, if there are education levels like high school, bachelor and graduate, then 3 new variables are created which take values as only 0 and 1. If it is high school, the value is 1 and if it is not, the value is 0 for high school variable. This method can be cumbersome, if there are many ordinal variables which take many values.

In this study, the second method is used. There are not too many variables creating huge work load and representing each value as a separate nominal variable is considered to give more flexibility in cluster analysis.

- Education: a new variable is created for high school, associate school, bachelor and graduate degree.
- Hierarchical occupation: Operational, supporting, low level decision making and high level decision making is represented by separate binary variables.

Nominal variables are stored as separate binary variables for each value of nominal variable.

- Region: Six new binary variables are produced for each region (Marmara, İç Anadolu, Ege, Karadeniz, Güneydoğu Anadolu and Doğu Anadolu)
- Functional occupation: Three new binary variables are generated for each functional occupation (Marketing and Selling, IT and Business Support)

Binary variables like gender, e-learning experience, course program completion and course program certification in the data set are already coded as 0 and 1. Course program content has the values 1 for vocational course programs and 2 for skill development course programs. These values are recoded as 1 into 0 and 2 into 1.

Data Reduction: Factor Analysis

Analysis of the data can be made easier by reduction of dimensionality. Dimensionality reduction means decreasing the number of variables and representing more than one variable with one component. Correlated p variables are transformed into uncorrelated k linear combinations (k<p) (Giudici, 2003).

For data reduction, factor analysis is applied to perceived usefulness data set. It is conducted to understand whether one or more components representing eight evaluation factors in the data set can be obtained to explain the variance in user's total score and completion duration. The reason of conducting a factor analysis is to reduce the number of independent variables by combining them and to reduce data size.

A crucial concern before applying factor analysis is to observe the correlations between variables. In order to make sure that there is sufficient correlation and make the model function correctly, some tests should be conducted. Kaiser-Meyer-Olkin Measure of Sampling statistic should be higher than 0.5 and p value should be less than 0.1 (Larose, 2006).

Table 3 shows that the data set is appropriate for factor analysis with KMO=0.839>0.5 and p value=0.000<0.1.

Table 3. KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,839
Bartlett's Test of Sphericity	Approx. Chi-Square	134252,167
	Df	28
	Sig.	,000

As mentioned, if there is not a certain degree of correlation, then the analysis may not be efficient. Since there is no correlation, then the model can reproduce the same variables and dimensionality cannot be reduced (Giudicci, 2003). Correlation matrices also show the level of correlations and whether the data is suitable for the analysis. In the Spearman's correlation matrix below in the table 4, it is seen that all the variables are significantly correlated supporting the appropriateness of conducting analysis.

Table 4. Perceived Usefulness Correlations

		CPInfoUseful	CPOverallSatisfaction	CPSampPrac	CPContQ	CPPerDur	CPVisualInteract	CPFluency	CPCoContEx
Spearman's rho	CPInfoUseful	1,000	,667**	,949**	,484**	,775**	,804**	,700**	,935**
		.	,000	,000	,000	,000	,000	,000	,000
		8683	8683	8683	8683	8683	8683	8683	8683
	CPOverallSatisfaction	,667**	1,000	,775**	,797**	,912**	,778**	,849**	,799**
		,000	.	,000	,000	,000	,000	,000	,000
		8683	8683	8683	8683	8683	8683	8683	8683
	CPSampPrac	,949**	,775**	1,000	,560**	,874**	,793**	,795**	,961**
		,000	,000	.	,000	,000	,000	,000	,000
		8683	8683	8683	8683	8683	8683	8683	8683
	CPContQ	,484**	,797**	,560**	1,000	,703**	,505**	,562**	,636**
		,000	,000	,000	.	,000	,000	,000	,000
		8683	8683	8683	8683	8683	8683	8683	8683
	CPPerDur	,775**	,912**	,874**	,703**	1,000	,835**	,905**	,861**
		,000	,000	,000	,000	.	,000	,000	,000
		8683	8683	8683	8683	8683	8683	8683	8683
	CPVisualInteract	,804**	,778**	,793**	,505**	,835**	1,000	,760**	,743**
		,000	,000	,000	,000	,000	.	,000	,000
		8683	8683	8683	8683	8683	8683	8683	8683
	CPFluency	,700**	,849**	,795**	,562**	,905**	,760**	1,000	,799**
		,000	,000	,000	,000	,000	,000	.	,000
		8683	8683	8683	8683	8683	8683	8683	8683
	CPCoContEx	,935**	,799**	,961**	,636**	,861**	,743**	,799**	1,000
		,000	,000	,000	,000	,000	,000	,000	.
		8683	8683	8683	8683	8683	8683	8683	8683

In the table 5 below, communality for each variable is presented. Communality means attribute variance shared with other attributes. It shows the severity of each variable in the analysis. If the communality of an attribute is lower than 0.5, then it means that this variable explains the common variability less than the other variables and its contribution to the analysis is small. This attribute should be excluded from factor analysis in order to increase the KMO value and total variance explained by the components (Larose, 2006). As seen in the table 5, all the attributes have high communality values, that is, all can be included in the analysis. Component column in the table 5 explains the weights of each attribute.

Table 5. Factor Analysis Communalities

	Communalities		Component
	Initial	Extraction	1
CPInfoUseful	1,000	,912	,955
CPOverallSatisfaction	1,000	,904	,951
CPSampPrac	1,000	,945	,972
CPContQ	1,000	,676	,822
CPPerDur	1,000	,935	,967
CPVisualInteract	1,000	,817	,904
CPFluency	1,000	,769	,877
CPCoContEx	1,000	,926	,962

Table 6 explains total variance explained by each component. Statistically, it is proposed that the components which has an Eigen value greater than 1 should be selected (Larose, 2006; Giudici, 2003). The table shows that just one component complies with the conditions and is selected. It can explain 86,058% of all variance in total score. This percentage is considered enough for explaining the variance in the data set. For this reason, factor score of this component can be used instead of eight distinct variables.

Table 6. Total Variance Explained (Factor Analysis)

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6,885	86,058	86,058	6,885	86,058	86,058
2	,475	5,934	91,992			
3	,271	3,383	95,376			
4	,178	2,219	97,595			
5	,103	1,283	98,878			
6	,050	,627	99,506			
7	,027	,341	99,846			
8	,012	,154	100,000			

As a result, only one component seems to be sufficient to represent these 8 evaluation criteria and explain the variance to a meaningful extent. When these 8 variables are observed, each of them seems to be related with the content of course program and seems to be indicators of usefulness of content from the user point of view. For this reason, extracted component as a result of PCA is named as perceived usefulness and factor score will be used in correlation analysis.

Factor score has values between -5 and +3,5. In order to use this score in analysis, values should be in a range of 0 and 1. There are different transformation methods as z score transformation, logarithmic transformation and min-max value transformation. Factor score is transformed by the use of min-max transformation to be able to put the values in 0-1 interval.

In order to be used in some statistical tests, these new factor scores are also discretized into three categories as all other evaluation criteria as unsatisfactory (>0 and <=0.55), relatively satisfactory (>0.55 and <=0.7) and satisfactory (>0.7 and <=1) and stored as a different variable.

Final Data Set Attributes

As mentioned in the previous section, during data preprocessing operations, some new variables are generated from the existing ones and some variables are renamed. In order to make the analysis results more understandable, all variable names used in the results section and corresponding descriptions are listed in the table 7 below:

Table 7. Final Data Set Attributes

Variable name	Description
Age	Learner age used in continuous form, categorical form with three groups and in 0-1 interval form
Gender	Female (0) or male (1)
Educ	Education level with 4 categories (High school, associate, bachelor and graduate)
HierOcc	Hierarchical occupation with 4 categories (Operational, support, low level decision making and high level decision making)
FuncOcc	Functional occupation with 3 categories (Marketing and Selling, IT and Business support
WorkExp	Work experience used in continuous form, categorical form with three groups and in 0-1 interval form
Reg	Region with 6 categories (Marmara, Ege, Karadeniz, İç Anadolu, Güneydoğu Anadolu and Doğu Anadolu)
FormalEdu	Formal education success used in continuous form, categorical form with three groups and in 0-1 interval form
NoofCP	Number of previous course programs used in continuous form, categorical form with three groups and in 0-1 interval form
AvgCPCompDur	Average course program completion duration used in continuous form, categorical form with three groups and in 0-1 interval form
AvgELSuc	Average e-learning success of learner used in continuous form, categorical form with three groups and in 0-1 interval form
CPCont	Course program content as vocational or skill development

Variable name	Description
CPDur	Course program duration used in continuous form, categorical form with three groups and in 0-1 interval form
CPCompDur	Course program completion duration used in continuous form, categorical form with three groups and in 0-1 interval form
CPCer	Course program certification as not certificated or certificated
CPScore	Learner’s course program score used in continuous form, categorical form with three groups and in 0-1 interval form
CPInfoUseful	Perceived information usefulness used in continuous form, categorical form with three groups and in 0-1 interval form
CPOverallSatisfaction	Perceived satisfaction used in continuous form, categorical form with three groups and in 0-1 interval form
CPSampPrac	Perceived sufficiency of sample practices used in continuous form, categorical form with three groups and in 0-1 interval form
CPContQ	Perceived content quality used in continuous form, categorical form with three groups and in 0-1 interval form
CPPerDur	Perceived sufficiency of permitted duration used in continuous form, categorical form with three groups and in 0-1 interval form
CPVisualInteract	Perceived sufficiency of visual and interactional content used in continuous form, categorical form with three groups and in 0-1 interval form
CPFluency	Perceived fluency used in continuous form, categorical form with three groups and in 0-1 interval form
CPCoContEx	Perceived cohesion of content and exam used in continuous form, categorical form with three groups and in 0-1 interval form
CPPercUseful (Generated component)	Perceived overall usefulness generated as a result of factor analysis and used in continuous form, categorical form with three groups and in 0-1 interval form

Selection of Statistical Methods

In data preprocessing phase, the data is observed; evaluated and required tasks are performed in order to prepare the data for the analysis based on the study objectives.

Next phase in knowledge discovery is selection of the most appropriate tests and models. Predictive or descriptive, supervised or unsupervised techniques are selected depending on the problem which is being studied and nature of the data including data types, data size and so on. Selected methods should be in parallel with the aim of the analysis.

Descriptive methods which are also known as symmetrical, unsupervised or indirect methods are used to define the data more briefly. Cluster analysis, association methods, graphical models are some of descriptive methods. On the other hand, predictive methods aim to establish relationships between the variables. These methods are asymmetrical, supervised and direct methods. Predictive methods are used to establish classification or prediction rules to be used for a future result. Generated models explain what will happen to target variable based on the changes in input variables. Neural networks, decision trees, linear and logistic regression models are the mostly used predictive methods (Giudici, 2003).

In this study, distinct data sets are generated from the database and SPSS 17.0 (Statistical Package for the Social Sciences) tool is used for applying data mining tests. Statistical correlational tests, chi-square tests, factor analysis as a part of exploratory analysis, k-means clustering analysis as a descriptive method, decision tree by CHAID growing method and logistic regression models as predictive classification methods are applied to the data set.

Correlational Tests

Correlational tests are conducted in order to discover how strongly two variables are correlated and have influence on each other. In this study, for statistical correlational tests as a part of exploratory analysis, Spearman's rank correlation coefficient, Kruskal-Wallis and Wilcoxon Mann-Whitney U tests are used for correlational analysis.

Spearman's rank correlation coefficient (Spearman's rho) is used to discover the correlations between variables. Kruskal–Wallis one-way analysis of variance by ranks and Wilcoxon Mann-Whitney U tests are used in order to test the differences among the groups. All these tests are non-parametric tests which are proposed to be used when the underlying distribution of data is not normal or data is not continuous or data is not equal variance (Brasel, and Neideen, 2007). Since the data does not have a normal distribution, these correlational tests are preferred. Using parametric tests which requires normality would cause to unreliable analysis results.

Spearman's rho is the corresponding statistical test to Pearson product correlation parametric test. It measures the degree of correlation between two variables, that is, it measures to what extent one variable can influence the other one. The test produces a correlation coefficient which is from -1 to 1. -1 represents perfect negative correlation and +1 shows perfect positive correlation between the variables. The coefficient which approximates to +1 and -1 shows that correlation between the variables are stronger and these variables can predict each other better (Brasel, and Neideen, 2007).

Kruskal Wallis test can be used to understand the differences among multiple groups in an ordinal data set which is not normally distributed. It is an analysis of variance which measures the similarities among two or more groups. In its logic, Kruskal Wallis test ranks all the data in the groups and aggregates the different ranks from the individual groups and ultimately, compares the mean ranks.

Mann Whitney U test or Wilcoxon rank test is also applied to ordinal data and especially proposed when the underlying distributions of data set is not normal. It is similar to t-test, but t- test is used for continuous data different than Wilcoxon rank test. Two independent groups are compared in order to discover whether these groups come from different or the same population. If the test statistic (p value) is less than the critical value (0.05), the null hypothesis which claims that the two groups come from the same population is rejected (Brasel, and Neideen, 2007).

It should be noted that while comparing two groups, z scores of less than 1.96 indicate that the two samples come from the same underlying distribution, at the p=.05 significance level (Hussain, Ismail, and Jamaluddin, 2010).

Cluster Analysis

In this study, cluster analysis is conducted in order to describe the data more briefly. It is aimed to explore similarities in the data based on existing characteristics in the data set and putting the similar samples into clusters. It is a descriptive analysis and there are no predefined classes different than classification which is a predictive method of data mining. It provides a general insight about the data and its distribution. As a result, it helps for choosing other suitable data mining algorithms. A good clustering has the ability to find all or some of the hidden patterns in the data set and produce high quality clusters with high intra-class similarity and low inter-class similarity (Giudici, 2003; Yang et al., 2002; Ganti et al., 1999; Gibson et al., 1998).

In general, it explores the similarities and dissimilarities among the groups by distance functions. Distance functions differ based on the nature of attributes. They are different for interval-scaled, boolean, categorical, ordinal or vector variables. Transforming all values into a range of 0-1 is a recommended method and the method changes depending upon the variable content (Yang et al., 2002; Ganti et al., 1999; Gibson et al., 1998).

There are two main types of clustering as hierarchical and non-hierarchical clustering. In this study, k-means clustering which is a non-hierarchical method is chosen, since non-hierarchical clustering methods are much faster and suitable for large data sets. This type of clustering enables to classify n observations into g groups which are determined at the beginning of the analysis. Each observation is classified in one of the groups based on a selected criterion like a distance function or means of an objective function. K-means clustering mainly functions looking at the distance between the observations and the centroids of the clusters. It uses Euclidean distance function. The aim is to increase the internal similarity in each group (Giudici, 2003).

Logistic Regression Models

Regression is not a complex, but a strong predictor tool. The aim of regression models is to explore whether the dependent variable can be explained as a function of some independent variables or determinants (Larose, 2006; Guidici, 2003).

In this study, logistic regression models are chosen, since logistic regression generates the function of a qualitative dependent variable, while linear regression models deal with a quantitative dependent variable (Larose, 2006; Guidici, 2003). The aim is to understand the effect of some statistically significant independent variables like age, gender, education level, course content, course duration and so on in explaining the dependent variables like course program success or failure, course program completion or withdrawal.

In logistic regression models, estimate values (B) are the coefficients of predictors in regression equation and show the strength of influence, that is, a unit of change in predictors has on the dependent variable. The sign of coefficient shows whether the probability of being in comparison category increases or decreases as a result of a unit of change in the predictor. If (B)>0, then a unit of change in the predictor has a positive effect for being in comparison category and vice versa. B values are named as log-odds units. Probability of being in one category of dependent variable over the other category of the dependent variable is expressed in the equation below decreases (Larose, 2006; Guidici, 2003; Norusis, 1999; UCLA Academic Technology Services [UCLA], n.d.).

$$log(p/1\text{-}p) = b0 + b1*x1 + b2*x2 + b3*x3 + b3*x3+b4*x4$$

Binary logistic regression tests enable establishing a prediction model which includes one or more categorical independent variables and a dichotomous dependent variable. It is also called binomial logistic regression. Multinomial logistic regression test is similar to logistic regression with the only difference in dependent variable. Dependent variable is not required to be dichotomous and can have more than two categories (Larose, 2006; Guidici, 2003).

Multinomial logistic regression model is used to understand the relationships between a non-metric (dictomous, nominal or ordinal) dependent variable and dictomous or metric (ordinal or continuous) independent variables. It does not assume normality, linearity or homogeneity of variance for independent variables. For this reason, it is applied instead of discriminant analysis when the data set do not satisfy these assumptions. It is stated that there should be at least 10 cases per independent variable in the data set. Other than exploring the overall relationship between a dependent variable and a combination of independent variables as a result of likelihood ratio test, the Wald test measures whether an independent variable is significantly powerful to differentiate between two groups of dependent variable. In other words, it evaluates the ability of each independent variable to classify a case in one of the categories of dependent variable (Larose, 2006; Guidici, 2003; Hosmer, Lameshow, and Taber 1991).

In order to prove the accuracy and usefulness of the model, a 25% improvement over the rate of accuracy achievable by chance alone in classification should be measured. 'By chance accuracy' means that even if there is no relationship between independent and dependent variable, predictions of group membership may be expected to be correct for some cases in some period of time. The proportional by chance accuracy rate is calculated by computing the proportion of cases for each group of dependent variable based on the number of cases and then, squaring and summing up all the proportions for each group. The proportional by chance accuracy criteria is calculated by multiplying the proportional by chance accuracy rate by 1.25, since 25% improvement is required for a significantly accurate model (Anderson, Black, Hair, and Tatham, 1998).

Decision Tree Model

Decision tree is another predictive classification model. It is applied in order to classify the learners into success groups, completion duration groups, completion or withdrawal groups and satisfaction groups. Decision tree classification is conducted as a secondary model after regression analysis in order to see whether there are differences between two models or not.

CHAPTER VII: RESULTS

The results of data mining analysis related to hypotheses are reported in this section. Analysis is started with a preliminary analysis which is conducted for similar group discovery. After preliminary analysis, hypotheses on e-learning effectiveness are tested via selected data mining algorithms and results are presented.

Preliminary Analysis for Similar Group Discovery

As a preliminary analysis, it is useful to understand general characteristics and patterns in the data set and to see the similarities and dissimilarities within the groups. To be able to measure the distance and connections among groups, clustering as a data mining method is applied and it is considered as providing insightful results about the data set before getting into deeper analysis.

In e-learning data sets used in this study, there are scale, ordinal, nominal and binary variables. They are transformed into 0-1 interval as mentioned in data preprocessing section.

Cluster Analysis: Learner Success

In order to explore the hidden patterns in the data set with respect to learner success, a cluster analysis is conducted. The aim is to get useful insights about the data before deeper analysis and to explore whether there are some similarities and dissimilarities among successful and unsuccessful e-learning course programs. If some common characteristics are determined, it can be concluded that there may be significant factors influencing learning success and deeper analysis may be conducted.

Two separate cluster analysis is performed by the assumptions of two and three clusters, distinctly. As a result of k-means clustering with 3 clusters, it is seen that one additional cluster does not contribute much for explaining dissimilarities and similarities within the data set, so that 2 clusters seem to be leading enough for further analysis. Since at least 2 clusters are discovered in the data set, it can be concluded that there are learner groups with some similarities with close success levels.

When two clusters are analyzed in the table 8 below, it can be understood that successful and unsuccessful course programs are collected in 2 distinct clusters. Cluster 1 is the cluster of successful course programs with a total score mean of 0.96. On the other hand, cluster 2 has an average score of 0.67 and can be considered as unsuccessful cluster.

Table 8. Final Cluster Centers (Success)

	Cluster	
	1	2
CPScore	,96	,67
Age	,62	,57
Male	,48	,38
Female	,52	,62
E_HighSchool	,30	,23
E_Associate	,14	,14
E_Bachelor	,55	,61
E_Grad	,01	,02
WorkExp	,26	,20
R_Marmara	,31	,34
R_IcAnadolu	,30	,28
R_Ege	,10	,12
R_Karadeniz	,11	,11
R_DoguAnadolu	,06	,05
R_GüneydoguAnadolu	,11	,10
HO_HighLvl	,44	,32
HO_LowLvl	,01	,00
HO_Supporting	,10	,12
HO_Operational	,46	,55
FO_MarketingSelling	,76	,77
FO_IT	,12	,11
FO_CorpBusinessSupport	,12	,13
CPDur	,45	,03
CPCompDur	,15	,01
NoofCP	,49	,44
AvgCPCompDur	,15	,11
AvgELSuc	,83	,77
NotFirstCP	,99	1,00
FirstCP	,01	,00
CPNotCer	,01	1,00
CPCer	,99	,00
CPVocational	,49	1,00
CPSkillDev	,51	,00

If the two clusters are compared in the table 8 above, it seems that there are no huge differences among demographics of learners. Average age of successful group is 38,44 (0,62*62)) and it is 35,34 (0,57*62) for unsuccessful group. While 48% of successful group is male, 38% of unsuccessful group is male. When the education distribution is analyzed, it is nearly the same for the two groups, mostly consisting of bachelor degree learners. There is no sharp differentiation in region distribution, as well. Marmara region has the dominance in the sample of two groups. In both clusters, high level decision makers constitute the majority. Both groups are consisted of learners from marketing and selling function. There is no obvious difference between groups with respect to functional occupation of learners. Previous e-learning performance of learners which is measured by existence of previous e-learning experience and number of previous e-learning course programs does not differ between groups, as well.

However, when the characteristics of the course programs are examined, major differences can be clearly seen. Course program duration and course program completion duration is much longer in cluster one which is the successful group. Furthermore, 99% of the course programs which are collected in successful group are certificated. In other words, a certificate is given at the end of the education. However, course programs which do not provide certification are collected in unsuccessful group.

Lastly, course program content attracts attention when two groups are compared. Cluster analysis results show that unsuccessful group is consisted from only vocational course programs, but not skill development course programs.

In the table 9 below, summarized attributes of each cluster can be seen:

Table 9. Comparison of clusters (Success)

Successful Group	Unsuccessful Group
Middle age Most of the men in successful cluster Mostly bachelor degree Marmara region High level decision maker Marketing and selling function	Middle age Most of the women in unsuccessful cluster Mostly bachelor degree Marmara region High level decision maker Marketing and selling function
Longer course program duration Longer course program completion duration	Shorter course program duration Shorter course program completion duration
Certificated	Not certificated
Mostly skill development education programs	Totally vocational education programs

Just by looking at cluster analysis results, it can be claimed that either the skill development course programs are easy for every learner or there is a poor assessment of these programs. Another view can claim that if the duration of vocational programs is increased, success level will increase, as well.

Cluster Analysis: Course Program Completion

It is also aimed to understand whether there are some similar characteristics of the learners who complete and who do not complete the course programs. K-Means clustering methodology is applied by the use of iterate and classify method. Number of clusters is predefined as 2 clusters. After running the cluster analysis with 2 clusters, in order to compare the results, analysis is performed with 3 clusters, as well.

As a result of the analysis, a cluster which consists of mostly from learners who complete the course program is generated. By looking at the characteristics (values of other variables) in this cluster, some similarities for the learners who complete the course program can be explored. This result can be interpreted as there are some outstanding common characteristics between the learners who complete the course programs. Moreover, the result of this analysis shows the requirement of further analysis on the data set, since it seems there are some influencing factors for completing a course program, so that correlations between variables can be analyzed. Furthermore, a predictive classification model can be generated in order to predict completion or withdrawal by looking at the learner's some significant characteristics.

Two clusters seem to explain all the dissimilarities and one more cluster does not contribute any further information. The final clusters as a result of analysis with the assignment of 2 clusters as default can be analyzed below.

According to the final cluster center table 10 below, there are two distinct groups each of which has intra-class similarity. According to the logic of clustering, each cluster collects the incidents with similar characteristics and excludes dissimilar characteristics, that is, learners or course programs which are closer to each other with respect to the characteristics included in the analysis are collected in the same group.

Table 10. Final Cluster Centers (Completion)

	Cluster	
	1	2
CPNotCompleted	,03	,42
CPCompleted	,97	,58
CPNotCer	1,00	,01
CPCer	,00	,99
CPVocational	,99	,59
CPSkillDev	,01	,41
Male	,34	,37
Female	,66	,63
E_HighSchool	,00	,00
E_Associate	,18	,17
E_Bachelor	,80	,80
E_Grad	,02	,02
O_AsstSpecialist	,13	,13
O_CustRep	,07	,05
O_BankOfficer	,29	,28
O_AuthCustRep	,18	,17
O_AsstManager	,00	,01
O_Manager	,13	,12
R_Marmara	,35	,35
R_IcAnadolu	,27	,28
R_Ege	,12	,12
R_Karadeniz	,10	,09
R_GüneydoguAnadolu	,11	,11
R_DoguAnadolu	,05	,05
HO_HighLvl	,33	,35
HO_LowLvl	,01	,01
HO_Supporting	,13	,13
HO_Operational	,54	,51
FO_MarketingSelling	,78	,78
FO_IT	,09	,07
FO_CorpBusinessSupport	,13	,15
CPScore	,68	,72
Age	,52	,53
CPDur	,04	,49
WorkExp	,15	,16
NoofCP	,44	,46

In cluster 1, almost all learners complete the course program (97%), so that the characteristics in cluster 1 can be considered as similarities of incidents in which the course program is completed. When the characteristics which differentiate two clusters are observed, it is seen that mostly course program characteristics are the outstanding factors. Vocational course programs which are assigned shorter duration and are not certificated are placed in cluster 1 and seem to be much more likely to be completed. However, learner characteristics like demographics, previous e-learning experience and some others do not seem as distinguishing two clusters. For example, in both clusters, 78% of sample is from marketing and selling function. Major characteristics differentiating completion and withdrawal group can be seen in the table 11 below:

Table 11. Comparison of Clusters (Completion)

Completion	Withdrawal
Shorter course program duration	Longer course program duration
Not Certificated	Certificated
Mostly vocational course programs	Vocational and skill development course programs

As a result, cluster analysis shows that there are minor differences between successful and unsuccessful groups and completion and withdrawal groups with respect to demographics and previous e-learning performance of learners. In order to understand whether these slight correlations and slight differences between groups are significant, further analysis is required. Furthermore, it is explored that the sample can be sharply divided into groups based on course program characteristics. Deeper analysis seems to be crucial to be able to discover the degree of significance of those relationships with respect to course program characteristics.

Hypotheses Testing for Learner Performance

In the section below, significant factors for learner performance are examined in terms of three components as: learner's success (represented by total score), learner's course program completion duration and whether the learner can complete the course program or not.

Learner Success

In order to test the hypothesis, learning-course program completed data set is used. The correlations between the variables and the influence of demographics, previous e-learning performance and course program characteristics on learner success are analyzed through correlational tests. Regression and decision tree success models are generated.

Learner's Demographics vs Learner's Success

- HA0: There is a statistically significant association between learner's success and learner's age.

According to Spearman rho correlational test statistic, there is a significant association between learner's success and learner's age with correlation coefficient=0.215 at the significance level p=0.000. HA0 is accepted.

Table 12. Correlations (Age vs. Success)

			Age	CPScore
Spearman's rho	Age	Correlation Coefficient	1,000	,215**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	CPScore	Correlation Coefficient	,215**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that learner's age has an influence on learner's success. It should also mean that different age groups have different success levels. In order to test whether age groups are significantly different from each other in terms of success, Kruskal Wallis non-parametric test is conducted. Table 14 below presents the statistical figures of test results:

Table 14.Test Statistics

	CPScore
Chi-Square	1127,696
df	2
Asymp. Sig.	,000

a. Kruskal Wallis Test

b. Grouping Variable: Age

According to the table 14 above, there is a statistically significant difference between the different age groups (Chi-Square = 11.270, P = 0.000). Mean of total score for each age group can be examined in the table 15 below which shows that older age groups performs better than both younger and middle age groups.

Table 15. CPScore

Age	Mean	N	Std. Deviation
Younger	70,21	5984	21,610
Middle age	70,46	5432	20,053
Older	81,11	7547	20,726
Total	74,62	18963	21,478

Even if it is clearly seen that mean of score for different age groups are different from each other in the table 15 above, additional post-hoc analysis should be conducted to be able to understand whether the differences among groups are statistically significant or not. For that reason, multiple comparisons are conducted by applying Mann Whitney- 2 independent samples test. If the p value is less than 0.05, then the null hypothesis which claims that two groups have statistically different distributions is accepted. All age groups are compared with each other based on these statistical assumptions and the results are presented as follows:

1. There is not a statistically significant difference between the underlying distributions of the total score of younger age group and the total score of middle age group ($z = -1.307$, $p = 0.191>0.05$).

Table 16. Test Statistics (Age)

	CPScore
Mann-Whitney U	1,604E7
Wilcoxon W	3,079E7
Z	-1,307
Asymp. Sig. (2-tailed)	,191

2. There is a statistically significant difference between the underlying distributions of the total score of younger age group and the total score of older age group ($z = -27.727$, $p = 0.000<0.05$).

Table 17. Test Statistics (Age)

	CPScore
Mann-Whitney U	1,669E7
Wilcoxon W	3,460E7
Z	-27,727
Asymp. Sig. (2-tailed)	,000

3. There is a statistically significant difference between the underlying distributions of the total score of middle age group and the total score of older age group (z = -29.147, p = 0.000 < 0.05).

Table 18. Test Statistics (Age)

	CPScore
Mann-Whitney U	1,472E7
Wilcoxon W	2,947E7
Z	-29,147
Asymp. Sig. (2-tailed)	,000

The results show that older age groups are more successful and in order to increase success level of younger age groups, their preferences on system usefulness may be taken into consideration.

- HA1: There is a statistically significant association between learner's success and learner's gender.

According to Spearman rho correlational test statistic, there is a significant association between learner's success and learner's gender with correlation coefficient=0.047 at the significance level p=0.000. HA1 is accepted.

Table 19. Correlations (Gender vs. Score)

			Gender	CPScore
Spearman's rho	Gender	Correlation Coefficient	1,000	,047**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	CPScore	Correlation Coefficient	,047**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that learner's gender has an influence on learner's success. It should also mean that female and male has different success levels. In order to test whether different genders are significantly different from each other in terms of success, Kruskal Wallis non-parametric test is conducted. Table 20 below presents the statistical figures of test results:

Table 20. Test Statistics

	CPScore
Chi-Square	41,420
df	1
Asymp. Sig.	,000

According to the table 20 above, there is a statistically significant difference between male and female (Chi-Square = 41.420, P = 0.000). Mean of total score for male and female can be examined in the table below which shows male performs better than female. H0 proves that there is a relationship between age and learner success and as age increases, success increases, as well. Relatedly, it is aimed to discover whether gender-success relationship is affected from age of the learner. The question is whether male is more successful due to his age. The table 22 below shows that there is a correlation between age and gender.

Table 21. Average Score-Gender

Gender	Mean	N	Std. Deviation
Female	73,95	11287	20,986
Male	75,61	7676	22,147
Total	74,62	18963	21,478

Table 22. Correlations (Age vs Gender)

			U_Age	U_Gender
Spearman's rho	U_Age	Correlation Coefficient	1,000	,217**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	U_Gender	Correlation Coefficient	,217**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

- HA2: There is a statistically significant association between learner's success and learner's education level.

According to Spearman rho correlational test statistic, there is a significant association between learner's success and learner's education level with correlation coefficient=-0.063 at the significance level p=0.000. HA2 is accepted.

Table 23. Correlations (Education vs. Score)

			Educ	CPScore
Spearman's rho	Educ	Correlation Coefficient	1,000	-,063**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	CPScore	Correlation Coefficient	-,063**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that learner's educational level has an influence on learner's success. It should also mean that different education groups have different success levels. In order to test whether education groups are significantly different from each other in terms of success, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 24. Ranks (Education vs. Score)

	Educ	N	Mean Rank
CPScore	HighSchool	4751	10120,75
	Associate	2690	9279,44
	Bachelor	11217	9275,68
	Graduate	305	8906,43
	Total	18963	

Table 25.Test Statistics

	CPScore
Chi-Square	98,632
df	3
Asymp. Sig.	,000

According to the tables above, there is a statistically significant difference between the different education groups (Chi-Square = 98.632, P = 0.000) with a mean rank of 10120,75 for high school, 9279,44 for associate school, 9275,68 for bachelor degree and 8906,43 for graduate degree. Additional to the mean ranks, mean of total score for each education group can be examined in the table 26 below which shows that high school graduates performs better than the others.

Table 26. Average Score (Education)

Educ	Mean	N	Std. Deviation
HighSchool	77,00	4751	21,686
Associate	73,30	2690	22,165
Bachelor	73,96	11217	21,181
Graduate	73,31	305	20,152
Total	74,62	18963	21,478

Even if it is clearly seen that score means of some education groups are different from each other in the table above, additional post-hoc analysis should be conducted to be able to understand whether the differences among groups are statistically significant or not. For that reason, multiple comparisons are conducted by applying Mann Whitney- 2 independent samples test. All education groups are compared with each other based on these statistical assumptions and the results are presented as follows:

1. There is a statistically significant difference between the underlying distributions of the total score of high school and the total score of associate school ($z = -6.683$, $p = 0.000<0.05$).

Table 27. Test Statistics (Education)

	CPScore
Mann-Whitney U	5829623,000
Wilcoxon W	9449018,000
Z	-6,683
Asymp. Sig. (2-tailed)	,000

2. There is a statistically significant difference between the underlying distributions of the total score of high school and the total score of bachelor degree ($z = -9.484$, $p = 0.000<0.05$).

Table 28. Test Statistics (Education)

	CPScore
Mann-Whitney U	2,426E7
Wilcoxon W	8,718E7
Z	-9,484
Asymp. Sig. (2-tailed)	,000

3. There is a statistically significant difference between the underlying distributions of the total score of high school and the total score of graduate degree ($z = -4.001$, $p = 0.000<0.05$).

Table 29.Test Statistics (Education)

	CPScore
Mann-Whitney U	631533,500
Wilcoxon W	678198,500
Z	-4,001
Asymp. Sig. (2-tailed)	,000

4. There is not a statistically significant difference between the underlying distributions of the total score of associate school and the total score of bachelor degree ($z = 0,000$, $p = 0.999>0.05$).

Table 30. Test Statistics (Education)

	CPScore
Mann-Whitney U	1,509E7
Wilcoxon W	1,871E7
Z	,000
Asymp. Sig. (2-tailed)	,999

5. There is not a statistically significant difference between the underlying distributions of the total score of associate school and the total score of graduate degree ($z = -1,166$, $p = 0.244>0.05$).

Table 31. Test Statistics (Education)

	CPScore
Mann-Whitney U	394500,500
Wilcoxon W	441165,500
Z	-1,166
Asymp. Sig. (2-tailed)	,244

6. There is not a statistically significant difference between the underlying distributions of the total score of bachelor degree and the total score of graduate degree (z = -1,237, p = 0.216>0.05).

Table 32. Test Statistics (Education)

	CPScore
Mann-Whitney U	1643761,000
Wilcoxon W	1690426,000
Z	-1,237
Asymp. Sig. (2-tailed)	,216

- HA3: There is a statistically significant association between learner's success and learner's functional occupation.

According to Spearman rho correlational test statistic, there is a significant association between learner's success and learner's functional occupation with correlation coefficient=-0.026 at the significance level p=0.000. HA3 is accepted.

Table 33. Correlations (Functional Occupation vs. Score)

			FuncOcc	CPScore
Spearman's rho	FuncOcc	Correlation Coefficient	1,000	-,026**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	CPScore	Correlation Coefficient	-,026**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that learner's functional occupation has an influence on learner's success. It should also mean that different functional occupation groups have different success levels. In order to test whether functional occupation groups are significantly different from each other in terms of success, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 34. Ranks (Occupation vs. Score)

	FuncOcc	N	Mean Rank
CPScore	MarketingandSales	14507	9522,99
	IT	2078	10337,39
	Business Support	2378	8484,45
	Total	18963	

Table 35.Test Statistics

	CPScore
Chi-Square	146,830
df	2
Asymp. Sig.	,000

According to the tables above, there is a statistically significant difference between the different age groups (Chi-Square = 146,830, P = 0.000) with a mean rank of 9522,99 for Marketing and Sales group, 10337,39 for IT group and 8484,45 for business support group. Additional to the mean ranks, mean of total score for each functional occupation group can be examined in the table 36 below which shows that IT group performs better than the other functional occupation groups.

Table 36. Average Score (Func. Occupation)

FuncOcc	Mean	N	Std. Deviation
MarketingandSales	74,77	14507	21,440
IT	79,02	2078	19,273
Business Support	69,89	2378	22,602
Total	74,62	18963	21,478

Even if it is clearly seen that score means of some functional occupation groups are different from each other in the table above, additional post-hoc analysis should be conducted to be able to understand whether the differences among groups are statistically significant or not. For that reason, multiple comparisons are conducted by applying Mann Whitney- 2 independent samples test. All functional occupation groups are compared with each other based on these statistical assumptions and the results are presented as follows:

1. There is a statistically significant difference between the underlying distributions of the total score of Marketing and Sales group and the total score of IT group (z = -6.750, p = 0.000<0.05).

Table 37. Test Statistics

	CPScore
Mann-Whitney U	1,377E7
Wilcoxon W	1,190E8
Z	-6,750
Asymp. Sig. (2-tailed)	,000

2. There is a statistically significant difference between the underlying distributions of the total score of Marketing and Sales group and the total score of Business Support group (z = -9.117, p = 0.000<0.05).

Table 38. Test Statistics

	CPScore
Mann-Whitney U	1,536E7
Wilcoxon W	1,818E7
Z	-9,117
Asymp. Sig. (2-tailed)	,000

3. There is a statistically significant difference between the underlying distributions of the total score of IT group and the total score of Business Support group (z = -11,854, p = 0.000<0.05).

Table 39. Test Statistics

	CPScore
Mann-Whitney U	1992102,000
Wilcoxon W	4820733,000
Z	-11,854
Asymp. Sig. (2-tailed)	,000

- HA4: There is a statistically significant association between learner's success and learner's hierarchical occupation.

According to Spearman rho correlational test statistic, there is a significant association between learner's success and learner's hierarchical occupation with correlation coefficient=0.112 at the significance level p=0.000. HA4 is accepted.

Table 40. Correlations (Hierarchical Occupation vs. Score)

			HierOcc	CPScore
Spearman's rho	HierOcc	Correlation Coefficient	1,000	,112**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	CPScore	Correlation Coefficient	,112**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test presented in the table 40 above, it can be claimed that learner's hierarchical occupation has an influence on learner's success. It should also mean that different hierarchical occupation groups have different success levels. In order to test whether the groups are significantly different from each other in terms of success, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 41. Ranks (Hierarchical Occ. vs. Score)

	HierOcc	N	Mean Rank
CPScore	Operational	9961	9092,68
	Supporting	2184	8211,22
	Low Level DM	89	9294,62
	High Level DM	6729	10473,25
	Total	18963	

Table 42. Test Statistics

	CPScore
Chi-Square	437,411
df	3
Asymp. Sig.	,000

According to the tables above, there is a statistically significant difference between the different hierarchical occupation groups (Chi-Square = 437,411, P = 0.000) with a mean rank of 9092.68 for operational group, 8211.22 for supporting group, 9294.62 for low level decision making group and 10473.25 for low level decision making group. Additional to the mean ranks, mean of total score for each hierarchical occupation group can be examined in the table 43 below which shows that high level decision making groups performs better than the other groups.

Table 43. Average Score (Hierarchical Occupation)

HierOcc	Mean	N	Std. Deviation
Operational	72,83	9961	21,533
Supporting	69,03	2184	22,067
Low Level DM	71,75	89	25,134
High Level DM	79,12	6729	20,304
Total	74,62	18963	21,478

Even if it is clearly seen that score means of some hiearchical occupation groups are different from each other in the table above, additional post-hoc analysis should be conducted to be able to understand whether the differences among groups are statistically significant or not. For that reason, multiple comparisons are conducted by applying Mann Whitney- 2 independent samples test. All hiearchical occupation groups are compared with each other based on these statistical assumptions and the results are presented as follows:

1. There is a statistically significant difference between the underlying distributions of the total score of operational group and the total score of supporting group ($z = -7.497$, $p = 0.000<0.05$).

Table 44. Test Statistics

	CPScore
Mann-Whitney U	9831088,500
Wilcoxon W	1,222E7
Z	-7,497
Asymp. Sig. (2-tailed)	,000

2. There is not a statistically significant difference between the underlying distributions of the total score of operational group and the total score of low level decision making group ($z = -0.364$, $p = 0.716>0.05$).

Table 45. Test Statistics

	CPScore
Mann-Whitney U	433939,000
Wilcoxon W	5,005E7
Z	-,364
Asymp. Sig. (2-tailed)	,716

3. There is a statistically significant difference between the underlying distributions of the total score of operational group and the total score of high level decision making group ($z = -17.077$, $p = 0.000<0.05$).

Table 46. Test Statistics

	CPScore
Mann-Whitney U	2,860E7
Wilcoxon W	7,821E7
Z	-17,077
Asymp. Sig. (2-tailed)	,000

4. There is a statistically significant difference between the underlying distributions of the total score of supporting group and the total score of low level decision making group ($z = -1,978$, $p = 0.048<0.05$).

Table 47.Test Statistics

	CPScore
Mann-Whitney U	86014,500
Wilcoxon W	2472034,500
Z	-1,978
Asymp. Sig. (2-tailed)	,048

5. There is a statistically significant difference between the underlying distributions of the total score of supporting group and the total score of high level decision

making group (z = -17.466, p = 0.000<0.05).

Table 48. Test Statistics

	CPScore
Mann-Whitney U	5630181,000
Wilcoxon W	8016201,000
Z	-17,466
Asymp. Sig. (2-tailed)	,000

6. There is a statistically significant difference between the underlying distributions of the total score of low level decision making group and the total score of high level decision making group (z = -2,152, p = 0.031<0.05).

Table 49. Test Statistics

	CPScore
Mann-Whitney U	262264,500
Wilcoxon W	266269,500
Z	-2,152
Asymp. Sig. (2-tailed)	,031

- HA5: There is a statistically significant association between learner's success and learner's region.

According to Spearman rho correlational test statistic, there is not a significant association between learner's success and learner's region with correlation coefficient=-0.010 at the significance level p=0.191. HA5 is rejected. Since HA5 is rejected, additional post-hoc analysis is not conducted.

Table 50. Correlations (Region vs. Score)

			Reg	CPScore
Spearman's rho	Reg	Correlation Coefficient	1,000	-,010
		Sig. (2-tailed)	.	,191
		N	18963	18963
	CPScore	Correlation Coefficient	-,010	1,000
		Sig. (2-tailed)	,191	.
		N	18963	18963

- HA6: There is a statistically significant association between learner's success and learner's current work experience.

According to Spearman rho correlational test statistic, there is a significant association between learner's success and learner's current work experience with correlation coefficient=0.141 at the significance level p=0.000. HA6 is accepted.

Table 51. Correlations (Work Experience vs. Score)

			WorkExp	CPScore
Spearman's rho	WorkExp	Correlation Coefficient	1,000	,141**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	CPScore	Correlation Coefficient	,141**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that learner's current work experience has an influence on learner's success. It should also mean that different current work experience groups have different success levels. In order to test whether the groups are significantly different from each other in terms of success, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 52. Ranks (Work Experience vs. Score)

	WorkExp	N	Mean Rank
CPScore	Low Experienced	5876	8791,23
	Experienced	5946	8957,63
	Very Experienced	7141	10487,02
	Total	18963	

Table 53. Test Statistics

	CPScore
Chi-Square	437,411
df	2
Asymp. Sig.	,000

According to the tables above, there is a statistically significant difference between the different current work experience groups (Chi-Square = 437,411, P = 0.000) with a mean rank of 8791.23 for low experienced group, 8957.63 for experienced group and 10487.02 for very experienced group. Additional to the mean ranks, mean of total score for each current work experience group can be examined in the table 54 which shows that very experienced groups performs better than the other groups.

Table 54. Average Score (Work Experience)

WorkExp	Mean	N	Std. Deviation
Low Experienced	71,23	5876	22,199
Experienced	72,61	5946	21,089
Very Experienced	79,09	7141	20,409
Total	74,62	18963	21,478

Even if it is clearly seen that score means of some current work experience groups are different from each other in the table above, additional post-hoc analysis should be conducted to be able to understand whether the differences among groups are statistically significant or not. For that reason, multiple comparisons are conducted by applying Mann Whitney- 2 independent samples test. All groups are compared with each other based on these statistical assumptions and the results are presented as follows:

1. There is not a statistically significant difference between the underlying distributions of the total score of low experienced group and the total score of experienced group ($z = -1.844$, $p = 0.065 > 0.05$).

Table 55. Test Statistics

	CPScore
Mann-Whitney U	1,715E7
Wilcoxon W	3,441E7
Z	-1,844
Asymp. Sig. (2-tailed)	,065

2. There is a statistically significant difference between the underlying distributions of the total score of low experienced group and the total score of very

experienced group (z = -18,586, p = 0.000<0.05).

Table 56. Test Statistics

	CPScore
Mann-Whitney U	1,724E7
Wilcoxon W	3,451E7
Z	-18,586
Asymp. Sig. (2-tailed)	,000

3. There is not a statistically significant difference between the underlying distributions of the total score of experienced group and the total score of very experienced group (z = -16.963, p = 0.000<0.05).

Table 57. Test Statistics

	CPScore
Mann-Whitney U	1,779E7
Wilcoxon W	3,547E7
Z	-16,963
Asymp. Sig. (2-tailed)	,000

- HA7: There is a statistically significant association between learner's success and formal education success of the learner.

According to Spearman rho correlational test statistic, there is not a significant association between learner's success and learner's formal education success (branch score) with correlation coefficient=0.006 at the significance level p=0.466. HA7 is rejected. Since HA7 is rejected, additional post-hoc analysis is not conducted.

Table 58. Correlations (Formal Education vs. Score)

			FormalEdu	CPScore
Spearman's rho	FormalEdu	Correlation Coefficient	1,000	,006
		Sig. (2-tailed)	.	,466
		N	14043	14043
	CPScore	Correlation Coefficient	,006	1,000
		Sig. (2-tailed)	,466	.
		N	14043	18963

Learner’s Previous E-Learning Performance vs. Learner Success

- HB0: There is a statistically significant association between learner’s success and number of e-learning course programs previously taken by the learner.

According to Spearman rho correlational test statistic, there is a significant association between learner’s success and learner’s total number of course programs with correlation coefficient=0.121 at the significance level p=0.000. HB0 is accepted.

Table 59. Correlations (Number of Course Programs vs. Score)

			NoofCP	CPScore
Spearman's rho	NoofCP	Correlation Coefficient	1,000	,121**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	CPScore	Correlation Coefficient	,121**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that learner’s total number of course programs has an influence on learner’s success. It should also mean that different groups have different success levels. In order to test whether the groups are significantly different from each other in terms of success, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 60. Ranks (Number of Course Programs vs. Score)

	NoofCP	N	Mean Rank
CPScore	Low	8005	8855,30
	Medium	5460	9502,59
	High	5498	10374,02
	Total	18963	

Table 61. Test Statistics

	CPScore
Chi-Square	282,347
df	2
Asymp. Sig.	,000

According to the tables above, there is a statistically significant difference between the different number of course program groups (Chi-Square = 282.347, P = 0.000) with a mean rank of 8855.30 for low number of course programs, 9502.59 for medium number of course programs and 10374.02 for high number of course programs. Additional to the mean ranks, mean of total score for each group can be examined in the table 62 below which shows that groups with high number of course programs perform better than the others.

Table 62. Average Score (Number of Course Programs)

NoofCP	Mean	N	Std. Deviation
Low	71,91	8005	21,992
Medium	74,91	5460	20,832
High	78,28	5498	20,782
Total	74,62	18963	21,478

Even if it is clearly seen that score means of some number of course program groups are different from each other in the table above, additional post-hoc analysis should be conducted to be able to understand whether the differences among groups are statistically significant or not. For that reason, multiple comparisons are conducted by applying Mann Whitney- 2 independent samples test. All groups are compared with each other based on these statistical assumptions and the results are presented as follows:

1. There is a statistically significant difference between the underlying distributions of total score of the group with low number of course programs and total score of the group with medium number of course programs ($z = -7.243$, $p = 0.000<0.05$).

Table 63. Test Statistics

	CPScore
Mann-Whitney U	2,034E7
Wilcoxon W	5,239E7
Z	-7,243
Asymp. Sig. (2-tailed)	,000

2. There is a statistically significant difference between the underlying distributions of total score of the group with low number of course programs and total score of the group with high number of course programs ($z = -16.710$, $p = 0.000<0.05$).

Table 64. Test Statistics

	CPScore
Mann-Whitney U	1,850E7
Wilcoxon W	5,054E7
Z	-16,710
Asymp. Sig. (2-tailed)	,000

3. There is a statistically significant difference between the underlying distributions of total score of the group with high number of course programs and total score of the group with medium number of course programs ($z = -8.969$, $p = 0.000<0.05$).

Table 65. Test Statistics

	CPScore
Mann-Whitney U	1,361E7
Wilcoxon W	2,852E7
Z	-8,969
Asymp. Sig. (2-tailed)	,000

- HB1: There is a statistically significant association between learner's success and learner's average success in e-learning.

According to Spearman rho correlational test statistic, there is a significant association between learner's success and learner's average success in e-learning with correlation coefficient=0.360 at the significance level p=0.000. HB1 is accepted.

Table 66. Correlations (Average E-Learning Success vs. Score)

			AvgELSuc	CPScore
Spearman's rho	AvgELSuc	Correlation Coefficient	1,000	,360**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	CPScore	Correlation Coefficient	,360**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that learner's average success in e-learning has an influence on learner's success. It should also mean that different groups have different success levels. In order to test whether the groups are significantly different from each other in terms of success, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 67. Ranks (Average Success vs. Score)

	AvgELSuc	N	Mean Rank
CPScore	Low Success	7312	7409,17
	Medium Success	6235	9748,42
	High Success	5416	11973,76
	Total	18963	

Table 68. Test Statistics

	CPScore
Chi-Square	2458,438
df	2
Asymp. Sig.	,000

According to the tables above, there is a statistically significant difference between the groups with different average success in e-learning (Chi-Square = 2458.438, P = 0.000) with a mean rank of 7409.17 for low success group, 9748.42 for medium success group and 11973.76 for high success group. Additional to the mean ranks, mean of total score for each success group can be examined in the table 69 below which shows that people who are highly successful in online learning course programs in average performs better than the others.

Table 69. Average Score (Average Success)

AvgELSuc	Mean	N	Std. Deviation
Low Success	65,34	7312	21,768
Medium Success	76,24	6235	20,001
High Success	85,28	5416	16,798
Total	74,62	18963	21,478

Even if it is clearly seen that score means of some success groups are different from each other in the table above, additional post-hoc analysis should be conducted to be able to understand whether the differences among groups are statistically significant or not. For that reason, multiple comparisons are conducted by applying Mann Whitney- 2 independent samples test. All groups are compared with each other based on these statistical assumptions and the results are presented as follows:

1. There is a statistically significant difference between the underlying distributions of the total score of low average success group and the total score of medium average success group ($z = -27.052$, $p = 0.000<0.05$).

Table 70. Test Statistics

	CPScore
Mann-Whitney U	1,705E7
Wilcoxon W	4,379E7
Z	-27,052
Asymp. Sig. (2-tailed)	,000

2. There is a statistically significant difference between the underlying distributions of the total score of low average success group and the total score of high average success group ($z = -48.727$, $p = 0.000<0.05$).

Table 71. Test Statistics

	CPScore
Mann-Whitney U	1,039E7
Wilcoxon W	3,712E7
Z	-48,727
Asymp. Sig. (2-tailed)	,000

3. There is a statistically significant difference between the underlying distributions of the total score of high average success group and the total score of medium average success group ($z = -24.192$, $p = 0.000<0.05$).

Table 72. Test Statistics

	CPScore
Mann-Whitney U	1,280E7
Wilcoxon W	3,224E7
Z	-24,192
Asymp. Sig. (2-tailed)	,000

- HB2: There is a statistically significant association between learner's success and learner's average course program completion duration.

According to Spearman rho correlational test statistic, there is a significant association between learner's success and learner's average course program completion duration with correlation coefficient=0.146 at the significance level p=0.000. HB2 is accepted. There is a positive correlation and it means that if duration spent on a course program increases, success on that course program increases, as well.

Table 73. Correlations (Average Completion Duration vs. Score)

			AvgCPCompDur	CPScore
Spearman's rho	AvgCPCompDur	Correlation Coefficient	1,000	,146**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	CPScore	Correlation Coefficient	,146**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that learner's average course program completion duration has an influence on learner's success. It should also mean that different groups have different success levels. In order to test whether different average course program completion duration groups are significantly different from each other in terms of success, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 74. Ranks (Average Completion Duration vs. Score)

	AvgCPCompDur	N	Mean Rank
CPScore	Short	6476	8459,62
	Medium	6687	9750,59
	Long	5800	10313,87
	Total	18963	

Table 75. Test Statistics

	CPScore
Chi-Square	422,905
Df	2
Asymp. Sig.	,000

According to the tables above, there is a statistically significant difference between the different groups (Chi-Square = 422.905, P = 0.000) with a mean rank of 8459.62 for the group with short average duration, 9750.59 the group with medium average duration and 10313.87 for the group with long average duration. Additional to the mean ranks, mean of total score for each group can be examined in the table 76 below which shows that people who complete the course programs within a longer time in average get higher scores than the others.

Table 76. Average Score (Average Completion Duration)

AvgCPCompDur	Mean	N	Std. Deviation
Short	70,81	6476	20,816
Medium	75,69	6687	21,138
Long	77,64	5800	21,971
Total	74,62	18963	21,478

Even if it is clearly seen that score means of some groups are different from each other in the table above, additional post-hoc analysis should be conducted to be able to understand whether the differences among groups are statistically significant or not. For that reason, multiple comparisons are conducted by applying Mann Whitney- 2 independent samples test. All groups are compared with each other based on these statistical assumptions and the results are presented as follows:

1. There is a statistically significant difference between the underlying distributions of the total score of the group with short average duration and the total score of the group with medium average duration ($z = -14.512$, $p = 0.000<0.05$).

Table 77. Test Statistics

	CPScore
Mann-Whitney U	1,868E7
Wilcoxon W	3,965E7
Z	-14,512
Asymp. Sig. (2-tailed)	,000

2. There is a statistically significant difference between the underlying distributions of the total score of the group with short average duration and the total score of the group with long average duration ($z = -19.719$, $p = 0.000<0.05$).

Table 78. Test Statistics

	CPScore
Mann-Whitney U	1,514E7
Wilcoxon W	3,611E7
Z	-19,719
Asymp. Sig. (2-tailed)	,000

3. There is a statistically significant difference between the underlying distributions of the total score of the group with long average duration and the total score of the group with medium average duration ($z = -6.250$, $p = 0.000<0.05$).

Table 79. Test Statistics

	CPScore
Mann-Whitney U	1,821E7
Wilcoxon W	4,057E7
Z	-6,250
Asymp. Sig. (2-tailed)	,000

Course Program-Related Factors vs. Learner's Success

- HC0: There is a statistically significant association between learner's success and learning course program's content, that is, whether it has a vocational or skill development content.

According to Spearman rho correlational test statistic, there is a significant association between learner's success and course program's content with correlation coefficient=0.491 at the significance level p=0.000. HC0 is accepted.

Table 80. Correlations (Course Program Content vs. Score)

			CPCont	CPScore
Spearman's rho	CPCont	Correlation Coefficient	1,000	,491**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	CPScore	Correlation Coefficient	,491**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that course program content has an influence on learner's success. It should also mean that people have different success levels for different course program contents. In order to test whether the success in different course program contents are significantly different from each other, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 81. Ranks (Content vs. Score)

	CPCont	N	Mean Rank
CPScore	Vocational	16315	8461,90
	Skill development	2648	15767,07
	Total	18963	

Table 82. Test Statistics

	CPScore
Chi-Square	4564,186
df	1
Asymp. Sig.	,000

According to the tables above, there is a statistically significant difference between the different course program contents (Chi-Square = 4564.186, P = 0.000) with a mean rank of 8461.90 for vocational course programs and 15767.07 for skill development course programs. Additional to the mean ranks, mean of total score for each course program content can be examined in the table 83 below which shows that people are more successful in course programs with skill development content which are personal development oriented.

Table 83. Average Score (Content)

CPCont	Mean	N	Std. Deviation
Vocational	70,84	16315	20,704
Skill development	97,91	2648	5,674
Total	74,62	18963	21,478

- HC1: There is a statistically significant association between learner's success and course program duration.

According to Spearman rho correlational test statistic, there is a significant association between learner's success and course program duration with correlation coefficient=0.497 at the significance level p=0.000. HC1 is accepted.

Table 84. Correlations (Duration vs. Score)

			CPDur	CPScore
Spearman's rho	CPDur	Correlation Coefficient	1,000	,497**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	CPScore	Correlation Coefficient	,497**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that course program duration has an influence on learner's success. It should also mean that people have different success levels dependent on course program durations. In order to test whether the success within different course program durations are significantly different from each other, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 85. Ranks (Duration vs. Score)

	CPDur	N	Mean Rank
CPScore	Short	8941	7574,15
	Medium	5864	8315,43
	Long	4158	15229,69
	Total	18963	

Table 86. Test Statistics

	CPScore
Chi-Square	6678,079
df	2
Asymp. Sig.	,000

According to the tables above, there is a statistically significant difference between the different groups (Chi-Square = 6678.079, P = 0.000) with a mean rank of 7574.15 for the course programs with short duration, 8315.43 for the course programs with medium duration and 15229.69 for the course programs with long duration. Additional to the mean ranks, mean of total score for each group can be examined in the table 87 below which shows that people perform better in course programs with longer duration.

Table 87. Average Score (Duration)

CPDur	Mean	N	Std. Deviation
Short	68,26	8941	18,849
Medium	69,46	5864	20,801
Long	95,58	4158	12,880
Total	74,62	18963	21,478

Even if it is clearly seen that score means of some groups are different from each other in the table above, additional post-hoc analysis should be conducted to be able to understand whether the differences among groups are statistically significant or not. For that reason, multiple comparisons are conducted by applying Mann Whitney- 2 independent samples test. All groups are compared with each other based on these statistical assumptions and the results are presented as follows:

1. There is a statistically significant difference between the underlying distributions of the total score in short duration course programs and the total score in medium duration course programs ($z = -6.718$, $p = 0.000<0.05$).

Table 88. Test Statistics (Duration)

	CPScore
Mann-Whitney U	2,464E7
Wilcoxon W	6,462E7
Z	-6,718
Asymp. Sig. (2-tailed)	,000

2. There is a statistically significant difference between the underlying distributions of the total score in short duration course programs and the total score in long duration course programs ($z = -81.681$, $p = 0.000<0.05$).

Table 89. Test Statistics (Duration)

	CPScore
Mann-Whitney U	3102453,000
Wilcoxon W	4,308E7
Z	-81,681
Asymp. Sig. (2-tailed)	,000

3. There is a statistically significant difference between the underlying distributions of the total score in long duration course programs and the total score in medium duration course programs ($z = -65.190$, $p = 0.000<0.05$).

Table 90. Test Statistics (Duration)

	CPScore
Mann-Whitney U	3778261,000
Wilcoxon W	2,097E7
Z	-65,190
Asymp. Sig. (2-tailed)	,000

- HC2: There is a statistically significant association between learner's success and whether course program is certificated or not.

According to Spearman rho correlational test statistic, there is a significant association between learner's success and whether the course program is certificated or not with correlation coefficient=0.691 at the significance level p=0.000. HC2 is accepted.

Table 91. Correlations (Certification vs. Score)

			CPCer	CPScore
Spearman's rho	CPCer	Correlation Coefficient	1,000	,691**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	CPScore	Correlation Coefficient	,691**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that course program certification has an influence on learner's success. It should also mean that people have different success levels depending upon whether the course program is certificated or not. In order to test whether the success in certificated and not certificated course programs are significantly different from each other, Kruskal Wallis non-parametric test is conducted. The table 92 presents the statistical figures of test results:

Table 92. Test Statistics

	CPScore
Chi-Square	9065,135
df	1
Asymp. Sig.	,000

According to the table 92, there is a statistically significant difference between the different groups (Chi-Square = 9065.135, P = 0.000). Mean of total score for each group can be examined in the table 93 below which shows that learners get higher score in certificated course programs. It is also analyzed whether there may be a relationship between course content and course certification and whether certificated programs are mostly vocational or skill development programs. In the table x below, it is seen that most of the vocational programs are not certificated, while skill development programs are certificated. As a result, learners are more successful in certificated programs and in skill development programs. This result exposes a question: are learners successful since course programs are certificated or since they are skill development programs?

Table 93.CPScore

CPCer	Mean	N	Std. Deviation
Not Certificated	66,75	13847	18,771
Certificated	95,93	5116	11,588
Total	74,62	18963	21,478

Table 94. Count (Content vs Certification)

		CP_Certificated		
		Not Certificated	Certificated	Total
CP_ Content	Vocational	13776	2539	16315
	Skill development	71	2577	2648
Total		13847	5116	18963

- HC3: There is a statistically significant association between learner's success and learner's course program completion duration.

According to Spearman rho correlational test statistic, there is a significant association between learner's success and learner's course program completion duration with correlation coefficient=0.276 at the significance level p=0.000. HC3 is accepted.

Table 95. Correlations (Completion Duration vs. Score)

			CPCompDur	CPScore
Spearman's rho	CPCompDur	Correlation Coefficient	1,000	,276**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	CPScore	Correlation Coefficient	,276**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that course program completion duration is an indicator for learner's success level. In order to test whether the success significantly changes as a result of different activity completion durations, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 96. Ranks (Completion Duration vs. Score)

	CPCompDur	N	Mean Rank
CPScore	Short	7365	8991,51
	Medium	6616	7073,60
	Long	4982	13405,41
	Total	18963	

Table 97. Test Statistics

	CPScore
Chi-Square	4386,126
df	2
Asymp. Sig.	,000

According to the tables above, there is a statistically significant difference between the different groups (Chi-Square = 4386.126, P = 0.000) with a mean rank of 8991.51 for short completion duration, 7073.60 for medium completion duration and 13405.41 for long completion duration. Additional to the mean ranks, mean of total score for each group can be examined in the table 98 below which shows that if people complete the course program within a longer duration, success will be probably higher.

Table 98. Average Score (Completion Duration)

CPComp Dur	Mean	N	Std. Deviation
Short	73,52	7365	20,537
Medium	65,17	6616	18,855
Long	88,81	4982	18,402
Total	74,62	18963	21,478

Even if it is clearly seen that score means of some duration groups are different from each other in the table above, additional post-hoc analysis should be conducted to be able to understand whether the differences among groups are statistically significant or not. For that reason, multiple comparisons are conducted by applying Mann Whitney- 2 independent samples test. All groups are compared with each other based on these statistical assumptions and the results are presented as follows:

1. There is a statistically significant difference between the underlying distributions of the total score for course programs completed within a short duration and the

total score for course programs completed within a medium duration (z = -25.267, p = 0.000<0.05).

Table 99. Test Statistics (Completion Duration)

	CPScore
Mann-Whitney U	1,880E7
Wilcoxon W	4,069E7
Z	-25,267
Asymp. Sig. (2-tailed)	,000

2. There is a statistically significant difference between the underlying distributions of the total score for course programs completed within a short duration and the total score for course programs completed within a long duration (z = -50.678, p = 0.000<0.05).

Table 100. Test Statistics (Completion Duration)

	CPScore
Mann-Whitney U	9170022,000
Wilcoxon W	3,630E7
Z	-50,678
Asymp. Sig. (2-tailed)	,000

3. There is a statistically significant difference between the underlying distributions of the total score for course programs completed within a long duration and the total score for course programs completed within a medium duration (z = -62.056, p = 0.000<0.05).

Table 101. Test Statistics (Completion Duration)

	CPScore
Mann-Whitney U	6110223,000
Wilcoxon W	2,800E7
Z	-62,056
Asymp. Sig. (2-tailed)	,000

Learner’s Perceived Usefulness vs. Leaner Success

- HD0: There is a statistically significant association between learner’s success and perceived usefulness of e-learning course program.

According to Spearman rho correlational test statistic, there is a significant association between learner’s success and learner’s perceived usefulness with correlation coefficient=-0.050 at the significance level p=0.000. HD0 is accepted.

Table 102. Correlations (Perceived Usefulness vs. Score)

			CPScore	CPPercUseful
Spearman's rho	CPScore	Correlation Coefficient	1,000	-,050**
		Sig. (2-tailed)	.	,000
		N	8884	8884
	CPPercUseful	Correlation Coefficient	-,050**	1,000
		Sig. (2-tailed)	,000	.
		N	8884	8884

Since perceived usefulness is a component extracted from eight success factors as a result of factor analysis, it can be claimed that learner success is also significantly correlated with most of these eight criteria. However, in order to examine the strongest correlation among learner success and success factors, correlation analysis is conducted for each factor, as well.

The correlation results presented in the following part shows that existence of sample practices and permitted course program duration has the strongest influence on learner’s success. On the other hand, satisfaction with content quality seems to have no significant correlation with learner success. In other words, it cannot be claimed that if the learners are very satisfied with the content quality, than they will get higher scores or vice versa.

- HD1: There is a statistically significant association between learner’s success and information usefulness of e-learning course program.

There is a significant correlation between learner success and information usefulness with a correlation coefficient = 0.077 and p value=0.000. HD1 is accepted.

Table 103. Correlations (Information Usefulness vs. Score)

			CPScore	CPInfoUseful
Spearman's rho	CPScore	Correlation Coefficient	1,000	,077**
		Sig. (2-tailed)	.	,000
		N	8884	8884
	CPInfoUseful	Correlation Coefficient	,077**	1,000
		Sig. (2-tailed)	,000	.
		N	8884	8884

- HD2: There is a statistically significant association between learner's success and sample practices in the e-learning course program.

There is a significant correlation between learner success and sample practices with a correlation coefficient = 0.116 and p value=0.000. HD2 is accepted.

Table 104. Correlations (Sample Practices vs. Score)

			CPScore	CPSampPrac
Spearman's rho	CPScore	Correlation Coefficient	1,000	,116**
		Sig. (2-tailed)	.	,000
		N	8884	8884
	CPSampPrac	Correlation Coefficient	,116**	1,000
		Sig. (2-tailed)	,000	.
		N	8884	8884

- HD3: There is a statistically significant association between learner's success and content quality of e-learning course program.

There is not a significant correlation between learner success and content with a correlation coefficient = -0.018 and p value=0.099. HD3 is rejected.

Table 105. Correlations (Sample Practices vs. Score)

			CPScore	CPContQ
Spearman's rho	CPScore	Correlation Coefficient	1,000	-,018
		Sig. (2-tailed)	.	,099
		N	8884	8884
	CPContQ	Correlation Coefficient	-,018	1,000
		Sig. (2-tailed)	,099	.
		N	8884	8884

- HD4: There is a statistically significant association between learner's success and permitted duration of e-learning course program.

There is a significant correlation between learner success and permitted course program duration with a correlation coefficient = 0.116 and p value=0.000. HD4 is accepted.

Table 106. Correlations (Permitted Duration vs. Score)

			CPScore	CPPerDur
Spearman's rho	CPScore	Correlation Coefficient	1,000	,116**
		Sig. (2-tailed)	.	,000
		N	8884	8884
	CPPerDur	Correlation Coefficient	,116**	1,000
		Sig. (2-tailed)	,000	.
		N	8884	8884

- HD5: There is a statistically significant association between learner's success and visual and interactional content of e-learning course program.

There is a significant correlation between learner success and visual and interactional content with a correlation coefficient = 0.108 and p value=0.000. HD5 is accepted.

Table 107. Correlations (Visual Interactional Content vs. Score)

			CPScore	CPVisualInteract
Spearman's rho	CPScore	Correlation Coefficient	1,000	,108**
		Sig. (2-tailed)	.	,000
		N	8884	8884
	CPVisualInteract	Correlation Coefficient	,108**	1,000
		Sig. (2-tailed)	,000	.
		N	8884	8884

- HD6: There is a statistically significant association between learner's success and fluency of e-learning course program.

There is a significant correlation between learner success and fluency with a correlation coefficient = 0.091 and p value=0.000. HD6 is accepted.

Table 108. Correlations (Fluency vs. Score)

			CPScore	CPFluency
Spearman's rho	CPScore	Correlation Coefficient	1,000	,091**
		Sig. (2-tailed)	.	,000
		N	8884	8884
	CPFluency	Correlation Coefficient	,091**	1,000
		Sig. (2-tailed)	,000	.
		N	8884	8884

- HD7: There is a statistically significant association between learner's success and cohesion of content and exam in the e-learning course program.

There is a significant correlation between learner success and cohesion of content and exam with a correlation coefficient = -0.055 and p value=0.000. HD7 is accepted.

Table 109. Correlations (Cohesion of Content and Exam vs. Score)

			CPScore	CPCoContEx
Spearman's rho	CPScore	Correlation Coefficient	1,000	-,055**
		Sig. (2-tailed)	.	,000
		N	8884	8884
	CPCoContEx	Correlation Coefficient	-,055**	1,000
		Sig. (2-tailed)	,000	.
		N	8884	8884

Multinomial Logistic Regression Model for Learner Success

In this study, it is aimed to explain the variance in some e-learning processes. The factors which are significant for the variance in learners' e-learning performance are discovered in the sections above by correlational analysis. Furthermore, differences among groups are also explored, that is, whether younger age group is different than older age group in terms of learner success is explored. In this part, the objective is modeling learner success as a function of some independent variables (predictors), so that it is possible to explore the relationships as a whole and to establish a prediction model based on some factors which at the end will be useful to classify a new case into proper success group based on the information it brings.

Demographics as age, gender, occupation, education, work experience; course program characteristics as content, duration, certification and learners' previous e-learning performance as number of course programs and average success are included in the model as predictors. Dependent variable is learner success (course program score). It is aimed to establish a function of learner success based on predictors. Reference category is successful and comparison category is unsuccessful. Since the dependent variable is not binary and has more than two categories, multinomial logistic regression is applied for learning success model (Norusis, 1999).

Since learner success is an ordinal variable with the values unsuccessful, medium success and successful, ordinal logistic regression model may be selected. Ordinal regression model is stated as simpler to apply and easier to interpret. However, multinomial logistic regression model is stated as more complex but more flexible, since it enables to distinguish between different categories of ordinal dependent variable. In other words, for the analysis on learner success classification, it is possible to compare unsuccessful vs. successful and medium success vs. successful, separately (Flom, n.d.). In order to benefit from the flexibility, multinomial logistic regression model is used.

As a result of multinomial logistic regression model, predictors which have significant influence in explaining the variance in learner success are selected in the function of learner success. Before generating the function of learner success, the overall reliability of the model is checked. Nagelkerke's pseudo r-square statistic is calculated as 67% which satisfies the threshold level (>65%) and indicates the reliability of this multinomial logistic regression model.

Model fitting information in the table 110 below presents whether the model is usable or not for predicting the learner success. It can be seen that the likelihood ratio tests statistic chi-square= 1,694E4 and corresponding p value=0.000<0.05, so that the model is significant and it is meaningful to create a prediction model for learner success based on those independent factors.

Table 110. Model Fitting Information (Learner Success)

	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	3,674E4			
Final	1,980E4	1,694E4	40	,000

In the parameter estimates in the table 111 below, the significance level of each independent variable is presented. Factors with sigma<0.05 are significant for the model and have a relationship with learner success. Estimate values (B) are the coefficients of predictors in multinomial logistic regression equation and show the strength of influence, that is, a unit of change in predictors has on the dependent variable-learner success. The sign of coefficient shows whether the probability of being in comparison category increases or decreases as a result of a unit of change in the predictor. If (B)>0, then a unit of change in the predictor has a positive effect for being in comparison category (unsuccessful) and vice versa (Larose, 2006; Guidici, 2003).

Table 111. Parameter Estimates (Successful vs Unsuccessful)

Learner Success The reference category: Successful								95% conf interval	
								LBound	UBound
Unsuccessful	Intercept	6,944	,747	86,352	1	,000			
	Age	-,037	,008	21,657	1	,000	,964	,949	,979
	WorkExp	-,013	,007	3,073	1	,080	,987	,973	1,002
	AvgELSuc	-,137	,004	970,578	1	,000	,872	,864	,879
	[Gender=,00]	-,147	,067	4,826	1	,028	,863	,757	,984
	[Gender=1,00]	0[b]	.	.	0	.	.	.	.
	[EducationCat=1,00]	-,553	,269	4,229	1	,040	,575	,340	,974
	[EducationCat=2,00]	-,455	,270	2,837	1	,092	,634	,374	1,077
	[EducationCat=3,00]	-,389	,261	2,217	1	,136	,678	,406	1,131
	[EducationCat=4,00]	0[b]	.	.	0	.	.	.	.
	[FuncOcc=1,00]	-1,138	,374	9,272	1	,002	,321	,154	,667
	[FuncOcc =2,00]	-1,205	,383	9,881	1	,002	,300	,141	,635
	[FuncOcc =3,00]	0[b]	.	.	0	.	.	.	.
	[HierOcc =1,00]	,100	,085	1,406	1	,236	1,106	,937	1,305
	[HierOcc =2,00]	-,736	,389	3,588	1	,058	,479	,224	1,026
	[HierOcc =3,00]	,168	,503	,111	1	,739	1,183	,441	3,169
	[HierOcc =4,00]	0[b]	.	.	0	.	.	.	.
	[CPCer=,00]	6,136	,231	705,963	1	,000	462,424	294,070	727,161
	[CPCer=1,00]	0[b]	.	.	0	.	.	.	.
	[CPCont=1,00]	4,914	,386	162,136	1	,000	136,151	63,906	290,069
	[CPCont=2,00]	0[b]	.	.	0	.	.	.	.
	[NoofCP=1]	-,565	,080	49,517	1	,000	,568	,486	,665
	[NoofCP=2]	-,237	,080	8,723	1	,003	,789	,674	,923
	[NoofCP=3]	0[b]	.	.	0	.	.	.	.
	[CPDuration =1]	-1,645	,235	48,987	1	,000	,193	,122	,306
	[CPDuration =2]	-2,061	,222	86,087	1	,000	,127	,082	,197
	[CPDuration =3]	0[b]	.	.	0	.	.	.	.
	[CPCompDur =1]	-1,369	,131	108,583	1	,000	,254	,197	,329
	[CPCompDur =2]	,239	,120	3,949	1	,047	1,270	1,003	1,608
	[CPCompDur =3]	0[b]	.	.	0	.	.	.	.

The estimates (B) are the coefficients of the independent variables in the equation of low success vs. high success classification and the equation is:

*P(unsuccessful/successful)= 6,136*Certification(No) +4,914*Course program content (Vocational course) -0,862*Course duration (short) -1,444*Course duration (medium) -0,519*Course completion duration (short) +0,245* Course completion duration (medium) -0,565*Number of e-learning programs(Less) -0,237 *Number of e-learning programs(Medium) -0,137*Learner average success -0,037*Age -0,553* Education (High school) -0,147*Gender(Female) -1,138*Functional Occupation(Marketing&Sales) -1,205*Functional Occupation(IT)*

The results of estimates for distinguishing unsuccessful vs. successful classification can be summarized as follows:

- Age, gender, education, functional occupation, course program certification, course program duration, course program completion duration and course program content, learner average success and number of course programs are significant, while work experience and hierarchical occupation is not significant for distinguishing a case between unsuccessful and successful.
- If age is increased by 1 unit, then the multinomial log-odds of being in low success group compared to high success group would be expected to decrease by 0.037 units. Older learners are more likely to fall in high success group.
- The multinomial odds (probability) for females (gender=0) relative to males (gender=1) is 0.147 unit lower for falling in unsuccessful group.
- The multinomial odds (probability) for learners with a high school degree relative

to other education levels is 0.553 unit lower for fallig in unsuccessful group.

- Multinomial odds for IT function (FuncOcc =2) relative to other functions is 1.205 unit lower for falling in unsuccessful group
- The multinomial odds for non- certificated learning course programs relative to the ones with certificates is 6,136 unit higher for falling in low success group. It is more likely to fall in successful group for certificated course programs.
- As the course program duration in short duration category is increased by 1 unit, the probability of falling in unsuccessful group decreases by 0,862 units. Course programs with longer duration are more likely to be successful.
- As the course program completion duration in short duration category is increased by 1 unit, the probability of falling in unsuccessful group decreases by 0,519 units. As the learners complete the course programs in longer duration, success increases.
- Vocational course programs have 4,914 unit higher probabilities for falling in unsuccessful group relative to skill development course programs. Skill development course programs are more likely to be successful.
- If number of course programs in less programs category is increased by 1 unit, then the multinomial odds of being in low success are decreased by 0.565 units. As number of course programs increase, it is more likely to be successful.
- Classification accuracy

It is stated that classification accuracy should be at a proper level to be able to accept the model as useful and accurate. The estimate of by chance accuracy criteria is proposed to be calculated and to be compared with the overall accuracy rate of the model.

*The estimate of by chance accuracy criteria= The estimate of by chance accuracy rate * 1,25*

An accurate model is defined as providing at least 25% improvements in the estimate by chance accurate rate (Anderson et al., 1998). In order to calculate this rate, all the ratios of groups in dependent variables are squared and summed up.

The estimate of by chance accuracy rate= 0,333

*The estimate of by chance accuracy criteria= 0,333 *1,25 = 0,416*

It is seen in the table 113 below that the overall classification accuracy of the model is 69,7% >41,6 % and the criteria is satisfied.

Table 112. Case Processing Summary

		N	Marginal Percentage
CPScore	Unsuccessful	6337	33,4%
	Medium	6367	33,6%
	Successful	6259	33,0%

Table 113. Regression Classification Accuracy

	Predicted			
Observed	Unsuccessful	Medium	Successful	Percent Correct
Unsuccessful	3920	2263	154	61,9%
Medium	1966	4313	88	67,7%
Successful	245	1032	4982	79,6%
Overall Percentage	32,3%	40,1%	27,5%	69,7%

A Decision Tree Model for Learner Success

Decision tree as another method of predictive data mining is applied additional to multinomial logistic regression model. The reason is to compare the results and to see whether the results are the same when the same input data is used in different models. Based on information provided like learner's age, occupation or course program content, by the use of decision tree classification model, a prediction is made on whether this learner will be successful or not.

For this decision tree model, CHAID (Chi-squared automatic interaction detector) growing method is used at a significance level of 0.05. For validation reasons, split sample validation method is applied and the sample is divided equally for training and testing (50% for training and 50% for testing). Misclassification costs are remained the same for incorrect prediction of each group (successful and unsuccessful).

In the model, the same variables in regression model which are demographics as age, gender, functional occupation, hierarchical occupation, region, education and work experience; course program characteristics as content, certification and duration, previous e-learning performance indicators s number of e-learning course programs and average course program completion duration is included in the model as predictors. Dependent variable is selected as total e-learning score of the learner. The model is trained for prediction of two groups: unsuccessful and successful.

- Classification accuracy

  Overall classification accuracy is 87,7% and the details can be seen in the table 114 below:

Table 114. Decision Tree Classification Accuracy

		Predicted		
Sample	Observed	Unsuccessful	Successful	Percent Correct
Training	Unsuccessful	3072	74	97,6%
	Successful	678	2440	78,3%
	Overall Percentage	59,9%	40,1%	88,0%
Test	Unsuccessful	3103	88	97,2%
	Successful	692	2449	78,0%
	Overall Percentage	59,9%	40,1%	87,7%

Decision tree is generated based on the included independent factors and given data set. The model selects only age and gender among demographics of the learner. Course program certification and course program content is determined as strong predictors in the model. Moreover, course program duration information is also included while predicting learner success. Additionally, information on learners' total number of e-learning course programs as a previous e-learning performance indicator is used for classification. Significant variables selected by the decision tree model are parallel with the ones in regression model. Two different models produce the same results, which shows the consistency of the models.

Terminal nodes of decision tree are node 7 through node 14 as seen in figure 3 below. A new incidence is classified as successful or unsuccessful based on association rules generated. For example, the information about a new incidence is a learner who is older and has a bachelor degree, has high participation in e-learning programs. Current course program titled "Fraud Management in Banking" is a certificated vocational course program which is assigned a really longer duration to be completed. From this information, the tree model firstly checks for whether the course program is certificated or not. According to the information, this is a certificated course program. Before classifying this incidence, the model is interested in course program content as a result of the logic. Since the course program is a vocational oriented course program, the next factor to be checked is course program duration. Longer duration information is given in new incidence, so that, final node for this new incidence is node 8 which predicts that learner will be successful by a probability of 89,1%. Association rule for this case is as follows:

IF (CPCer = "Certificated") AND (CPCont = "Vocational") AND
(CP_Duration IS MISSING OR (CP_Duration > "Medium"))
THEN
Node = 8
Prediction = 3
Probability = 0.898072

All association rules can be found in Appendix A. P values and chi-square values of each predictor and probabilities can be seen in decision tree below.

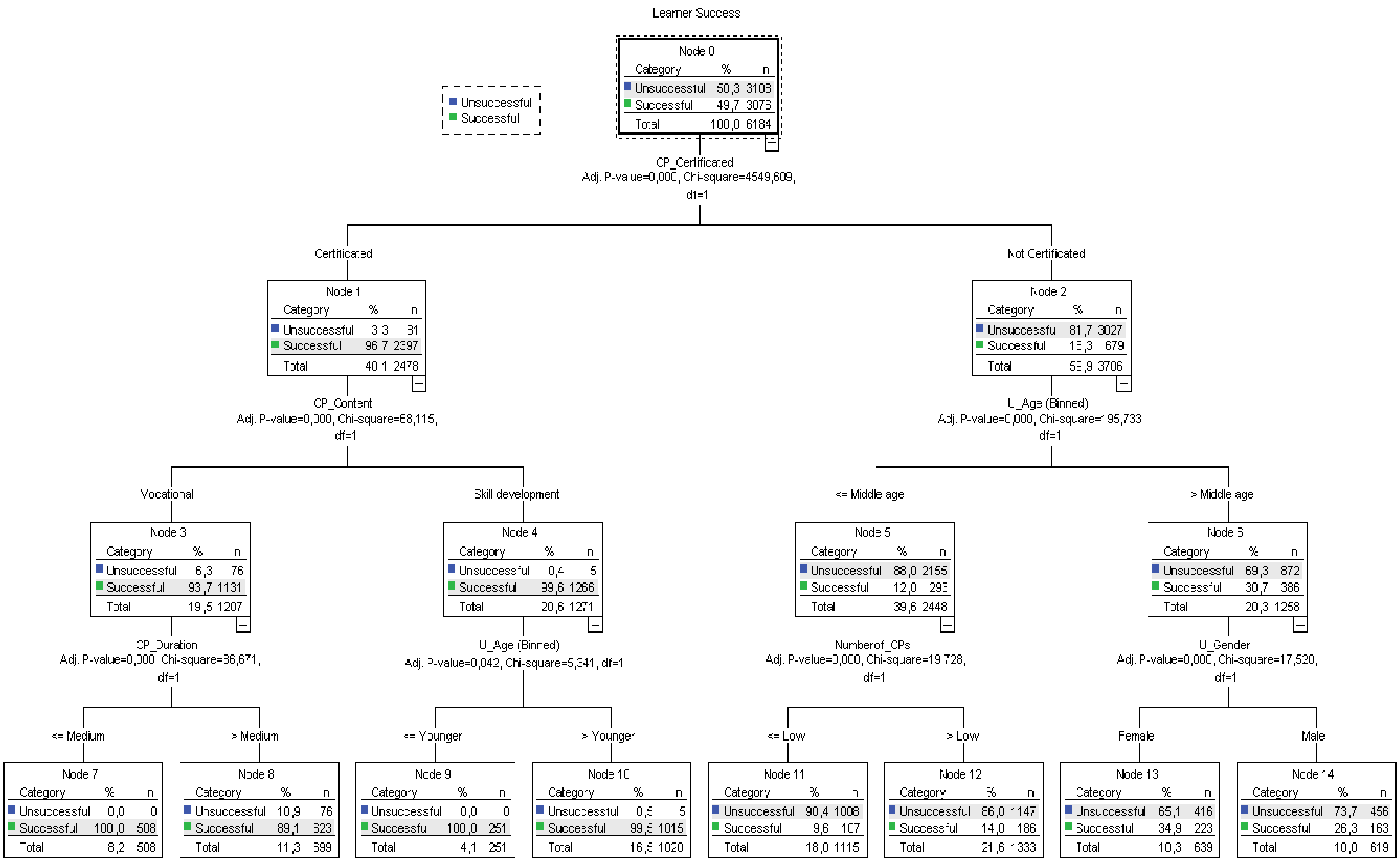

Fig. 3 Decision tree classification-learner success

<u>Course Program Completion</u>

In order to make analysis to explore the factors influencing course program completion of learners, learner-course program completion or withdrawal data set is used. Course program completion is a dichotomous variable which can take only two values as ‘completed’ and ‘not completed’. Due to the nature of this variable we cannot conduct statistical tests which require an interval or at least ordinal dependent variable. Kruskal Wallis and Mann- Whitney tests are non-parametric tests which do not assume normal distribution, but requires at least an ordinal dependent variable. At this point, for ‘course program completion’ analysis, chi-square tests are applied to explore the relationship between completion decision and demographics, course program characteristics and previous e-learning performance. Then, logistic regression tests are performed for generating a prediction model on completion decision by including the effect of some predictor variables like age, gender, occupation and so on.

To discover the power of only one independent variable like age, education or course content and dependent variable course program completion or withdrawal, logistic regression model is applied separately for each independent variable. The aim is whether independent variable provides information on its own for prediction of course completion or withdrawal. After that, other logistic regression models are produced, this time, including only all demographics related or only course program related or only previous e-learning performance related variables. It is aimed to understand how strongly a group of information predicts the completion or withdrawal. Lastly, all the information at hand is included in logistic regression model in order to create a prediction model on whether the learner completes or withdraw the course program.

Logistic regression models enable to explore how strongly course program characteristics, demographics like age, gender, education and the others influence to complete or withdraw the course program. If the model is significant to predict the completion decision, power of each predictor variable to distinguish two categories of dependent variable (completion or withdrawal) is discovered. The estimate ratio in the model tells the power of influence of each predictor on the probability of course program to be 'completed'. The sign of estimate ratio shows the direction of relationship. If the sign is negative, then, there is a negative correlation. It means that the probability of course program to be completed increases, if the predictor variable decreases (Larose, 2006; Guidici, 2003; Norusis, 1999; Logistic Regression, 2008).

Learner's Demographics vs. Course Program Completion

- HE0: Learner's age significantly influence whether the learner completes or withdraw the course program.

According to Spearman rho correlational test statistic, there is a significant association between whether the learner completes the course program or not and learner's age with correlation coefficient=-0.061 and p=0.000 at the significance level p=0.05. HE0 is accepted.

Table 115. Symmetric Measures

	Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Interval by Interval Pearson's R	-,061	,006	-10,442	,000[c]
Ordinal by Ordinal Spearman Correlation	-,061	,006	-10,435	,000[c]
N of Valid Cases	29029			

The table 116 below summarizes the cross tabulation results. 77,6% of younger learners, 74,4% of middle age group and 71,2% of older learners are reported as completed the course program.

Table 116. Age vs. Completion Crosstabulation

			CP_Completed		
			Withdrawal	Completed	Total
Age	Younger	Count	2583	8945	11528
		% within Age	22,4%	77,6%	100,0%
	Middle age	Count	2221	6449	8670
		% within Age	25,6%	74,4%	100,0%
	Older	Count	2543	6288	8831
		% within Age	28,8%	71,2%	100,0%
Total		Count	7347	21682	29029
		% within Age	25,3%	74,7%	100,0%

In order to understand the strength of influence age has on the probability of course program completion, multiple logistic regression tests is applied. The results provide information about whether there is a significant relationship between age and course program completion and whether a significant prediction model for course program completion can be established by using the age information. Furthermore, the model provides information about whether age as a predictor variable can significantly distinguish between the categories of dependent variable, that is, the model evaluates whether it is possible to say a learner will less or more likely complete or withdraw the course program by looking at the age information of this learner.

The tables below show the model fitting information for predicting the probability of course program completion. These tables answer the question whether there is a significant relationship between the dependent variable and independent variable and whether the model with the independent variables included is significantly better than a model with just intercept and no independent variables. The presence of a significant relationship between age and course program completion is supported based on the statistical significance of the final model chi-square in 'model fitting information table' below.

In this analysis, as can be seen in the table 117, the likelihood ratio test statistic chi-square= 106,694 and corresponding p value=0.000<0.05, so that the model is significant and it is meaningful to create a prediction model based on age information. The null hypothesis that there was no difference between the model without age variable and the model with age variable is rejected. The existence of a significant relationship between age and course program completion is supported. Based on learner's age information, it is possible to make a prediction with some probabilities on whether this learner will complete or withdraw the course program.

Table 117. Model Fitting Information

	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	Df	Sig.
Intercept Only	134,763			
Final	28,069	106,694	1	,000

Table 118. Likelihood Ratio Tests

	Model Fitting Criteria	Likelihood Ratio Tests		
Effect	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	1,833E3	1,805E3	1	,000
Age	134,763	106,694	1	,000

The parameter estimates in the table 119 below presents the comparisons for groups of dependent variable course program completion. In this analysis, since dependent variable is dichotomous with only two values as completed or not completed, just one comparison is made. Completed group is compared to not completed group. Looking at the age information, likelihood of a learner to be in completed group or in not completed group is evaluated. The information below shows that age is significant in distinguishing completed group from not completed group (sig.=0.000<0.05).

In the table 119 below, first of all, standard error of independent variables should be checked to see whether it is greater than 2,0. Standard errors larger than 2,0 indicate numerical problems, so that such analyses should not be evaluated. Standard error of age is less than 2,0 satisfying this precondition of analysis.

Table 119. Parameter Estimates (Completion vs Withdrawal)

CPCont		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	95% Confidence Interval for Exp(B) Upper Bound
Withdrawal	Intercept	-1,408	,035	1656,987	1	,000			
	Age	,167	,016	106,640	1	,000	1,182	1,145	1,220

B value represents the estimated multinomial logistic regression coefficients for the model. For a unit change in predictor variable, the probability of outcome being the referent group is expected to change by B value (parameter estimate). If age is increased by 1 unit, then the multinomial log-odds (probability) of being in group ‘withdrawal’ would be expected to increase by 0,167 units. (Larose, 2006; Guidici, 2003; Norusis, 1999; UCLA, n.d.).

Exp(B) value in the table below is relative risk and indicates ratio odds ratios for predictor variables and exponentiation of coefficients. Odds ratio>1 usually indicates that the risk of falling in comparison group (withdrawal) relative to the risk of falling referent group (completed) increases as the variable increases. Odds ratio<1 usually indicates that the risk of falling in comparison group (withdrawal) relative to the risk of falling referent group (completed) decreases as the variable increases. Since 1,182 >1, then, as age increases the risk of falling in completed group which is the referent group decreases. That is, the outcome of withdrawal is more likely to occur as age increases (Larose, 2006; Guidici, 2003; Norusis, 1999; UCLA, n.d.).

- HE1: Learner's gender significantly influence whether the learner completes or withdraw the course program.

According to Spearman rho correlational test statistic, there is a significant association between learner's course program completion or withdrawal and learner's gender with correlation coefficient=-0.013 at the significance level p=0.026. HE1 is accepted.

Table 120. Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Interval by Interval	Pearson's R	-,013	,006	-2,231	,026[c]
Ordinal by Ordinal	Spearman Correlation	-,013	,006	-2,231	,026[c]
N of Valid Cases		29029			

The table 121 below summarizes the cross tabulation results. 75,1% of female learners, 73,9% of male learners are reported as completed the course program.

Table 121. Gender vs. Completed Crosstabulation

			CP_Completed		Total
			Withdrawal	Completed	
Gender	Female	Count	4644	14018	18662
		% within Gender	24,9%	75,1%	100,0%
	Male	Count	2703	7664	10367
		% within Gender	26,1%	73,9%	100,0%
Total		Count	7347	21682	29029
		% within Gender	25,3%	74,7%	100,0%

In order to understand the strength of influence gender has on the probability of course program completion, multiple logistic regression tests is applied. In this analysis, as can be seen in the table 122 below, the likelihood ratio test statistic chi-square= 4,904 and corresponding p value=0.027<0.05, so that the model is significant and it is meaningful to create a prediction model based on gender information. The null hypothesis that there was no difference between the model without gender variable and the model with gender variable is rejected. Based on learner's gender information, it is possible to make a prediction with some probabilities on whether this learner will complete or withdraw the course program.

Table 122. Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	24,334			
Final	19,431	4,904	1	,027

Table 123. Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	19,431[a]	,000	0	.
Gender	24,334	4,904	1	,027

The information in the table 124 below shows that age is significant in distinguishing completed group from not completed group (sig.=0.027<0.05). Standard error of age is less than 2,0 satisfying this precondition of analysis.

The multinomial odds (probability) for females (gender=0) relative to males (gender=1) is 0.062 unit lower for falling in withdrawal group. Males seem to be more likely to withdraw the course program. Since Exp(B)=0,940 <1, the outcome completed is more likely to occur for female.

Table 124. Parameter Estimates (Completion vs Withdrawal)

CPCont		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
Withdrawal	Intercept	-1,044	,022	2175,075	1	,000			
	[Gender=0]	-,062	,028	4,917	1	,027	,940	,889	,993
	[Gender=1]	0[b]	.	.	0	.	.	.	.

- HE2: Learner's hierarchical occupation significantly influence whether the learner completes or withdraw the course program.

According to Spearman rho correlational test statistic, there is a significant association between learner's course program completion or withdrawal and learner's hierarchical occupation with correlation coefficient=-0.060 at the significance level p=0.000. HE2 is accepted.

Table 125. Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Interval by Interval	Pearson's R	-,062	,006	-10,592	,000[c]
Ordinal by Ordinal	Spearman Correlation	-,060	,006	-10,270	,000[c]
N of Valid Cases		29029			

The table below summarizes the cross tabulation results. 76,9% of operational level learners, 75,7% of supporting level learners, 65,1% of low level decision makers and 71,1% of high level decision makers is reported as completed the course program.

Table 126. Hierarchical Occupation vs. Completion Crosstabulation

			CP_Completed		Total
			Withdrawal	Completed	
HierOcc	Operational	Count	3485	11629	15114
		% within HierOcc	23,1%	76,9%	100,0%
	Supporting	Count	910	2836	3746
		% within HierOcc	24,3%	75,7%	100,0%
	Low level decision making	Count	101	188	289
		% within HierOcc	34,9%	65,1%	100,0%
	High level decision making	Count	2851	7029	9880
		% within HierOcc	28,9%	71,1%	100,0%
Total		Count	7347	21682	29029
		% within HierOcc	25,3%	74,7%	100,0%

In order to understand the strength of influence, hierarchical occupation has on the probability of course program completion, multiple logistic regression tests is applied. In this analysis, as can be seen in the table 127 below, the likelihood ratio test statistic chi-square= 108, 985 and corresponding p value=0.000<0.05, so that the model is significant and it is meaningful to create a prediction model based on hierarchical occupation information. The null hypothesis that there was no difference between the model without hierarchical occupation variable and the model with hierarchical occupation variable is rejected. Based on learner's hierarchical occupation information, it is possible to make a prediction with some probabilities on whether this learner will complete or withdraw the course program.

Table 127. Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	151,934			
Final	42,949	108,985	1	,000

Table 128. Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	2,887E3	2,844E3	1	,000
HierOcc	151,934	108,985	1	,000

The information in the table 129 below shows that hierarchical occupation is significant in distinguishing completed group from not completed group (sig.=0.000<0.05). Standard error of hierarchical occupation is less than 2,0 satisfying this precondition of analysis.

B value in the table below represents the coefficients multinomial logistic regression equation and in this analysis, it seems that if hierarchical occupation is increased by 1 unit, then the multinomial log-odds (probability) of being in group 'withdrawal' would be expected to increase by 0,102 unit. It is interpreted as learners in higher level of hierarchy in the organization are more likely withdraw the course program. Exp(B)=1,108>1 supports the result that the outcome is more likely falling in withdrawal group for learners in higher hierarchical levels

Table 129. Parameter Estimates (Completion or Withdrawal)

CPCont		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
Withdrawal	Intercept	-1,311	,026	2554,937	1	,000			
	HierOcc	,102	,010	109,716	1	,000	1,108	1,087	1,129

- HE3: Learner's functional occupation significantly influence whether the learner completes or withdraw the course program.

According to Spearman rho correlational test statistic, there is not a significant association between learner's course program completion or withdrawal and learner's functional occupation with correlation coefficient=-0.002 at the significance level p=0.727. HE3 is rejected. Post-hoc analysis is not conducted, since there is no significant correlation.

Table 130. Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Interval by Interval	Pearson's R	-,002	,006	-,264	,792[c]
Ordinal by Ordinal	Spearman Correlation	-,002	,006	-,349	,727[c]
N of Valid Cases		29029			

- HE4: Learner's region significantly influence whether the learner completes or withdraw the course program.

According to Spearman rho correlational test statistic, there is a slightly significant association between learner's course program completion or withdrawal and learner's region with correlation coefficient=0.027 at the significance level p=0.000. HE4 is accepted.

Table 131. Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Interval by Interval	Pearson's R	,029	,006	4,897	,000[c]
Ordinal by Ordinal	Spearman Correlation	,027	,006	4,685	,000[c]
N of Valid Cases		29029			

The table 132 below summarizes the cross tabulation results. 73,4% of learners from Marmara, 75% of learners from İç Anadolu, 71,9% of learners from Ege, 79,3% of learners from Karadeniz, 76,1% of learners from Güneydoğu Anadolu and 76,9% of learners from Doğu Anadolu is reported as completed the course program.

Table 132. Region vs. Completion Crosstabulation

			CP_Completed		
			Withdrawal	Completed	Total
Reg	Marmara	Count	2697	7430	10127
		% within Reg	26,6%	73,4%	100,0%
	İç Anadolu	Count	2030	6076	8106
		% within Reg	25,0%	75,0%	100,0%
	Ege	Count	952	2438	3390
		% within Reg	28,1%	71,9%	100,0%
	Karadeniz	Count	583	2235	2818
		% within Reg	20,7%	79,3%	100,0%
	Güneydoğu Anadolu	Count	757	2413	3170
		% within Reg	23,9%	76,1%	100,0%
	Doğu Anadolu	Count	328	1090	1418
		% within Reg	23,1%	76,9%	100,0%
Total		Count	7347	21682	29029
		% within Reg	25,3%	74,7%	100,0%

In order to understand the strength of influence gender has on the probability of course program completion, multiple logistic regression tests is applied. In this analysis, as can be seen in the table 133 below, the likelihood ratio test statistic chi-square= 62,597 and corresponding p value=0.000<0.05, so that the model is significant and it is meaningful to create a prediction model based on region information. The null hypothesis that there was no difference between the model without region variable and the model with region variable is rejected. Based on learner's region information, it is possible to make a prediction with some probabilities on whether this learner will complete or withdraw the course program.

Table 133. Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	113,091			
Final	50,493	62,597	5	,000

Table 134. Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	50,493[a]	,000	0	.
Reg	113,091	62,597	5	,000

The table 135 below presents the influence of different region categories. It is seen that only region Marmara (region=1) and Ege (region=3) is significant in distinguishing completed and withdrawal categories of dependent variable (CP_completed) and has a significant influence on predicting the probability of course program to be completed with the estimate rate B= 0.188 and p=0.005 and estimate rate B= 0,261 and p=0.000, respectively. The multinomial odds for Marmara (region=1) relative to other regions is 0.186 unit higher for falling in withdrawal group. The multinomial odds for Ege (region=3) relative to other regions is even higher with 0.258 unit for falling in withdrawal group.

Table 135. Parameter Estimates (Completion vs. Withdrawal)

CPCont		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
Withdrawal	Intercept	-1,201	,063	363,623	1	,000			
	[Reg=1]	,186	,067	7,709	1	,005	1,204	1,056	1,373
	[Reg=2]	,102	,068	2,256	1	,133	1,108	,969	1,265
	[Reg=3]	,258	,074	12,303	1	,000	1,295	1,121	1,496
	[Reg=4]	-,143	,078	3,331	1	,068	,867	,744	1,011
	[Reg=5]	,042	,076	,304	1	,581	1,043	,899	1,209
	[Reg=6]	0[b]	.	.	0	.	.	.	.

- HE5: Learner's work experience significantly influence whether the learner completes or withdraw the course program.

According to Spearman rho correlational test statistic, there is a significant association between learner's course program completion or withdrawal and learner's current work experience with correlation coefficient=-0.084 at the significance level p=0.000. HE5 is accepted.

Table 136. Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Interval by Interval	Pearson's R	-,084	,006	-14,442	,000[c]
Ordinal by Ordinal	Spearman Correlation	-,085	,006	-14,601	,000[c]
N of Valid Cases		29029			

The table 137 below summarizes the cross tabulation results. 79,6% of low experienced learners, experience, 72,4% of experienced learners and 70,9% of very experienced learners are reported as completed the course program.

Table 137. Work Experience vs. Completion Crosstabulation

			CP_Completed		Total
			Withdrawal	Completed	
U_WorkExperience (Binned)	Little experienced	Count	2265	8838	11103
		% within U_WorkExperience (Binned)	20,4%	79,6%	100,0%
	Experienced	Count	2478	6493	8971
		% within U_WorkExperience (Binned)	27,6%	72,4%	100,0%
	Very Experienced	Count	2604	6351	8955
		% within U_WorkExperience (Binned)	29,1%	70,9%	100,0%
Total		Count	7347	21682	29029
		% within U_WorkExperience (Binned)	25,3%	74,7%	100,0%

In order to understand the strength of influence, work experience has on the probability of course program completion; multiple logistic regression tests are applied. In this analysis, as can be seen in the table 138 below, the likelihood ratio test statistic chi-square= 203,948 and corresponding p value=0.000<0.05, so that the model is significant and it is meaningful to create a prediction model based on work experience information. The null hypothesis that there was no difference between the model without work experience variable and the model with work experience variable is rejected. Based on learner's work experience information, it is possible to make a prediction with some probabilities on whether this learner will complete or withdraw the course program.

Table 138. Model Fitting Information

	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	263,681			
Final	59,733	203,948	1	,000

Table 139. Likelihood Ratio Tests

	Model Fitting Criteria	Likelihood Ratio Tests		
Effect	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	2,150E3	2,090E3	1	,000
WorkExp	263,681	203,948	1	,000

The information in table 140 below shows that age is significant in distinguishing completed group from not completed group (sig.=0.000<0.05). Standard error of work experience is less than 2,0 satisfying this precondition of analysis.

B value in the table 140 below represents the coefficients multinomial logistic regression equation and in this analysis, it seems that if work experience is increased by 1 unit, then the multinomial log-odds (probability) of being in group 'withdrawal' would be expected to increase by 0,233 unit. It is interpreted as more experienced learners are more likely withdraw the course program. Exp(B)=1,262>1 supports the result that the outcome is more likely fall in comparison group withdrawal for more experienced learners.

Table 140. Parameter Estimates (Completion vs Withdrawal)

CPCont		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
Withdrawal	Intercept	-1,542	,035	1890,228	1	,000			
	WorkExp	,233	,016	203,085	1	,000	1,262	1,223	1,303

- HE6: Learner's education level significantly influence whether the learner completes or withdraw the course program.

According to Spearman rho correlational test statistic, there is a significant association between learner's course program completion or withdrawal and learner's education level with correlation coefficient=-0.016 at the significance level p=0.007. HE6 is accepted.

Table 141. Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Interval by Interval	Pearson's R	-,016	,006	-2,688	,007[c]
Ordinal by Ordinal	Spearman Correlation	-,016	,006	-2,681	,007[c]
N of Valid Cases		29029			

The table 142 below summarizes the cross tabulation results. 60% of learners from high school , 76% of learners with an associate degree, 74,5% of learners with bachelor degree and 71,4% of learners with graduate degree is reported as completed the course program.

Table 142. Education vs. Completion Crosstabulation

			CP_Completed		Total
			Withdrawal	Completed	
Educ	High School	Count	4	6	10
		% within Educ	40,0%	60,0%	100,0%
	Associate School	Count	1210	3822	5032
		% within Educ	24,0%	76,0%	100,0%
	Bachelor Degree	Count	5931	17349	23280
		% within Educ	25,5%	74,5%	100,0%
	Graduate Degree	Count	202	505	707
		% within Educ	28,6%	71,4%	100,0%
Total		Count	7347	21682	29029
		% within Educ	25,3%	74,7%	100,0%

In order to understand the strength of influence, education level has on the probability of course program completion, multiple logistic regression tests is applied. In this analysis, as can be seen in the table 143 below, the likelihood ratio test statistic chi-square= 7,300 and corresponding p value=0.007<0.05, so that the model is significant and it is meaningful to create a prediction model based on education level information. The null hypothesis that there was no difference between the model without education level variable and the model with education level variable is rejected. Based on learner's education level information, it is possible to make a prediction with some probabilities on whether this learner will complete or withdraw the course program.

Table 143. Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	38,089			
Final	30,790	7,300	1	,007

Table 144. Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	242,061	211,271	1	,000
Educ	38,089	7,300	1	,007

The information in the table 145 below shows that education is significant in distinguishing completed group from not completed group (sig.=0.007<0.05). Standard error of education is less than 2,0 satisfying this precondition of analysis.

B value in the table 145 below represents the coefficients multinomial logistic regression equation and in this analysis, it seems that if education level is increased by 1 unit, then the multinomial log-odds (probability) of being in group 'withdrawal' would be expected to increase by 0,087 unit. It is interpreted as learners with higher education levels are more likely withdraw the course program. Exp(B)=1,091>1 supports the result that the outcome is more likely falling in withdrawal group for learners with higher education levels

Table 145. Parameter Estimates (Completion vs Withdrawal)

CPCont		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
Withdrawal	Intercept	-1,333	,094	202,647	1	,000			
	Educ	,087	,032	7,255	1	,007	1,091	1,024	1,163

<u>A Logistic Regression Model for Course Program Completion Based on Learner Demographics</u>

In order to predict course program completion category of a learner based on all his/her known demographics, a logistic regression model is generated including all the variables related with demographics and course program completion dependent variable. With the model, it is aimed to measure the strength of influence, each demographics has on the probability of course program completion.

In this analysis, the likelihood ratio test statistic chi-square= 286,627 and corresponding p value=0.000<0.05, so that the model is significant and it is meaningful to create a prediction model based on demographics. The null hypothesis that there was no difference between the model without demographics and the model with demographics is rejected. Based on learner's demographics information, it is possible to make a prediction with some probabilities on whether this learner will complete or withdraw the course program.

When all the demographics are included in the model, it is explored that some of the demographics lose their significance in predicting course program completion or withdrawal. While age and education level is significant when introduced alone in the model, likelihood ratio test results below in the table 146 show that these demographics are insignificant in this regression model (age p=0.657>0.05 and education p=0.079>0.05).

Table 146. Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	2,608E3			
Final	2,321E3	286,627	10	,000

Table 147. Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	2,321E3	,000	0	.
Educ	2,324E3	3,084	1	,079
WorkExp	2,416E3	94,726	1	,000
Age	2,321E3	,197	1	,657
HierOcc	2,328E3	6,550	1	,010
Reg	2,383E3	61,514	5	,000
Gender	2,328E3	7,319	1	,007

The information below in the table 148 presents the variables which are significant in distinguishing completed group from not completed group. Work experience, some region categories, hierarchical occupation and gender has a significant power for predicting whether the course program will be completed or not. Additionally, standard error of these variables is less than 2,0 satisfying this precondition of analysis.

Table 148. Parameter Estimates (Completion vs Witdrawal)

CPCont		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
Withdrawal	Intercept	-1,685	,118	203,781	1	,000			
	Educ	,058	,033	3,073	1	,080	1,060	,993	1,130
	WorkExp	,215	,022	93,481	1	,000	1,240	1,187	1,296
	Age	-,011	,025	,197	1	,657	,989	,941	1,039
	HierOcc	,035	,014	6,535	1	,011	1,036	1,008	1,064
	[Reg=1]	,080	,068	1,381	1	,240	1,083	,948	1,237
	[Reg=2]	-,067	,070	,924	1	,336	,935	,816	1,072
	[Reg=3]	,168	,074	5,107	1	,024	1,183	1,023	1,369
	[Reg=4]	-,224	,079	8,079	1	,004	,799	,685	,933
	[Reg=5]	-,020	,076	,069	1	,792	,980	,845	1,138
	[Reg=6]	0^b	.	.	0	.	.	.	.
	[Gender=0]	-,079	,029	7,340	1	,007	,924	,873	,978
	[Gender=1]	0^b	.	.	0	.	.	.	.

The statistical results can be interpreted as:

- If work experience is increased by one unit, then the multinomial odds of being in withdrawal groups is increased by 0,215 units. More experienced people are more likely fall in withdrawal group.
- If hierarchical level is increased by one unit, then the multinomial odds of being in withdrawal groups is increased by 0,035 units. Learners at the higher hierarchical levels people are more likely fall in withdrawal group.
- Ege (Region=3) and Karadeniz (region=4) is significant in differentiating categories of dependent variable. The multinomial odds for Ege relative to other regions is 0.168 higher for falling in withdrawal group and the multinomial odds for Karadeniz relative to other regions is 0.224 lower for falling in withdrawal group.

- The multinomial odds (probability) for females (gender=0) relative to males (gender=1) is 0.079 unit lower for falling in withdrawal group. Males seem to be more likely to withdraw the course program. Since Exp(B)=0,924 <1, the outcome completed is more likely to occur for female.

As a result of regression analysis, an equation is generated based on significant independent variables. In the equation, B values are used as coefficients for significant predictors.

The equation can be expressed as follows:

P(withdrawal/completion) = 0.215 Work Experience + 0.035*Hierarchical Occupation + 0.168*Region(Ege) - 0.224*Region(Karadeniz) – 0.079*Gender(Female)*

- Model Classification Accuracy

  In order to prove the accuracy of this classification model, the estimate of by chance accuracy criteria should be calculated. As mentioned before, firstly, the estimate of by chance accuracy rate should be computed as 62% (0,253^2 + 0,747^2=0,62). The estimate of by chance accuracy criteria aims 25% improvement (Anderson et al., 1998), so that it is 77,5% (0,62*1,25=0,775).The classification accuracy of this model can be seen in the classification table 150 below as 74,7% which does not satisfy the classification accuracy criteria, so that only the information about demographics does not seem to provide a good classification.

Table 149. Case Processing Summary

		N	Marginal Percentage
CP_Completed	Withdrawal	7335	25,3%
	Completed	21682	74,7%
Reg	Marmara	10122	34,9%
	İç Anadolu	8101	27,9%
	Ege	338	11,7%
	Karaden z	2818	,7%
	Güneydoğu An dolu	3170	10,9%
	Doğu Anadolu	1418	4,9%
Gender	Fem le	186 5	,3%
	Mal	10362	35,7%
Valid		29017	100,0%
Missing		0	
Total		29017	
Subpopulation		373[a]	

Table 150. Classification Accuracy

Observed	Predicted		
	With drawal	Completed	Percent Correct
Withdrawal	0	7335	,0%
Completed	0	21682	100,0%
Overall Percentage	,0%	100,0%	74,7%

<u>Learner's Previous E-Learning Performance vs. Course Program Completion</u>

- HF0: Number of online learning course programs previously taken significantly influence whether the learner completes or withdraw the course program.

According to Spearman rho correlational test statistic, there is a significant association between learner's course program completion or withdrawal and learner's number of online courses with correlation coefficient=0.124 at the significance level p=0.000. HF0 is accepted.

Table 151. Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Interval by Interval	Pearson's R	,124	,006	21,285	,000[c]
Ordinal by Ordinal	Spearman Correlation	,124	,006	21,268	,000[c]
N of Valid Cases		29029			

The table 152 below summarizes the cross tabulation results. 68,4% of learners with low number of previous course programs, 74,7% of learners with medium number of previous course programs, 81,8% of learners with high number of previous course programs is reported as completed the course program.

Table 152. Number of Course Programs vs Completion Crosstabulation

			CP_Completed		
			Withdrawal	Completed	Total
NoofCP	Low	Count	3146	6804	9950
		% within NoofCP	31,6%	68,4%	100,0%
	Medium	Count	2597	7659	10256
		% within NoofCP	25,3%	74,7%	100,0%
	Hgh	Count	1604	7219	8823
		% within NoofCP	18,2%	81,8%	100,0%
Total		Count	7347	21682	29029
		% within NoofCP	25,3%	74,7%	100,0%

In order to understand the strength of influence number of previous programs has on the probability of course program completion, multiple logistic regression tests is applied. In this analysis, as can be seen in the table 153 below, the likelihood ratio test statistic chi-square= 448,074 and corresponding p value=0.000<0.05, so that the model is significant and it is meaningful to create a prediction model based on number of previous programs. The null hypothesis that there was no difference between the model without number of previous programs variable and the model with number of previous programs variable is rejected. Based on learner's number of previous programs, it is possible to make a prediction with some probabilities on whether this learner will complete or withdraw the course program.

Table 153. Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	479,831			
Final	31,757	448,074	1	,000

Table 154. Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	164,890	133,133	1	,000
NoofCP	479,831	448,074	1	,000

The information in the table 155 below shows that number of previous programs is significant in distinguishing completed group from not completed group (sig.=0.000<0.05). Standard error of number of previous programs is less than 2,0 satisfying this precondition of analysis.

B value in the table 155 below represents the coefficients multinomial logistic regression equation. In this analysis, it seems that if number of previous programs is increased by 1 unit, then the multinomial log-odds (probability) of being in group 'withdrawal' would be expected to decrease by 0,361 unit. It is interpreted as learners with high number of previous programs in the organization are more likely to complete the course program. Exp(B)=0,697<1 supports the result that the outcome is more likely falling in withdrawal group for learners low number of previous programs.

Table 155. Parameter Estimates (Completion vs Withdrawal)

CPCont		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
Withdrawal	Intercept	-,397	,035	131,649	1	,000			
	NoofCP	-,361	,017	437,934	1	,000	,697	,674	,721

- HF1: Learner's average success in e-learning significantly influence whether the learner completes or withdraw the course program.

According to Spearman rho correlational test statistic, there is a significant association between learner's course program completion or withdrawal and learner's average success with correlation coefficient=0.284 at the significance level p=0.000. HF1 is accepted.

Table 156. Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Interval by Interval	Pearson's R	,284	,005	50,380	,000[c]
Ordinal by Ordinal	Spearman Correlation	,284	,005	50,414	,000[c]
N of Valid Cases		29029			

The table 157 below summarizes the cross tabulation results. 58,7% of unsuccessful learners, 77,2% of successful learners and 88,7% of very successful learners are reported as completed the course program. It shows that as the success level increases, completion ratio increases, as well.

Table 157. Average E-Learnig Success vs Completion Crosstabulation

			CP_Completed		Total
			Withdrawal	Completed	
AvgELSuc	Unsuccessful	Count	4104	5838	9942
		% within AvgELSuc	41,3%	58,7%	100,0%
	Succesful	Count	2157	7303	9460
		% within AvgELSuc	22,8%	77,2%	100,0%
	Very Successful	Count	1086	8541	9627
		% within AvgELSuc	11,3%	88,7%	100,0%
Total		Count	7347	21682	29029
		% within AvgELSuc	25,3%	74,7%	100,0%

In order to understand the strength of influence average success level has on the probability of course program completion, multiple logistic regression tests is applied. In this analysis, as can be seen in the table 158 below, the likelihood ratio test statistic chi-square= 2,426 and corresponding p value=0.000<0.05, so that the model is significant and it is meaningful to create a prediction model based on average success level information. The null hypothesis that there was no difference between the model without average success variable and the model with average success variable is rejected. Based on learner's average success information, it is possible to make a prediction with some probabilities on whether this learner will complete or withdraw the course program.

Table 158. Model Fitting Information

	Model Fitting Criteria	Likelihood Ratio Tests		
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	2,453E3			
Final	27,750	2,426E3	1	,000

Table 159. Likelihood Ratio Tests

	Model Fitting Criteria	Likelihood Ratio Tests		
Effect	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	238,758	211,009	1	,000
AvgELSuc	2,453E3	2,426E3	1	,000

The information in the table 160 below shows that average success is significant in distinguishing completed group from not completed group (sig.=0.000<0.05). Standard error of is less than 2,0 satisfying this precondition of analysis.

B value in the table 160 below represents the coefficients multinomial logistic regression equation and in this analysis, it seems that if average success is increased by 1 unit, then the multinomial log-odds (probability) of being in group 'withdrawal' would be expected to decrease by 0,858 unit. It is interpreted as learners who have a higher average success are less likely to withdraw the course program.

Exp(B)=0,424<1 supports the result that the outcome is more likely falling in withdrawal group for learners with low average success.

Table 160. Parameter Estimates (Completion vs Withdrawal)

CPCont		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
Withdrawal	Intercept	,502	,035	210,981	1	,000			
	AvgELSuc	-,858	,018	2167,545	1	,000	,424	,409	,440

<u>A Logistic Regression Model for Course Program Completion Based on Learner Previous E-Learning Performance</u>

A regression model based on learner's previous e-learning performance is designed in order to understand the relationships between course program completion and all related predictors. Learner's total number of e-learning course programs and learner's average e-learning success is included in the model as independent predictors. Course program completion variable which is a dichotomous variable taking the values of 'completed' or 'not completed' is included in the model as dependent variable. In the following part, detailed information about the model can be seen.

In this analysis, as can be seen in the table 161 below, the likelihood ratio test statistic chi-square= 2,439 and corresponding p value=0.000<0.05, so that the model is significant and it is meaningful to create a prediction model based on learners' previous e-learning performance. The null hypothesis that there was no difference between the model without previous e-learning performance variables and the model with those variables is rejected. Based on learner's previous e-learning performance information, it is possible to make a prediction with some probabilities on whether this learner will complete or withdraw the course program.

Table 161. Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	2,524E3			
Final	85,345	2,439E3	2	,000

Table 162. Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	282,925	197,580	1	,000
NoofCP	98,679	13,335	1	,000
AvgELSuc	2,076E3	1,991E3	1	,000

The information in the table 163 below shows that all variables are significant in distinguishing completed group from not completed group (NoofCP sig.=0.031<0.05, average success sig.=0.000<0.05). Standard error of all variables is less than 2,0 satisfying the precondition of analysis.

Table 163. Parameter Estimates

CPCont		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
Withdrawal	Intercept	,588	,042	196,945	1	,000			
	NoofCP	-,070	,019	13,333	1	,000	,933	,899	,968
	AvgELSuc	-,833	,020	1806,243	1	,000	,435	,418	,452

B value in the table 163 represents the coefficients multinomial logistic regression equation and results can be summarized as:

- If number of course programs is increased by 1 unit, then the multinomial log-odds (probability) of being in group ‘withdrawal’ would be expected to decrease by 0.070 unit. As leaners participate in more e-learning course programs, the likelihood of being in the group of withdrawal decreases.
- If e-learning average success is increased by 1 unit, then the odds of being in withdrawal group decrease by 0.833 units. More successful learners are more

likely to complete the course program.

- Model Classification Accuracy

In order to prove the accuracy of this classification model, the estimate of by chance accuracy criteria should be calculated. As mentioned before, firstly, the estimate of by chance accuracy rate should be computed as 62% (0,253^2 + 0,747^2=0,62). The estimate of by chance accuracy criteria aims 25% improvement (Anderson et al., 1998), so that it is 77,5% (0,62*1,25=0,775). The classification accuracy of this model can be seen in the classification table 165 below as 74,7% which does not satisfy the classification accuracy criteria, so that only the information about learners' previous experience does not seem to provide a good classification.

Table 164. Case Processing Summary

		N	Marginal Percentage
CP_Completed	Withdrawal	7335	25,3%
	Completed	21682	74,7%
Valid		29017	100,0%
Missing		0	
Total		29017	
Subpopulation		9	

Table 165. Regression Classification Accuracy

Observed	Predicted		
	Withdrawal	Completed	Percent Correct
Withdrawal	0	7335	,0%
Completed	0	21682	100,0%
Overall Percentage	,0%	100,0%	74,7%

<u>Course Program Related Factors vs. Course Program Completion</u>

- HG0: Course program content significantly influence whether the learner completes or withdraw the course program.

According to Spearman rho correlational test statistic, there is a significant association between learner's course program completion or withdrawal and course program content with correlation coefficient=-0.127 at the significance level p=0.000. HG0 is accepted.

Table 166. Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Interval by Interval	Pearson's R	-,127	,006	-21,878	,000[c]
Ordinal by Ordinal	Spearman Correlation	-,127	,006	-21,878	,000[c]
N of Valid Cases		29017			

The table 167 below summarizes the cross tabulation results. 77,8% of vocational course programs and 64,8% of skill development course programs is reported to be completed.

Table 167. Content vs Completion Crosstabulation

			CP_Completed		Total
			Withdrawal	Completed	
CPCont	Vocational	Count	4910	17218	22128
		% within CPCont	22,2%	77,8%	100,0%
	Skill development	Count	2425	4464	6889
		% within CPCont	35,2%	64,8%	100,0%
Total		Count	7335	21682	29017
		% within CPCont	25,3%	74,7%	100,0%

In order to understand the strength of influence, course program content has on the probability of course program completion, multiple logistic regression tests is applied. In this analysis, as can be seen in the table 168 below, the likelihood ratio test statistic chi-square= 448,954 and corresponding p value=0.000<0.05, so that the model is significant and it is meaningful to create a prediction model based on course program content. The null hypothesis that there was no difference between the model without course program content variable and the model with course program content variable is rejected. Based on learner's course program content, it is possible to make a prediction with some probabilities on whether this learner will complete or withdraw the course program.

Table 168. Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	468,237			
Final	19,284	448,954	1	,000

Table 169. Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	19,284[a]	,000	0	.
CPCont	468,237	448,954	1	,000

The information in table 170 below shows that course program content is significant in distinguishing completed group from not completed group (sig.=0.000<0.05). Standard error of course program content is less than 2,0 satisfying this precondition of analysis.

Table 170. Parameter Estimates (Completion vs Withdrawal)

CPCont		B	Std. Error	Wald	df	Sig.	Exp(B)
Withdrawal	Intercept	-,610	,025	585,118	1	,000	
	[CPCont=1]	-,644	,030	462,448	1	,000	,525
	[CPCont=2]	0[b]	.	.	0	.	.

The multinomial odds (probability) for vocational course program (CPCont=1) relative to skill development course program (CPCont=2) is 0.644 unit lower for falling in withdrawal group. Skill development course programs seem to be more likely to be withdrawn. Since Exp(B)=0,525 <1, the outcome completed is more likely to occur for vocational course program.

- HG1: Whether the course program is certificated or not significantly influence whether the learner completes or withdraw the course program.

According to Spearman rho correlational test statistic, there is a significant association between learner's course program completion or withdrawal and course program certification with correlation coefficient=-0.439 at the significance level p=0.000. HG1 is accepted.

Table 171. Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Interval by Interval	Pearson's R	-,439	,004	-83,230	,000[c]
Ordinal by Ordinal	Spearman Correlation	-,439	,004	-83,230	,000[c]
N of Valid Cases		29017			

The table 172 below summarizes the cross tabulation results. 96,4% of course programs which are not certificated and 57,9% of course programs which are certificated are completed according to cross tabulation results.

Table 172. Certification vs Completion Crosstabulation

			CP_Completed		Total
			Withdrawal	Completed	
CPCer	Not Certificated	Count	461	12227	12688
		% within CPCer	3,6%	96,4%	100,0%
	Certificated	Count	6874	9455	16329
		% within CPCer	42,1%	57,9%	100,0%
Total		Count	7335	21682	29017
		% within CPCer	25,3%	74,7%	100,0%

In order to understand the strength of influence, course program certification has on the probability of course program completion, multiple logistic regression tests is applied. In this analysis, as can be seen in the table 173 below, the likelihood ratio test statistic chi-square= 6,622 and corresponding p value=0.000<0.05, so that the model is significant and it is meaningful to create a prediction model based on course program certification information. The null hypothesis that there was no difference between the model without course program certification variable and the model with course program certification variable is rejected. Based on learner's course program certification information, it is possible to make a prediction with some probabilities on whether this learner will complete or withdraw the course program.

Table 173. Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	6,640E3			
Final	18,062	6,622E3	1	,000

Table 174. Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	18,062[a]	,000	0	.
CPCer	6,640E3	6,622E3	1	,000

The information in the table 175 below shows that course program certification is significant in distinguishing completed group from not completed group (sig.=0.000<0.05). Standard error of course program certification is less than 2,0 satisfying this precondition of analysis.

Table 175. Parameter Estimates (Completion vs Withdrawal)

CPCont		B	Std. Error	Wald	df	Sig.	Exp(B)
Withdrawal	Intercept	-,319	,016	404,521	1	,000	
	[CPCer=0]	-2,959	,050	3499,648	1	,000	,052
	[CPCer=1]	0[b]	.	.	0	.	.

The multinomial odds (probability) for not certificated course program (CPCer=0) relative to certificated course program (CPCer=1) is 2.959 unit lower for falling in withdrawal group. Certificated course programs seem to be more likely to be withdrawn. Since Exp(B)=0,050 <1, the outcome completed is more likely to occur for not certificated course programs.

- HG2: Course program duration assigned by the system significantly influence whether the learner completes or withdraw the course program.

According to Spearman rho correlational test statistic, there is a significant association between learner's course program completion or withdrawal and course program duration allowed by the system with correlation coefficient=-0.411 at the significance level p=0.000. HG2 is accepted.

Table 176. Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Interval by Interval	Pearson's R	-,410	,005	-76,597	,000[c]
Ordinal by Ordinal	Spearman Correlation	-,411	,005	-76,719	,000[c]
N of Valid Cases		29017			

The table 177 below summarizes the cross tabulation results. 97,3% of course programs which last shorter, 72% of course programs with normal duration and 52,2% of course programs with longer duration are reported as completed. This result shows that as the duration of the course program gets longer, completion ratio decreases.

Table 177. Duration vs Completion Crosstabulation

			CP_Completed		
			Withdrawal	Completed	Total
CPDur	Short	Count	266	9448	9714
		% within CPDur	2,7%	97,3%	100,0%
	Normal	Count	3060	7855	10915
		% within CPDur	28,0%	72,0%	100,0%
	Long	Count	4009	4379	8388
		% within CPDur	47,8%	52,2%	100,0%
Total		Count	7335	21682	29017
		% within CPDur	25,3%	74,7%	100,0%

In order to understand the strength of influence, course program duration has on the probability of course program completion, multiple logistic regression tests is applied. In this analysis, as can be seen in the table 178 below, the likelihood ratio test statistic chi-square= 5,208 and corresponding p value=0.000<0.05, so that the model is significant and it is meaningful to create a prediction model based on course program duration information. The null hypothesis that there was no difference between the model without course program duration variable and the model with course program duration variable is rejected. Based on learner's course program duration information, it is possible to make a prediction with some probabilities on whether this learner will complete or withdraw the course program.

Table 178. Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	5,835E3			
Final	627,028	5,208E3	1	,000

Table 179. Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	1,010E4	9,470E3	1	,000
ActDuration	5,835E3	5,208E3	1	,000

The information in the table 180 below shows that course program duration is significant in distinguishing completed group from not completed group (sig.=0.000<0.05). Standard error of course program duration is less than 2,0 satisfying this precondition of analysis.

Table 180. Parameter Estimates (Completion vs Withdrawal)

CPCont		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
Withdrawal	Intercept	-4,058	,052	6037,739	1	,000			
	CPDuration	1,380	,021	4141,486	1	,000	3,976	3,812	4,146

B value in the table 180 above represents the coefficients multinomial logistic regression equation and in this analysis, it seems that if course program duration is increased by 1 unit, then the multinomial log-odds (probability) of being in group ‘withdrawal’ would be expected to increase by 1,380 unit. It is interpreted as course programs with longer duration are more likely to be withdrawn. Exp(B)=3,976>1 tells that the risk of falling in the referent group (completed) decreases as course program duration increases and the outcome is more likely falling in withdrawal group for course programs with longer duration.

A Logistic Regression Model for Course Program Completion Based on Course Program Characteristics

A regression model based on course program characteristics is designed in order to understand the relationships between course program completion and all related predictors. Course program content, course program certification and course program duration information is included in the model as independent predictors. Course program completion variable which is a dichotomous variable taking the values of ‘completed’ or ‘not completed’ is included in the model as dependent variable. In the following part, detailed information about the model can be seen.

In this analysis, as can be seen in the table 181 below, the likelihood ratio test statistic chi-square= 7,059 and corresponding p value=0.000<0.05, so that the model is significant and it is meaningful to create a prediction model based on course program characteristics. The null hypothesis that there was no difference between the model without course program characteristics and the model with those variables is rejected. Based on course program information, it is possible to make a prediction with some probabilities on whether this learner will complete or withdraw the course program.

Table 181. Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	7,694E3			
Final	634,943	7,059E3	3	,000

Table 182. Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	6,349E2	,000	0	.
CPCont	709,708	74,764	1	,000
CP_Duration	930,492	295,549	1	,000
CPCer	2,466E3	1,832E3	1	,000

The information in the table 183 below shows that all variables are significant in distinguishing completed group from not completed group (course program duration sig.=0.000<0.05, course program content sig.=0.000<0.05 and course program certification sig.=0.000<0.05). Standard error of all variables is less than 2,0 satisfying this precondition of analysis.

Table 183. Parameter Estimates (Completion vs Withdrawal)

CPCont		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
Withdrawal	Intercept	-1,250	,098	164,197	1	,000			
	CPCont	-,285	,033	74,279	1	,000	,752	,705	,802
	CP_Duration	,529	,031	297,101	1	,000	1,697	1,598	1,802
	[CPCer=0]	-2,422	,064	1439,522	1	,000	,089	,078	,101
	[CPCer=1]	0^b	.	.	0	.	.	.	.

B values in the table 183 above represents the coefficients multinomial logistic regression equation and results can be summarized as:

- If course program duration is increased by 1 unit, then the multinomial log-odds (probability) of being in group 'withdrawal' would be expected to increase by 0.529 units. As the duration increases, the likelihood of being in the group of withdrawal increases.

- The multinomial odds (probability) for vocational course program (course program content=1) relative to skill development course program (course program content=2) is 0.285 unit lower for falling in withdrawal group. Learners are more likely to complete vocational course programs.
- The multinomial odds (probability) for not certificated course program (CPCer= no) relative to certificated course program (CPCer= yes) is 2.422 unit lower for falling in withdrawal group. Learners are more likely to complete uncertificated course programs.
- Model Classification Accuracy

In order to prove the accuracy of this classification model, the estimate of by chance accuracy criteria should be calculated. As mentioned before, firstly, the estimate of by chance accuracy rate should be computed as 62% (0,253^2 + 0,747^2=0,62). The estimate of by chance accuracy criteria aims 25% improvement (Anderson et al., 1998), so that it is 77,5% (0,62*1,25=0,775).The classification accuracy of this model can be seen in the classification table 185 below as 74% which does not satisfy the classification accuracy criteria, so that only the information about course program does not seem to provide a good classification.

Table 184. Case Processing Summary

		N	Marginal Percentage
CP_Completed	Withdrawal	7335	25,3%
	Completed	21682	74,7%
CPCer	Not Certificated	12688	43,7%
	Certificated	16329	56,3%
Valid		29017	100,0%
Missing		0	
Total		29017	
Subpopulation		8	

Table 185. Classification

Observed	Predicted		
	Withdrawal	Completed	Percent Correct
Withdrawal	2762	4573	37,7%
Completed	2969	18713	86,3%
Overall Percentage	19,8%	80,2%	74,0%

<u>A Logistic Regression Model for Course Program Completion Based on Demographics, Course Program Characteristics and Previous E-Learning Experience</u>

It is seen that when the variables are included in regression model separately, classification accuracy criteria is not satisfied. It is considered that providing more information for the model will lead to a better classification. For this reason, a regression model based on demographics, course program characteristics and previous e-learning experience is designed.

In this analysis, as can be seen in the table 186 below, the likelihood ratio test statistic chi-square= 7,059 and corresponding p value=0.000<0.05, so that the model is significant and it is meaningful to create a prediction model based on course program characteristics. The null hypothesis that there was no difference between the model without demographics, course program characteristics and previous e-learning experience and the model with those variables is rejected. Based on provided information, it is possible to make a prediction with some probabilities on whether this learner will complete or withdraw the course program.

Table 186. Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	2,160E4			
Final	1,067E4	1,094E4	15	,000

Table 187. Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	1,067E4	,000	0	.
Educ	1,067E4	,782	1	,377
Age	1,067E4	,480	1	,489
WorkExp	1,068E4	9,159	1	,002
HierOcc	1,067E4	2,153	1	,142
NoofCP	1,078E4	111,148	1	,000
AvgELSuc	1,342E4	2,753E3	1	,000
CPCont	1,070E4	33,641	1	,000
ActDuration	1,110E4	431,760	1	,000
CPCer	1,262E4	1,952E3	1	,000
Reg	1,068E4	9,342	5	,096
Gender	1,067E4	4,606	1	,032

The information in the table 188 below shows that work experience, gender, course program content, course program duration, course program certification, number of previous course programs and average e-learning success are significant in distinguishing completed group from not completed group. Standard error of all variables is less than 2,0 satisfying this precondition of analysis.

Table 188. Parameter Estimates (Completion vs Withdrawal)

CPCont		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
Withdrawal	Intercept	,607	,192	9,989	1	,002			
	Educ	,036	,041	,781	1	,377	1,037	,957	1,123
	Age	,022	,031	,480	1	,489	1,022	,961	1,086
	WorkExp	,085	,028	9,147	1	,002	1,089	1,030	1,151
	HierOcc	-,026	,018	2,154	1	,142	,974	,941	1,009
	NoofCP	-,254	,024	110,944	1	,000	,776	,740	,813
	AvgELSuc	-1,152	,024	2365,958	1	,000	,316	,302	,331
	CPCont	-,216	,037	33,533	1	,000	,806	,749	,867
	CPDuration	,717	,035	428,966	1	,000	2,049	1,915	2,193
	[CPCer=0]	-2,677	,068	1547,218	1	,000	,069	,060	,079
	[CPCer=1]	0^b	.	.	0	.	.	.	.
	[Reg=1]	,062	,083	,563	1	,453	1,064	,904	1,253
	[Reg=2]	,107	,085	1,564	1	,211	1,113	,941	1,315
	[Reg=3]	,009	,092	,009	1	,926	1,009	,842	1,208
	[Reg=4]	,022	,097	,051	1	,821	1,022	,846	1,235
	[Reg=5]	-,064	,093	,478	1	,489	,938	,781	1,125
	[Reg=6]	0^b	.	.	0	.	.	.	.
	[Gender=0]	-,078	,036	4,598	1	,032	,922	1,007	1,161
	[Gender=1]	0^b	.	.	0	.	.	.	.

B values in the table 188 above represents the coefficients multinomial logistic regression equation.The equation and results are presented as follows:

*P(withdrawal/completion)= 0,85*Work experience -0,254*Number of e-learning programs +0,717*Course duration - 0,078*Gender(Female) -2,677*Certification(No) -0,216*Course program content (Vocational course)*

- If work experience is increased by one unit, then the multinomial odds of being in withdrawal groups is increased by 0,085 units. More experienced people are more likely fall in withdrawal group.
- The multinomial odds (probability) for females (gender=0) relative to males (gender=1) is 0.078 unit lower for falling in withdrawal group. Males seem to be more likely to withdraw the course program. Since Exp(B)=0,922 <1, the outcome completed is more likely to occur for female.
- The multinomial odds (probability) for vocational course program (course program content=1) relative to skill development course program (course program content=2) is 0.216 unit lower for falling in withdrawal group. Learners are more likely to complete vocational course programs.
- If course program duration is increased by 1 unit, then the multinomial log-odds (probability) of being in group 'withdrawal' would be expected to increase by 0.717 units. As the duration increases, the likelihood of being in the group of withdrawal increases.
- The multinomial odds (probability) for not certificated course program (CPCer= no) relative to certificated course program (CPCer= yes) is 2.677 unit lower for falling in withdrawal group. Learners are more likely to complete uncertificated course programs.
- If number of course programs is increased by 1 unit, then the multinomial log-odds (probability) of being in group 'withdrawal' would be expected to decrease by 0.254 unit. As leaners participate in more e-learning course programs, the likelihood of withdrawal decreases.
- If e-learning average success is increased by 1 unit, then the odds of being in

withdrawal group decrease by 1,152 units. More successful learners are more likely to complete the course program.

- Model Classification Accuracy

In order to prove the accuracy of this classification model, the estimate of by chance accuracy criteria should be calculated. As mentioned before, firstly, the estimate of by chance accuracy rate should be computed as 62% (0,253^2 +0,747^2=0,62). The estimate of by chance accuracy criteria aims 25% improvement (Anderson et al., 1998), so that it is 77,5% (0,62*1,25=0,775).The classification accuracy of this model can be seen in the classification table 190 below as 83,1% which satisfies the classification accuracy criteria. It is clear that information about each group: demographics, course program characteristics and previous e-learning experience is valuable for the model and provides a better classification model.

Table 189. Case Processing Summary

		N	Marginal Percentage
CP_Completed	Withdrawal	7335	25,3%
	Completed	21682	74,7%
CPCer	Not Certificated	12688	43,7%
	Certificated	16329	56,3%
Reg	Marmara	10122	34,9%
	İç Anadolu	8101	27,9%
	Ege	338	1,7%
	Karadeniz	2818	9,7%
	Güneydoğu Anadolu	3170	10,9%
	Doğu Anadolu	1418	4,9%
Gender	Female	1865	64,3%
	Male	10362	35,7%
Valid		29017	100,0%
Missing		0	
Total		29017	
Subpopu ation		5630[a]	

Table 190. Classification

Obs rve	Predicted		
	Withdrawal	Comple e	Percent Correct
Withdrawal	480	2855	61,1%
Completed	2039	19643	90,6%
Overall Percentage	22,5%	77,5%	83,1%

<u>A Decision Tree Model for Course Program Completion</u>

Decision tree as another method of predictive data mining is applied additional to logistic regression model. The reason is to compare the results and to see whether the results are the same when the same input data is used in different models. A predictive model is generated in order to classify a new incidence into groups of ‘completion’ or ‘withdrawal’ by the use all the information given for that new incidence.

For this decision tree model, CHAID (Chi-squared automatic interaction detector) growing method is used at a significance level of 0.05. For validation reasons, split sample validation method is applied and the sample is divided equally for training and testing (50% for training and 50% for testing). Misclassification costs are remained the same for incorrect prediction of each group (successful and unsuccessful).

In the model, the same variables in regression model which are demographics like age, gender, functional occupation, hierarchical occupation, region, education and work experience; course program characteristics like content, certification and duration, previous e-learning performance indicators like number of e-learning course programs and average course program completion duration is included in the model as predictors. Dependent variable is selected as course program completion. The model is trained for prediction of two groups: completion of the course program and withdrawal the course program.

- Classification accuracy

  Overall classification accuracy is 82,9% and the details can be seen in the table 191 below:

Table 191. Decision Tree Classification Accuracy

		Predicted		
Sample	Observed	Withdrawal	Completed	Percent Correct
Training	Withdrawal	1949	1684	53,6%
	Completed	782	10074	92,8%
	Overall Percentage	18,8%	81,2%	83,0%
Test	Withdrawal	1988	1714	53,7%
	Completed	764	10062	92,9%
	Overall Percentage	18,9%	81,1%	82,9%

Decision tree is generated based on the included independent factors and given data set. Course program characteristics as course program duration, course program certification and course program content information is determined as strong predictors in the model. Additionally, two of previous e-learning performance indicators as learners' total number of e-learning course programs and leaners' average e-learning success are used for classification model. Significant variables selected by the decision tree model are parallel with the ones in regression model. Two different models produce almost the same results, which increases the reliability of the models.

Terminal nodes are node 8 through node 17 as can be seen in the figure 4 below. Classification decision on each node is determined by some association rules. A new incidence is classified as 'will be completed' or 'will not be completed' based on which association rule it satisfies. For example, the information about a new incidence is a learner who is older and has a bachelor degree, has high participation in e-learning course programs, but unsuccessful in those course programs in average. Current e-learning course program is a certificated vocational course program about fraud management in banking which is assigned a really longer duration to be completed. From this information, the tree model firstly checks for the course program certification information. According to the information, a longer duration is assigned to this course program. If the course program has a long duration, the model is interested in learner's average e-learning success. Since learner is stated as unsuccessful in average, the next factor to be checked is duration of the course program. According to the model, a terminal node is reached at this level. Final node for this new incidence is node nine and since the course program has a long duration, learner is predicted to withdraw the course program by a probability of 80,8%.

Association rule for this case is as follows:

IF (CPCer != "Not Certificated") AND (AvgELSuc NOT MISSING AND (AvgELSuc <= "Unsuccessful")) AND (CPDur NOT MISSING AND (CPDur > "Normal"))
THEN
Node = 9
Prediction = Withdrawal
Probability = 0.801958

All association rules can be found in Appendix B. P values and chi-square values of each predictor can be seen in decision tree below.

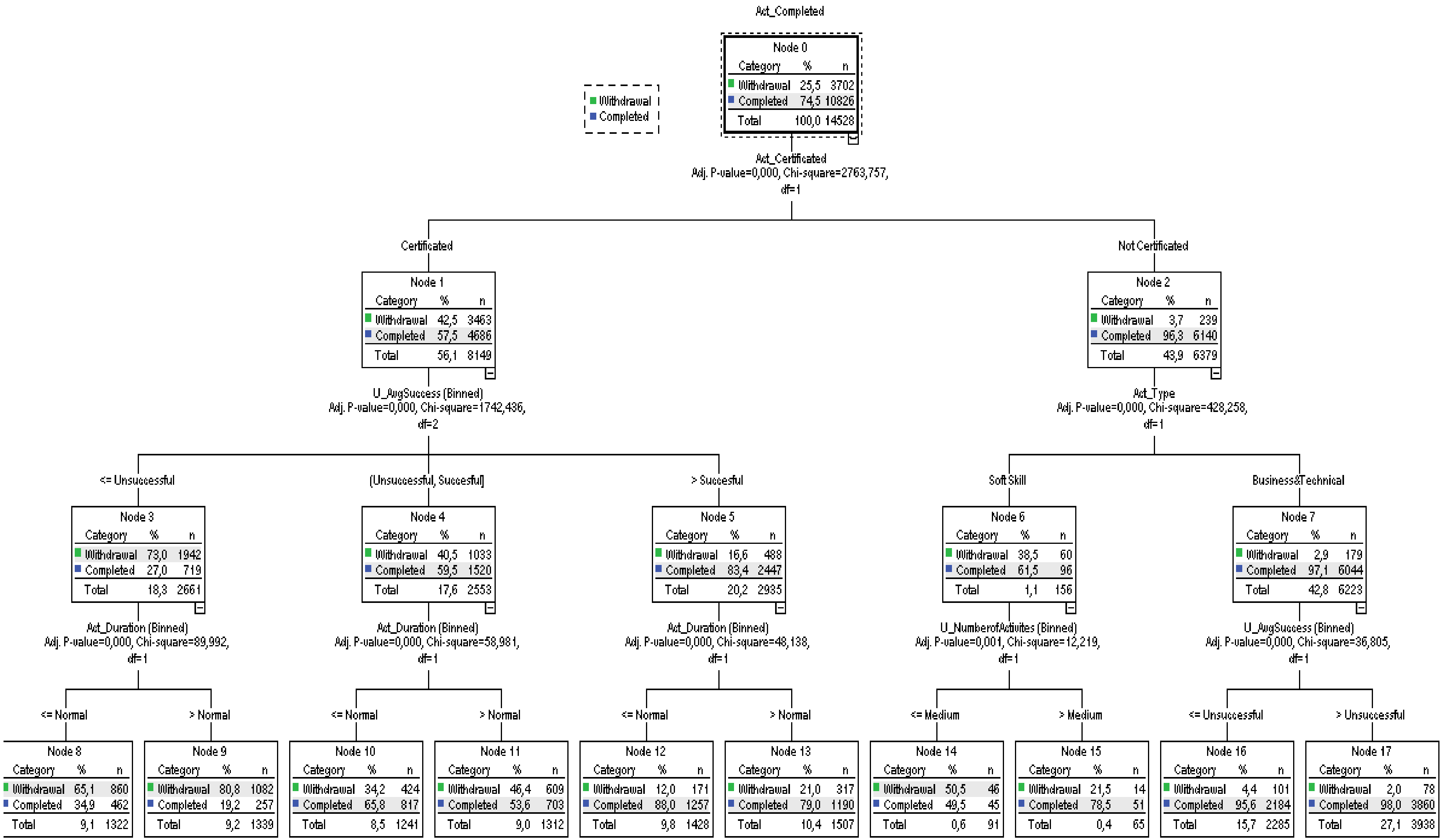

Fig. 4 Decision tree model – course program completion

Course Program Completion Duration

It is aimed also to discover the factors influencing course program completion duration, since learner success has a positive correlation with completion duration and if learners finish the course program in a longer duration, they get higher score from the course program. For this reason, it is considered to be useful to uncover the hidden factors making learners complete in different durations. For example, if the occupation is discovered to be a significant factor, then occupation may be selected as a concern area. Results may be interpreted as people from high level decision making level may not be dedicating sufficient time for e-learning course programs and corrective actions may be taken, accordingly.

In order to test the hypothesis, learning-course program completed data set is used.

Learner's Demographics vs. Course Program Completion Duration

- HH0: There is a statistically significant association between learner's course program completion duration and learner's age.

According to Spearman rho correlational test statistic, there is a significant association between learner's course program completion duration and learner's age with correlation coefficient=0.059 at the significance level p=0.000. HH0 is accepted.

Table 192. Correlations (Age vs. Completion Duration)

			CPCompDur	Age
Spearman's rho	CPCompDur	Correlation Coefficient	1,000	,059**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	Age	Correlation Coefficient	,059**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that learner's age group has an influence on learner's course program completion duration. It should also mean that people from different age groups complete the course program in different durations. In order to test whether the duration is significantly different for young, medium age and older people, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 193. Ranks (Age vs. Completion Duration)

	Age	N	Mean Rank
CPCompDur	Younger	5984	9217,51
	Middle age	5432	9186,14
	Older	7547	9904,66
	Total	18963	

Table 194. Test Statistics

	CPCompDur
Chi-Square	84,948
df	2
Asymp. Sig.	,000

According to the tables above, there is a statistically significant difference between the different age groups (Chi-Square = 84,948, $p = 0.000$) with a mean rank of 9217,51 for younger age group, 9186,14 for middle age group and 9904,66 for older age group. Additional to the mean ranks, mean of completion duration for each age group can be examined in the table 195 below which shows that older age group completes the course program in a longer time than young and middle age groups do.

Table 195. Average Completion Duration (Age)

Age	Mean	N	Std. Deviation
Younger	19,3402	5984	41,47844
Middle age	20,1423	5432	46,55648
Older	32,4493	7547	58,82391
Total	24,7872	18963	50,78963

Even if it is clearly seen that duration means of some age groups are different from each other in the table 195 above, additional post-hoc analysis should be conducted to be able to understand whether the differences among groups are statistically significant or not. For that reason, multiple comparisons are conducted by applying Mann Whitney- 2 independent samples test. All age groups are compared with each other and results show that younger and middle age groups do not differ from each other in terms of completion duration. The results are presented in detail in the table 196 below:

Table 196. Comparison of Age Groups

<table>
<tr>
<td>1. Younger vs. middle age group
There is not a statistically significant difference between the underlying distributions of course program completion durations of younger age and middle age groups (z = -0,323, p = 0.747>0.05).</td>
<td>Test Statistics
<table>
<tr><td></td><td>CPCompDur</td></tr>
<tr><td>Mann-Whitney U</td><td>1,620E7</td></tr>
<tr><td>Wilcoxon W</td><td>3,096E7</td></tr>
<tr><td>Z</td><td>-,323</td></tr>
<tr><td>Asymp. Sig. (2-tailed)</td><td>,747</td></tr>
</table>
</td>
</tr>
<tr>
<td>2. Younger vs. older age group
There is a statistically significant difference between the underlying distributions of course program completion durations of younger age and older age groups (z = -7.712, p = 0.000<0.05).</td>
<td>Test Statistics
<table>
<tr><td></td><td>CPCompDur</td></tr>
<tr><td>Mann-Whitney U</td><td>2,094E7</td></tr>
<tr><td>Wilcoxon W</td><td>3,885E7</td></tr>
<tr><td>Z</td><td>-7,712</td></tr>
<tr><td>Asymp. Sig. (2-tailed)</td><td>,000</td></tr>
</table>
</td>
</tr>
<tr>
<td>3. Older vs. middle age group
There is a statistically significant difference between the underlying distributions of course program completion durations of older age and middle age groups (z = -7,853, p = 0.000 < 0.05).</td>
<td>Test Statistics
<table>
<tr><td></td><td>CPCompDur</td></tr>
<tr><td>Mann-Whitney U</td><td>1,894E7</td></tr>
<tr><td>Wilcoxon W</td><td>3,370E7</td></tr>
<tr><td>Z</td><td>-7,853</td></tr>
<tr><td>Asymp. Sig. (2-tailed)</td><td>,000</td></tr>
</table>
</td>
</tr>
</table>

- HH1: There is a statistically significant association between learner's course program completion duration and learner's gender.

According to Spearman rho correlational test statistic, there is a significant association between learner's course program completion duration and learner's gender with correlation coefficient=0.026 at the significance level p=0.000. HH1 is accepted.

Table 197. Correlations (Gender vs. Completion Duration)

			CPCompDur	Gender
Spearman's rho	CPCompDur	Correlation Coefficient	1,000	,026**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	Gender	Correlation Coefficient	,026**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that gender has an influence on learner's course program completion duration. It should also mean that male and female differ from each other regarding course program completion durations. In order to test whether the duration for male and female learners is significantly different from each other, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 198. Ranks (Gender vs. Completion Duration)

	Gender	N	Mean Rank
CPCompDur	Female	11287	9370,67
	Male	7676	9645,70
	Total	18963	

Table 199. Test Statistics

	CPCompDur
Chi-Square	13,093
df	1
Asymp. Sig.	,000

According to the tables above, there is a statistically significant difference between the different gender groups (Chi-Square = 13,093, p = 0.000) with a mean rank of 9370,67 for female and 9645,70 for male. Additional to the mean ranks, mean of total score for each gender group can be examined in the table 200 below which shows that female learners completes the course program in a shorter duration than the male learners do.

Table 200. Average Completion Duration (Gender)

Gender	Mean	N	Std. Deviation
Female	22,4590	11287	47,00331
Male	28,2107	7676	55,71997
Total	24,7872	18963	50,78963

- HH2: There is a statistically significant association between learner's course program completion duration and learner's education level.

According to Spearman rho correlational test statistic, there is a significant association between learner's course program completion duration and learner's education level with correlation coefficient=-0.020 at the significance level p=0.005. HH2 is accepted.

Table 201. Correlations (Education vs. Completion Duration)

			CPCompDur	Educ
Spearman's rho	CPCompDur	Correlation Coefficient	1,000	-,020**
		Sig. (2-tailed)	.	,005
		N	18963	18963
	Educ	Correlation Coefficient	-,020**	1,000
		Sig. (2-tailed)	,005	.
		N	18963	18963

Based on the correlational test, it can be claimed that education level has an influence on learner's course program completion duration. It should also mean that course program completion duration may change depending upon the education level of the learner. In order to test whether the completion duration of learners with different education levels is significantly different from each other, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 202. Ranks (Education vs. Completion Duration)

	Educ	N	Mean Rank
CPCompDur	High School	4751	9707,61
	Associate Program	2690	9360,73
	Bachelor Degree	11217	9422,25
	Graduate Degree	305	9234,52
	Total	18963	

Table 203. Test Statistics

	CPCompDur
Chi-Square	12,885
df	3
Asymp. Sig.	,005

According to the tables above, there is a statistically significant difference between the different education groups (Chi-Square = 12,885, p= 0.000) with a mean rank of 9707,61 for high school, 9360,73 for associate school, 9422,25 for bachelor degree and 9234,52 for graduate degree. Additional to the mean ranks, mean of course program completion duration for each education group can be examined in the table 204 below which shows that graduate level learners complete the course program in a shorter duration.

Table 204. Average Completion Duration (Education)

Educ	Mean	N	Std. Deviation
High School	28,2113	4751	57,21126
Associate Program	24,5353	2690	50,65648
Bachelor Degree	23,5041	11217	48,08744
Graduate Degree	20,8590	305	38,54359
Total	24,7872	18963	50,78963

Even if it is clearly seen that course program completion duration means of some education groups are different from each other in the table above, additional post-hoc analysis should be conducted to be able to understand whether the differences among groups are statistically significant or not. For that reason, multiple comparisons are conducted by applying Mann Whitney- 2 independent samples test. All education groups are compared with each other and it is discovered that completion duration differs only between high school vs. associate school and high school vs. bachelor degree. The results are presented in detail in table 205 below:

Table 205. Comparison of Education Groups

1. High vs. associate school

There is a statistically significant difference between the underlying distributions of course program completion durations of high school and associate school (z = -2,754, p = 0.006<0.05).

Test Statistics

	CPCompDur
Mann-Whitney U	6159700,000
Wilcoxon W	9779095,000
Z	-2,754
Asymp. Sig. (2-tailed)	,006

2. High school vs. bachelor degree

There is a statistically significant difference between the underlying distributions of course program completion durations of high school and bachelor degree (z = -3,223, p = 0.001<0.05).

Test Statistics

	CPCompDur
Mann-Whitney U	2,584E7
Wilcoxon W	8,876E7
Z	-3,223
Asymp. Sig. (2-tailed)	,001

3. High school vs. graduate degree

There is not a statistically significant difference between the underlying distributions of course program completion durations of high school and graduate degree (z = -1.537, p = 0.124<0.05).

Test Statistics

	CPCompDur
Mann-Whitney U	688797,500
Wilcoxon W	735462,500
Z	-1,537
Asymp. Sig. (2-tailed)	,124

4. Associate and bachelor degree

There is not a statistically significant difference between the underlying distributions of course program completion durations of associate school and bachelor degree (z = -0,577, p = 0.564>0.05).

Test Statistics

	CPCompDur
Mann-Whitney U	1,499E7
Wilcoxon W	1,861E7
Z	-,577
Asymp. Sig. (2-tailed)	,564

5. Associate and graduate degree

There is not a statistically significant difference between the underlying distributions of course program completion durations of associate school and graduate degree (z = -0,399, p = 0.690>0.05).

Test Statistics

	CPCompDur
Mann-Whitney U	404875,000
Wilcoxon W	451540,000
Z	-,399
Asymp. Sig. (2-tailed)	,690

6. Bachelor and graduate degree There is not a statistically significant difference between the underlying distributions of course program completion durations of bachelor degree and graduate degree (z = -0,640, p = 0,522>0.05).	Test Statistics | | CPCompDur | | Mann-Whitney U | 1676192,500 | | Wilcoxon W | 1722857,500 | | Z | -,640 | | Asymp. Sig. (2-tailed) | ,522 |

- HH3: There is a statistically significant association between learner's course program completion duration and learner's functional occupation.

According to Spearman rho correlational test statistic, there is not a significant association between learner's course program completion duration and learner's functional occupation with correlation coefficient=0.012 at the significance level p=0.106. HH3 is rejected.

Table 206. Correlations (Functional Occupation vs. Completion Duration)

			CPCompDur	FuncOcc
Spearman's rho	CPCompDur	Correlation Coefficient	1,000	,012
		Sig. (2-tailed)	.	,106
		N	18963	18963
	FuncOcc	Correlation Coefficient	,012	1,000
		Sig. (2-tailed)	,106	.
		N	18963	18963

Kruskal Wallis non-parametric test also indicates that there is no difference among functional groups regarding course program completion duration. According to the statistical figures below, mean ranks slightly differ from each other and p=0.201>0.05. Since HH3 is rejected, additional post-hoc analysis is not conducted.

Table 207. Ranks (Functional Occupation vs. Comp. Duration)

	FuncOcc	N	Mean Rank
CPCompDur	Marketing&Selling	14507	9451,01
	IT	2078	9502,14
	Business Support	2378	9653,46
	Total	18963	

Table 208. Test Statistics

	CPCompDur
Chi-Square	3,208
df	2
Asymp. Sig.	,201

- HH4: There is a statistically significant association between learner's course program completion duration and learner's hierarchical occupation.

According to Spearman rho correlational test statistic, there is a significant association between learner's course program completion duration and learner's hierarchical occupation with correlation coefficient=0.041 at the significance level p=0.000. HH4 is accepted.

Table 209. Correlations (Hierarchical Occupation vs. Comp. Duration)

			CPCompDur	HierOcc
Spearman's rho	CPCompDur	Correlation Coefficient	1,000	,041**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	HierOcc	Correlation Coefficient	,041**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that learner's hierarchical occupation has an influence on learner's course program completion duration. It should also mean that different hierarchical occupation groups complete the course programs in different durations. In order to test whether the groups are significantly different from each other in terms of completion duration, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 210. Ranks (Hierarchical Occupation vs. Comp. Duration)

	HierOcc	N	Mean Rank
CPCompDur	Operational	9961	9294,46
	Supporting	2184	9493,59
	Low Level DM	89	9946,08
	High Level DM	6729	9749,71
	Total	18963	

Table 211. Test Statistics

	CPCompDur
Chi-Square	32,279
df	3
Asymp. Sig.	,000

According to the tables above, there is a statistically significant difference between the different hierarchical occupation groups (Chi-Square = 437,411, P = 0.000) with a mean rank of 9294,46 for operational group, 9493,59 for supporting group, 9946,08 for low level decision making group and 9749,71 for low level decision making group. Additional to the mean ranks, mean of completion duration for each hierarchical occupation group can be examined in the table 212 below which shows that low level decision making groups spend more time to complete the course program.

Table 212. Average Completion Duration (Hierarchical Occupation)

HierOcc	Mean	N	Std. Deviation
Operational	22,3550	9961	47,97159
Supporting	21,6319	2184	45,85468
Low Level DM	32,5843	89	65,57002
High Level DM	29,3087	6729	55,60358
Total	24,7872	18963	50,78963

Even if it is clearly seen that score means of some hierarchical occupation groups are different from each other in the table above, additional post-hoc analysis should be conducted to be able to understand among which groups, the differences are statistically significant. For that reason, multiple comparisons are conducted by applying Mann Whitney- 2 independent samples test. All hierarchical occupation groups are compared with each other and it is explored that there is difference only between operational and high level decision making group in terms of course program completion duration. The results are presented in detail in the table 213 below:

Table 213. Comparison of Hierarchical Occupation Groups

<table>
<tr>
<td>1. Operational vs. supporting group
There is not a statistically significant difference between the underlying distributions of course program completion durations of operational and supporting groups (z = -1,698, p = 0.089>0.05).</td>
<td>Test Statistics
<table>
<tr><td></td><td>CPCompDur</td></tr>
<tr><td>Mann-Whitney U</td><td>1,064E7</td></tr>
<tr><td>Wilcoxon W</td><td>6,026E7</td></tr>
<tr><td>Z</td><td>-1,698</td></tr>
<tr><td>Asymp. Sig. (2-tailed)</td><td>,089</td></tr>
</table>
</td>
</tr>
<tr>
<td>2. Operational vs. low level decision making group
There is not a statistically significant difference between the underlying distributions of course program completion durations of operational and low level decision making groups (z = -1,207, p = 0.228>0.05).</td>
<td>Test Statistics
<table>
<tr><td></td><td>CPCompDur</td></tr>
<tr><td>Mann-Whitney U</td><td>412479,500</td></tr>
<tr><td>Wilcoxon W</td><td>5,003E7</td></tr>
<tr><td>Z</td><td>-1,207</td></tr>
<tr><td>Asymp. Sig. (2-tailed)</td><td>,228</td></tr>
</table>
</td>
</tr>
<tr>
<td>3. Operational vs. high level decision making group
There is a statistically significant difference between the underlying distributions of course program completion durations of operational and high level decision making groups (z = -5,587, p = 0.000<0.05).</td>
<td>Test Statistics
<table>
<tr><td></td><td>CPCompDur</td></tr>
<tr><td>Mann-Whitney U</td><td>3,191E7</td></tr>
<tr><td>Wilcoxon W</td><td>8,153E7</td></tr>
<tr><td>Z</td><td>-5,587</td></tr>
<tr><td>Asymp. Sig. (2-tailed)</td><td>,000</td></tr>
</table>
</td>
</tr>
<tr>
<td>4. Supporting vs. low level decision making group
There is not a statistically significant difference between the underlying distributions of course program completion durations of supporting and low level decision making groups (z = -0,845, p = 0.398>0.05).</td>
<td>Test Statistics
<table>
<tr><td></td><td>CPCompDur</td></tr>
<tr><td>Mann-Whitney U</td><td>92388,000</td></tr>
<tr><td>Wilcoxon W</td><td>2478408,000</td></tr>
<tr><td>Z</td><td>-,845</td></tr>
<tr><td>Asymp. Sig. (2-tailed)</td><td>,398</td></tr>
</table>
</td>
</tr>
<tr>
<td>5. Supporting vs. high level decision making group
There is not a statistically significant difference between the underlying distributions of course program completion durations of supporting and high level decision making groups (z = -2,095, p = 0.036<0.05).</td>
<td>Test Statistics
<table>
<tr><td></td><td>CPCompDur</td></tr>
<tr><td>Mann-Whitney U</td><td>7142224,000</td></tr>
<tr><td>Wilcoxon W</td><td>9528244,000</td></tr>
<tr><td>Z</td><td>-2,095</td></tr>
<tr><td>Asymp. Sig. (2-tailed)</td><td>,036</td></tr>
</table>
</td>
</tr>
<tr><td></td><td></td></tr>
</table>

6. High level decision making group vs. low level decision making group There is not a statistically significant difference between the underlying distributions of course program completion durations of low level decision making and high level decision making groups (z = -0,329, p = 0.742>0.05).	Test Statistics | | CPCompDur | Mann-Whitney U: 293722,000 Wilcoxon W: 2,294E7 Z: -,329 Asymp. Sig. (2-tailed): ,742

- HH5: There is a statistically significant association between learner's course program completion duration and learner's region.

According to Spearman rho correlational test statistic, there is a slightly significant association between learner's course program completion duration and learner's region with correlation coefficient=0.019 at the significance level p=0.010. HH5 is accepted.

Table 214. Correlations (Region vs. Completion Duration)

			CPCompDur	Reg
Spearman's rho	CPCompDur	Correlation Coefficient	1,000	,019*
		Sig. (2-tailed)	.	,010
		N	18963	18963
	Reg	Correlation Coefficient	,019*	1,000
		Sig. (2-tailed)	,010	.
		N	18963	18963

Based on the correlational test, it can be claimed that region has an influence on learner's course program completion duration. In order to test whether the time spent by learners from different regions is significantly different from each other, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 215. Ranks (Region vs. Comp. Duration)

	Reg	N	Mean Rank
CPCompDur	Marmara	6297	9287,68
	İç Anadolu	5468	9633,99
	Ege	2160	9518,03
	Karadeniz	2057	9607,62
	Güneydoğu Anadolu	2017	9462,85
	Doğu Anadolu	64	95 0 51
	Total	18963	

Table 216. Test Statistics

	CPCompDur
Chi-sq are	15 512
df	5
Asymp. Sig.	,008

According to the tables above, there is a statistically significant difference between the different regions (Chi-Square = 15,512, p= 0.008) with a mean rank of 9287,68 for Marmara, 9633,99 for İç Anadolu, 9518,03 for Ege, 9607,62 for Karadeniz, 9462,85 for Güneydoğu Anadolu and 9580,51 for Doğu Anadolu. Additional to the mean ranks, mean of completion duration for each region can be examined in the table below which shows that while learners from Doğu Anadolu complete in a longer duration, learners from Marmara complete inn a shorter duration.

Table 217. Average Completion Duration (Region)

Reg	Mean	N	Std. Deviation
Marmara	22,8374	6297	46,70111
İç Anadolu	26,3952	5468	53,49779
Ege	25,4000	2160	53,53523
Karadeniz	24,2202	2057	48,39658
Güneydoğu Anadolu	25,0015	2017	52,05231
Doğu Anadolu	27,7915	964	56,01892
Total	24,7872	18963	50,78963

Even if it is clearly seen that score means of some regions are different from each other in the table above, additional post-hoc analysis should be conducted to be able to understand whether the differences among groups are statistically significant or not. For that reason, multiple comparisons are conducted by applying Mann

Whitney- 2 independent samples test. All regions are compared with each other with respect to completion duration. Statistical results below show that only Marmara-İç Anadolu and Marmara-Karadeniz is different from each other in terms of course program completion duration. Results are presented in detail in the table 218 below:

Table 218. Comparison of Regions

<table>
<tr>
<td>1. Marmara vs. İç Anadolu
There is a statistically significant difference between the underlying distributions of the course program completion durations of learners from Marmara and İç Anadolu (z = -3,661, p = 0.000<0.05).</td>
<td>Test Statistics
<table>
<tr><td></td><td>CPCompDur</td></tr>
<tr><td>Mann-Whitney U</td><td>1,658E7</td></tr>
<tr><td>Wilcox n W</td><td>3,641E7</td></tr>
<tr><td>Z</td><td>-3,661</td></tr>
<tr><td>Asymp. Sig. (2-tailed)</td><td>,00</td></tr>
</table>
</td>
</tr>
<tr>
<td>2. Marmara vs. Ege
There is not a statistically significant difference between the underlying distributions of the course program completion durations of learners from Marmara and Ege (z = -1,795, p = 0.073>0.05).</td>
<td>Test Statistics
<table>
<tr><td></td><td>CPCompDur</td></tr>
<tr><td>Mann-Whitney U</td><td>6636110,500</td></tr>
<tr><td>Wilcoxon W</td><td>2,647E7</td></tr>
<tr><td>Z</td><td>-1,795</td></tr>
<tr><td>Asymp. Sig. (2-tailed)</td><td>,073</td></tr>
</table>
</td>
</tr>
<tr>
<td>3. Marmara vs. Karadeniz
There is a statistically significant difference between the underlying distributions of the course program completion durations of learners from Marmara and İç Anadolu (z = -2,452, p = 0.014<0.05).</td>
<td>Test Statistics
<table>
<tr><td></td><td>CPCompDur</td></tr>
<tr><td>Mann-Whitney U</td><td>6258231,500</td></tr>
<tr><td>Wilcoxon W</td><td>2,609E7</td></tr>
<tr><td>Z</td><td>-2,452</td></tr>
<tr><td>Asymp. Sig. (2-tailed)</td><td>,014</td></tr>
</table>
</td>
</tr>
<tr>
<td>4. Marmara vs. Güneydoğu Anadolu
There is not a statistically significant difference between the underlying distributions of the course program completion durations of learners from Marmara and Güneydoğu Anadolu (z = -1,338, p = 0.181>0.05).</td>
<td>Test Statistics
<table>
<tr><td></td><td>CPCompDur</td></tr>
<tr><td>Mann-Whitney U</td><td>6232982,000</td></tr>
<tr><td>Wilcoxon W</td><td>2,60 E7</td></tr>
<tr><td>Z</td><td>-1,338</td></tr>
<tr><td>Asymp. Sig. (2-tailed)</td><td>,181</td></tr>
</table>
</td>
</tr>
<tr><td></td><td></td></tr>
</table>

5. Marmara vs. Doğu Anadolu

There is not a statistically significant difference between the underlying distributions of the course program completion durations of learners from Marmara and Doğu Anadolu (z = -1,623, p = 0.105<0.05).

Test Statistics

	CPCompDur
Mann-Whitney U	2943012,000
Wilcoxon W	2,277E7
Z	-1,623
Asymp. Sig. (2-tailed)	,105

6. İç Anadolu vs. Ege

There is not a statistically significant difference between the underlying distributions of the course program completion durations of learners from İç Anadolu and Ege (z = -0,880, p = 0.379>0.05).

Test Statistics

	CPCompDur
Mann-Whitney U	5833753,0 0
Wilcoxo W	8167633,000
Z	-,880
Asymp. Sig. (2-tailed)	,379

7. İç Anadolu vs. Karadeniz

There is not a statistically significant difference between the underlying distributions of the course program completion durations of learners from İç Anadolu and Karadeniz (z = -0,189, p = 0.850>0.05).

Test Statistics

	CPCompDur
Mann-Whitney	5 088 2,500
Wilc xon W	7725535,500
Z	-,189
Asymp. Sig. (2-tailed)	,850

8. İç Anadolu vs. Güneydoğu Anadolu

There is not a statistically significant difference between the underlying distributions of the course program completion durations of learners from İç Anadolu and Güneydoğu Anadolu (z = -1,280, p = 0.200>0.05).

Test Statistics

	CPCompDur
Mann-Whitney U	541 728,000
W lcoxon W	7449881,000
Z	-1,280
Asymp. Sig. (2-tailed)	,200

9. İç Anadolu vs. Doğu Anadolu

There is not a statistically significant difference between the underlying distributions of the course program completion durations of learners from İç Anadolu and Doğu Anadolu (z = -0,272, p = 0.785>0.05).

Test Statistics

	CPCompDur
Mann-Whitney U	2621971,500
Wilcoxon W	3087101,500
Z	,272
Asymp. Sig. (2 tailed)	,785

10. Ege vs. Karadeniz

There is not a statistically significant difference between the underlying distributions of the course program completion durations of learners from Ege and Karadeniz (z = -0,563, p = 0.574>0.05).

Test Statistics

	CPCompDur
Mann-Whitney U	2200671,500
Wilcoxon W	4534551,500
Z	-,563
Asymp. Sig. (2-tailed)	,574

11. Ege vs. Güneydoğu Anadolu

There is not a statistically significant difference between the underlying distributions of the course program completion durations of learners from Ege and Güneydoğu Anadolu (z = -0,347, p = 0,729>0.05).

Test Statistics

	CPCompDur
nn-W itney U	2165687,000
Wilcoxon W	4200840,000
Z	-,347
Asymp. Sig. (2-tailed)	,729

12. Ege vs. Doğu Anadolu

There is not a statistically significant difference between the underlying distributions of the course program completion durations of learners from Ege and Doğu Anadolu (z = -0,316, p = 0.752>0.05).

Test Statistics

	CPCompDur
Mann-Whi ney U	1034202,500
Wilcoxon W	3368082,500
Z	-,316
Asymp. Sig. (2-tailed)	,752

13. Karadeniz vs. Güneydoğu Anadolu

There is not a statistically significant difference between the underlying distributions of the course program completion durations of learners from Karadeniz and Güneydoğu Anadolu (z = -0,900, p = 0.368>0.05).

Test Statistics

	CPCompDur
Mann-Whitney U	2042775,000
Wilcoxon W	4077928,000
Z	,90
Asymp. Sig. (2-tailed)	,368

14. Karadeniz vs. Doğu Anadolu

There is not a statistically significant difference between the underlying distributions of the course program completion durations of learners from Karadeniz and Doğu Anadolu (z = -0,120, p = 0.904>0.05).

Test Statistics

	CPCompDur
Mann-Whitney U	988953,000
Wilcoxon W	1454083,000
Z	-,120
Asymp. Sig. (2-tailed)	,904

15. Güneydoğu Anadolu vs. Doğu Anadolu There is not a statistically significant difference between the underlying distributions of the course program completion durations of learners from Güneydoğu Anadolu and Doğu Anadolu (z = -0,583, p = 0.560>0.05).	Test Statistics <table><tr><td></td><td>CPCompDur</td></tr><tr><td>Mann-Whitney U</td><td>960163,500</td></tr><tr><td>Wilcoxon W</td><td>2 95316,500</td></tr><tr><td>Z</td><td>-,583</td></tr><tr><td>Asymp. Sig. (2-tailed)</td><td>,560</td></tr></table>

- HH6: There is a statistically significant association between learner's course program completion duration and learner's current work experience.

According to Spearman rho correlational test statistic, there is a significant association between learner's course program completion duration and learner's current work experience with correlation coefficient=0.031 at the significance level p=0.000. HH6 is accepted.

Table 219. Correlations (Work Experience vs. Completion Duration)

			CPCompDur	WorkExp
Spearman's rho	CPCompDur	Correlation Coefficient	1,000	,031**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	WorkExp	Correlation Coefficient	,031**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that learner's current work experience has an influence on learner's course program completion duration. It should also mean that different experience levels have different completion durations. In order to test whether the groups are significantly different from each other in terms of duration, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 220. Ranks (Work Experience vs. Comp. Duration)

	WorkExp	N	Mean Rank
CPCompDur	Low Experienced	5876	9333,88
	Experienced	5946	9361,61
	Very Experienced	7141	9704,13
	Total	18963	

Table 221. Test Statistics

	CPCompDur
Chi-Square	21,497
df	2
Asymp. Sig.	,000

According to the tables above, there is a statistically significant difference between the different experience levels (Chi-Square = 21,497, p= 0.000) with a mean rank of 9333,88 for low experienced group, 9361,61 for experienced group and 9704,13 for very experienced group. Additional to the mean ranks, mean of duration for each work experience group can be examined in the table 222 below which shows that very experienced learners complete the course programs in a longer duration than the others.

Table 222. Average Completion Duration (Work Experience)

WorkExp	Mean	N	Std. Deviation
Low Experienced	20,5551	5876	43,08077
Experienced	23,2185	5946	48,63492
Very Experienced	29,5758	7141	57,57072
Total	24,7872	18963	50,78963

Even if it is clearly seen that duration means of some work experience levels are different from each other in the table above, additional post-hoc analysis should be conducted to be able to understand among which groups, the differences are statistically significant. For that reason, multiple comparisons are conducted by applying Mann Whitney- 2 independent samples test. All groups are compared with each other based on these statistical assumptions and the results are presented in the table 223 below:

Table 223. Comparison of Work Experience Groups

<table>
<tr>
<td>1. Low experienced vs. experienced
There is not a statistically significant difference between the underlying distributions of the total score of low experienced group and the total score of experienced group (z = -1.844, p = 0.065>0.05).</td>
<td>Test Statistics
<table>
<tr><td></td><td>CPCompDur</td></tr>
<tr><td>Mann-Whitney U</td><td>1,742E7</td></tr>
<tr><td>Wilcoxon W</td><td>3,469E7</td></tr>
<tr><td>Z</td><td>-,280</td></tr>
<tr><td>Asymp. Sig. (2-tailed)</td><td>,779</td></tr>
</table>
</td>
</tr>
<tr>
<td>2. Low experienced vs. very experienced
There is a statistically significant difference between the underlying distributions of the total score of low experienced group and the total score of very experienced group (z = -18,586, p = 0.000<0.05).</td>
<td>Test Statistics
<table>
<tr><td></td><td>CPCompDur</td></tr>
<tr><td>Mann-Whitney U</td><td>2,016E7</td></tr>
<tr><td>Wilcoxon W</td><td>3,743E7</td></tr>
<tr><td>Z</td><td>-4,101</td></tr>
<tr><td>Asymp. Sig. (2-tailed)</td><td>,000</td></tr>
</table>
</td>
</tr>
<tr>
<td>3. Experienced vs. very experienced
There is not a statistically significant difference between the underlying distributions of the total score of experienced group and the total score of very experienced group (z = -16.963, p = 0.000<0.05).</td>
<td>Test Statistics
<table>
<tr><td></td><td>CPCompDur</td></tr>
<tr><td>Mann-Whitney U</td><td>2,047E7</td></tr>
<tr><td>Wilcoxon W</td><td>3,815E7</td></tr>
<tr><td>Z</td><td>-3,782</td></tr>
<tr><td>Asymp. Sig. (2-tailed)</td><td>,000</td></tr>
</table>
</td>
</tr>
</table>

- HH7: There is a statistically significant association between learner’s course program completion duration and learner’s formal education success.

According to Spearman rho correlational test statistic, there is not a significant association between learner’s course program completion duration and learner’s formal education success (branch score) with correlation coefficient=0.006 at the significance level p=0.488. HH7 is rejected.

Table 224. Correlations (Formal Education Success vs. Completion Duration)

			CPCompDur	FormalEdu
Spearman's rho	CPCompDur	Correlation Coefficient	1,000	,006
		Sig. (2-tailed)	.	,488
		N	18963	14043
	FormalEdu	Correlation Coefficient	,006	1,000
		Sig. (2-tailed)	,488	.
		N	14043	14043

As can also be seen from Kruskal Wallis non-parametric test below, there is very slight variance in the mean ranks and p=0.260>0.05. This statistical result shows that learners' formal education success level does not have an influence on completion duration. Since HH7 is rejected, additional post-hoc analysis is not conducted.

Table 225. Ranks (Formal Education vs. Comp. Duration)

	FormalEdu	N	Mean Rank
CPCompDur	Low	2261	7064,83
	Medium	4893	6950,03
	High	6889	7059,06
	Total	14043	

Table 226. Test Statistics

	CPCompDur
Chi-Square	2,696
df	2
Asymp. Sig.	,260

<u>Learner's Previous E-Learning Performance vs. Course Program Completion Duration</u>

- HI0: There is a statistically significant association between learner's course program completion duration and number of e-learning course programs previously taken by the learner.

According to Spearman rho correlational test statistic, there is a significant association between learner's course program completion duration and learner's total number of course programs with correlation coefficient=0.026 at the significance level p=0.000. HI0 is accepted.

Table 227. Correlations (Number of Course Programs vs. Comp. Duration)

			CPCompDur	NoofCP
Spearman's rho	CPCompDur	Correlation Coefficient	1,000	,026**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	NoofCP	Correlation Coefficient	,026**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Table 228. Test Statistics

	CPCompDur
Chi-Square	13,084
df	2
Asymp. Sig.	,001

Based on the correlational test, it can be claimed that learner's total number of course programs has an influence on learner's course program completion duration. In order to test whether the groups are significantly different from each other in terms of course program completion duration, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 229. Ranks (Number of Course Programs vs. Comp. Duration)

	NoofCP	N	Mean Rank
CPCompDur	Low	8005	9350,45
	Medium	5460	9479,58
	High	5498	9675,94
	Total	18963	

According to the tables above, there is a statistically significant difference between the groups with different number of course programs (Chi-Square = 13,084 p= 0.001) with a mean rank of 9350,45 for low number of course programs, 9479,58 for medium number of course programs and 9675,94 for high number of course programs. Additional to the mean ranks, mean of duration for each group can be examined in the table below which shows that groups with high number of course programs complete the course programs within a longer duration than the others.

Table 230. Average Completion Duration (Number of Course Programs)

NoofCP	Mean	N	Std. Deviation
Low	22,0811	8005	45,60476
Medium	24,8352	5460	50,24002
High	28,6797	5498	57,77177
Total	24,7872	18963	50,78963

Even if it is clearly seen that score means of some number of course program groups are different from each other in the table 230 above, additional post-hoc analysis should be conducted to be able to understand whether the differences among groups are statistically significant or not. For that reason, multiple comparisons are conducted by applying Mann Whitney- 2 independent samples test. All groups are compared with each other based on these statistical assumptions and the results are presented in the table 231 below:

Table 231. Comparison of Different Number of Course Programs

<table>
<tr><td>1. Low vs. medium number of course programs
There is not a statistically significant difference between the underlying distributions of course program completion duration of the group with low number of course programs and duration of the group with medium number of course programs (z = -1,1440, p = 0.150>0.05).</td><td>Test Statistics
<table><tr><td></td><td>CPCompDur</td></tr><tr><td>Mann-Whitney U</td><td>2,155E7</td></tr><tr><td>Wilcoxon W</td><td>5,360E7</td></tr><tr><td>Z</td><td>-1,440</td></tr><tr><td>Asymp. Sig. (2-tailed)</td><td>,150</td></tr></table></td></tr>
<tr><td>2. Low vs. high number of course programs
There is a statistically significant difference between the underlying distributions of course program completion duration of the group with low number of course programs and duration of the group with high number of course programs (z = -3,611, p = 0.000<0.05).</td><td>Test Statistics
<table><tr><td></td><td>CPCompDur</td></tr><tr><td>Mann-Whitney U</td><td>2,125E7</td></tr><tr><td>Wilcoxon W</td><td>5,330E7</td></tr><tr><td>Z</td><td>-3,611</td></tr><tr><td>Asymp. Sig. (2-tailed)</td><td>,000</td></tr></table></td></tr>
<tr><td>3. High vs. medium number of course programs
There is a statistically significant difference between the underlying distributions of course program completion duration of the group with high number of course programs and duration of the group with medium number of course programs (z = -2.005, p = 0.045<0.05).</td><td>Test Statistics
<table><tr><td></td><td>CPCompDur</td></tr><tr><td>Mann-Whitney U</td><td>1,470E7</td></tr><tr><td>Wilcoxon W</td><td>2,961E7</td></tr><tr><td>Z</td><td>-2,005</td></tr><tr><td>Asymp. Sig. (2-tailed)</td><td>,045</td></tr></table></td></tr>
</table>

- HI1: There is a statistically significant association between learner’s course program completion duration and learner’s average success in e-learning.

According to Spearman rho correlational test statistic, there is a significant association between learner’s course program completion duration and learner’s average success in e-learning with correlation coefficient=0.118 at the significance level p=0.000. HI1 is accepted.

Table 232. Correlations (Average E-Learning Success vs. Completion Duration)

			CPCompDur	AvgELSuc
Spearman's rho	CPCompDur	Correlation Coefficient	1,000	,118**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	AvgELSuc	Correlation Coefficient	,118**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that learner's average success in e-learning has an influence on course program completion duration. Groups with different success levels complete e-learning course programs in different durations. In order to test whether the groups are significantly different from each other in terms of duration, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 233. Ranks (Average E-Learning Success vs. Completion Duration)

	AvgELSuc	N	Mean Rank
CPCompDur	Low Success	7312	8860,43
	Medium Success	6235	9434,09
	High Success	5416	10376,32
	Total	18963	

Table 234. Test Statistics

	CPCompDur
Chi-Square	271,672
df	2
Asymp. Sig.	,000

According to the tables above, there is a statistically significant difference between groups with different average success in e-learning with respect to course program completion duration (Chi-Square = 271,672, P = 0.000) with a mean rank of 8860,43 for low success group, 9434,09 for medium success group and 10376,32 for high success group. Additional to the mean ranks, mean of durations for each success group can be examined in the table 235 below which shows that people who are highly successful in online learning programs complete in a longer duration.

Table 235. Average Completion Duration (Average E-Learning Success)

AvgELSuc	Mean	N	Std. Deviation
Low Success	17,7458	7312	39,28301
Medium Success	24,3824	6235	49,36357
High Success	34,7598	5416	63,06885
Total	24,7872	18963	50,78963

Even if it is clearly seen that score means of some success groups are different from each other in the table above, additional post-hoc analysis should be conducted to be able to understand whether the differences among groups are statistically significant or not. For that reason, multiple comparisons are conducted by applying Mann Whitney- 2 independent samples test. All groups are compared with each other based on these statistical assumptions and the results are presented in the table 236 below:

Table 236. Comparison of Average E-Learning Success Groups

1. Low vs. medium success level

There is a statistically significant difference between the underlying distributions of course program completion duration of low average success and the medium average success groups (z = -6,486, p = 0.000<0.05).

Test Statistics

	CPCompDur
Mann-Whitney U	2,142E7
Wilcoxon W	4,816E7
Z	-6,486
Asymp. Sig. (2-tailed)	,000

2. Low vs. high success level

There is a statistically significant difference between the underlying distributions of course program completion duration of low average success and the high average success groups (z = -16,485, p = 0.000<0.05).

Test Statistics

	CPCompDur
Mann-Whitney U	1,663E7
Wilcoxon W	4,337E7
Z	-16,485
Asymp. Sig. (2-tailed)	,000

3. High vs. medium success level

There is a statistically significant difference between the underlying distributions of course program completion duration of high average success and the medium average success groups (z = -9,805, p = 0.000<0.05).

Test Statistics

	CPCompDur
Mann-Whitney U	1,521E7
Wilcoxon W	3,465E7
Z	-9,805
Asymp. Sig. (2-tailed)	,000

Course Program Related Factors vs. Course Program Completion Duration

- HJ0: There is a statistically significant association between learner's course program completion duration and learning course program content.

According to Spearman rho correlational test statistic, there is a significant association between learner's course program completion duration and course program's content with correlation coefficient=0.212 at the significance level p=0.000. HJ0 is accepted.

Table 237. Correlations (Content vs. Completion Duration)

			CPCompDur	CPCont
Spearman's rho	CPCompDur	Correlation Coefficient	1,000	,212**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	CPCont	Correlation Coefficient	,212**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that course program content has an influence on learner's course program completion duration. It should also mean that based on the course program content, people complete the course program in different time durations. In order to test whether the duration in different course program contents are significantly different from each other, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 238. Ranks (Content vs. Completion Duration)

	CPCont	N	Mean Rank
CPCompDur	Vocational	16315	9043,26
	Skill development	2648	12185,16
	Total	18963	

Table 239. Test Statistics

	CPCompDur
Chi-Square	852,006
df	1
Asymp. Sig.	,000

According to the tables above, there is a statistically significant difference between the different course program contents (Chi-Square = 852,006, p= 0.000) with a mean rank of 9043,26 for vocational course programs and 12185,16 for skill development course programs. Additional to the mean ranks, mean of durations for each course program content can be examined in the table 240 below. However, there is an exceptional case for this correlational result. It is expected that vocational course programs should take more time to be completed than the skill development course programs do, since they should have a more difficult content and requires specialization. The result which presents that people spend more time in skill development course programs is misleading, since course program duration assigned by the system is different for vocational and skill development activities which can be seen in the table 241 below. Skill development course programs are allowed to be finished in a longer time period as can be seen in the course program duration table below, so that this longer permitted duration makes skill development course program be completed in a longer time than vocational course program, relatively. Hypothesis 43 also proves that as the duration assigned to a course program increases, completion duration increases, as well.

To understand the real relationship, ratio of completion duration/permitted duration can be calculated.

Completion duration/permitted duration (Vocational)= 18,3996/49,0266= 0,375
Completion duration/permitted duration (Skill development)= 64,1431/227,6511=0,281

It can be claimed that skill development course programs are completed in a shorter duration when permitted duration is also taken into consideration (0,281<0,375).

Table 240. Average Completion Duration (Content)

CPCont	Mean	N	Std. Deviation
Vocational	18,3996	16315	44,47987
Skill development	64,1431	2648	66,96620
Total	24,7872	18963	50,78963

Table 241. Average Duration (Content)

CPCont	Mean	N	Std. Deviation
Vocational	49,0266	16315	99,31197
Skill development	227,6511	2648	52,63335
Total	73,9698	18963	112,71983

- HJ1: There is a statistically significant association between learner's course program completion duration and whether the course program is certificated or not.

According to Spearman rho correlational test statistic, there is a significant association between learner's course program completion duration and whether the course program is certificated or not with correlation coefficient=0.546 at the significance level p=0.000. HJ1 is accepted.

Table 242. Correlations (Certification vs. Completion Duration)

			CPCompDur	CPCer
Spearman's rho	CPCompDur	Correlation Coefficient	1,000	,546**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	CPCer	Correlation Coefficient	,546**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that course program certification has an influence on learner’s course program completion duration. It should also mean that people complete the course program in different durations depending upon whether the course program is certificated or not. In order to test whether the duration in certificated and not certificated course programs are significantly different from each other, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 243. Ranks (Certification vs. Comp. Duration)

	CPCer	N	Mean Rank
CPCompDur	Not Certificated	13847	7776,29
	Certificated	5116	14098,69
	Total	18963	

Table 244. Test Statistics

	CPCompDur
Chi-Square	5657,246
df	1
Asymp. Sig.	,000

According to the tables above, there is a statistically significant difference between the different groups (Chi-Square = 5657,246, p= 0.000) with a mean rank of 7776,29 for not certificated course programs and 14098,69 for certificated activities. Additional to the mean ranks, mean of duration for each group can be examined in the table 245 below which shows that learners spend much more time on certificated course programs.

Table 245. Average Completion Duration (Certification)

CPCer	Mean	N	Std. Deviation
Not Certificated	6,5972	13847	9,49795
Certificated	74,0203	5116	77,45052
Total	24,7872	18963	50,78963

- HJ2: There is a statistically significant association between learner’s course program completion duration and course program duration assigned by the system.

According to Spearman rho correlational test statistic, there is a significant association between learner's course program completion duration and course program duration with correlation coefficient=0.616 at the significance level p=0.000. HJ2 is accepted.

Table 246. Correlations (Duration vs. Completion Duration)

			CPCompDur	CPDur
Spearman's rho	CPCompDur	Correlation Coefficient	1,000	,616**
		Sig. (2-tailed)	.	,000
		N	18963	18963
	CPDur	Correlation Coefficient	,616**	1,000
		Sig. (2-tailed)	,000	.
		N	18963	18963

Based on the correlational test, it can be claimed that course program duration has an influence on learner's course program completion duration. It can be interpreted as people may complete an activity in different durations depending on total duration permitted for that activity. In order to test whether completion duration of the course programs with different permitted durations significantly changes, Kruskal Wallis non-parametric test is conducted. The following tables present the statistical figures of test results:

Table 247. Ranks (Duration vs. Comp. Duration)

	CPDur	N	Mean Rank
CPCompDur	Short	8941	6146,04
	Medium	5864	11738,53
	Long	4158	13472,98
	Total	18963	

Table 248. Test Statistics

	CPCompDur
Chi-Square	7409,762
Df	2
Asymp. Sig.	,000

According to the tables above, there is a statistically significant difference between the different groups (Chi-Square = 7409,762, p= 0.000) with a mean rank of 6146,04 for the course programs with short duration, 11738,53 for the course programs with medium duration and 13472,98 for the course programs with long duration.

Additional to the mean ranks, mean of duration for each group can be examined in the table 249 below and parallel with correlational analysis results, course programs which are assigned longer total durations are completed within a longer duration.

Table 249. Average Completion Duration (Duration)

CPDur	Mean	N	Std. Deviation
Short	4,6245	8941	8,55517
Medium	19,4313	5864	22,72966
Long	75,6967	4158	85,86833
Total	24,7872	18963	50,78963

<u>A Multinomial Regression Model for Course Program Completion Duration</u>

A multinomial regression model based on demographics, course program characteristics and previous e-learning experience is designed in order to understand the relationships between course program completion duration and all significant predictors. Age, gender, education, functional occupation, hierarchical occupation, region, work experience as demographics, course program content, course program certification and course program duration as course program information and number of previous e-learning programs and average e-learning success as previous experience information is included in the model as independent predictors. Dependent variable is course program completion duration. It is an ordinal variable with the values short, medium and long.

In this model, Nagelkerke’s pseudo r-square statistic is calculated as 77% which satisfies the threshold level (>65%) and indicates the reliability of this multinomial logistic regression model. Furthermore, as can be seen in the table 250 below, the likelihood ratio test statistic chi-square= 5,292 and corresponding p value=0.000<0.05, so that the model is significant and it is meaningful to create a prediction model based on those independent variables. The null hypothesis that there was no difference between the model without demographics, course program characteristics and previous e-learning experience and the model with those variables is rejected. Based on provided information, it is possible to make a prediction with some probabilities on whether this learner will complete or withdraw the course program.

Table 250. Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	1,681E4			
Final	4,585E3	1,222E4	25	,000

Table 251. Likelihood Ratio Tests

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	4,585E3	,000	0	.
WorkExp	4,591E3	6,614	1	,010
Gender	4,589E3	3,912	1	,048
Age	4,590E3	5,232	2	,073
CPCont	4,930E3	345,451	1	,000
CPDur	4,741E3	156,264	2	,000
Educ	4,591E3	6,174	3	,103
FuncOcc	4,586E3	1,355	2	,508
HierOcc	4,587E3	1,943	3	,584
Reg	4,588E3	2,791	5	,732
AvgELSuc	4,609E3	24,259	2	,000
NoofCP	4,595E3	10,535	2	,005
CPCer	9,152E3	4,567E3	1	,000

The information in the table 252 below shows that age, gender, work experience, course program content, course program duration, course program certification, number of previous course programs and average e-learning success are significant in distinguishing completed group from not completed group. Standard error of all variables is less than 2,0 satisfying this precondition of analysis.

Table 252. Parameter Estimates (Completion Duration)

CompDur_binary[a]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
Short	Intercept	,198	,409	,234	1	,628			
	WorkExp	-,017	,007	6,598	1	,010	,983	,970	,996
	[Gender=,00]	,135	,068	3,908	1	,048	1,145	1,001	1,309
	[Gender=1,00]	0[b]	.	.	0	.	.	.	.
	[Age=1]	-,004	,123	,001	1	,974	,996	,783	1,267
	[Age=2]	-,198	,102	3,726	1	,054	,821	,671	1,003
	[Age=3]	0[b]	.	.	0	.	.	.	.
	[CPCont=1,00]	-1,380	,078	309,173	1	,000	,252	,216	,293
	[CPCont=2,00]	0[b]	.	.	0	.	.	.	.
	[CPDur=1]	1,951	,616	10,022	1	,002	7,037	2,103	23,553
	[CPDur=2]	-1,268	,146	75,775	1	,000	,281	,211	,374
	[CPDur=3]	0[b]	.	.	0	.	.	.	.
	[Educ=1,00]	,297	,289	1,051	1	,305	1,345	,763	2,372
	[Educ=2,00]	,082	,291	,079	1	,779	1,085	,613	1,921
	[Educ=3,00]	,091	,280	,106	1	,745	1,095	,632	1,897
	[Educ=4,00]	0[b]	.	.	0	.	.	.	.
	[FuncOcc=1,00]	,045	,253	,032	1	,858	1,046	,638	1,717
	[FuncOcc=2,00]	-,083	,272	,094	1	,759	,920	,540	1,569
	[FuncOcc=3,00]	0[b]	.	.	0	.	.	.	.
	[HierOcc=1,00]	,124	,093	1,779	1	,182	1,132	,943	1,359
	[HierOcc=2,00]	,127	,282	,202	1	,653	1,135	,653	1,975
	[HierOcc=3,00]	-,081	,504	,026	1	,872	,922	,343	2,475
	[HierOcc=4,00]	0[b]	.	.	0	.	.	.	.
	[Reg=1,00]	-,066	,144	,211	1	,646	,936	,705	1,242
	[Reg=2,00]	-,112	,146	,587	1	,443	,894	,672	1,190
	[Reg=3,00]	-,070	,165	,182	1	,670	,932	,675	1,288
	[Reg=4,00]	-,023	,162	,020	1	,887	,977	,711	1,343
	[Reg=5,00]	,069	,162	,182	1	,670	1,071	,780	1,471
	[Reg=6,00]	0[b]	.	.	0	.	.	.	.
	[AvgELSuc=1]	-,431	,091	22,499	1	,000	,650	,544	,777
	[AvgELSuc=2]	-,222	,076	8,514	1	,004	,801	,690	,930
	[AvgELSuc=3]	0[b]	.	.	0	.	.	.	.
	[NoofCP=1]	-,249	,084	8,833	1	,003	,779	,661	,919
	[NoofCP=2]	-,208	,082	6,480	1	,011	,812	,692	,953
	[NoofCP=3]	0[b]	.	.	0	.	.	.	.
	[CPCer=,00]	7,630	,207	1358,493	1	,000	2058,349	1371,885	3088,305
	[CPCer=1,00]	0[b]	.	.	0	.	.	.	.

B values in the table above represents the coefficients multinomial logistic regression equation. The equation and results are presented as follows:

*P(short/long duration)=-0,198*Age – 0,17*Work experience -0,249*Number of e-learning programs(low) -0,208*Number of e-learning programs(medium) +1,951*Course duration (short) - 1,268*Course duration (medium) + 0,135*Gender(Female) -0,431*Average Success(Low) - 0,222*Average Success(Medium)+ 7,630*Certification(No) – 1,380*Course program content (Vocational course)*

- If age is increased by one unit in middle age group, then the multinomial odds of completing in a longer duration is increased by 0,198 units. Older people are more likely to complete the course program in a longer duration.
- The multinomial odds (probability) for females (gender=0) relative to males (gender=1) is 0.135 unit higher for completing in a shorter duration. Males seem more likely to complete the course program in a longer duration.
- If work experience is increased by one unit, then the multinomial odds of completion in a longer duration is increased by 0,017 units. More experienced people more likely complete in a longer duration.
- The multinomial odds (probability) for vocational course program (course program content=1) relative to skill development course program (course program content=2) is 1.380 unit lower for completing in short duration. Vocational course programs are more likely completed in longer duration.
- If course program duration is increased by 1 unit, then the multinomial log-odds (probability) of completing the course program in a longer duration would be

expected to increase by 1,268 units.

- The multinomial odds (probability) for not certificated course program (CPCer= no) relative to certificated course program (CPCer= yes) is 7,630 unit higher for falling in the group of short completion duration. Learners are more likely to complete certificated course programs in a longer duration.
- If low number of course programs is increased by 1 unit, then the multinomial log-odds (probability) of completing in a long duration would be expected to increase by 0.249 units. As leaners participate in more e-learning course programs, they are more likely to complete in a longer duration.
- If average success of a learner in low success group is increased by 1 unit, then the odds of completing in longer duration increase by 0,431 units. More successful learners are more likely to complete in a longer duration.

- Model Classification Accuracy

In order to prove the accuracy of this classification model, the estimate of by chance accuracy criteria should be calculated. As mentioned before, firstly, the estimate of by chance accuracy rate should be computed as 69,6% (0,814^2 +0,186^2=0,62). The estimate of by chance accuracy criteria aims 25% improvement (Anderson et al., 1998), so that it is 87% (0,696*1,25=0,87).The classification accuracy of this model can be seen in the classification table 254 below as 92,2% which satisfies the classification accuracy criteria. It is clear that information of demographics, course program characteristics and previous e-learning experience is valuable for the model and provides a good classification model.

Table 253. Case Processing Summary

		N	Marginal Percentage
CompDur_binary	Short	15430	81,4%
	Long	3533	18,6%

Table 254. Classification Accuracy

Observed	Predicted		
	Short	Long	Percent Correct
Short	14479	951	93,8%
Long	519	3014	85,3%
Overall Percentage	79,1%	20,9%	92,2%

Decision Tree Model for Course Program Completion Duration

Decision tree as another method of predictive data mining is applied additional to logistic regression model. The reason is to compare the results and to see whether the results are the same when the same input data is used in different models. A predictive model is generated in order to classify a new incidence into groups of ‘completion in short duration’ or ‘completion in long duration’ by the use all the information given for that new incidence.

For this decision tree model, CHAID (Chi-squared automatic interaction detector) growing method is used at a significance level of 0.05. For validation reasons, split sample validation method is applied and the sample is divided equally for training and testing (50% for training and 50% for testing). Misclassification costs are remained the same for incorrect prediction of each group (successful and unsuccessful).

In the model, the same variables in regression model which are demographics as age, gender, functional occupation, hierarchical occupation, region, education and work experience; course program characteristics like content, certification and duration, previous e-learning performance indicators like number of e-learning course programs and average course program completion duration are included in the model as predictors. Dependent variable is selected as course program completion duration of the learner. The model is trained for prediction of two groups: completion in short duration and completion in long duration.

- Classification accuracy

  Overall classification accuracy is 87,1% and the details can be seen in the table below:

Table 255. Classification Accuracy

Sample	Observed	Predicted		
		Short time	Long time	Percent Correct
Training	Short time	2914	771	79,1%
	Long time	22	2506	99,1%
	Overall Percentage	47,3%	52,7%	87,2%
Test	Short time	2924	756	79,5%
	Long time	35	2419	98,6%
	Overall Percentage	48,2%	51,8%	87,1%

Decision tree is generated based on the included independent factors and given data set. The model selects only age and work experience information among demographics of the learner. Moreover, course program duration, course program certification and course program content information is determined as strong predictors in the model. Additionally, information on learners' total number of e-learning course programs as a previous e-learning performance indicator is used for classification. Significant variables selected by the decision tree model are parallel with the ones in regression model. Two different models produce almost the same results, which increases the reliability of the models.

Terminal nodes are node 8 through node 15 as can be seen in the figure 5 below. Classification decision on each node is determined by some association rules. A new incidence is classified as 'will be completed in short duration' or 'will be completed in long duration' based on which association rule it satisfies. For example, the information about a new incidence is a learner who is older and has a bachelor degree, has high participation in e-learning course programs. Current e-learning course program is a certificated vocational course program about fraud management in banking which is assigned a really longer duration to be completed. From this information, the tree model firstly checks for the course program duration. According to the information, a longer duration is assigned to this course program. If the course program has a long duration, the model is interested in course program content. Since the course program is a vocational course program, the next factor to be checked is learner's age. According to the model, a terminal node is reached when age information is known at this level and final node for this new incidence is node 13 which predicts that learner will be complete the course program in long duration by a probability of 98%. Association rule for this case is as follows:

IF (CPDur NOT MISSING AND (CPDur > "Medium")) AND (CPCont = "Vocational") AND (Age NOT MISSING AND (Age > "Middle age"))
THEN
Node = 13
Prediction = Long duration
Probability = 0.954098

All association rules can be found in Appendix C. P values and chi-square values of each predictor can be seen in decision tree below.

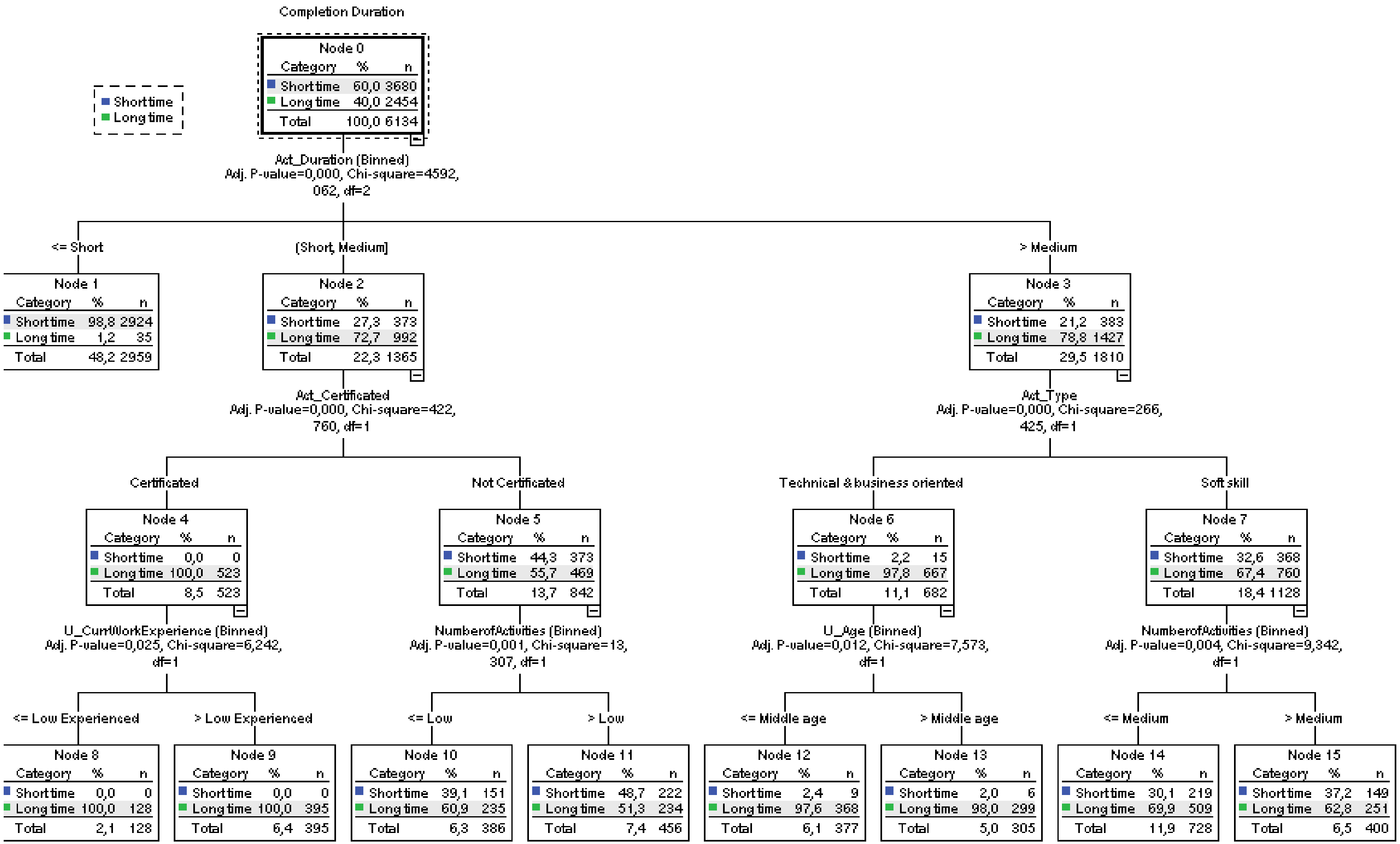

Fig. 5 Decision tree model-course program completion duration

CHAPTER VIII: DISCUSSION

In this study, significant factors on e-learning effectiveness in corporations are discovered through some statistical tests. E-learning effectiveness is considered as a combination of three components as learner success, course program completion or withdrawal and course program completion duration if the learner completes the course program.

Two predictive models as regression analysis and decision tree classification is conducted in order to establish success models. It is aimed to make a comparison between these two seperate methods to see whether there are differences in the results obtained from each model. Both of the models also support the correlational analysis results. Not demographics, but course program related factors are selected as major predictors in both analysis.

Briefly, some of the demographics, previous e-learning performance and course program characteristics are discovered to have power at different levels for explaining variance in e-learning effectiveness. It is important to highlight that no strong correlations are discovered between all the factors and e-learning effectiveness. Especially, demographics seem to have relatively small influence. On the other hand, course program characteristics as course program certification content and duration attract attention in explaining the variance in dependent variables. Number of previous e-learning programs as an indicator of previous e-learning performance is also discovered as a strong factor in learner success. Among all the factors influencing e-learning success, the strongest and the weakest influencers are discovered as course program certification and functional occupation, respectively. It is obvious that deeper consideration should be given to those significant program characteristics in order to control e-learning effectiveness.

However; a matter for discussion arises about the certification of course programs. In this study, it is explored that most of the skill development programs are certificated, whereas most of the vocational programs are not certificated. A related result is that learners are more successful in skill development programs. The question is: Is it possible to increase the success in vocational programs by providing certification or is it a strategy of corporations to provide certification mostly for skill development programs to increase motivation for participation in such programs?

Even if the correlation is not very strong, a relationship is discovered between demographics and e-learning success. One question is whether this outcome is in alignment with the one in formal classical education. In classical education, learning success is explored to be influenced by learner characteristics, as well (Clifton, Perry, and Schönwetter, 2002; Beekhoven, Hout and Jong, 2003). Gender (Clifton et al., 2002; Beekhoven et al., 2003), locus of control, test anxiety, high school GPA (Clifton et al., 2002), repeating the course, subjective chance of success (Beekhoven et al., 2003) are among key influencers of success. Learners' motivation and commitment level is also stated as a success factor in e-learning (Kerr, et al., 2006; Macher et al., 2010). Additionally, some course program related factors are explored to be significant in formal classical education. Content familiarity is presented as another success factor (Clifton et al., 2002). Additionally, Vermunt (2005) states that different academic diciplines effect learning patterns. Depending upon the disicpline, learners show the characteristics of meaning, reproduction, application directed or undirected learning. Percentage of women in the course influences outcomes due to seriousness of women and their effective working ability. Average number of work hours students spend for the course is also among influencers (Beekhoven et al., 2003).

As can be seen, some strong correlations for e-learning effectiveness are discovered in this study. These statistical figures can be made use of to know crucial components of e-learning environment and to take actions, accordingly. Even if all the conditions for effectiveness are satisfied, a crucial question here is: how to optimize the content in an e-learning system?

A crucial concern while designing e-learning systems is whether provided content is useful or not or to what extent the learners get useful information from the e-learning content. Even if all the required information is included in the e-learning system, it may be difficult for learners to understand the content design and to find the correct paths for retrieving the right content. Even if the content is useful, it may not appeal to each learner. The profile and capability of each learner may be different from each other. Furthermore, each learner may not make connections among different contents and may ignore related useful information provided in the system.This idea is supported by Aslan, İnceoğlu, and Uğur (2004) who state that e-learning content should present an optimum amount of knowledge. Huge amounts of knowledge just lead to confusion and learners can lose the focus. It is proposed that educational content should be customized based on the personal needs of each learner. Another key point here is customizing the content design also based on the course program. As presented in this study, learners' performance changes according to the course program content which is either vocational or skill development. The complexity of program is subject to change based on content. Some contents may require prior knowledge and expertism. It is the best to perform deeper investigation for understanding the effect of different contents. As mentioned, capability and background of each learner differs which at the end affects how much the learner can understand the content and gain useful information from the content. Failure may be because of content design complication or content difficulty. For this reason, different characteristics of learners should be taken into consideration together with the content while designing the e-learning contents.

At this point, artificial intelligience systems seem to be an effective solution. They can make connections between the learner and course program content based on the learner's profile and can make recommendations to the learner to increase e-learning efficiency (Chen, 2008; Romero, and Ventura, 2007; Aslan, İnceoğlu, and Uğur, 2004)

The results of this study supports the fact that learners are more enthusiastic when they are provided proper motivating factors. Even if a high-quality content is presented, if willingness of learners cannot be ensured, then, the overall program may fail. It is obvious that learners should participate in the program voluntarily in order to absorb useful information from the content as much as possible. In this study the effect of certification is obvious. It can be regarded as a kind of motivator which encourage learners spend time in e-learning program effectively. Similar motivating factors like reward systems or reflecting positive or negative effect on their annual scorecards based on their e-learning outcomes can be designed.

CHAPTER IX: CONCLUSION

This study provides statistical results on e-learning effectiveness to provide useful insights for practioners, designers and decision makers of e-learning systems. Logistic regression and decision tree models are generated as e-learning effectiveness models and have the ability to classify learners into different groups with respect to success, completion duration and completion or withdrawal decision.

Course certification, course program content, course duration and previous e-learning experience are among the strongest influencers. Majorly, not demographics, but course program related factors are selected as major predictors in decision tree classification and regression analysis. It can be proposed that deeper consideration should be given to course program characteristics to control e-learning success.

Course program content is one of the most significant influencers in generated success models. Learners' success changes based on the content. It is explored that they are more successful in skill development programs. It may be resulted from different design of those contents and content complexity or it may be an issue arising from assigned duration. Together with course program content, it is crucial how to present the content and how to make diversified learners benefit from the information presented at an optimum level as discussed above. Many different age groups, different occupations, different backgrounds come to the scene in corporate e-learning and just providing huge amounts of knowledge may make learners get lost in the system and may cause to failure in achieving the core objectives of an e-learning system. It can be proposed that content-learner relationship may be managed by using personalized e-learning systems which guide the learners throughout their e-learning process for the best benefit.

More importantly, course program certification is explored as the strongest influencer of e-learning success. All the analysis results prove that learners are more successful in certificated programs. Course certification seems to be an important motivator for the learner's complete dedication to the process. It can be claimed that learners should be provided valid reasons and motivators for learning online. The fact may be that learners do not give much importance to those uncertificated course programs and during the e-learning process, they may just aim finishing the program by clicking the NEXT button. A certificate given at the end of the program may make learners be convinced about the benefits. It may increase their enthusiasism and success in the program. If certification cannot be applied for all programs, proper precautions and motivators may be designed for increasing willingness of learners.

Course duration is also a factor which is out of learners' control. It is assigned by the program designers based on the content. In this study, it is discovered that as the duration increases, the success increases. This result may indicate two possible results: Firstly, the duration may be insufficient for completion of the program, so learners cannot complete the whole program. Secondly, as the duration increases, learners may use the time for cheating. Taking these possibilities into consideration, duration should be carefully designed for each course program.

Another design issue arises as a result of previous e-learning experience effect. Learner's previous e-learning experience is explored to be another important determinant of success in e-learning programs. As the number of online learning programs participated by the learner increases, then, the learner performs better. Higher success of learners who have previous e-learning experience may be due to their familarity with the environment and process. This outcome can lead the e-learning designers to the opinion that as the learner's aptitude for online learning platforms increases, learner experiences a less difficult and more enjoyable e-learning program. As a result, overall learning success may increase. At this point, a crucial concern is how to eliminate disadvantageous situation of inexperienced learners. It seems that easy-to-use design of e-learning systems, well-prepared user instructions and technical support during the process may accelerate the adaptation of inexperienced learners.

In many e-learning programs, the most significant measure of e-learning success is considered as the score of learners taken at the end of the education. If the exam is not sufficient to measure the success of learner precisely, then, the overall perception and possible actions about the e-learning process may be improper. Even if the exam is carefully designed to measure how much information the learners get from the program, an exam at the end cannot measure the learner's behavior throughout the course program. As mentioned by Chao and Chen (2009), learning record is reported as essential for grading and monitoring, but it is sometimes misleading, since the learners may spend time without really studying the material. Learner may complete the course program just by clicking the NEXT button and may cheat in the exam which is applied at the end. To clear out these possibilities and to provide a reliable measure of success, additional assessment tools may be applied. Smart content which tracks learners' action during e-learning process by mouse movements or by the time spent on each page may be an additional tool. Moreover, each learner may be assigned an usage score at the end of the course program based on learners' participation in e-learning programs, for example, by messaging or chatting with other learners or instructors, by participating in forums and so on.

As a result, it is crucial to highlight that success measure is critical to provide meaningful and reliable results on e-learning analysis. Incomplete and incorrect measure of success may lead to unreliable outcomes and inappropriate actions. The crucial fact here is that e-learning designers should carefully study on the application of proper and thorough success evaluation techniques for online learning programs.

All these results may provide guidance for selecting the improvements areas especially in corporate e-learning education. However, it should be highlighted that the effectiveness or ineffectiveness of e-learning is absolutely a result of nested relationships from demographics to course program specific attributes, so that based on the context, results may differ to some extent.

CHAPTER X: LIMITATIONS OF THE STUDY

This study is conducted based on large data sets. However, there are some limitations related to data which prevents analysis to some extent. Most importantly, there is no normal distribution in the data set. As a result, parametric tests which are statistically more powerful cannot be conducted. Many academical resources indicate the non-parametric tests as powerful. However, these tests are limited and there are no corresponding non-parametric test for every parametric test. This fact prevents further analysis on data which may provide richer information on e-learning if could be conducted.

APPENDICES

Appendix A: Association Rules for Learner Success

/ Node 7 */*
IF (CPCer = "Certificated") AND (CPCont = "Vocational") AND (CP_Duration NOT MISSING AND (CP_Duration <= "Medium"))
THEN
Node = 7
Prediction = 3
Probability = 1.000000

/ Node 8 */*
IF (CPCer = "Certificated") AND (CPCont = "Vocational") AND (CP_Duration IS MISSING OR (CP_Duration > "Medium"))
THEN
Node = 8
Prediction = 3
Probability = 0.898072

/ Node 9 */*
IF (CPCer = "Certificated") AND (CPCont != "Vocational") AND (Age NOT MISSING AND (Age <= "Younger"))
THEN
Node = 9
Prediction = 3
Probability = 0.983051

/ Node 10 */*
IF (CPCer = "Certificated") AND (CPCont != "Vocational") AND (Age IS MISSING OR (Age > "Younger"))
THEN
Node = 10
Prediction = 3
Probability = 0.997186

/ Node 11 */*
IF (CPCer != "Certificated") AND (Age IS MISSING OR (Age <= "Middle age")) AND (Numberof_CPs NOT MISSING AND (Numberof_CPs <= "Low"))
THEN
Node = 11
Prediction = 1
Probability = 0.912752

/ Node 12 */*
IF (CPCer != "Certificated") AND (Age IS MISSING OR (Age <= "Middle age")) AND (Numberof_CPs IS MISSING OR (Numberof_CPs > "Low"))
THEN

```
        Node = 12
        Prediction = 1
        Probability = 0.856727

/* Node 13 */
IF (CPCer != "Certificated")  AND  (Age NOT MISSING   AND  (Age > "Middle age"))  AND  (Gender != "Male")
THEN
        Node = 13
        Prediction = 1
        Probability = 0.640432

/* Node 14 */
IF (CPCer != "Certificated")  AND  (Age NOT MISSING   AND  (Age > "Middle age"))  AND  (Gender = "Male")
THEN
        Node = 14
        Prediction = 1
        Probability = 0.748397
```

Appendix B: Association Rules for Course Completion

```
/* Node 8 */
IF (CPCer != "Not Certificated")  AND  (AvgELSuc NOT MISSING   AND
(AvgELSuc <= "Unsuccessful"))  AND  (CPDur IS MISSING  OR (CPDur
<= "Normal"))
THEN
        Node = 8
        Prediction = Withdrawal
        Probability = 0.636637

/* Node 9 */
IF (CPCer != "Not Certificated")  AND  (AvgELSuc NOT MISSING   AND
(AvgELSuc <= "Unsuccessful"))  AND  (CPDur NOT MISSING   AND
(CPDur > "Normal"))
THEN
        Node = 9
        Prediction = Withdrawal
        Probability = 0.801958

/* Node 10 */
IF (CPCer != "Not Certificated")  AND  (AvgELSuc NOT MISSING   AND
(AvgELSuc > "Unsuccessful"  AND  AvgELSuc <= "Succesful"))  AND
(CPDur IS MISSING  OR (CPDur <= "Normal"))
THEN
        Node = 10
        Prediction = Completion
        Probability = 0.685428

/* Node 11 */
IF (CPCer != "Not Certificated")  AND  (AvgELSuc NOT MISSING   AND
(AvgELSuc > "Unsuccessful"  AND  AvgELSuc <= "Succesful"))  AND
(CPDur NOT MISSING   AND  (CPDur > "Normal"))
THEN
        Node = 11
        Prediction = Completion
        Probability = 0.537170

/* Node 12 */
IF (CPCer != "Not Certificated")  AND  (AvgELSuc IS MISSING  OR
(AvgELSuc > "Succesful"))  AND  (CPDur IS MISSING  OR (CPDur <=
"Normal"))
THEN
        Node = 12
        Prediction = Completion
        Probability = 0.875922

/* Node 13 */
```

IF (CPCer != "Not Certificated") AND (AvgELSuc IS MISSING OR (AvgELSuc > "Succesful")) AND (CPDur NOT MISSING AND (CPDur > "Normal"))
THEN
Node = 13
Prediction = Completion
Probability = 0.779878

/ Node 14 */*
IF (CPCer = "Not Certificated") AND (CPCont = "Skill_Dev") AND (NoofCP IS MISSING OR (NoofCP <= "Medium"))
THEN
Node = 14
Prediction = Withdrawal
Probability = 0.507042

/ Node 15 */*
IF (CPCer = "Not Certificated") AND (CPCont = "Skill_Dev") AND (NoofCP NOT MISSING AND (NoofCP > "Medium"))
THEN
Node = 15
Prediction = Completion
Probability = 0.803922

/ Node 16 */*
IF (CPCer = "Not Certificated") AND (CPCont != "Skill_Dev") AND (AvgELSuc NOT MISSING AND (AvgELSuc <= "Unsuccessful"))
THEN
Node = 16
Prediction = Completion
Probability = 0.954745

/ Node 17 */*
IF (CPCer = "Not Certificated") AND (CPCont != "Skill_Dev") AND (AvgELSuc IS MISSING OR (AvgELSuc > "Unsuccessful"))
THEN
Node = 17
Prediction = Completion
Probability = 0.981335

Appendix C: Association Rules for Course Completion Duration

```
/* Node 1 */
IF (CPDur IS MISSING  OR (CPDur <= "Short"))
THEN
    Node = 1
    Prediction = Short duration
    Probability = 0.992507

/* Node 8 */
IF (CPDur NOT MISSING   AND  (CPDur > "Short"  AND  CPDur <=
"Medium"))  AND  (CPCer = "Certificated")  AND  (WorkExp NOT MISSING
AND  (WorkExp <= "Low Experienced"))
THEN
    Node = 8
    Prediction = Long duration
    Probability = 0.981982

/* Node 9 */
IF (CPDur NOT MISSING   AND  (CPDur > "Short"  AND  CPDur <=
"Medium"))  AND  (CPCer = "Certificated")  AND  (WorkExp IS MISSING  OR
(WorkExp > "Low Experienced"))
THEN
    Node = 9
    Prediction = Long duration
    Probability = 1.000000

/* Node 10 */
IF (CPDur NOT MISSING   AND  (CPDur > "Short"  AND  CPDur <=
"Medium"))  AND  (CPCer != "Certificated")  AND  (NoofCP NOT MISSING
AND  (NoofCP <= "Low"))
THEN
    Node = 10
    Prediction = Long duration
    Probability = 0.625935

/* Node 11 */
IF (CPDur NOT MISSING   AND  (CPDur > "Short"  AND  CPDur <=
"Medium"))  AND  (CPCer != "Certificated")  AND  (NoofCP IS MISSING  OR
(NoofCP > "Low"))
THEN
    Node = 11
    Prediction = Long duration
    Probability = 0.504970

/* Node 12 */
IF (CPDur NOT MISSING   AND  (CPDur > "Medium"))  AND  (CPCont =
"Vocational")  AND  (Age IS MISSING  OR (Age <= "Middle age"))
THEN
```

Node = 12
Prediction = Long duration
Probability = 0.987654

/ Node 13 */*
IF (CPDur NOT MISSING AND (CPDur > "Medium")) AND (CPCont = "Vocational") AND (Age NOT MISSING AND (Age > "Middle age"))
THEN
Node = 13
Prediction = Long duration
Probability = 0.954098

/ Node 14 */*
IF (CPDur NOT MISSING AND (CPDur > "Medium")) AND (CPCont != "Vocational") AND (NoofCP IS MISSING OR (NoofCP <= "Medium"))
THEN
Node = 14
Prediction = Long duration
Probability = 0.724274

/ Node 15 */*
IF (CPDur NOT MISSING AND (CPDur > "Medium")) AND (CPCont != "Vocational") AND (NoofCP NOT MISSING AND (NoofCP > "Medium"))
THEN
Node = 15
Prediction = Long duration
Probability = 0.635897

REFERENCES

Adkins, S. S. (2011). *The US market for self-paced elearning products and services: 2010-2015 forecast and analysis.* Retrieved January 30, 2011, from http://www.ambientinsight.com/Resources/Documents/Ambient_Insight_2010_2015_US_eLearningMarket_Executive_Overview.pdf.

Ağaoğlu, M. & Kırlıdoğ, M. (2004). Can e-learning help for student based learning. *Proceedings of the First International Conference on Innovations in Learning for the Future: E-learning,* İstanbul: İstanbul University Rectorate Publication.

Akdağ, M & Tok, H. (2008). The effects of traditional instruction and powerpoint presentation–supported instruction on student's achievement. *Eğitim ve Bilim*, 147.

Alexander, S. (2001). E-learning developments and experiences. *Education & Training, 43,* 4(5), p.240.

Altıkardeş, A. (2004). E-education culture in Turkish educational system. *Proceedings of the First International Conference on Innovations in Learning for the Future: E-learning,* İstanbul: İstanbul University Rectorate Publication.

Anderson, R., Black W., Hair, J. & Tatham, R. (1998). *Multivariate data analysis* (5th Ed.). Upper Saddle River, N.J.: Prentice Hall.

Arbak, Y., Özmen, Ö., & Saatçioğlu, Ö. (2004). Important parameters on the way to knowledge society. *Proceedings of the First International Conference on Innovations in Learning for the Future: E-learning,* İstanbul: İstanbul University Rectorate Publication.

Arıkan, A. & Khezerlou, A. (2010). Prospective English language teachers' views on computer and paper-based instructional materials in developing language components. *Procedia Social and Behavioral Sciences, 2,* 4006–4009.

Aslan, B. G., İnceoğlu, M. M. & Uğur. A. (2004). Intelligent approaches for web based e-learning systems. *Proceedings of the First International Conference on Innovations in Learning for the Future: E-learning,* İstanbul: İstanbul University Rectorate Publication.

Baltaş, A., Baltaş, Z., Dedehayır, H., & Sakar, E. (2004).How do e-learning learn: metacognition. *Proceedings of the First International Conference on Innovations in Learning for the Future: E-learning,* İstanbul: İstanbul University Rectorate Publication.

Beekhoven, S., Hout, U. D., & Jong, H. V. (2003). Different courses, different students, same results? An examination of differences in study progress of students in different courses. *Higher Education, 46*.

Belle, J. V. (2004). A proposed low-cost architecture for a novel smart whiteboard: the "textbook-on-the-wall" project. *Proceedings of the First International Conference on Innovations in Learning for the Future: E-learning,* İstanbul: İstanbul University Rectorate Publication.

Brasel, K. & Neideen, T. (2007). Understanding statistical tests. *Journal of Surgical Education, 64*(2).

Broadhead, G., Halton, R., Jung, G., & Patterson, D. (2010). *The UK e-learning market 2010*. Retrieved January 30, 2011, from http://www.e-learningcentre.co.uk/Resource/CMS/Assets/5c10130e-6a9f-102c-a0be-003005bbceb4/Learning_Light_The_UK_e_learning_Market_2010_summary_v3_21.12.10.pdf.

Broadhead, G., Jung, G., & Patterson, D. (2009). *The UK e-learning market 2009*. Retrieved January 30, 2011, from http://e-learningcentre.co.uk/Resource/CMS/Assets/5c10130e-6a9f-102c-a0be-003005bbceb4/UK%20e-learning%20market%20report%20by%20Learning%20Light%202009%20(1).pdf.

Brusilovsky, P. & Peylo, C. (2003). Adaptive and intelligent web-based educational systems. *International Journal of Artificial Intelligence in Education, 13*, 156–169.

Cavanaugh, C. (2001).The effectiveness of interactive distance education technologies in K-12 learning: A Meta-Analysis. *International Journal of Educational Telecommunications*, *7*(1), 73-88.

Chao, R. & Chen, Y. (2009). Evaluation of the criteria and effectiveness of distance e-learning with consistent fuzzy preference relations. *Expert Systems with Applications*, *36*, 10657–10662.

Charmonman, S. & Chorpothong, N. (2004). An elearning project for 100,000 students per year in Thailand. *International Journal of The Computer, the Internet and Management*, *12*(2), 111-118.

Chartered institute of personnel and development (CIPD). (2008). *Learning and Development*. Retrieved January 31, 2011, from http://www.cipd.co.uk/NR/rdonlyres/3A3AD4D6-F818-4231-863B-4848CE383B46/0/learningdevelopmentsurvey.pdf.

Chartered institute of personnel and development (CIPD). (2009). *Learning and Development*. Retrieved January 31, 2011, from http://www.cipd.co.uk/.

Chartered institute of personnel and development (CIPD). (2010). *Learning and Talent Development*. Retrieved January 31, 2011, from http://www.cipd.co.uk/NR/rdonlyres/BC060DD1-EEA7-4929-9142-1AD7333F95E7/0/5215_Learning_talent_development_survey_report.pdf.

Chen, C.-M. (2008). Intelligent web-based learning system with personalized learning path guidance. *Computers & Education*, *51*, 787–814.

Chen, Y., Finger, G., Sun, P., Tsai, R. J. & Yeh, D. (2008). What drives a successful e-learning? An empirical investigation of the critical factors influencing learner satisfaction. *Computers & Education, 50,* 1183–1202.

Clifton, R. A., Perry, R. P., & Schönwetter, D. J. (2002). Content familiarity: Differential impact of effective teaching on student achievement outcomes. *Research in Higher Education, 43*(6).

Coleman, J. & Furnborough, C. (2010). Learner characteristics and learning outcomes on a distance Spanish course for beginners. *System, 38*, 14–29

Cuéllar, M. P., Delgado, M. & Pegalajar, M.C. (2011). A common framework for information sharing in e-learning management systems. *Expert Systems with Applications, 38,* 2260–2270.

Dang, X. & Serfling, R. (2010). Nonparametric depth-based multivariate outlier identifiers, and masking robustness properties. *Journal of Statistical Planning and Inference, 140*, 198 – 213.

Demirors, O., & Serce, F. C. (2004). A web-based synchronous collaborative review tool. *Proceedings of the First International Conference on Innovations in Learning for the Future: E-learning,* İstanbul: İstanbul University Rectorate Publication.

E-learning market update December 2010. (n.d.) Retrieved January 30, 2011, from http://www.kineo.com/elearning-market/e-learning-market-update-december-2010.html.

E-learning trends. (2010). Retrieved May 12, 2010, from http://www.worldwidelearn.com/elearning-industry/trends.htm.

Erorta, Ö. Ö., Mutlu, M. E. & Yılmaz, Ü. (2004). Efficiency of e-learning in open education. *Proceedings of the First International Conference on Innovations in Learning for the Future: E-learning,* İstanbul: İstanbul University Rectorate Publication.

Eurostat. (n.d.). *Education and Training Introduced*. Retrieved February 03, 2011, from http://epp.eurostat.ec.europa.eu/statistics_explained/index.php/Education_and_training_introduced.

Fayyad, U. & Stolorz, P. (1997). Data mining and KDD: Promise and challenges. *Future Generation Computer Systems, 13*, 99-115.

Fernandez-Breis, J. T., Garcia-Sanchez, F., Gladun, A., Martinez-Bejar, R., & Rogushina, J. (2009). An application of intelligent techniques and semantic web technologies in e-learning environments. *Expert Systems with Applications*, *36*, 1922–1931.

Flom, P. L. (n.d.). *Multinomial and ordinal logistic regression using proc logistic*. Retrieved August 22, 2010, from http://www.nesug.org/proceedings/nesug05/an/an2.pdf.

Galusha, J. M. (1997). *Barriers to learning in distance education.* Retrieved July 11, 2010, from http://74.125.155.132/scholar?q=cache:8HilBF3j3lAJ:scholar.google.com/+Barriers+to+Learning+in+Distance+Education&hl=en&as_sdt=2000&as_vis=1.

Ganti, V., Gehrke, J., & Ramakrishan, R. (1999). *CACTUS clustering categorical data using summaries*. Retrieved September 5, 2010, from http://www.cs.cornell.edu/johannes/papers/1999/kdd1999-cactus.pdf.

Garcia, E., Romero, C. & Ventura, S. (2008). Data mining in course management systems: Moodle case study and tutorial. *Computers & Education, 51*, 368–384.

Garrett, R. (2009) *Online higher education market update 2008 New York and national data.* Retrieved January 30, 2011, from http://www.slideshare.net/alexandrapickett/richard-garretts-online-higher-education-market-update-2008-national-new-york-data.

Gibson, D., Kleinberg, J. & Raghavan, P. (1998). Clustering categorical data: An approach based on dynamic systems. *Proceedings of the 24th VLDB Conference.*

Giudicci, P. (2003). *Applied data mining: Statistical methods for business and industry.* New York: J. Wiley.

Goffe, W. L. & Sosin, K. (2005). Teaching with technology: May you live in interesting times. *The Journal of Economic Education, 36*(3), 278-291.

Gudanescu, N. (2010). Using modern technology for improving learning process at different educational levels. *Procedia Social and Behavioral Sciences, 2,* 5641–5645.

Hamid, A. A. (2002). E-learning: Is it the ‘‘e’’ or the learning that matters?. *Internet and Higher Education, 4*, 311–316.

Heindel, J. A., Smith, G. & Torres-Ayala, A. T. (2008). E-learning commodity or community: Disciplinary differences between online courses. *Internet and Higher Education, 11*, 152–159.

Hellerstein, J.M. (2008). *Quantitative data cleaning for large databases.* Retrieved May 28, 2010, from http://db.cs.berkeley.edu/jmh/papers/cleaning-unece.pdf.

Horton, K & Horton, W. (2003). *E-learning tools and technologies: A consumer's guide for trainers, teachers, educators, and instructional designers*. Newyork: Wiley Publishing, Inc.

Hosmer, D., Lameshow, S. & Taber, S. (1991). The importance of assessing the fit of logistic regression models: A case study. *American Journal of Public Health, 81*(12).

Hullet, C. R. & Mitra, A. (1997). Toward evaluating computer aided instruction: attitudes, demographics, context. *Evaluation and Program Planning*, *20*(4), 379-391.

Hussain, R. M. R., Ismail, A. & Jamaluddin,S. (2010). Assessment of students' learning styles, preferences in the faculty of science. *Procedia Social and Behavioral Sciences*, *2*, 4087–4091.

Jones, A. Y.M., Dean, E., & Hui-Chan, C. (2010). Comparison of teaching and learning outcomes between video-linked, web-based, and classroom tutorials: An innovative international study of profession education in physical therapy. C*omputers and Education*, *54*, 1193–1201.

Kerr, M. C., Kerr, M. S., & Rynearson, K. (2006). Student characteristics for online learning success. *Internet and Higher Education*, 9, 91–105.

Kopf, D. (2007). *E-learning market to hit $52.6B by 2010*. Retrieved May 28, 2010, from http://thejournal.com/articles/2007/07/30/elearning-market-to-hit-526b-by-2010.aspx.

Kor, B. & Tanrikulu, Z. (2008). Evaluation of e-learning systems: Standards and choosing test tools. *Proceedings of the 2nd International Future-learning Conference on Innovations in Learning for the Future 2008: e-learning*, 764-771.

Koseler, R. & Ozkan, S. (2009). Multi-dimensional students' evaluation of e-learning systems in the higher education context: An empirical investigation. *Computers & Education, 53*, 1285–1296.

Larose, D. T. (2005). *Discovering knowledge in data: An introduction to data mining.* Hoboken, N.J.: Wiley-Interscience.

Larose, D. T. (2006). *Data mining methods and models*. Hoboken, NJ : Wiley Interscience.

Levy, Y. (2006). *Assessing the value of e-learning systems*. Hershey, PA: Information Science Pub.

Levy, Y. (2008). An empirical development of critical value factors (CVF) of online learning activities: An application of course program theory and cognitive value theory. *Computers & Education, 51*, 1664–1675.

Logistic regression, dichotomous dependent variable. (2008). Retrieved August 22, 2010, from http://www.uky.edu/ComputingCenter/SSTARS/www/documentation/logisticregression_2.htm#LRDI.

Lonn, S. & Teasley, S. D. (2009). Saving time or innovating practice: Investigating perceptions and uses of learning management systems. *Computers & Education*, *53*, 686–694.

Lööf, A. & Sybert, H. (2010). *Industry, trade and services.* Retrieved February 03, 2011, from http://epp.eurostat.ec.europa.eu/cache/ITY_OFFPUB/KS-QA-10 050/EN/KS-QA-10-050-EN.PDF.

Macher, D., Maier, B. & Paechter, M. (2010). Students' expectations of, and experiences in e-learning: Their relation to learning achievements and course satisfaction. *Computers & Education, 54*, 222–229.

Maimon, O. & Rocah, L. (eds.). (2008). *Soft computing for knowledge discovery and data mining.* Boston, MA: Springer Science+Business Media, Inc.

Mason, R., Pegler, C., & Weller, M. (2005). Use of innovative technologies on an e-learning course. *Internet and Higher Education*, *8*, 61–71.

Norusis, M. J. (1999). *SPSS regression models 10.0.* Chicago: SPSS Inc.

Nunnally, J. C. (1974). Psychometric theory-25 years ago and now. *Educational Research*, *4*(10), 7-14 + 19-21.

Romero, C. & Ventura, S. (2007). Educational data mining: A survey from 1995 to 2005. *Expert Systems with Applications*, *33*, 135–146.

Sachs, G. (2000). *Internet: E-learning United States*. Retrieved May 23, 2010, from http://www.internettime.com/itimegroup/Goldman%20Sachs%20e-learning%20initiating%20report%20-%20July%2025%202000.pdf.

Selim, H. M. (2007). Critical success factors for e-learning acceptance: Confirmatory factor models. *Computers & Education, 49*, 396-413.

Shee, D., Wang, H., & Wang, Y. (2007). Measuring e-learning systems success in an organizational context: Scale development and validation. *Computers in Human Behavior, 23*, 1792–1808.

Solvie, P. A. (2004). The digital whiteboard: A tool in early literacy. *The Reading Teacher*, *57*(5), 484-487.

Süral, İ. (2010). Characteristics of a sustainable learning and content management system (LCMS). *Procedia Social and Behavioral Science*, *9*, 1145–1152.

Tanrikulu, Z., Tugcu, C., & Yilmaz, S. (2010). E-university: Critical success factors. *Procedia - Social and Behavioral Sciences, 2*, 1253-1259.

TUIK.(n.d.).*Eğitim kurumlarının kademelere göre okul, öğrenci, öğretmen ve derslik sayısı.* Retrieved February 06, 2011, from http://www.tuik.gov.tr/VeriBilgi.do?tb_id=14&ust_id=5.

TUIK. (n.d.). *ÖSYS okul türü ve öğrenim durumuna göre başvuran ve yükseköğrenim programlarına yerleşen aday sayıları*. Retrieved February 06, 2011, from http://www.tuik.gov.tr/VeriBilgi.do?tb_id=14&ust_id=5.

UCLA Academic Technology Services. (n.d.). *Annotated SPSS output logistic regression.* Retrieved August 28, 2010 from http://www.ats.ucla.edu/stat/spss/output/logistic.htm.

Vermunt, J. D. (2005). Relations between student learning patterns and personal and contextual factors and academic performance. *Higher Education, 49*, 205-234.

Yang, J., Yu, P.S., Wang, H., and Wang, W. (2002). Clustering by pattern similarity in large data sets. *Proceedings of the 2002 ACM SIGMOD international conference on Management of data*. Retrieved September 5, 2010, from http://portal.acm.org/citation.cfm?id=564737.

Wang, Y. (2003). Assessment of learner satisfaction with asynchronous electronic learning systems. *Information & Management, 41*, 75–86.