DEVELOPMENT OF AN INTELLIGENT TUTORING SYSTEM USING BAYESIAN NETWORKS AND FUZZY LOGIC

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ABSTRACT

DEVELOPMENT OF AN INTELLIGENT TUTORING SYSTEM USING BAYESIAN NETWORKS AND FUZZY LOGIC

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Recently, there has been a rapid growth in web-based Intelligent Tutoring Systems (ITSs) to support the teaching process with the aim of helping students adaptively navigate through online learning materials. Students who use these systems come from different backgrounds with different needs, preferences and characteristics. Therefore, the challenges for ITSs are their ability to provide dynamic adaptation to each individual user and a user-friendly interface in order to deliver knowledge effectively. The efficiency of ITSs depends on the methods used to collect and examine information related to the characteristics of students and their needs. Moreover, depends on the way in which this information is processed to form an adaptive educational context. There are various artificial intelligence methods such as fuzzy logic and the Bayesian network that facilitate the learning process in order to adapt the course content to meet the goal of each student and which deal with uncertainty in the student assessment process.

In this thesis, an intelligent tutoring system, called FB-ITS is proposed using a hybrid method based on fuzzy logic and Bayesian networks techniques to adaptively support students in learning in which the adaptation is achieved by modelling the students according to their knowledge level. FB-ITS takes the advantages of fuzzy logic and the Bayesian network, where the fuzzy logic is used to determine student performance in a particular topic of domain according to her/his prior and current knowledge and the Bayesian network is used to identify the state of the related topics based on the evidence that comes from the fuzzy logic system.

The effectiveness of FB-ITS was evaluated by comparing it with the two other versions of ITS that were developed and implemented using fuzzy logic and the Bayesian network separately in addition to it having been evaluated by comparing it with an existing traditional e-learning system. The study was conducted with undergraduate students at Atilim University, Turkey. Three dependent variables were utilized to evaluate the effectiveness of the proposed system, including students' academic performance, students' satisfaction, and system usability. The results showed that students who studied using FB-ITS had significantly higher academic performance (82.95) on average compared to other students who studied with ITS using the Bayesian network (79.09), ITS using fuzzy logic (69.77) and the traditional e-learning system (64.33). Regarding the time taken to perform the post-test, the results indicated that students who used the FB-ITS needed less time (7.87 minutes) on average compared to students who used the traditional e-learning system (13.86 minutes). From the results, it could be concluded that the new system contributed in terms of the speed of performing the final exam and high academic success. Additionally, the evaluation of the system showed moderate results in terms of students' satisfaction and the system usability.

Keywords: Intelligent tutoring system, Adaptive e-learning, Knowledge level, Bayesian network, fuzzy logic.

ÖZ

BAYESYAN AĞLARI VE BULANIK MANTIK KULLANILARAK ZEKİ ÖĞRETİM SİSTEMİ GELİŞTİRİMİ

Adabashi, Afaf
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Nisan 2020, 118 sayfa

Son zamanlarda, öğretim sürecini desteklemek amacı ile öğrencilerin çevrimiçi öğrenme materyalleri arasında uyum içinde gezinmelerine yardımcı olmak için web tabanlı Zeki Öğretim Sistemlerinde (ZÖS) hızlı bir artış olmuştur. Bu sistemleri kullanan öğrenciler farklı ihtiyaçlara, tercihlere ve özelliklere sahip farklı geçmişlerden gelmektedirler. Bu nedenle, her bir kullanıcıya dinamik uyarlama ve bilgiyi etkili bir şekilde sunmak için kullanıcı dostu bir arayüz sağlama yeteneği ZÖS lerinin önemli bir özelliğidir. ZÖS'lerinin etkinliği, öğrencilerin özellikleri ve ihtiyaçları ile ilgili bilgileri toplamak ve incelemek için kullanılan yöntemlere bağlıdır. Aynı zamanda uyarlanabilir eğitim bağlamında sistemlerin etkinliği bilginin işlenme biçimine de bağlıdır. Bulanık mantık ve Bayes ağı gibi ders içeriğini her öğrencinin amacına göre uyarlayan ve öğrenci değerlendirme sürecinde belirsizlikle başa çıkmak için kolaylaştıran çeşitli yapay zeka yöntemleri vardır. Bu tezde, öğrenmede uyarlanabilir destek sağlamak amacı ile öğrencilerin bilgi düzeylerine göre modellenerek uyarlamaların gerçekleştirildiği, bulanık mantık ve Bayes ağları tekniklerine dayanan hibrit bir yöntem kullanılarak FB-ITS adı verilen zeki bir öğretim sistemi geliştirilmiştir. FB-ITS, bulanık mantığın ve Bayes ağının avantajlarını kullanmaktadır. FB-ITS sisteminde bulanık mantık, öğrencinin önceki ve güncel bilgilerine göre belirli bir alan konusundaki performansını belirlemek için kullanılmış ve Bayes ağı, bulanık mantık sisteminden gelen kanıtlara dayanarak öğrencinin ilgili konulardaki durumunu belirlemek için kullanılmıştır. Bu çalışmada FB-ITS'nin etkinliği, mevcut geleneksel e-öğrenme sistemiyle karşılaştırılarak değerlendirilmiş, aynı zamanda, bulanık mantık ve Bayes ağı kullanılarak ayrı ayrı geliştirilen ve uygulanan iki ZÖS ile de karşılaştırılmıştır. Çalışma, Atılım Üniversitesi lisans öğrencileri ile yürütülmüştür. Önerilen sistemin etkinliğini değerlendirmek için öğrencilerin akademik performansı, öğrencilerin memnuniyeti ve sistem kullanılabilirliği olmak üzere üç bağımlı değişken kullanılmıştır. Sonuçlar, FB-ITS kullanarak eğitim alan öğrencilerin Bayes ağı (79.09), bulanık mantık (69.77) ve geleneksel e-öğrenme sistemi (64.33) kullanan diğer öğrencilere kıyasla ortalama olarak daha yüksek akademik performansa (82.95) sahip olduğunu göstermiştir. Son testin yapılması için geçen süre ile ilgili sonuçlara göre; FB-ITS kullanan öğrenciler (7.87 dakika), geleneksel e-öğrenme sistemini (13.86 dakika) kullanan öğrencilere kıyasla ortalama olarak daha az zamana ihtiyaç duymuşlardır. Elde edilen bulgulara göre geliştirilen yeni sistemin, final sınavını yapma hızı ve yüksek akademik başarı açısından alan yazına katkıda bulunduğu sonucuna varılabilir. Ayrıca, FB-ITS sisteminin değerlendirilme sonuçları, öğrencilerin memnuniyeti ve kullanışlığı açısından olumlu sonuçlar göstermiştir.

Anahtar Kelimeler: Zeki öğretim sistemi, Uyarlanabilir e-öğrenme, Bilgi düzeyi, Bayes ağı, Bulanık mantık.

To the soul of my father.

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LIST OF ABBREVIATIONS

ITS	Intelligent Tutoring System
AESs	Adaptive e-learning systems
AI	Artificial Intelligence
BNs	Bayesian Networks
FL	Fuzzy Logic
FLS	Fuzzy Logic System
ANN	Artificial Neural Network
RBF	Radial Basis Function
GAs	Genetic Algorithms
KL	Knowledge Level
ILS	Index of Learning Styles
MOOCs	Massive Open Online Courses
OER	Open Educational Resources
VLE	Virtual Learning Environment
LMS	Learning Management System
AI-ED	Artificial Intelligence in Education
CAI	Computer-AIded learning
ICAI	Intelligent Computer-Aided Instruction
FCMs	Fuzzy Cognitive Maps
DAG	Direct Acyclic Graph
ANN	Artificial Neural Network
CoG	Centre of Gravity method
CPD	Conditional Probability Distribution
ASP	Active Server Page
Vb	Visual basic
SQL	Structured Query Language
BITS	Bayesian Intelligent Tutoring System
BIP	BASIC Instructional Program

ADiL	Automated Debugger in Learning
IMITS	Interactive Multimedia Intelligent Tutoring System
ViPS	Virtual Physics System
ITSB	Intelligent Tutoring System Builder
FuzKPBE	Fuzzy Knowledge definer with Personalized Brilliancy Evaluation
IT2FLS	Interval Type-2 Fuzzy Logic based System
FuzKSD	Fuzzy Knowledge State Definer
PHP	PHP: Hypertext Preprocessor
LSID-ANN	Learning Styles Identify-Artificial Neural Network
ELS	E-Learner Satisfaction
SUS	System Usability Scale
SPSS	Statistical Package for Social Sciences
ANOVA	Analysis of Variance
ANCOVA	Analysis of Covariance

CHAPTER 1

INTRODUCTION

The internet plays an increasingly important role in improving communication, collaboration, sharing of resources, and delivery of education in distance learning mode. Web-based educational systems facilitate distance learning and offer easy access to any knowledge domain and learning process at any time for learners from different backgrounds with different needs, preferences and characteristics [1]. According to Yang et al. [2], the differences among students’ characteristics play an important role in developing web-based educational environments. Therefore, successful online teaching demands multimedia techniques, adaptive techniques, and reasoning abilities in addition to a user-friendly interface. Thus, the challenge is to develop web-based learning systems that are dynamically adapted to each individual user in order to deliver knowledge effectively. Therefore, web-based educational systems have to be dynamically adaptable for the individual learner and they must be capable of monitoring learner activities and provide personalization for specific needs, preferences, and knowledge. Moreover, these systems have to offer students more freedom in order to navigate through online course content and control their learning pace and learning sequence.

Adaptive navigation support technology, which has the ability to help students acquire knowledge faster and improve learning outcomes, is one of the common technologies applied to web-based educational systems [3]. Many Intelligent Tutoring Systems (ITSs) adopt such technology such as the ITSPL platform, which supports student navigation in cyberspace by adapting to the goals and knowledge of the individual user [4]. Graesser et al. in [5] defined ITSs as “a computerized learning environments that incorporate computational models from the cognitive sciences, learning sciences, computational linguistics, artificial intelligence, mathematics, and other fields”.

Additionally, the Intelligent Tutoring System (ITS) supports student navigation in e-learning environments by adapting to the goals, preferences, and knowledge level of the individual student [6]. The ability of an ITS to provide adaptivity is based on the technology of student modeling. According to John Self [7], student modeling is a process that is responsible for representing a student's goals and needs, analyzing student performance and determining prior and gained knowledge. However, the student modeling process is not a black-or-white but often deals with uncertainty and it cannot be accurately said that a student has learned the concept or not [1]. Therefore, the challenge is to construct an effective student model, which is the key component in an ITS to deal with uncertainty.

ITSs use Artificial Intelligence (AI) techniques to automatically adapt the teaching content to fit learners' needs and goals. Personalized and adapted e-learning environments can be established using AI techniques, which are mainly applied in knowledge representation, managing learning strategies and monitoring students' status [8]. AI is a branch of computer science interested in making computers behave like human beings. Its rich resources of tools, technologies and paradigms of computing include Fuzzy logic, Bayesian Networks, Neural Networks, Genetic algorithms, etc., and it has proved to be extremely useful in solving challenging problems in different fields as well as educational environments involving incomplete and/or uncertain knowledge. Uncertainty in e-learning systems can occur from examining student variables such as assessing the level of student knowledge [9].

Bayesian networks and fuzzy logic are widely used in the literature to develop the student model and solve the problem of uncertainty in adaptive e-learning systems [10],[11]. The Bayesian Network is a tool used to manage knowledge from different situations and model the interdependencies between domain topics. Moreover, the Bayesian network is able to increase the ability of an ITS to make the appropriate decision based on students' characteristics. Fuzzy logic is able to increase the ability of an ITS to examine and assess a student's academic performance, which is one of the most important parts of the educational process. In the literature, a Bayesian Network is applied to develop many student models such as Andes, an ITS developed by Gertner and VanLehn [12] to teach physics. In addition to Andes, there is also an ITS called BITS that teaches Computer Programming [6]. In BITS, each concept of the course material is represented as a node in the Bayesian Network. BITS represents student knowledge for each concept and predicts the knowledge level of subsequent concepts never having been studied by the student. Fuzzy logic is often used to develop the student model in an ITS. For example, it has been used in [13] to create the student model for an ITS to teach the Pascal programming language. This model describes a student's level of knowledge and cognitive abilities.

The comparison of the accuracy of the Bayesian network and fuzzy logic techniques in developing the student model that are used to predict a student's knowledge level is discussed in [14]. This comparison is based on two variables, namely prediction_time and correct_prediction. The study concluded that the Bayesian Network has higher accuracy than Fuzzy Logic in predicting student knowledge level. Therefore, this thesis attempts to enhance the efficiency of a student model by benefitting from the advantages of both techniques and to overcome their limitations. Integrating fuzzy logic and the Bayesian network into a student model of an ITS is a good idea since both techniques are more consistent with the human being decision making processes. In spite of combining Bayesian networks with fuzzy logic techniques in different domains such as machinery fault detection [15], this hybrid technique has not been considered in designing adaptive e-learning systems. This thesis uses these techniques to build the student model in order to deal with uncertainty in the learning process.

The user interface module is the other important component of ITS which is responsible for displaying the knowledge domain, as well as handling the communication between the system and their students. Therefore, the developers of ITSs should take into account how students interact with the system and provide a usable interaction that is as natural as possible. One of the important software quality factors used to measure the performance of software is usability. Usability means the "ease of use," so an e-learning system that is not easily used by its students can be considered a poor quality system [16]. Therefore, consideration should be given to educational aspects and usability when evaluating intelligent tutoring systems.

Since this thesis presents a study concerning the combination of two techniques of artificial intelligence that include the Bayesian network and fuzzy logic in the development of ITSs where educational materials can be personalized for individual learners, it takes a step toward the evaluation of the proposed system by comparing it with the existing models that have used only the Bayesian network [6] and which have used only fuzzy logic [13]. Therefore, this thesis develops three versions of the ITS where the first version is created using the Bayesian network only according to [6], while the second version is created using fuzzy logic only according to [13], and the third version is created using a combination of the Bayesian network and fuzzy logic and called an FB-ITS. Moreover, this thesis evaluates the proposed system by comparing the proposed system with a traditional e-learning system.

This chapter presents a brief introduction to this work and the problem statement. It also clarifies the research aims being investigated. The chapter also defines the research questions. It then highlights the contribution of this research. Ultimately, this chapter outlines the entire thesis by presenting the material covered by each chapter.

1.1 Problem Statement

The student model in intelligent tutoring systems builds from data coming from registration, diagnosis and assessment processes during the interaction of a student with the system. These data may be incomplete or imprecise, which may cause vagueness and uncertainty problems. For example, when a student has studied a new topic, it cannot exactly be said whether or not the topic has been learned. Thus, uncertainty is one of the challenges facing ITSs in modeling students [1]. Many AI techniques, such as Bayesian Networks (BNs) and fuzzy logic, have been used in the literature to solve the problem of uncertainty in ITSs [6], [11], [13].

Furthermore, students' learning performance is influenced not only by learning contexts but also by their general prior knowledge. Therefore, the student model needs some specific information about a student's prior knowledge [17]. In the literature, the Bayesian student model [4],[18] infers the student knowledge level based on evidence collected from the result of answering exam questions of a particular topic without paying attention to the prior knowledge of the student. Therefore, a method that can integrate a student's prior knowledge and current knowledge for the inference process is highly desirable. A solution to these problems is the use of a hybrid method that combines both the advantages of BN and fuzzy logic techniques. The use of fuzzy logic with Bayesian networks makes the student model more expressive.

In the context of challenges facing ITSs, designing an adaptable and usable user interface to satisfy its users' needs requires more attention. Chughtai et al. in their study [16] stated that most of researchers have been interested in developing an e-learning environment by focusing on learning sciences and the mechanism of learning, ignoring the design of a usable interface. However, usability evaluation is not commonly considered to be one of the main criteria in designing these systems or in identifying their ease of use [19]. According to Zaharias and Poylymenakou in [20], "very little has been done to critically examine the usability of e-learning applications". Moreover, Chughtai et al. [21] stated that although current ITSs are strong in the areas of teaching and learning strategies, there is little evidence that they have a strong usability foundation. Pedagogical and usability aspects should be considered when evaluating an adaptive e-learning system.

In summary, designing an acceptable ITS must take into account many aspects. This research thesis aims to develop an intelligent tutoring system, called FB-ITS, which uses Fuzzy logic and Bayesian networks techniques for student modeling incorporating an adaptive approach to learning. Moreover, this work focuses on designing a usable learning interface to teach the principle of Microsoft Excel in order to help students accomplish their learning goals and to enhance user satisfaction. Adaptation of the e-learning environment based on knowledge of the student and designing a usable interface will increase the efficiency of an adaptive e-learning system. In this thesis, a variety of experiments were conducted to evaluate the effectiveness and efficiency of the proposed system. Moreover, the usability of its user interface was tested from the perspective of users.

1.2 Research Aims

This study attempts to provide a step towards creating an adaptive e-learning environment. The thesis is directed toward achieving the following aims:

I. To propose a novel hybrid method based on Bayesian network and fuzzy logic techniques to identify a student’s knowledge level.

II. To build a usable and adaptive user interface in order to increase the learning performance and satisfaction of learners and to enhance their learning process.

III. To develop an intelligent tutoring system known as FB-ITS with adaptive behavior based on the above objectives.

This thesis studies the development, implementation and comparison of three versions of an ITS using AI techniques. These three versions are: 1) ITS using Bayesian networks only; 2) ITS using fuzzy logic only; and 3) ITS using a combination of both Bayesian and fuzzy logic techniques known as FB-ITS. The principles of the student model which is based on the above objectives were given central importance in designing this tutor. Moreover, this thesis compares the proposed system with a traditional e-learning system which is a standard online learning system.

1.3 Research Questions

The main aim of the present study was to determine whether combining fuzzy logic and Bayesian network techniques into developing the student model in ITS contributes to improving students’ academic performance and enhancing their educational competence. The research aims are set in the following research questions:

I. Does the building of a student model using Bayesian networks based on fuzzy logic increase the performance of ITS in terms of students’ academic performance compared to using fuzzy logic and Bayesian networks separately?

II. Do students who studied with FB-ITS have higher academic performance than students who studied using the traditional e-learning system?

III. Are there any differences according to gender, department, and GPA in students’ academic performance?

IV. Is there a difference in the time taken by students who studied with the FB-ITS to perform the post-test compared to students who studied with ITS using fuzzy logic only, ITS using Bayesian networks only and with traditional e-learning?

V. Does adaptation based on the level of student knowledge in the FB-ITS lead to a high level of student satisfaction compared to a traditional e-learning system?

VI. Does a user interface of the FB-ITS has a high level of system usability compared to a traditional e-learning system?

1.4 Research Contributions

The contributions of this study to the field of e-learning are given below.

One of the contributions relates to the review of artificial intelligence methods in adaptive e-learning systems [8]. In addition, the intelligent tutoring system is also covered in the review, taking into account their main components, including the student model, domain model, adaptation model and user interface.

The major contribution of the presented study is the development of a new model. It is a novel hybrid student model that combines Bayesian networks and fuzzy logic techniques and which is designed to promote adaptation and personalization in educational systems. In this manner, the presented student model helps students who already have prior knowledge about the domain to save time and effort during the learning process. Moreover, it tracks the changes of the knowledge level of students and dynamically adapt the learning material accordingly.

The other contribution comes from the development of a unique online intelligent tutoring system named FB-ITS by the researcher using Microsoft Visual Studio and SQL Server Management Studio. FB-ITS can provide adaptation based on a student's knowledge level using adaptive navigation support, including adaptive learning techniques such as link annotation and link hiding [22], where the link annotation is used to highlight each topic with an appropriate color. Link hiding is used to hide any links for topics that are not yet ready to be learned.

In addition, the proposed ITS framework can be used as a reference model to develop instances of intelligent tutoring systems by focusing on different views of the domain model as well as the adaptation model.

1.5 Organization of the Thesis

This thesis is divided into six chapters: an introduction, literature review, research methodology, system design and implementation, experiment and results, and conclusions and discussion. The thesis chapters are organized as follows:

Chapter 1 introduces some basic concepts, the problems to be addressed, the aims of this research, research questions, and thesis contributions.

Chapter 2 presents a brief overview of existing research performed in the area of adaptive e-learning. The chapter presents a brief introduction to artificial intelligence and reviews some existing intelligent tutoring systems. It also includes a survey of the AI techniques applied in adaptive e-learning systems. Finally, it covers usability issues in adaptive e-learning.

Chapter 3 discusses the overall methodology used in this study and includes: research design, population and sample, data collection tools and data analysis.

Chapter 4 presents the design and implementation details of the intelligent tutoring system developed in the present study. It presents the architecture of FB-ITS including all its components, namely knowledge domain model, student model, adaption model, and user interface. Furthermore, it discusses in detail the use of fuzzy logic and the Bayesian network in the development of FB-ITS.

Chapter 5 presents the experiment conducted to evaluate the developed system and summaries of the results of the experiment, including results of a comparison of the three versions of the ITS which were designed based on 1) fuzzy logic; 2) Bayesian networks; and 3) a combination of Bayesian networks with the fuzzy logic technique. It presents the results of a comparison of the developed system made with a traditional e-learning system.

Finally, **Chapter 6** provides a discussion for the conclusion and directions for future research.

Appendix A lists a sample of the pre-test and post-test questions, Appendix B shows the student satisfaction questionnaire, Appendix C shows the system usability questionnaire, and Appendix D contains conditional probability distribution tables of the Bayesian network.

CHAPTER 2

LITERATURE REVIEW

This chapter presents a literature review to provide the important concepts and background for the research as well as previous related studies in the area covered by this thesis. It gives an introduction and review of e-learning and Artificial Intelligence (AI). The chapter also reviews some existing Intelligent Tutoring Systems.

A discussion of the issue of AI techniques and how they have been applied in adaptive e-learning systems and, in particular, investigates how their performance has been evaluated is also included. Moreover, this chapter concisely introduce an overview of the Fuzzy Logic (FL) method along with a description of the general architecture of the fuzzy logic system. An overview of Bayesian networks is also presented. Finally, the usability issues and challenges in adaptive e-learning systems are also covered.

2.1 E-Learning

E-Learning has been seen by many as a major shift from the teacher-centered model in the traditional learning system to a learner-centered one, where students are actively learning and they can decide what they learn, how they want to learn , and where and when they learn it [23]. Furthermore, Rosenberg [24] defines the term ‘e-learning’ as “the use of Internet technologies to deliver a broad array of solutions that enhance knowledge and performance”. Longmire in [25] states that “e-Learning covers a wide set of applications and processes such as computer-based learning systems, Web-based learning systems, virtual classrooms, and digital collaborative learning GroupWare packages”. E-Learning contents are for the most part conveyed by means of Internet, satellite communication, TV, DVD and CD-ROM.

Both computers and software have evolved with the development of the Internet to the point that online learning has become widespread worldwide.

Such learning also removes distance barriers to education, thereby helping students and other learners access web-based material at anytime from anywhere in the world by being connected to the Internet. Figure 2.1 shows the advantages of e-learning systems.

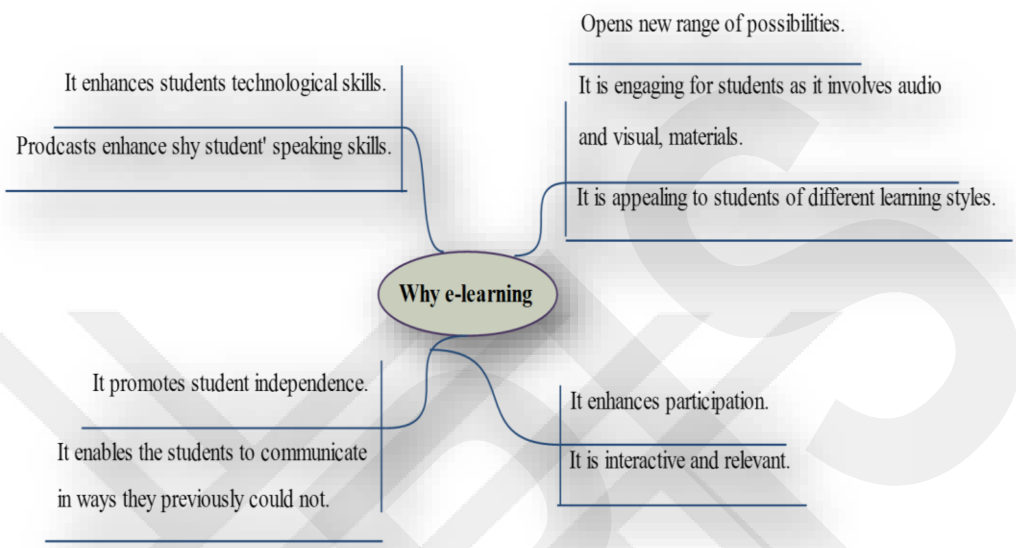


Figure 2.1 Advantages of e-learning systems

Through the evolution of the Internet and the growth of Web technology, distance learning environments have been created to support learning processes such as Massive Open Online Courses (MOOCs), which first emerged from Open Educational Resources (OER) in 2008. MOOCs allow learners around the world to access courses offered by different educational institutions via the Internet [26]. There are many commercial and non-profit providers of MOOCs such as Coursera[1] , and FutureLearn[2].

Many applications including the Virtual Learning Environment (VLE) and Learning Management System (LMS) have been developed to make online learning much easier. These software systems or platforms are widely used by several universities to help instructors in creating online courses that are easily accessible to students in order to facilitate learning [27]. The other trending term that is common in online learning

[1] https://www.coursera.org/
[2] https://www.futurelearn.com/

is computer-supported collaborative learning, which emphasizes social interaction to facilitate both learner-learner and learner-teacher interaction to help expedite learning tasks that require group work [28].

In the context of technology-enhanced learning, software developers have endeavored to utilize the modeling potential of computers to develop systems that support learners through adaptive or intelligent operations [28]. Adaptive and intelligent systems are model-based and intended to support learning. Adaptive e-learning systems (AESs) are an enhancement to the traditional approach to learning by personalizing and recommending learning material to meet the individual needs and preferences of learners [29]. These system also provide new ways to break away from "one size fits all" approach of traditional educational models and they make it possible to be customized to individual needs. An AES operates differently for different learners, taking into account information accumulated in the individual student model to provide learner-tailored support during the problem solving process [30]. To achieve this, developers of intelligent systems apply techniques from the field of Artificial Intelligence (AI) and implement extensive modeling of the problem solving process in the specific domain of application.

2.2 Artificial Intelligence and E-Learning

Artificial Intelligence (AI) is the branch of computer science interested in making computers behave like human beings. The term "artificial intelligence" was coined by John McCarthy in [31], who defines it as "the science and engineering of making intelligent machines".

In order to achieve a good learning stage, which has an ability to learn from uncertain, vague and incomplete data, numerous AI techniques including Fuzzy logic, Bayesian Networks, Artificial Neural Networks, Genetic algorithms, etc. have been widely used in solving problems from other domains and can be quite useful in solving problems related to education. Furthermore, the ability of AI techniques to imitate the intelligence of a human being and a human's ability to solve complex problems makes AI techniques an ideal tool in e-learning.

According to Abdel-Badeeh and Cakula [32], the field of Artificial Intelligence in Education (AI-ED) has become an important and challenging research area in recent years, and aims to deliver educational knowledge-based systems to be used in actual teaching and training. According to “Artificial Intelligence in Education (AI-ED)”, the main research areas of AI in education include: Intelligent Systems, Teaching Aspects, Learning Aspects, Cognitive Science, Knowledge Structure, Tools and Shells, and Interfaces, as shown in Figure 2.2 below.

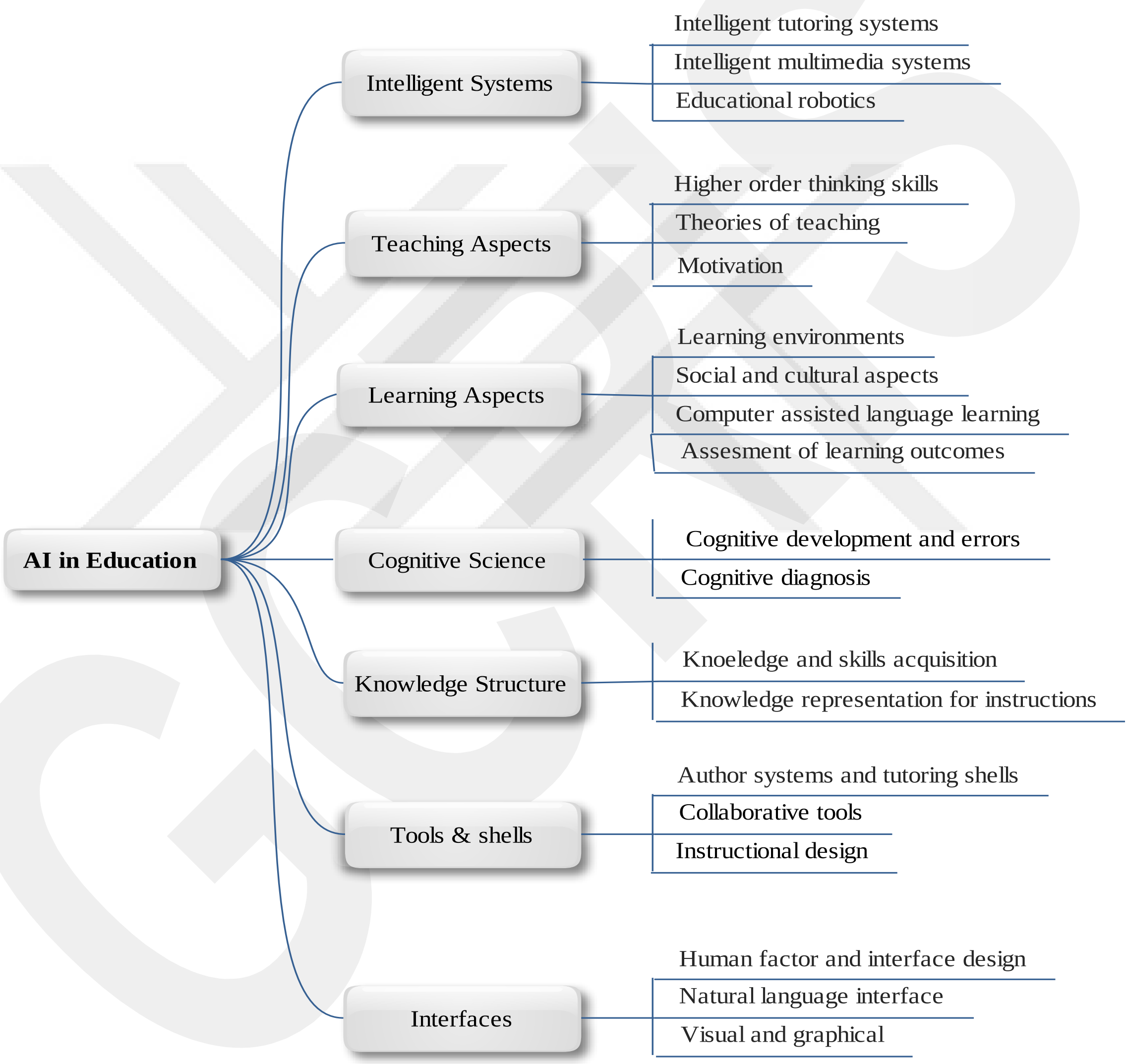


Figure 2.2 Areas of research in AI in Education (AI-ED) [32]

The use of AI techniques in educational systems has influenced the evolution from Computer Assisted Instruction (CAI) to Intelligent Tutoring Systems (ITSs). Researchers have attempted to incorporate intelligence into knowledge and problem-solving areas, as well as in tutoring students in order to create expert learning systems capable of providing individualized instruction.

2.3 Intelligent Tutoring Systems

The term Intelligent Tutoring System (ITS) is a broad term which involves any computer program that contains some intelligence and can be used in learning. The 1970 was the first time when referred to ITS as the term of artificial intelligence for computer-aided learning (CAI) by Carbonell [33]. Shortly thereafter, Sleeman and Brown [28] mentioned that the term of ITS is identical with the meaning of the term Intelligent Computer-Aided Instruction (ICAI) and emphasized on making differentiations from the early stages in CAI systems. However, these early systems did not consider the diversity of learner's knowledge levels and as such, failed to provide adaptive learning environments for learners. Many studies have been conducted in the field of ITS to make computer-based tutoring more flexible and adaptive to the needs of each learner by giving them a satisfactory knowledge of the relevant learning process components and the reasoning ability to transform this knowledge into intelligent behavior [34].

ITS appears in an intersection area that included computer science, psychology, and educational research. This area as shown in Figure 2.3 is referred to as 'cognitive science' [35]. With the unprecedented growth in the AI field, incorporating its techniques into education systems has become a popular subject.

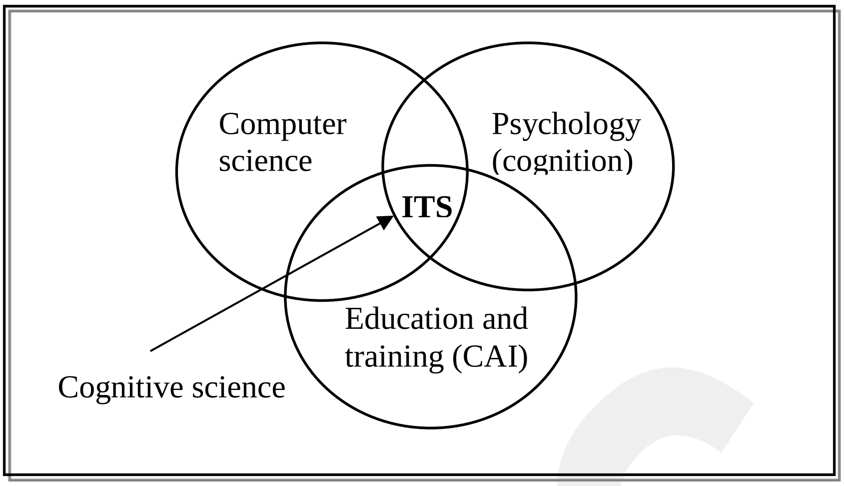


Figure 2.3 ITS domains [35]

ITSs should be able to diagnose a student's knowledge level using principles rather than pre-programmed responses, and then provide feedback according to this knowledge. ITSs have also been shown to be highly effective in increasing students' performance and motivation levels in comparison to traditional instructional methods [6].

According to Sleeman and Brown, ITSs can be classified as computer-based (1) problem-solving monitors, (2) coaches, (3) laboratory instructors, and (4) consultants [36].

ITSs, as stated by Conde et al. [37], have to involve the following features:

- Allow tutoring people with disabilities regarding their tasks to give them more autonomy in working environments;
- Have a multimodal task management system for data integration from different sources (speech, images, videos, and text) associated with each personalized profile;
- Be integrated into a mobile platform, i.e. a mobile or smart telephone;
- Contain a multimedia interface that is friendly, reliable, flexible, and ergonomically adapted.

- Include a human emotion prediction system in order to prevent risk, emergency and blockage situations that can harm individuals and interfere with their integration into working and social environments;
- Be entirely configurable by stakeholders without technological knowledge for easy and flexible access; and
- Have the ability to be transferred and applied to other groups; e.g., the elderly.

ITS provides instructions or customized feedback directly to students in their learning processes through AI techniques, that are primarily applied to knowledge representation and the managing educational strategy by experts in both educational and pedagogical issues so as assess the learning status of students at any time.

2.3.1 The Architecture of Intelligent Tutoring Systems

ITSs are typically classified into several different parts, and each part plays an important role. The basic architecture of an ITS, as shown in Figure 2.4, consists of four components, namely, i) student model, ii) knowledge domain model, iii) tutoring model and iv) user interface model [38]. These basic components interact with each other to achieve different functions. More detail about these components are presented below.

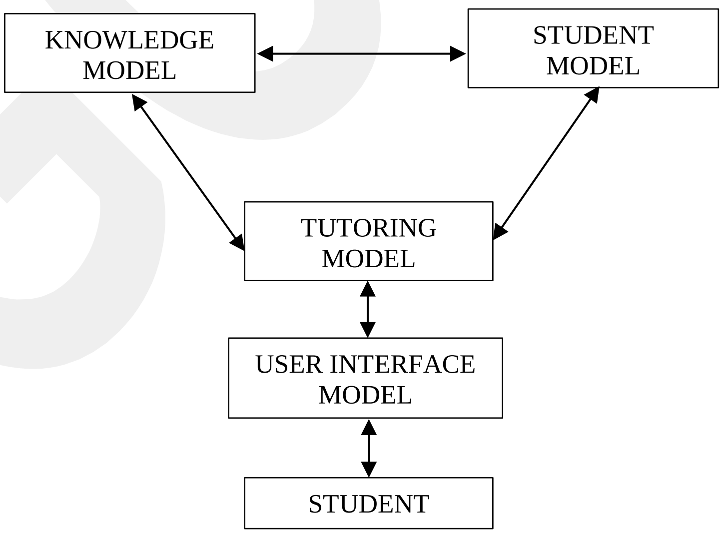


Figure 2.4 Intelligent Tutoring Systems architecture [38]

- **Student Model**

A student model (Who is taught?) is the base for adaptation in ITSs allowing for understanding the student. This model can be defined as "the process of gathering relevant information in order to infer the current cognitive state of the student, and to represent it so as to be accessible and useful to the pedagogical module" [39] and, hence, can be applied in any tutoring system offering adaptation. The aim of a student model is to construct a student profile based on student's characteristics.

According to Wenger et al. [40], the student model should:

- gather implicit and explicit data about the student;
- use this data to create a representation of the student's knowledge state; and
- be able to assess the student's knowledge level by comparing this knowledge state to that of an expert.

In the initial stage of building a student model, the appropriate students' characteristics should be selected. Here the question ‘‘What aspects of the student should we model in a specific intelligent tutoring system?" needs to be answered [41]. The student model stores both static and dynamic characteristics. According to Jeremic et al. [42], static characteristics such as age, email, native language, learning style, etc. are set by the student during the registration session, usually by completing a specific questionnaire. This information remains unchanged; whereas dynamic characteristics, which include knowledge level, preferences, etc., are updated during the learning process. The most important point in the student model is the representation of the knowledge level of the student in the domain model [43].

The ability of an educational system to provide adaptation and personalization is based on the technology of student modeling. The student model is used for accurate student diagnosis in order to predict students' needs and adapt the learning material and process to each individual student. It is used to produce highly accurate estimations of the student's knowledge level and cognitive state in order to deliver the most appropriate learning material. Furthermore, an adaptive tutoring system can use the student model in order to recognize the learning style, goals and preferences of a student and make a decision about an effective learning strategy. In addition, a student model can be used to identify a student's strengths and weaknesses in order to provide individualized advice and feedback [44].

- **Knowledge Domain Model**

The knowledge domain model (What to teach?) stores information about a topic and learning materials that students are required to study and it refers to the curriculum being taught. A specific module has been introduced in ITSs, and its use is extended to most current adaptive and personalized educational systems. Generally, this model requires significant knowledge of engineering to represent a domain so that other parts of the system can access it. One of the related research issues in this model is how to represent domain knowledge so that it easily scales up to larger domains.

Therefore, the knowledge representation in a domain model is an important factor in creating adaptiveness to ITSs and all adaptive and personalized e-learning systems. Peylo et al., have pointed that, to enable communication between the system and student at the course content level, the domain model of the system has to be adequate with respect to inferences and relations of domain entities with the mental domain of a human expert [45]. The most commonly used approaches of knowledge domain representation in adaptive tutoring systems are hierarchies and networks of concepts.

- **Tutoring Model**

The tutor model (How to teach?) provides a model of the teaching process such as presenting or revisiting an old topic, and which topic is to be presented according the needs of each individual student. This model takes input from the knowledge domain model and student model and makes decisions about teaching strategies and actions. In this manner, pedagogical decisions reflect the different needs of each student. Creating the tutoring model is a difficult task because related functions are not uniformly represented and not consistently distinct from other functions or components in the system.

In ITSs, the tutoring task involves guidance from the teacher and interactions between the teacher and students. The main challenge in creating adaptive tutoring systems is guiding students' behavior using real-time data from regular interaction between the student and the system. One of the common method that enables the natural form of interaction is dialogue boxes. For example, in Andes [12], which is an adaptive tutoring system developed to teach physics, popup messages are used to inform the student about the occurrence of errors.

- **User Interface Model**

Finally, the user interface model provides communication between the student and the system. Essentially, the user interface model is concerned with the presentation of course materials to students in the most effective way. A well designed interface model can enhance the capabilities of an ITS by allowing the system to present instructions and feedback to the student in a clear and direct manner. According to Sampson and Karagiannidis in [46], two dimensions for designing user interface have been proposed: multimedia content and user exploration. The use of multimedia objects such as audio, pictures, video and animations can enhance the performance of ITSs. However, only using multimedia objects without the proper interaction of the student with the interface components cannot guarantee efficient learning, especially when learning is recognized as a complex activity due to different factors such as navigation, information retrieval, and memorization [46]. Another aspect of user interface design is to consider a user's ability and preferences to explore domain concepts through the learning environment.

In the context of the architecture of ITSs, different architectures of ITSs have been proposed, some of which are very similar, but others are significantly different from the general architectures, as shown in Figure 2.4. For instance, the architecture of ACT (Anderson's Advanced Computer Tutoring) ITS [47], shown in Figure 2.5, contains the following four components:

- Domain expert: contains rules that are used for solving problems in a particular domain;
- Bug catalogue: contains common misconceptions and errors for the domain;
- Teaching knowledge: the tutoring model; and
- User interface.

The same architecture has been used by Lisp tutor [48] and Geometry tutor [49].

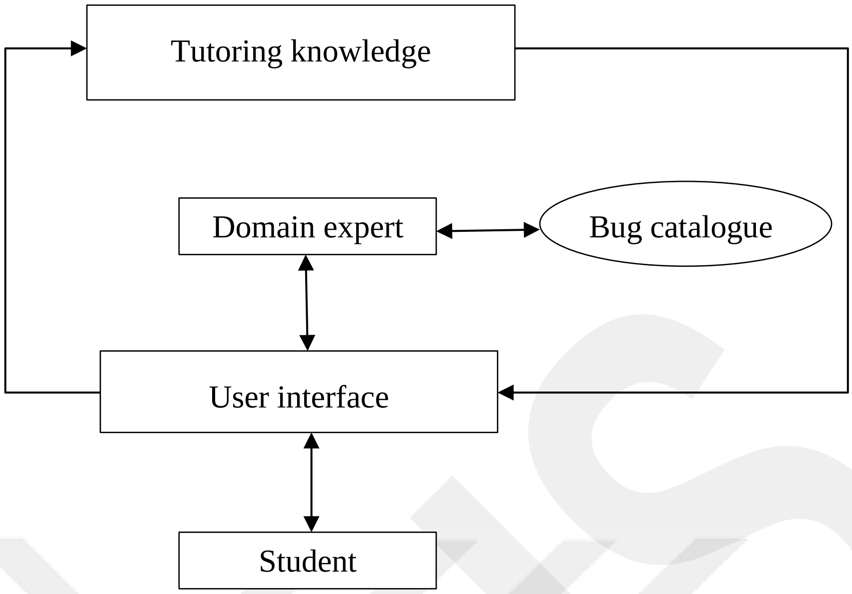


Figure 2.5 ACT’s architecture [47]

General ITS architecture has been modified in [50] in order to improve the performance of intelligent tutoring systems. In the study, the Knowledge Manipulation Module and the Reporting Module added to the general structure, as shown in Figure 2.6. The role of the knowledge manipulation module is to allow instructors to add, delete, and modify test questions and lecture content. Accordingly, the reporting module aims to facilitate the perception of each student’s learning situation by different instructors, who can see the outcome of their educational strategies as the system evaluates and educates each student.

Furthermore, ZOSMAT is another ITS created by Keles et al. [51] that has modified the general architecture of ITS. This system is used for teaching students either in classrooms or in any place in the world. The architecture of ZOSMAT consists of six components: ZOSMAT manager, student model, content structure, question bank, expert module, and user interface. The ZOSMAT manager is responsible for coordinating these components so they can smoothly work together.

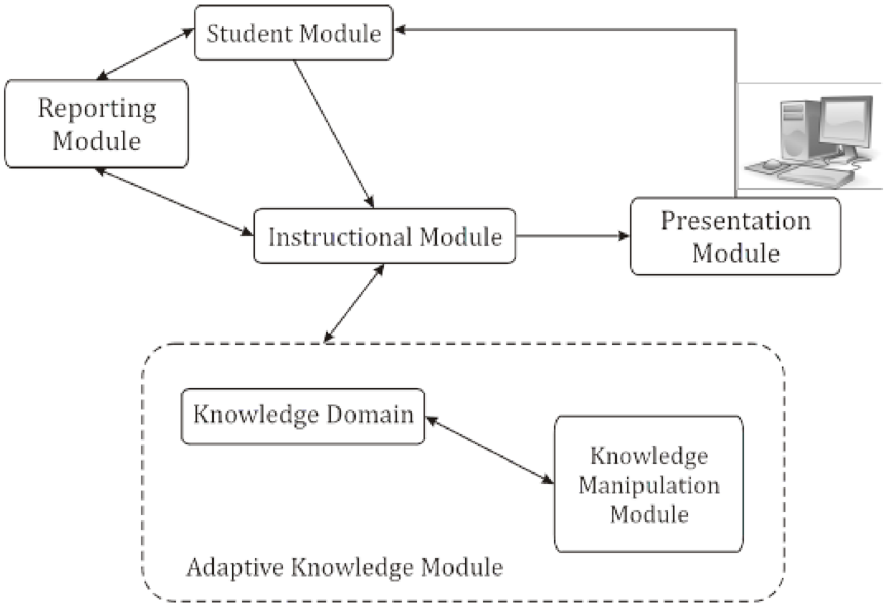


Figure 2.6 Modified architecture of an ITS [50]

2.3.2 Review of Existing Intelligent Tutoring Systems

Several Intelligent Tutoring Systems (ITSs) have been developed for learners in different areas with various strategies in order to improve teaching ways and help students learn better. Table 2.1 lists some ITSs and their respective aims. The following are some examples of existing intelligent tutoring systems that were created between 1970 and 2019.

SCHOLAR is often considered to be the first ITS. It was created by Carbonell in 1970, and used natural language to review student knowledge about South American geography through limited and mixed initiative dialogues with the student in a comfortable subset of English [33]. SCHOLAR has the capability detecting when it does not understand the student, and it can detect misspellings and answer students' questions. Moreover, it can generate questions and their corresponding answers as well as determine when answers are correct or incorrect. Another early ITS called **BIP** (BASIC Instructional Program) was developed in 1976 by Barr et al., [52]. BIP is an interactive problem-solving system that provides educational assistance to students to solve programming problems in the BASIC programming language.

AutoTutor-3D is an online client-server intelligent tutoring system developed by Graesser et al. [53] and implemented using ASP.NET and C#. AutoTutor-3D simulates a human tutor by having conversations with students in natural language. AutoTutor-3D asks a student a few difficult questions that requires a paragraph of correct answers. Each question in this system is associated with a specific set of expectations (ideal answers) and misconceptions (wrong answers) that are stored in a curriculum script. AutoTutor-3D is programmed to be able to correct misconceptions and provide suitable feedback to the student so that the system can assess students' answers and match them with the expectations and misconceptions.

Zin et al. [54] developed **ADiL** (Automated Debugger in Learning System), an ITS for automated debugging based on knowledge. It helps students intelligently debug their programs in the C programming language by localizing, identifying, and explaining logical errors. If the program is error free, ADiL is able to explain its meaning. **Mathtutor** is an open-access website created by Aleven et al. [55] to improve students' understanding of mathematics and help them in solving math problems with step-by-step guidance from the ITS. An Interactive Multimedia Intelligent Tutoring System (**IMITS**) was developed to assist students' understanding in the area of electrical engineering and help their students to solve real life problems [56].

In [48], Anderson and Reiser developed an ITS called **LISP** Tutor, which is a computer-based tutor that is effective in teaching LISP programming language as a human tutor. LISP tutor provides helpful information that guides the student while writing lisp code and finding the correct path to a solution. **BITS** is a web-based intelligent tutoring system developed by Butz et al. [6] to teach students the C++ programming language. BITS can help a student to navigate through online course materials and it can recommend learning goals and generate appropriate reading sequences.

Table 2.1 Examples of ITSs

ITS Name	Learning Field	Year	Aim of the system
SCHOLAR	Knowledge about South American geography	1970	Diagnose students’ errors
BIP	BASIC language	1976	Problem solving and feedback
LISP	LISP programming	1985	Provide helpful information and friendly environment
ADiL	C programming language	2000	Automating the debugging process and error diagnosis
BITS	C++ programming language	2004	Adaptive guidance
Auto-Tutor	Conceptual physics and computer literacy	2005	Natural language interaction, feedback and adaptive response
IMITS	Electrical engineering	2006	Personalized learning
ZOSMAT	Mathematics	2009	Adaptive learning content and recommendation generation
ViPS	Physics	2012	Adaptation and hint generation
ELaC	C++ programming language	2014	Individualized instruction and adaptation
ITSB	Multidisciplinary fields (e.g., Java language)	2016	Adaptive learning
ASP.NET-Tutor	ASP.NET	2018	Adaptive learning
SQLTOR	SQL programming language	2019	Adaptation and hints generation

ZOSMAT [51] is a student-centered ITS for teaching mathematics implemented in ASP.NET with Visual C# and SQL Server. It can be used for two purposes: an individual learning and in a real classroom with the guidance of a human teacher throughout the learning process.

In recent years, many ITSs have been developed by researchers with a focus on personalization and adaptation strategy. For example, **ELaC** is an ITS presented by Chrysafiadi in her PhD thesis [44], which was built to teach students the C programming language. ELaC helps students to save time and effort during the learning process by providing adapted educational materials, taking into account the personality of students in terms of background, skills and speed of learning. Myneni and Narayanan [57] constructed an ITS named **ViPS** (Virtual Physics System) for learning physics concepts in middle schools. ViPS is used to identify student misconceptions in physics and guides them in solving problems through virtual experiments. **ITSB** (Intelligent Tutoring System Builder) is an authoring tool constructed using Delphi 2015 by Abu Naser in [58] for teaching multidisciplinary fields (e.g., Java language). ITSB has two interfaces in the Arabic and English languages. One for teachers to add the instructional material, examples and questions, and the other for students to help them to studying lessons at different levels, and respond by answering questions.

In [59], an ITS named **ASP.NET-Tutor** was designed for the smooth and easy teaching of students in beginner level in ASP.net. SQLTOR is an ITS developed by Vagin et al., [60] to support students in learning the SQL programming language. SQLTOR provides the creative tools necessary for helping teachers in teaching SQL. Moreover, it supports the self-learning and self-testing process.

2.4 Review of AI Techniques Used in Intelligent Tutoring Systems

Intelligent tutoring systems aim at adapting a comprehensive learning approach to meet the needs of students. Therefore, it is essential that the students' model be created accurately while considering their knowledge levels, learning skills and preferences [61]. Then the information required must be used and developed in order to improve the e-learning environments. AI techniques are regarded as useful tools for several reasons as they have the ability to develop the human decision making process and build automatic learning models [61]. There are several AI techniques that have been used to build and develop intelligent e-learning systems, including Fuzzy Logic, Bayesian networks, Neural Networks, and Genetic algorithms. Table 2.2 shows and summarizes some examples from previous studies in intelligent e-learning systems using AI techniques.

AI techniques have been used in various ways in intelligent e-learning systems. For example, some focus has been given to examining and assessing student characteristics to generate student profiles for the purpose of evaluating their level of knowledge to be used as bases for building educational systems [62],[63]. Various AI approaches are also used to facilitate the diagnostic process in order to adjust course content to meet the needs and preferences of each learner [64],[65]. Adaptive e-learning systems that are based on the ideas of some experts or developers who are used to dealing with students' behavior may face different uncertainties in terms of assessing learners' responses to adaptive e-learning system when student variables such as students' knowledge or level of participation are considered.

2.4.1 Fuzzy Logic

Fuzzy logic can be viewed as an extension of the concept of a fuzzy set theory proposed by Lotfi Zadeh (1965). It reflects how people think and attempts to model the human sense of words and decision making. Fuzzy logic is a form of multi-valued logic that allows the definition of intermediate values between conventional evaluations such as true/false, yes/no, high/low, and big/small. The fuzzy logic technique with its ability to handle imprecise information and uncertainty, has been used to improve the performance of an adaptive e-learning system and provide a human description of student's knowledge and learning capabilities.

The applications of fuzzy logic are seen in various fields, such as medicine, commerce, education, etc. Fuzzy reasoning techniques are based on fuzzy rules that have been used in [66] in order to generate concept maps automatically based on students' assessment records, which leads to the development of adaptive learning systems. An evaluation method for e-learning systems was introduced by Hogo [67] to help decision-makers to evaluate learners' behavior. This research used two types of fuzzy clustering techniques, fuzzy c-means and kernelized fuzzy c-means to cluster the learners into separate groups based on their behavior in order to predict their profiles. As a conclusion, the author proved that both fuzzy clustering techniques have a satisfactory ability in predicting the behavior of e-learners.

Hsieh et al. [68] proposed a personalized recommendation system for English article based on accumulated learner profiles. This system employs the fuzzy inference method, memory cycle updates, learner preferences and analytic hierarchy process to improve the English language abilities of students in an intensive reading environment.

Goyal et al. [69] proposed a student preference electronic test based on Bloom's classification. This classification method is known as the "Taxonomy of learning objectives" and aims to classify these objectives into different types of student model, such as the analytical learner, example based learner, rote learner, analogy and deductive learner and commonsense-based learner. In this research, the role of the fuzzy logic based-approach is to personalize and determine the most preferable test for any student in an e-learning environment in order to automatically generate the test sheet according to the student model.

Moreover, in the research conducted by Priya and Keerthy [70], the Rule-Based Fuzzy logic technique has been used for an automatic learning process to provide adaptive instructions to learners through an e-learning system. The Fuzzy Knowledge definer with Personalized Brilliancy Evaluation (FuzKPBE) is introduced in this paper to predict the related course and concepts based on the specific individual skills of each concept.

Almohammadi et al. [71] introduced (IT2FLS) a type-2 fuzzy logic technique based system using visual RGB-D features used to measure the degree of students' levels of engagement in remote and onsite education.They presented another self-learning type-2 fuzzy logic system that helps teachers with recommendations of how to adaptively vary their teaching methods to suit the level of learners and enhance the course delivery method. The same authors, in another study [11], developed an adaptive e-learning system which is able to identify students' preferred learning strategies and knowledge delivery. This system used a novel interval type-2 fuzzy logic technique in generating an adaptive learning environment based on the students' characteristics and the knowledge level.

In the domain of computer programming, various tutoring systems have been designed using fuzzy logic techniques to assess the learning skill and knowledge level of students and to dynamically adapt the users' needs. Chrysafiadi and Virvou [1] presented an approach to web-based educational systems that would perform individualized instruction in the domain of programming languages. This approach was implemented and evaluated in an educational application module called "Fuzzy Knowledge State Definer" (FuzKSD). FuzKSD operates based on Fuzzy Cognitive

Maps (FCMs) to perform user modeling by dynamically identifying and updating the knowledge level of students related to all the domain subjects. FCMs are used to represent the dependencies between the domain concepts. Additionally, a system has been presented by Asopa et al. [72] to evaluate student performance in ITS environments, in which a fuzzy inference system provides the students with step-by-step instructions as to their learning status.

2.4.2 Bayesian Networks

Another well-known AI technique used to construct intelligent e-learning systems is Bayesian Networks. The Bayesian Network is a Direct Acyclic Graph (DAG) that is used to model dependency between various concepts of a particular domain based on a probability distribution [73]. Bayesian networks have been used as a probabilistic framework to solve the problem of dynamically managing and updating student models [74]. These networks can represent different components of a student model such as knowledge level, learning styles, goals, motivation, etc. According to Mayo and Mitrovic [75], Bayesian student modeling approaches can be classified into three types according to how the network and probabilities are constructed. These types are expert centric, efficiency centric and data-centric models. In the expert centric models, the structure of the network and its probabilities are specified by experts. Efficiency centric models restrict the structure of the network in order to maximize efficiency. Finally, data-centric models use data from previous experiments or pre-tests to generate the network and its prior and conditional probabilities.

Bayesian networks receive a much attention from designers and developers of adaptive educational systems due to their sound mathematical foundations and also for their ability to handle uncertainty using probabilities. Andes, which is an adaptive educational system developed by Gertner and VanLehn [12], uses Bayesian networks to find former probabilities of knowing a set of knowledge elemental parts in teaching physics. Dynamic learner profiling to meet changing learner behaviors, goals, preferences, performance, level of knowledge, learner status, difficulty of contents, and feedback are developed using the Bayesian network [76]. Another Bayesian student model has been proposed to measure the difficulty of the problem of parameter specification [77]. This research conducted many experiments to compare the performance of two Bayesian student models. In one of them, the parameters were specified by experts, in the other, these parameters were learned from the data. It was concluded that both student models provided a satisfactory result in estimating the variables of knowledge.

The PHP Intelligent Tutoring System (PHP ITS) was developed by Weragama and Reye in [78]. PHP ITS aims to support novices in learning the PHP language for the purpose of developing dynamic web pages. This system provides exercises for students to solve and then provides appropriate feedback based on the answers. In PHP ITS, the Bayesian network is used to update the students' knowledge level of each topic based on student progress. Moreover, Bayesian networks have been used in [57] to constructed an ITS named ViPS (Virtual Physics System) to teach physics concepts in middle schools. In this system, the Bayesian network is used to represent the domain knowledge, to find the possible setups that can be created using components created by an individual student during the learning processes, as well as to generate an adaptive feedback and dynamic hints regarding student actions.

In addition to the use of the Bayesian network in building adaptive e-learning systems, it has been used to develop an ITS called ITSPL to support students with navigating the learning environment by adapting to the goals, knowledge and learning styles of the individual student [4]. The Bayesian network is employed to detect which concept the student needs to learn and then the system displays relevant contents of the topic.

2.4.3 Artificial Neural Networks

The Artificial Neural Network (ANN) is a supervised learning model consisting of a large number of simple processing units, called "neurons" arranged in different layers known as the input layer, hidden layer and output layer. A multilayer neural network is a connections of simple neurons called a "perceptron". Neural networks can be utilized to develop intelligent e-learning systems to assist the educational process and act as the teacher in the traditional classroom. Elena Şuşnea [79] used the multilayer perceptron, a type of ANN and Radial Basis Function (RBF) in order to model the performance of the predictor of students attending an e-learning course. The database that was utilized in this research contains information gathered over a period of two years from the exams given to military and non-military students. The results show that the error rates of the predictor are very low.

Parminder K. et al. [80], discussed how to effectively classify learners depending upon various factors such as their learning abilities, professional background, learning goals and so on, using a neural network model. To train the model, they used a database that was collected throughout the period of one year from the tests administered to rural and urban students. The assessment of the performance of students was conducted online with a questionnaire containing 25 questions according to the teaching principles with a standard degree of difficulty. In conclusion, this study stated that, the neural network technique was successful in enhancing e-learning systems and making them more dynamic, thereby allowing the learning environment to be tailored to student needs.

Furthermore, Mohamed and Faris [81], produced a converging mathematical model using an ANN as a type of supervised learning in order to efficiently predict the performance of students and reduce the danger of enrollment failing in an e-learning courses. For the experiment and the educational inquiry, the authors used a sample of dataset consisting of 1879 students observed during one semester using student information criteria. They divided the dataset into three samples: 70% of the data for training, 15% for validation and 15% of the data for the testing task. The results of the experiment indicated that the algorithm generates a good prediction students' performance with fewer outliers.

LSID-ANN, an approach based on artificial neural networks, was used by Bernard et al. [82], for identifying students learning styles based on the Felder-Silverman learning style model. LSID-ANN used four artificial neural networks with a 3-layer perceptron configuration. Each network was designed for one of the four learning style dimensions, namely active/reflective, sensing/intuitive, visual/verbal, and sequential/global. In addition, the authors evaluate the LSID-ANN approach by using real data from 127 computer science undergraduate students, including their behavior data in a university course and their results on the Index of Learning Styles (ILS) questionnaire. This study achieved a good accuracy level of learning style identification, thus helping teachers in giving good advice to their students and also increasing students' performance and learning satisfaction.

2.4.4 Genetic Algorithms

Genetic Algorithms (GAs) are an evolutionary computing method of artificial intelligence used to solve complex problems because they provide a large number of approximate alternative solutions for optimal solutions. The idea of genetic algorithms is based on the mechanism of natural selection and the natural gene system. The basic three operations of this algorithm are the selection of solutions based on their fitness of the population, re-production of genes, and mutation. This algorithm finds better solutions to a problem in order to help species to adapt better to their environments. The use of genetic algorithms is particularly useful with regard to understanding the needs and preferences of end-users and, as a result, it has become common in educational systems [83].

An e-learning system to provide a personalized online learning course for individual learners was developed in [84] based on the use of the stochastic convergence of genetic algorithms. This system addressed three aspects of e-learning systems: the difficulty of the concept, the time spent on each concept, and the learning performance of an individual student throughout the learning process with good learning performance. Moreover, Azough et al. [85] studied the problems facing the development of e-learning systems as an optimization problem and addressed them using genetic algorithms. They described an adaptive system used to generate adaptive pedagogical paths based on learners' profile and current basic learning objectives. A genetic algorithm was successfully applied by Han in [86] to evaluate a personalized learning system able to dynamically update the process of a course and the target user model during the learning process. As a result, the study provides a good framework with the ability to generate the personalized courses in an e-learning environment.

Table 2.2 Examples from previous studies in intelligent e-learning systems using AI techniques.

Author	System Name	Learning Field	AI technique	Purposes of AI technique	Learner's characteristics	Population	performance criteria
Almohammadi et al. (2015) [71]	IT2FLS	Microsoft word and PowerPoint	Type-2 fuzzy logic	Adaptive learning Content and recommendations	Students' engagement degree, knowledge and preference	Students at university	Comparison with other technique
Azough et al. (2010) [79]	--	--	Genetic algorithm	Generating adaptive pedagogical paths, update learners' profile	Learners' knowledge level and objective	--	Students performance , Experiments
Bernard et al. (2015) [82]	LSID-ANN	Computer science	Artificial Neural networks	Identify Learning Styles, Personalized content	Learning styles	undergraduate students	Experiments
Chrysafiadi and Virvou (2015) [1]	FuzKSD	Programming languages	Fuzzy cognitive maps (FCMs)	Individualized instruction	Learner's knowledge level, cognitive state and needs	Students at university	Experimental/ control group and questionnaires
Han (2014) [86]	--	--	Genetic algorithm	Personalized learning and update student model	Students' knowledge level, cognitive ability and goals	--	experiments

Table 2.2 Continued.

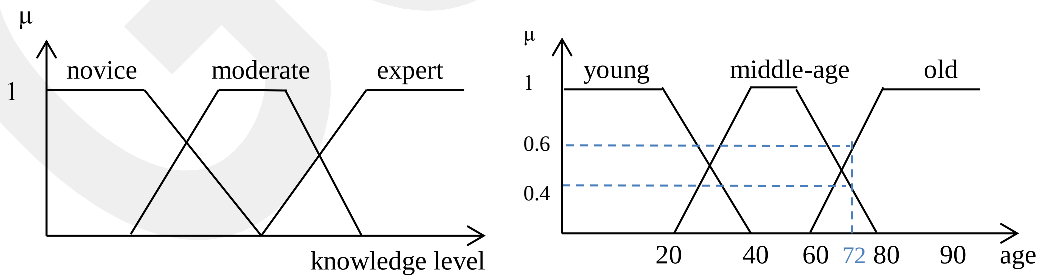
Author	System Name	Learning Field	AI technique	Purposes of AI technique	Learner's characteristics	Population	performance criteria
Hsieh et al. (2012) [68]	English article recommending system	English article	Fuzzy inference system	Personalized recommendation	Learner' preferences	Sophomore students at university	Pretest/posttest, experimental/control group and questionnaires
Myneni and Narayanan (2012) [57]	ViPS	physics	Bayesian network	Domain knowledge representation, Prediction adaptive learning content, and hint generation	Student's knowledge level	middle schools	Students performance Pretest/posttest experimental/ control group
Priya & Keerthy (2015) [70]	**FuzKPBE**	Programming languages	Fuzzy logic	Adaptive instructions updating the student's knowledge level	Student's knowledge level events and preferences	learners	Pretest and posttest
Weragama and Reye (2014) [78]	PHP ITS	Programming languages	Bayesian network	Determining and updating the student model	Student's knowledge level	Students at university	Students performance Pretest/posttest experimental/ control group
Yang (2009) [4]	ITSPL	C++ programming languages	Bayesian network	Adaptive learning content, update student model	Student's knowledge level and learning styles	Undergraduate students at university	Experiments and questionnaires

Table 2.2 illustrates that the purpose of applying AI techniques to ITSs is to adapt and personalize the learning content based on learners' characteristics. Moreover, the table shows that the level of knowledge and learning styles are the most interesting characteristics of students in building a student model. Most of the ITSs presented in Table 2.2 have been designed to teach students in the subject area of programming languages. It has been observed that there are numerous studies in the literature on Fuzzy Logic and the Bayesian model used in developing learning environments. However, while creating a student model, studies that use these two models together have not been encountered.

2.5 An Overview of Fuzzy Logic

Fuzzy logic method can be seen as an extension of the concept of the fuzzy set theory proposed by Lotfi Zadeh, in 1965 [87]. Fuzzy logic reflects how people think and attempts to model the human sense of words and decision making. It has an ability to handle uncertainty and vagueness caused by imprecise and incomplete data. As a result, it is leading to new and more human intelligent systems.

A fuzzy set which is a basic element of fuzzy logic theory uses sets of linguistic variables and predicates of multi valued logic to describe a characteristics, things, or facts. For instance, the terms "young", "middle-age", and "old" used to describe the person's age, and "novice", "moderate", and "expert" used to describe the student's knowledge level are shown in Figure 2.7.



(a) Fuzzy sets for student's knowledge level (b) Fuzzy sets for age

Figure 2.7 Fuzzy sets

Fuzzy logic variables may have a truth-value which ranges in degree between 0 (completely false) and 1 (completely true). That value declares the degree of membership or membership value (μ) in which the particular variable belongs to a fuzzy set. For example, according to the fuzzy set described in Figure1-b, if a person's age is 72 years old, then he/she is considered to be 40% in a middle age with a membership value is 0.4 and 60% old with a membership value of 0.6. Therefore, a fuzzy element can be a member of two adjacent fuzzy sets simultaneously but with different degrees of membership.

Generally, there are different types of membership functions that can be used for the fuzzification process, such as Trapezoidal, Triangular and Gaussian as shown in Figure 2.8. The type of membership function can be context-based and generally arbitrarily chosen according to user experience [88].

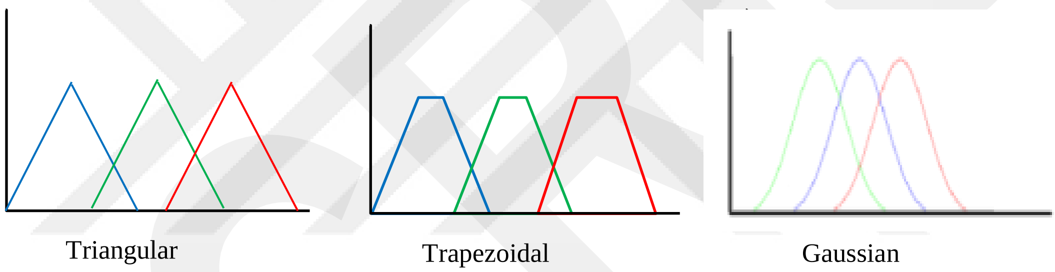


Figure 2.8 Types of Membership Functions.

2.5.1 Fuzzy Logic System

Fuzzy Logic System (FLS) maps a crisp input into a crisp output using the fuzzy sets theory. In general, an FLS consists of four stages (shown in Figure 2.9), namely the fuzzifier, rule base, inference engine and defuzzifier stages.

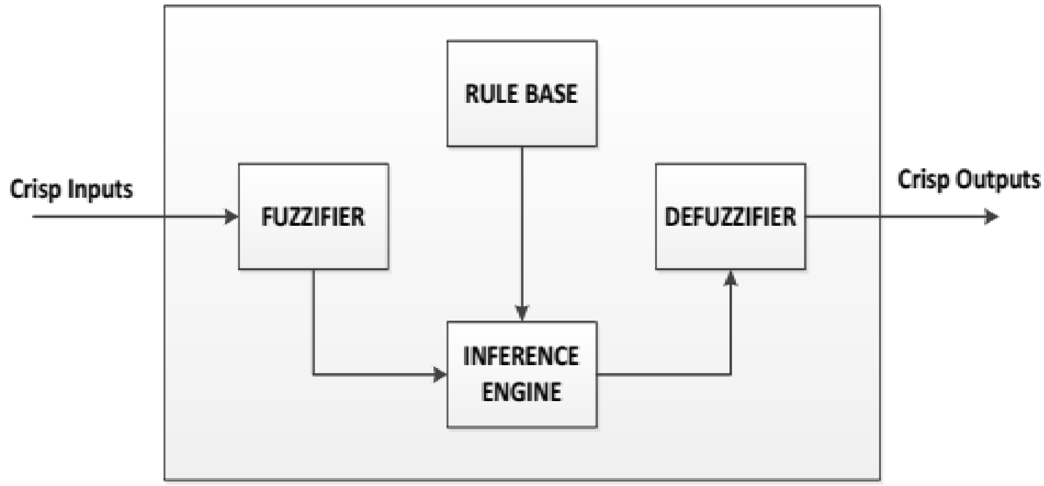


Figure 2.9 General architecture of fuzzy logic system.

- **Fuzzifier:**

The fuzzifier is responsible for converting classical data or crisp data into fuzzy data using the membership functions stored in the knowledge base. Fuzzification involves two processes, which are: derive the membership functions for input and output variables and represent them with linguistic variables. The exact type of the fuzzifier depends on the type of the application. For example, a triangular or trapezoidal fuzzifier is appropriate for the system requiring significant dynamic variation in a short period of time [89] and the Gaussian fuzzifier is used for systems that need very high control.

- **Rule base:**

Fuzzy rules can be considered to be the knowledge of an expert in any related field of application which is used to model the problem to be solved. A typical fuzzy rule can be described as a conditional statement in the (IF-THEN) structure. Generally, the fuzzy rule is shown in the form of (if x is A then y is B) where A and B are linguistic values and x and y are linguistic variables determined by their fuzzy sets. The first part of the rule is called the antecedent, and can consist of multiple parts with the operators AND or OR between them. The AND and OR operators are max and min, respectively.

The latter part is called the consequent, and can also include several outputs. For example, in an air conditioner system, the fuzzy rule can be derived as follows:

"IF the temperature is high, THEN the fan speed should be fast."

After evaluating the consequence of each rule, these results should really be combined to acquire one last result. This technique is known as inference.

- **Inference Engine:**

This phase of the fuzzy logic system is used to derive the fuzzy output by combining membership functions with the fuzzy rules in the knowledge base. Both the inputs and outputs of the inference engine are fuzzy values. The most widely used fuzzy inference method is Mamdani. This method was proposed by Ebrahim Mamdani in 1975 as a trial to manage a steam engine and boiler combination by compiling a group of linguistic control rules obtained from the experience of human operators [90]. The Mamdani fuzzy inference system is widely used in forecasting weather, product markets, health monitoring systems, temperature controllers, etc. It also has been used in students' performance evaluation systems [63], [91], [92].

- **Defuzzifier:**

The defuzzifier is responsible for translating the fuzzy output from the inference engine to a single number (crisp output) using membership functions analogous to those utilized by the fuzzifier. This process called the defuzzification, which is the final step in a FLS. Many defuzzification techniques have been developed, and the most common one is the Center of Gravity method (CoG) [89]. The CoG method also known as the centroid method that provides a crisp value based on the center of gravity of a fuzzy set. The entire area of the membership function distribution is used to represent the combined control action is split into a number of sub-areas. The area and the centroid of every sub-area is calculated and then the summation of all these sub-areas is taken to locate the defuzzified value for a discrete fuzzy set. Mathematically, the CoG can be expressed as the formula given below:

$$\mathrm{CoG} = \frac{\sum_{i=a}^{b} \mu_A(x_i)x_i}{\sum_{i=a}^{b} \mu_A(x_i)} \tag{2.1}$$

where $\mu_A(xi)$ is a membership value in the membership function, xi is a sample element and b represents the number of samples in the fuzzy set A. A graphic representation of the CoG method is shown below in Figure 2.10.

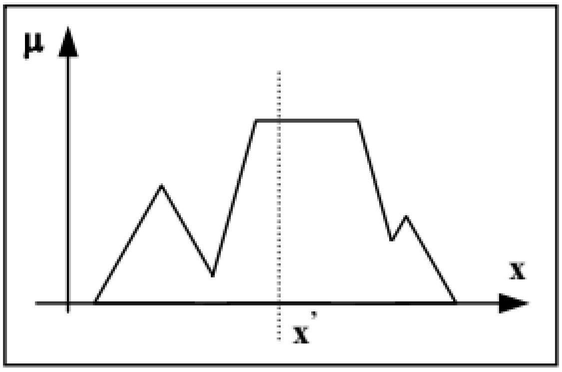


Figure 2.10 Graphic representation of the CoG method

Additionally, the Center of Sums Method (COS) and the Mean of Maxima (MOM) defuzzifiers are also commonly used.

With this basis, the fuzzy logic method allows mathematical computation and programming similar to human thinking and reasoning. The fuzzy logic method is the modern approach used to generate the wide areas of mapping given information from an input to an output.

2.6 An Overview of Bayesian Networks

Bayesian Network (BN) is a type of probabilistic graphical model that combines principles from graph theory, probability theory and statistics. It has an ability to deal with the problem of how to reason under uncertainty. The particular issues a BN deals with are how exactly to represent uncertain beliefs, and given those uncertain beliefs, how exactly to update them when evidence arrives or other beliefs change [93]. Hua Shan in his research [18] gave the answer to the question "*Why do we need uncertainty reasoning?*", which lies in the fact that real world problems usually involve uncertainty. Uncertainty is an essential and inevitable feature of everyday life. People are constantly asked to make decisions based on incomplete observations, inconsistent or conflicting evidence, and inaccurate knowledge of causal relationships. Probability theory can provide a firm basis for managing uncertain knowledge by representing it as a joint probability distribution. Before going into exactly what Bayesian networks are, the next section presents the basics of probability theory.

2.6.1 Probability Basics

Bayesian probability theory deals with events and the probabilities of these events. For instance, if A is an event, then the probability of this event is indicated by P(A), a number with a real value in the interval [0,1]. The basic axioms of probability theory [94] are:

- P(A) = 1 if and only if A is definitely true.
- P(A) = 0 if and only if A is definitely false.
- If A and B are mutual events, then $P(A \cup B) = P(A) + P(B)$.

The conditional probability is a basic concept, in which the statement takes the following form:

The probability of the event A = a given that the event B = b is r, this conditional probability can be written as P(A = a | B = b) = r.

The table that specifies the conditional probabilities for each possible combination of values that events A and B can take is called the conditional probability distribution and is denoted by P (A | B).

Conditional probabilities are important for building Bayesian networks. However, Bayesian networks are also built to facilitate the calculation of conditional probabilities, namely the conditional probabilities for variables of interest given the data (also called evidence) at hand. The basic rule for defining the probability of a conjunction of events is the product rule:

$$P(A \text{ and } B) = P(A \mid B)P(B) = P(B \mid A)P(A) \tag{2.2}$$

This equation illustrates how to combine conditional probabilities for individual variables to define joint probabilities for sets of variables.

Frequently, the joint probability P(A and B) is written as P(A, B). In the general case, a joint probability distribution over n variables can be defined repeatedly using the product rule as illustrated in Equation 2.3:

$$P(X1, X2,\ldots, Xn) = P(X1 \mid X2,\ldots, Xn)P(X2,\ldots, Xn) \tag{2.3}$$

By rearrangement, Equation (2.2) can easily obtain Equation (2.4). This equation is Bayes' theorem which is used for reasoning about an uncertain hypothesis A given evidence B.

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)} \tag{2.4}$$

where P(A|B) is the posterior probability of A, P(A) is the prior probability of A, and P(B|A) is the likelihood of A.

2.6.2 Bayesian Networks Basics

Bayesian networks are a probabilistic graphical and reasoning model that perform uncertain inference based-on probability theory. A Bayesian network is a Directed Acyclic Graph (DAG), in which nodes represent a set of variables, X = X1,..Xi,...Xn, from a particular domain and arcs (or links), Xi → Xj, represents direct probabilistic dependencies between these variables. Figure 2.11 shows a DAG of a Bayesian network in a set of variables {A, B, C and D}. In the graph, all the edges are directed and there are no cycles (i.e., no way to start from any node and travel across a set of these edges in the right direction then back to the same node) [95].

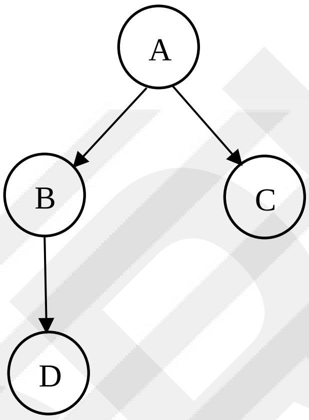


Figure 2.11 A DAG representing a Bayesian Network

For each node (variable) in the network there is a probability distribution function which is defined depending on the edges leading to the variable. This function can be continuous or discrete. For example, in Figure 2.11, the probability distribution for variable C depends only on the value of variable A, where the variable A is a parent set of variable C in the DAG. The probability of C given A is denoted as P(C | A). To fully specify the network, additionally to construct it, the following probabilities must be defined:

- **Prior probabilities for root nodes**: This probability represents the a priori probability of every value of the corresponding variables.

- **Conditional probabilities:** These represent the probability of every node given their parents, which quantify the probabilistic dependencies between the corresponding variables.

The construction of a Bayesian network can be manual, data-driven, or by combining the manual and data-driven process. Manual construction of Bayesian networks require a great deal of skill and creativity along with good communication with problem domain experts. Once the BN structure is determined, the next step is to identify the relationships between the connected nodes, which is done by determining the Conditional Probability Distribution (CPD) for every node. CPDs for the entire network can be specified by domain experts [18].

Moreover, the inference in Bayesian networks is the process of finding a new information when observing a set of input values (evidence), also called reasoning, probability propagation or belief updating. It derives the posterior probability using Bayes' theorem (Equation 2.4) for a set of queries about a target of interest and the target value with the highest probability known as prediction.

2.7 Usability Issues

The interface model, which is one of the main components of ITS structure, it has a very significant function. When an ITS has good tutoring, knowledge, and student models, but the interface model is not good, the ITS will not be useful because the interface model is the door of the entire system and has the ability to attract student attention. To develop a good and strong interface model, it is necessary to take into account the usability issues of the user's computer interface, since this model is responsible for communication between the user and the other models of the system [96].

Usability is an important quality factor for any system used to measure system performance. In the context of ITSs, usability means the "ease of use", which reflects the satisfaction of students during the interaction experience with the e-learning system. Therefore, the system that is not easy for student to use can be considered a poor quality system [16]. A high level of usability when interacting with the e-learning system is expected to result in more satisfied, engaged and motivated students that will be reflection of their educational achievement [20].

According to Nielsen [97], the usability of software systems includes numerous components and is traditionally related to the following five attributes:

- **Learnability:** The system must be easy to understand so that users can quickly and easily handle it.
- **Efficiency:** The system must be efficient to use so that a higher level of productivity is achievable.
- **Memorability:** The system must be easy to remember so that user can return to the system after a certain period of not having used it without having to relearn everything.
- **Errors:** The system must include a low error rate to ensure that user make a few errors as possible while using the system.
- **Satisfaction:** The system must be enjoyable to use to ensure user satisfaction when using it; i.e., they must like using it.

Furthermore, Dix et al. [98] classified usability principles into three categories to use for designing an interactive system namely learnability, flexibility, and robustness.

Intelligent tutoring systems are similar to other software systems that are developed to be utilized by users. Although the current ITSs are strong in the areas of teaching and learning strategies, there is little evidence that they have strong usability foundations [21]. Recently, researchers have been focused more towards the educational aspects of ITS and while mostly ignoring usability. The question here, is whether applying usability testing and commitment to the principles of usability can indicate the performance of ITSs. Commitment to these features should improve ITSs and help to apply them on a larger scale [21].

Chrysafiadi and Virvou [99] stated that the usability of ITSs include factors from the fields of Human Computer Interactions (HCI), pedagogy and psychology. They also stated that the user interface model in ITSs should comply with the following usability factors:

- **Personalizatio**n: The ITS user interface must be adapted to each individual student dynamically according to her/ his needs.
- **Unobtrusive:** The interface must be clear and natural. Font types, colours and sizes of texts have to be selected carefully in order for the interface to be clear and easily readable.
- **Ubiquitous:** Users must interact properly with the system according to their skills. They should be able to explore interfaces quickly with minimal mental fatigue.
- **Help and Safety:** The system should prevent users from making errors and also provide them with many recovery methods. Moreover, effective assistance must be provided.

Granić and Glavinić [100] concluded that, improving the usability of ITSs, which are emulators of human teachers in the learning and teaching process, is perhaps the most significant goal of the research in the area of intelligent e-learning system. Because users can interpret these systems as user interfaces for some knowledge in a given domain, their degree of effectiveness and efficiency must inevitably depend on the usable system design. The System Usability Scale (SUS) [101] is a widely used questionnaire to test the usability of a system interface based on the perspective of users. The SUS provides a single score on an easy to understand scale to measure the overall usability of a system. The score ranges between 0 and 100 with higher scores indicating better usability. A satisfactory system should score between 70 and 80 [102].

2.8 Summary

This chapter presented the main concept of the present study, Intelligent Tutoring System (ITS). As the study was conducted in e-learning environments, it has reviewed and explained the concept of e-learning and the advantages of e-learning systems.

After that, this chapter has introduced the role of Artificial Intelligence in e-learning systems. Following by a description of the main components of ITS and their respective functions. Further, this chapter reviewed a number of studies linked to how artificial intelligence techniques are used in designing ITSs. It presented the advantages of these techniques and their significance in enhancing learning. At the end of this chapter, the concept of usability and usability issues of e-learning systems was discussed.

CHAPTER 3

METHODOLOGY

As explained in the previous chapters, the present study aims to develop an ITS using fuzzy logic and Bayesian networks techniques, taking into consideration the implementation of adaptation issues based on the knowledge level of a student including the investigation of usability issues and its evaluation. This chapter explains the methodology used to achieve the goals of this study. In further detail, it starts by describing the research design, followed by explaining the population and sampling, data collection and data analysis tools. Finally, the summary of the chapter is provided.

3.1 Research Design

The research design is the plan and structure used to combine the different components of the research study in a reasonably logical manner conceived as to handle the research problem efficiently. It is also referred to as a blueprint that provides the researcher with a detailed plan for the collection and analysis of the required data [103].

This research study follows the research process shown in Figure 3.1 to satisfy its objectives. In the first phase, the theoretical studies related to this research are reviewed in Chapter 2, such as adaptive e-learning, intelligent tutoring systems, and artificial intelligence techniques, especially fuzzy logic and Bayesian networks, which have been used to develop ITSs. Furthermore, the usability of adaptive e-learning systems is reviewed. Information on previous works related to the research topic was obtained from different sources such as books, conference papers, journals, etc. Afterward, the research problem and research goals and objectives were identified.

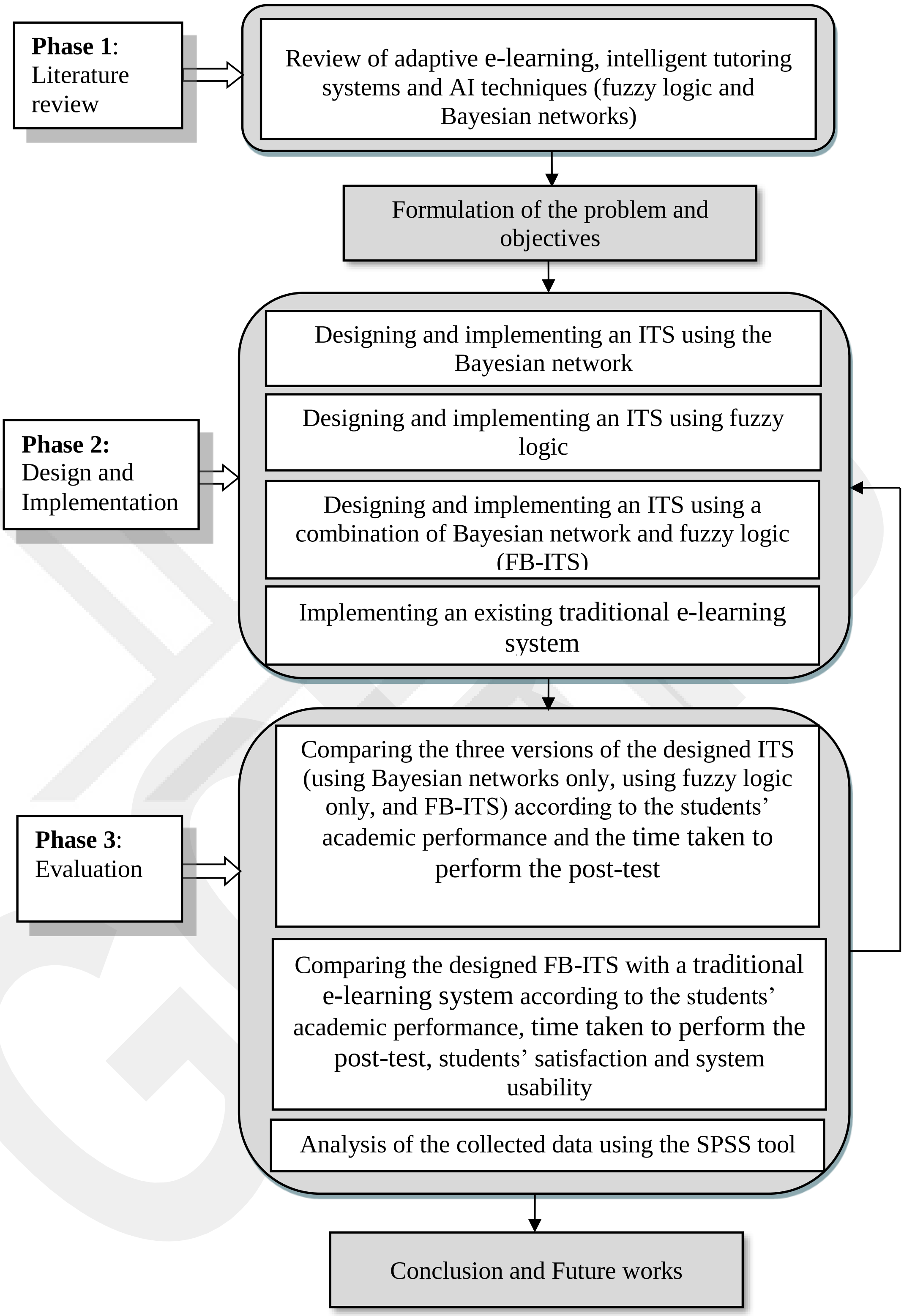


Figure 3.1 Research design process

In the second phase, the three versions of ITS were designed and implemented in the Microsoft Visual Studio development environment using ASP.net and Vb.net. The first version was created using the Bayesian network only according to [6], while the second version was created using fuzzy logic only according to [13], and the third version was created using a combination of the Bayesian network and fuzzy logic, named FB-ITS. The architecture of the systems, discussed in Chapter 4, is follows the main architecture of ITS, which includes the student model, domain model, adaptation module and user interface. Furthermore, the architecture is based on a client/server architecture of software systems.

In the third phase and after designing and implementing the proposed ITS environment, the pilot study was conducted on a small group of students in order to test the developed system, assess its functionality and check data collection reliability. The results and feedback of the students were then taken into consideration to make the necessary corrections. The pilot study is discussed in more detail in Chapter 5. Furthermore, the experiment was conducted over a period of six weeks to validate the proposed system under practical use including all its components. In addition, the performance and effectiveness of the system was evaluated by comparing it with a traditional e-learning system where they have the same lecture notes. Furthermore, the experiment was used to evaluate the students' satisfaction and system usability. Further details about the experiment and results are found in Chapter 5. Finally, the research finding and recommendations are concluded in the final chapter.

3.2 Population and Sample

The participants of this study were undergraduate students attending the Introduction to Computers and Information Systems course (CMPE 105) at Atilim University in the 2019-2020 academic year. This course was selected by considering the fact that it has been incorporated into the curriculum of most undergraduate disciplines, so it is expected that more participants will be able to contribute to the evaluation of the proposed system. The students who participated in this course were from various departments, including Arts and Sciences, Management and Civil Aviation.

The study was conducted on a total of 120 students in order to evaluate FB-ITS. Because most of the participants are at the basic level in Excel skill according to the result of the pre-survey, the sample of participants was firstly divided randomly into two groups. The first group (Group A), which is an experimental group, contained 60 students and the second group (Group B), which is a control group, contained 60 students.

The sample distribution of Group A contained 60 students was presented according to gender, prior knowledge in excel, department and Grade Point Average (GPA), as given below in Table 3.1, Table 3.2, Table 3.3 and Table 3.4, respectively.

Table 3.1 Distribution of Group A according to the gender.

Gender	No. of participants	Average
Male	28	47%
Female	32	53%

Table 3.2 Distribution of group A according to prior knowledge in Excel.

Prior knowledge in Excel	No. of participants	Average
Basic	34	57%
Average	20	33%
High	6	10%

Table 3.3 Distribution of Group A according to department.

Department	No. of participants	Average
Civil Aviation	9	15%
Management	24	40%
Arts and Sciences	27	45%

Table 3.4 Distribution of Group A according to GPA.

GPA	No. of participants	Average
0 < GPA <= 2	13	22%
2 < GPA <= 3	29	48%
3 < GPA <= 4	18	30%

Table 3.1 above shows that the sample of the Group A during the study consisted of 47% males and 53% females. As shown in Table 3.2, the level of knowledge about Excel for most of the participating students involved in this study is the basic level, accounting for 57% of the sample. Moreover, this table shows that, 33% were at an average level and only 10% of the students were at a high level. Table 3.3 shows that about 45% of students were from the Arts and Sciences department, 40% from the Management department and 15% from the Civil Aviation department. Table 3.4 presents the distribution of the participating students according to their GPA, with 33% of the students falling between 0 and 2 and 43% had GPAs between 2 and 3 and the remaining students, about 24% were in the range of 3 to 4.

The sample of students in the Group A was separated into three major subgroups, namely A1 (control group 1), A2 (control group 2), and A3 (experimental group). Each group contains 20 participants.

The sample distribution of the Group B which contained 60 students was presented according to gender, prior knowledge in Excel, department and Grade Point Average (GPA), as given below in Table 3.5, Table 3.6, Table 3.7 and Table 3.8, respectively.

Table 3.5 Distribution of Group B according to the gender.

Gender	**No. of participants**	**Average**
Male	27	45%
Female	33	55%

Table 3.6 Distribution of Group B according to prior knowledge in Excel.

Prior knowledge in Excel	**No. of participants**	**Average**
Basic	41	68%
Average	16	27%
High	3	5%

Table 3.7 Distribution of Group B according to department.

Department	**No. of participants**	**Average**
Civil Aviation	7	12%
Management	34	57%
Arts and Sciences	19	32%

Table 3.8 Distribution of Group B according to GPA.

GPA	No. of participants	Average
0 < GPA <=2	14	23%
2 < GPA <=3	35	58%
3 < GPA <=4	11	18%

Table 3.5 illustrated above shows that the sample of Group A during the study consisted of 45% males and 55% females. As shown in Table 3.6, the level of knowledge about Excel for most of the students involved in this study is the basic level, accounting for 68% of the sample. Moreover, this table shows that 27% were at an average level and only 5% of the students were at a high level. Table 3.7 shows that about 32% of students were in the Arts and Sciences department, 57% in the Management department and 12% in the Civil Aviation department. Table 3.8 presents the distribution of the participating students according to their GPA, where 23% of the students fell between 0 and 2 and 58% fell between 2 and 3 and the remaining, about 18%, fell between 3 and 4.

3.3 Data Collection Tools

The data is obtained and collected from the questionnaires and tests that have been used to measure the experimental variables which include:

Students' Academic Performance: to measure the extent to which the students gained knowledge in Excel. The academic performance of the students was measured by tests including a pre-test and a post-test. Every test contained 22 questions from multiple options, each with four answer options. The pre-test and the post-test were similar except for their sequence. These tests were carefully designed and reviewed by experts who checked the expression of each question and its related multiple-choice answers as well as the content validity. A sample of the test questions is seen in Appendix A.

Students completed the pre-test before interacting with the FB-ITS to determine their prior knowledge level in Excel. After completing the course, a post-test was given to the students to determine what they had learned.

Students Satisfaction: measured by a reliable and validated e-learner satisfaction (ELS) tool [104], which is a questionnaire that aims to measure different aspects of the e-learning system, such as the learner interface, course content, learning community, and personalization. This questionnaire consists of 17 questions with 5-point Likert scales ranging from “Strongly disagree” (1) to “Strongly agree” (5). This study used only 12 questions which were related to the implemented systems as presented in Appendix B. The student satisfaction questionnaire consisted of three components: “Personalization”, “Learning Content”, and “System Interface”, where each factor would cover four items.

System Usability: A quick and reliable System Usability Scale (SUS) tool [101] was used to measure the usability of the system from the perspective of users. This tool is widely used to test system usability in both academia and industry [19]. The SUS tool is a questionnaire consisting of 10 questions with 5 point Likert scales ranging from “Strongly disagree” (1) to “Strongly agree” (5), as presented in Appendix C.

In further detail, the data were collected throughout three phases. In the first phase, a pre-survey that was prepared based on experts’ opinion was provided to participants in order to collect preliminary information prior to enrolment into the systems, such as gender, department, GPA, and their experience with Excel. In the second phase, a pre-test was presented to the participating students before they started learning to use the systems. In the last phase, two types of questionnaire and a post-test were submitted to the participants after completing the course material. These questionnaires related to the students’ satisfaction with the systems and system usability. The post-test was provided to students for the purpose of measuring their academic performance. In the developed ITS, a total of 11 topics were included according to the syllabus of the Introduction to Computers and Information Systems course (CMPE 105) at Atilim University, which are the same contents as the traditional e-learning system.

3.4 Data Analysis

The collected data from the study were analysed using SPSS (Statistical Package for Social Sciences) software package. The analysis is based on descriptive statistics, the t-test, One-way ANOVA (Analysis of Variance), and ANCOVA (Analysis of Covariance). In testing every hypothesis of the research, a 0.05 significance level that was based on and the differences which are significant at 0.01 were also highlighted. The results of the analysis are presented in tables.

3.5 Summary

This chapter has described the methodology of this study including the research design, the population and sample, the data collection tools and its reliability, and finally it discussed the methods of analysing the collected data of this study.

CHAPTER 4

SYSTEM DESIGN AND IMPLEMENTATION

This chapter starts with identifying the major objectives of the presented FB-ITS. The chapter also describes the architecture of FB-ITS. It explains each component of the proposed systems in detail. Moreover, this chapter discusses the general features of FB-ITS with a presentation of the implementation details. Finally, the summary of the chapter is provided.

The primary goal of FB-ITS is to provide adaptivity in order to support students during the learning process. Therefore, it has the ability to assess a student's knowledge level and identify the needs of an individual student. This was achieved by using AI techniques including fuzzy logic and Bayesian networks, which deal with uncertainty in the learning process and student assessment. FB-ITS was developed to teach Microsoft Excel, which covers a range of subjects taught in the Introduction to Computers and Information Systems (CMPE105) course at Atilim University.

The major objectives of developing FB-ITS are to:

- identify and update the Knowledge Level (KL) of a student;
- provide adaptation of the course material in which topics should be delivered, which topics need revision and which topics have been learned;
- allow each individual student to finish the e-learning course at his/her own pace; and
- provide feedback and hints for an individual student.

4.1 The architecture of FB-ITS

The main architecture of the FB-ITS is presented in Figure 4.1. It is based on the classical architecture of intelligent tutoring systems. The components of FB-ITS are the student model, knowledge domain model, user interface and the adaptation model (this model corresponds with the tutoring component in the general architecture of an ITS discussed in Chapter 2).

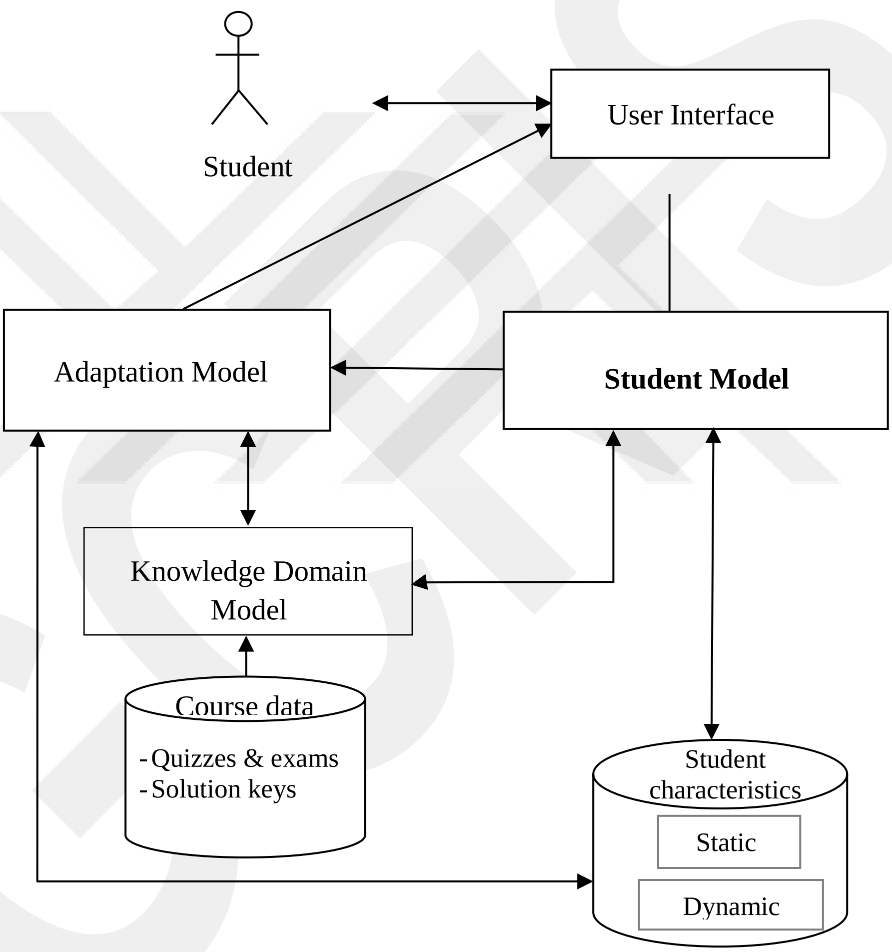


Figure 4.1 Main architecture of FB-ITS

- **Student model:** It is responsible for tracking the changes on a student's knowledge and identifying which parts of the knowledge domain the student knows and has learned.

- **Knowledge domain model:** It is responsible for storing course materials related to Excel, including test questions, quizzes, and solution keys to each question.
- **Adaptation model:** It is responsible for the adaptation of course material and controls the tutoring process and gives appropriate feedback.
- **Interface model:** It is responsible for communication between students and other components of the system. It must be usable and adaptable to every individual student according to her/his knowledge. Furthermore, the user interface is responsible for displaying the course material.

Further details about each component of the FB-ITS are explained in the following subsections.

Three versions of the ITS were developed and implemented in this research based on the architecture presented in Figure 4.1. These versions have the same components except for the student model. The student model in the first version was created using the Bayesian network only according to the Bayesian student model proposed by Butz et al. [6], while in the second version, it is created using fuzzy logic only according to study of Chrysafiadi and Virvou [13], and in the third version the student model is created using a combination of the Bayesian network and fuzzy logic named FB-ITS to meet the objectives of this thesis. The purpose of creating these three versions is to answer the research questions and demonstrate that combining Bayesian network and fuzzy logic technology increase the performance of the ITS compared to using fuzzy logic and Bayesian networks separately.

The three versions are integrated into the same environment where the student can select one of them, as shown in Figure 4.2 below.

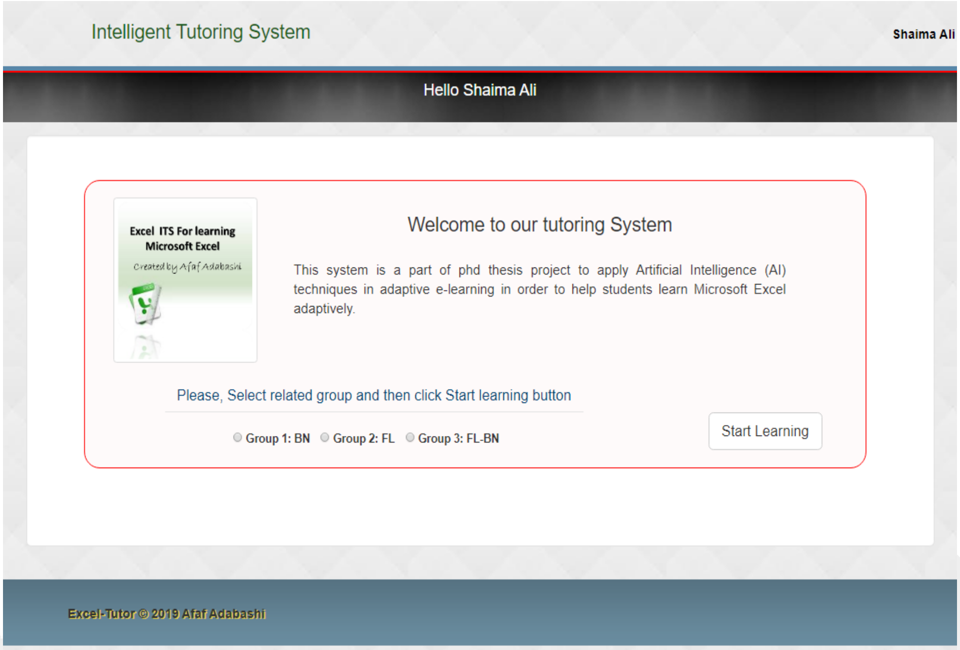


Figure 4.2 The welcome page in the ITS environment

The importance of the developed FB-ITS is that it is a web-based system which can be used anywhere at any time. This system has been tested in Google Chrome, Mozilla Firefox, Microsoft Edge and Internet Explorer browsers. It therefore allows a multitude of learners to access the FB-ITS from different platforms.

This ITS was implemented in the Microsoft Visual Studio 2015 development environment using ASP.net, an open-source server-side web application framework designed for developing dynamic web applications. The functionality of the system was written using VB.net, which is a multi-paradigm, object-oriented programming language, implemented on the .NET Framework.

Since an FB-ITS is a web-based system, there should be some mechanism for representing, storing and retrieving data related to the components of the system (the knowledge domain model and the student model) and any data related to student-system interaction in order to provide adaptation. Microsoft SQL Server 2014 was used to create and manage the database. Microsoft SQL Server is compatible with ASP.net and they interact with each other properly.

4.2 Knowledge Domain Model

The knowledge domain model in the FB-ITS contains the repository of course materials related to Excel, including test questions, quizzes, and solution keys for each question. All questions and related solution keys are separated from the tutoring system, which are stored in the database. This separation allows developers to create or modify questions without modifying the system itself. The tests and quizzes are displayed when the system attempts to determine the student's knowledge level and determine whether or not the student has understood a particular topic. Each topic corresponds to one node in the Bayesian network as seen in Figure 4.9.

Table 4.1 List of Excel Course Topics

Topic name	**Topic Description**
Working with Excel Environment	Introduction to excel, Components of Excel, Ribbon and Quick Access toolbar.
Creating a Workbook	Creating a new workbook, opening an existing workbook and saving a workbook.
Worksheet Basics	Rename Worksheets, Insert new worksheet, Copy and Delete a worksheet
Cells Basics	What is a Cell? , Insert content into a Cell, Delete a cell, Copy and paste cell content.
Columns and Rows	Modifying Columns and Rows, Insert and Delete Columns and Rows.
Wrapping text and merging cells	Wrapping text and merging cells.
Creating Tables	Creating a table, Formatting and Modifying a table.
Sorting and Filtering Data	Sorting and Filtering Data.
Create an Excel Chart	Chart elements, Types of charts, and Creating a chart.
Simple Formulas	Creating simple formulas and Creating formula using cell references.
Basic Functions	Creating a basic function and Function Library.

The goal of the application of e-training provided is to teach students the principles of Excel. At the beginning of the course, students learn how to work with the environment of Excel, such as understanding the Ribbon and Quick Access toolbar. T They also learn how to create workbooks, open them and save them. Then students continue to learn all the learning material until they reach the final test. Table 4.1 presents and describes each of the Excel topics that constitute the learning material used in this study. Experts of the knowledge domain have specified all the lecture notes and test questions according to the syllabus of the Introduction to Computers and Information Systems course (CMPE 105) at Atilim University. The lecture notes of the Excel course are provided by the system in various formats, particularly in HTML files including text, images, and videos.

The domain model is represented as a hierarchical structure as illustrated in Figure 4.3, which associated with the Bayesian networks in the student model. These topics of the learning material are presented to the students in sequence. In particular, topic 1 is presented first, topic 2 follows, then the content of topic 3 or topic 4 is delivered, etc.

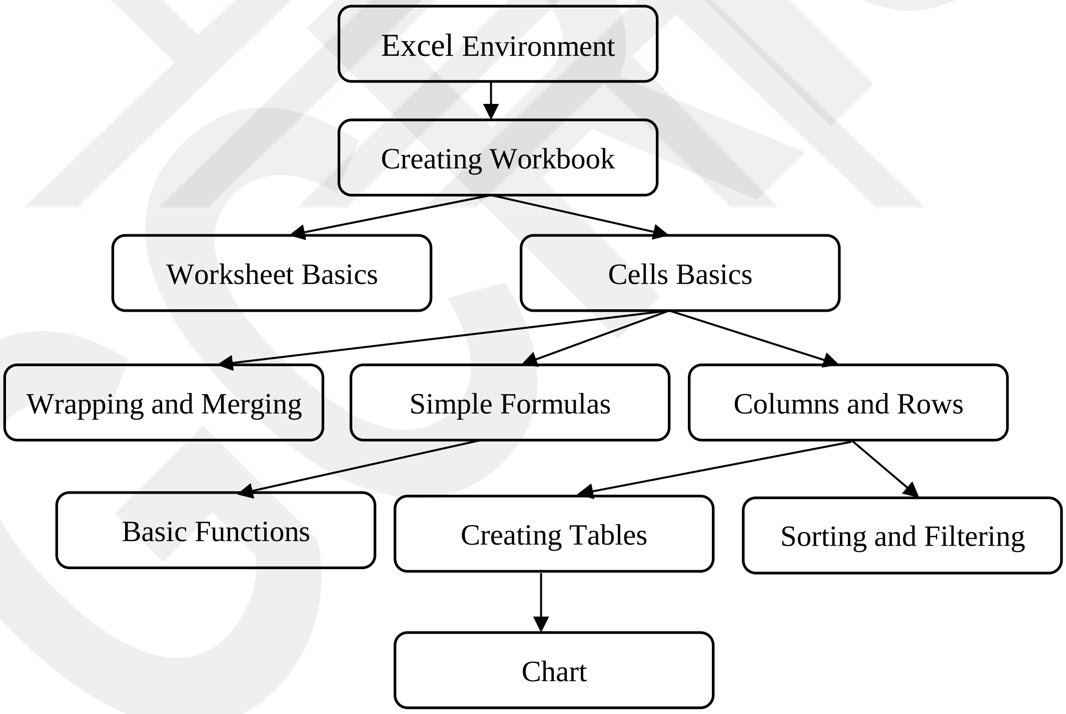


Figure 4.3 Structure of domain topics

4.3 Student Model

Student modeling is one of the main factors that impact automatic tutoring systems in making educational decisions and assessments, considering that it is the procedure of gathering information from the student in order to infer their state of knowledge and to represent that knowledge so as to be useful and accessible to the ITS for the provision of adaptation [44]. A student model allows an e-learning system to understand and identify student needs. By preserving a model for each student, an ITS can effectively personalize its content and utilize available resources accordingly in addition to achieving an accurate student diagnosis and predict a student's needs. To support the student model, the database contains data related to each student including student personal information, educational progress and online test results.

In FB-ITS, the student model stores both the static and the dynamic characteristics of each learner, as shown in Figure 4.4. Static characteristics include student name, username, gender, department and password. This information is set by students during the registration session and this information remains unchanged except for the password that the student can change from her/his profile. The dynamic characteristics which include the student's knowledge level, is updated during the learning process depending on the student's performance on learning the Excel topics.

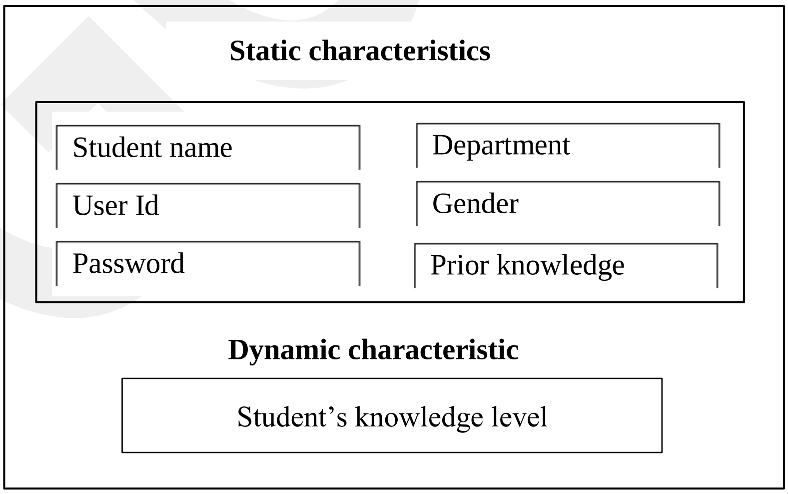


Figure 4.4 Student model characteristics

The student model in FB-ITS is a hybrid model that brings together features of fuzzy logic and the Bayesian network. The reason for using the hybrid method is the fact that the student model needs to combine various aspects of students' characteristics in order to carry out the personalization efficiently [2]. The student model is responsible for tracking changes students' knowledge and identifying which parts of knowledge topic a student knows and has learned, and which parts are still not learned. It consists of two layers as shown below in Figure 4.5.

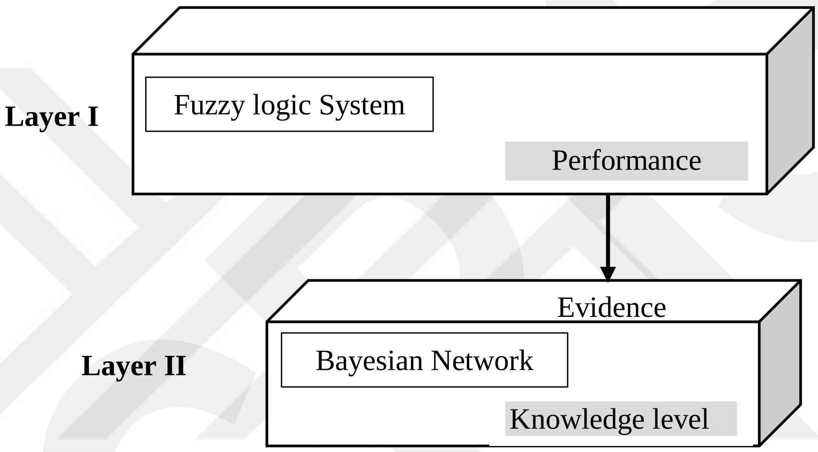


Figure 4.5 Student model of FB-ITS

The first layer includes a fuzzy logic system which determines the performance of a student based on the student's prior and present knowledge. The second layer includes Bayesian networks, which represent the student's knowledge level (KL) of the domain topics. The second layer receives information from the fuzzy logic system and then determines the knowledge level of the student. Further details about the fuzzy logic system and Bayesian network is presented in Section 4.2 and Section 4.3, respectively.

4.3.1 Fuzzy Logic in FB-ITS

In the FB-ITS, the fuzzy logic system is used to determine the student's performance in a particular topic taking into account two factors, the pre-test grade and topic test grade. These tests are multiple-choice questions used as variables for gathering evidence to update the Bayesian network.

In the FLS used in this study as a part of the student model (as shown in Figure 4.6), two variables were utilized for the inputs "Pretest-Grade" and "TopicTest-Grade", and one variable which is the student' performance in a particular topic of the course material was utilized for the output "Performance". A correlating model of the input and output variables is achieved by the established fuzzy rules created by experts. The input and output variables are defined as thus:

- **Pretest-Grade:** The score of the pre-test given to the student to measure her/his prior knowledge in a particular domain.
- **TopicTest-Grade:** the score of the test given to the student after completing the study of each topic of course material.
- **Performance:** The degree of success in a domain topic.

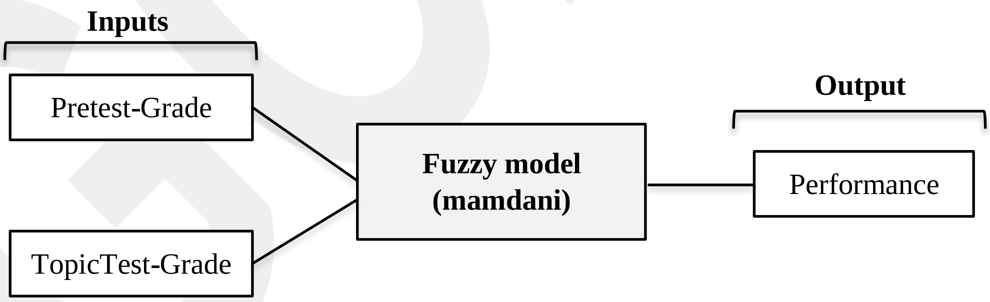


Figure 4.6 Fuzzy logic system in FB-ITS

This research followed the main steps of the Fuzzy Logic System (FLS) in order to build the first layer of the student model as follows:

Step 1: Defining the fuzzy sets:

For the input variables, three fuzzy sets are defined for each input variable to describe the student test grade as it was calculated out of 100 points for both the pre-test and topic test as thus:

- **Poo**r**:** The degree of success in the domain topic ranges from 0% to 50%.
- **Good:** The degree of success in the domain topic ranges from 40% to 80%.
- **Excellent:** The degree of success in the domain topic ranges from 70% to 100%.

Moreover, two fuzzy sets are defined for the output variable to describe the student's performance of a particular topic of the learning material as follows:

- **Low**: The level of performance in the domain topic ranging from 0% to 80%.
- **High**: The level of performance in the domain topic ranging from 70% to 100%.

Step 2: Defining membership functions:

Each input variable determines three intervals of membership functions. The membership functions of the test grade consist of poor, good and excellent as shown in Figure 4.7. An input and output variable is placed in a scale ranging from 0 to 100. Figure 4.8 shows the membership functions of the output. This membership function includes the low and high of a student's performance in a particular topic.

- Input variables: TopicTest-Grade and Pretest-Grade

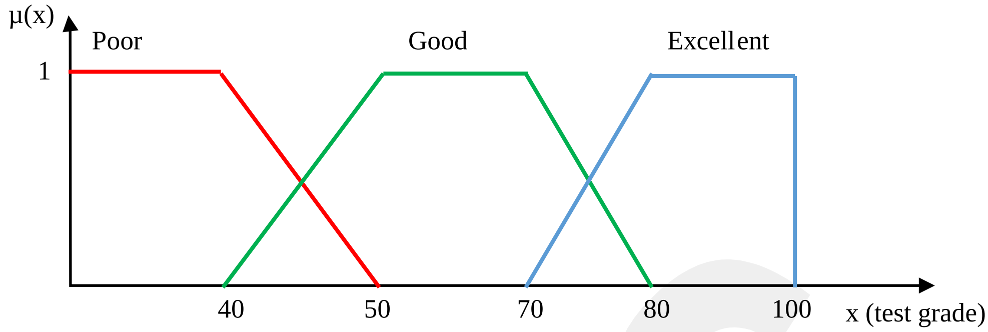


Figure 4.7 Membership functions of input variables

$$\mu_{Poor}(x) = \begin{cases} 1 & x \leq 40 \\ 1 - \frac{x-40}{10} & 40 < x < 50 \\ 0 & x \geq 50 \end{cases} \tag{4.1}$$

$$\mu_{Good}(x) = \begin{cases} \frac{x-40}{10} & 40 < x < 50 \\ 1 & 50 \leq x \leq 70 \\ 1 - \frac{x-70}{10} & 70 < x < 80 \\ 0 & x \leq 40 \text{ or } x \geq 80 \end{cases} \tag{4.2}$$

$$\mu_{Excellent}(x) = \begin{cases} \frac{x-70}{10} & 70 < x < 80 \\ 1 & 80 \leq x \leq 100 \\ 0 & x > 100 \end{cases} \tag{4.3}$$

- Output variable: a student’s performance in a particular topic

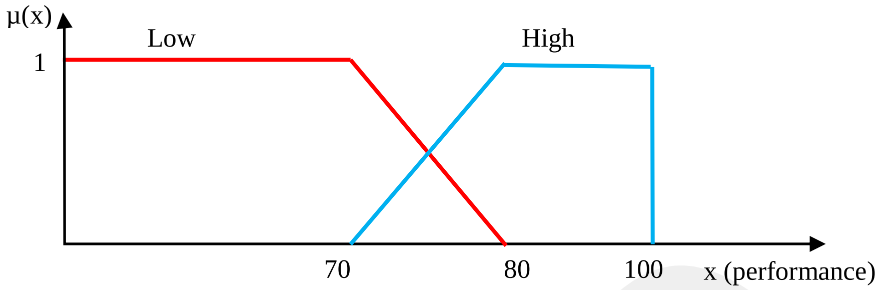


Figure 4.8 Membership functions of the output variable

$$\mu_{Low}(x) = \begin{cases} 1 & x \leq 70 \\ 1 - \frac{x-40}{10} & 70 < x < 80 \\ 0 & x \geq 80 \end{cases} \tag{4.4}$$

$$\mu_{High}(x) = \begin{cases} \frac{x-70}{10} & 70 < x < 80 \\ 1 & 80 \leq x \leq 100 \\ 0 & x > 100 \end{cases} \tag{4.5}$$

Step 3: Applying fuzzy rules:

In this study, the fuzzy rules are provided by experts. All the rules are configured with two inputs variables (pretest-Grade and TopicTest-Grade) and one output variable (Performance). Given below are the sets of rules using IF-THEN logic:

- If (pretest-Grade is poor) and (TopicTest-Grade is poor) then Performance is Low
- If (pretest-Grade is poor) and (TopicTest-Grade is good) then Performance is Low
- If (pretest-Grade is poor) and (TopicTest-Grade is excellent) then Performance is High

- If (pretest-Grade is good) and (TopicTest-Grade is poor) then Performance is Low
- If (pretest-Grade is good) and (TopicTest-Grade is good) then Performance is High
- If (pretest-Grade is good) and (TopicTest-Grade is excellent) then Performance is High
- If (pretest-Grade is excellent) and (TopicTest-Grade is poor) then Performance is Low
- If (pretest-Grade is excellent) and (TopicTest-Grade is good) then Performance is High
- If (pretest-Grade is excellent) and (TopicTest-Grade is excellent) then Performance is High

Fuzzy rules are triggered after any change in the value of the test result of a particular topic and it updates the performance level of this topic. The output of the fuzzy model is passed to the Bayesian network model as evidence to update the knowledge level of the related topics.

4.3.2 Bayesian Network in FB-ITS

The Bayesian network is a Directed Acyclic Graph (DAG) in which nodes represent variables and arcs represent probabilistic dependence or causal relationships among variables [105]. In the student model, the nodes of a Bayesian network can represent the different characteristics of a student such as course topics, knowledge levels, learning styles, goals, etc. Further details about Bayesian networks and how they are applied in building a student model can be found in [106]. In order to develop a Bayesian network model, variables, connections between these variables and probability distributions must be defined. Very often the construction of the Bayesian network model needs the expertise of instructors and experts in a particular area. The building process of the Bayesian network model is divided into the following four steps [107]:

1. Defining a knowledge domain: selecting the work area;
2. Designing a hierarchical structure of the knowledge domain: classification of the knowledge at different levels;
3. Constructing the Bayesian Network: creating nodes and establishing the dependence relations among them; and
4. Designing the conditional probability tables (CPT): assigning the conditional probabilities to every node according to their relationship with their parents.

This study uses MSBNx, the Microsoft Bayesian Network Toolkit to construct the Bayesian network model, which is a component-based Windows application for creating and evaluating Bayesian networks [108]. The components of this Microsoft tool can be integrated into programs, enabling them to perform inference under uncertainty. After implementation, the Bayesian network is saved in a XML format, into which it is easy to load the Bayesian network model in programming for probability inference. Where the Bayesian network in FB-ITS is implemented by MSBNx, the Excel topics network can be easily modified to address another learning domain.

In FB-INT, the Bayesian network model consists of 11 nodes, which represent the topics of the Excel course. The 11 Excel topics included in the student model are presented in Table 4.2. Moreover, the dependencies existing among the course topics can be represented as prerequisite relationships. For instance, Topic-1 has to be learned before Topic-2, because understanding Topic-1 is a prerequisite to understanding Topic-2. The node of Topic-1 being depended upon is also called the pre-requisite node. The entire DAG of the Bayesian network implemented in the FB-ITS is shown in Figure 4.9.

Table 4.2 Excel topics consistent with BNs nodes

Topic No.	Topic name
1	Working with Excel Environment
2	Creating workbook
3	Worksheet Basics
4	Cells Basics
5	Columns and Rows
6	Wrapping text and merging cells
7	Creating Tables
8	Sorting and Filtering Data
9	Create an Excel Chart
10	Simple Formulas
11	Basic Functions

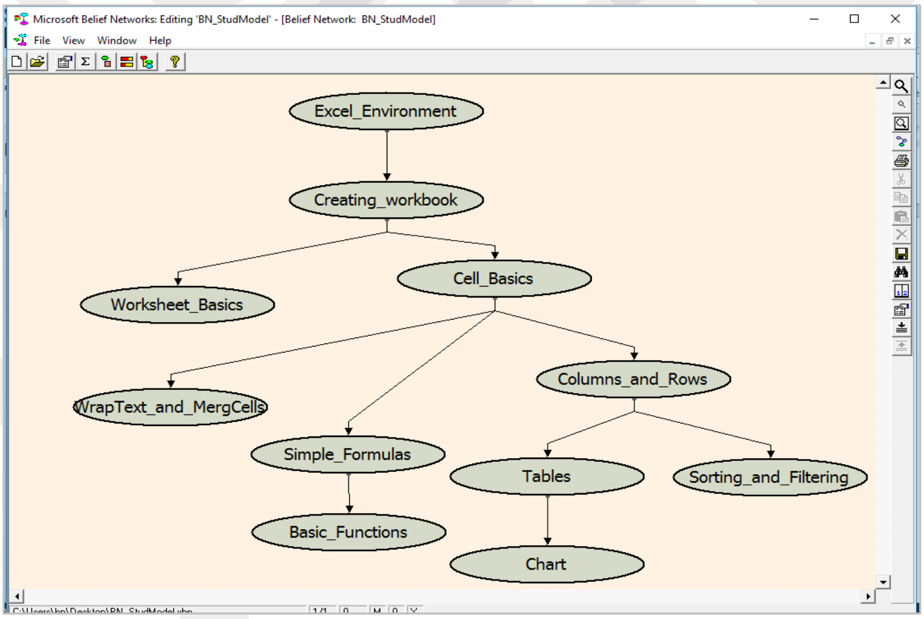


Figure 4.9 Bayesian network implemented in FB-ITS.

After constructing the Bayesian network, a Conditional Probability Distribution (CPD) table is designed for each topic node, taking into account its parents in the network. These probability values will then be used by the model for inference about the problem. The CPD value for Y given X is denoted by P(Y | X). In the context of Excel topics, the probability of a student having learned topic-1 (Excel Environment) is denoted by P(Topic-1). Moreover, the probability of a student having learned Topic-2 given Topic-1 is denoted by P(Topic-2 | Topic-1). P(Topic-2 = Learned / Topic-1 = Learned) is the probability that the student has learned Topic 2 given evidence that the prerequisite Topic-1 has been learned.

In most existing research, the conditional probability distribution table would be obtained by experts and based on the experience of teachers [10]. In addition, Butz et al. [6], obtained a CPD table for each node in the DAG from the results of previous course final exams. They considered a topic is known if the student answers the question correctly and unknown (not known) if the student answers the question incorrectly.

In this thesis, all CPD values were obtained by experts and the experience of instructors. For example, the CPD of the node (Worksheet_Basics) with its parent node (Creating_workbook) is P(Worksheet_Basics|Creating_workbook) as shown in Table 4.3. The CPD tables for every Bayesian network node is listed in Appendix D.

Table 4.3 CPD corresponding to the *Worksheet_Basics* node

Parent Node(s)	**Worksheet_Basics**	
Creating_workbook	Learned	notLearned
Learned	0.75	0.25
notLearned	0.37	0.63

In FB-ITS, every student is associated with an individual BN model stored in the .xbn file type with his/her name and the unique ID. This corresponding model is loaded every time a student logs into the system.

4.3.3 Updating the Student Model

The primary purpose of tracking a student's behavior during the interaction with the system is to collect evidence to update the Bayesian network model, where the evidence is the already observed information about this student. Several assessment approaches used to collect evidence to update the Bayesian network such as student's direct responses or answers to exam questions [18]. Furthermore, some systems include the student's performance scores, time spent on questions, sequences of read pages or reading times to enhance the student's assessment. In this study, the fuzzy logic system is used to collect the evidence taking into account the prior and current knowledge in a particular topic. The main purpose of the Bayesian network model is to predict the KL of related topics and to identify which topic is ready to learn and which are not based on the probability.

For each topic node in the Bayesian network model, there are two states: learned or not learned by the student. The learned state of certain topics in the Excel course can be assessed by calculating the posterior probability P(topic = learned/evidence), where the evidence is the student's performance on a prerequisite topic obtained from the fuzzy logic model. If the posterior probability of the topic is greater than or equal to a certain threshold (this work defines it as being equal to 0.8), this topic is marked as "Learned". Otherwise, the topic is marked as "notLearned". After that, the entire Bayesian network is updated and the system can decide what the next topic is ready for the student to learn based on the probabilities of the topic nodes in the Bayesian network. It should be mentioned that the choice of threshold value being equal to 0.8 to indicate a topic having been learned was randomly selected.

For example, if we suppose that a student has read the lecture notes for the topic Creating Workbook, and he/she has passed the topic test successfully the FB-ITS then calculates the probabilities given evidence for all the related topics of the Creating Workbook node (i.e., Worksheet Basics and Cells Basics), as shown in Figure 4.10. This means that the BN answers the query such as: "What would be the probability of Worksheet Basics and Cells Basics topics given that, the Creating_Workbook topic has been learned?" MSBNx uses a formula in Equation 2.4 and the CPD values presented in Appendix D to calculate the probabilities for each topic node.

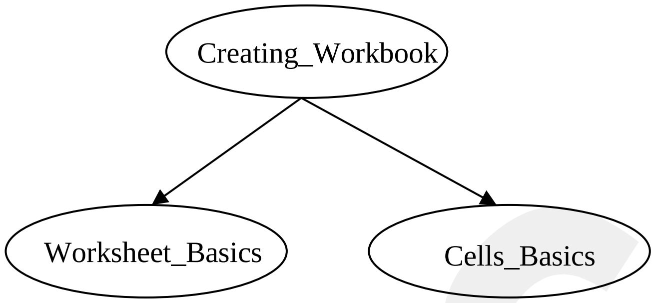


Figure 4.10 Creating_Workbook node and related topics

Finally, FB-ITS updates the dropdown menu to display the topics links in different colors based on these probabilities.

4.4 Adaptation Model

The adaptation model uses the information stored in the student model and knowledge domain model to adapt relevant learning materials. The output of this model is transferred to the system interface to be presented to the student. The adaptation model offers a pedagogical option to support the individual student during the learning process. The adaptive navigation support method [22] is a one of the common adaptation methods used in web-based educational systems to support a student to navigate in the learning environment by adapting to the preferences, goals and knowledge of the individual student [6] [43]. This method is used here by FB-ITS to support a student during the learning process, which involves link hiding and link annotations.

FB-ITS uses drop-down menus to help the student to navigate and browse the course materials. The drop-down menu is more helpful since it guides the student to learn Excel topics step-by-step. This menu can be dynamically updated in terms of font color based on the current knowledge state of the student and the student is not able to proceed to the next topic until she/he masters the pre-requisite topics by hiding the links for topics that are not yet ready to be learned. Moreover, through the drop-down menu, FB-ITS can notify the student as to which topic is ready to be learned and which not.

The link annotation is used for highlighting each topic with an appropriate color based on the student's knowledge level. After a student starts learning and does the tests related to the topics, each topic in the drop-down menu is highlighted with an appropriate color, indicating the student's knowledge level regarding these topics. A topic is highlighted in a blue color and considered already learned if the Bayesian network indicates the probability P(topic = learned/evidence) is greater than or equal to 0.8, where the evidence is the student's knowledge state of the previous topics. The topic is highlighted in green and considered ready to learn if all prerequisite topics are learned by the student. This means the probability P(topic = learned/evidence) is less than 0.8 for the current topic and all of the prerequisites topics are already learned. Finally, a topic is highlighted in red and considered not ready to learn if at least one of the prerequisites topics is not learned by the student. Figure 4.11 shows possible navigation in the drop-down menu that reflects the status of the student's knowledge at a given point.

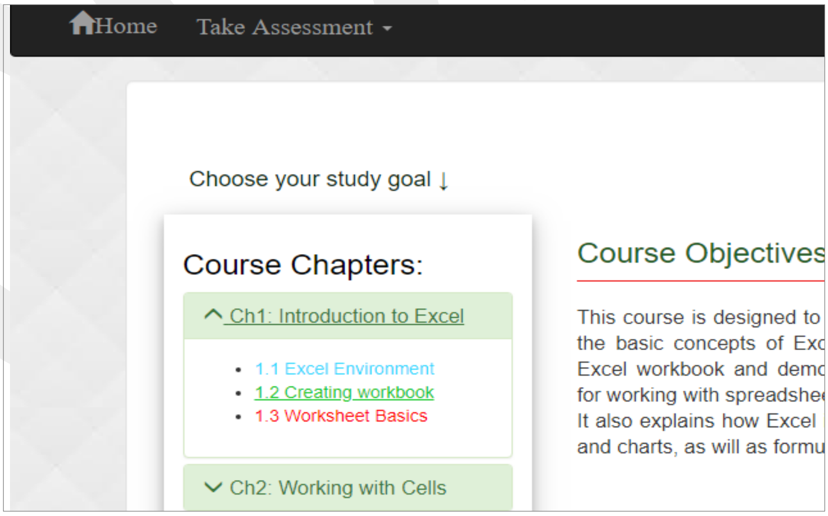


Figure 4.11 Drop-down menu of Excel topics

In addition to the navigation support method, an adaptive presentation mechanism is used by FB-ITS to present the contents of a course topic in various ways, such as text, images, and videos, in order to meet the individual student needs and preferences and to understand the topic effectively.

4.5 User Interface Model

The FB-ITS is a completely web-based system that can be accessed through a web browser. A student interacts with the proposed system via the user interface. In order to use the system for the first time, a student has to create an account through the registration page shown in Figure 4.12. Then student can log in to the system with a user name and the relevant password through the login page illustrated in Figure 4.13.

Figure 4.12 Registration Page

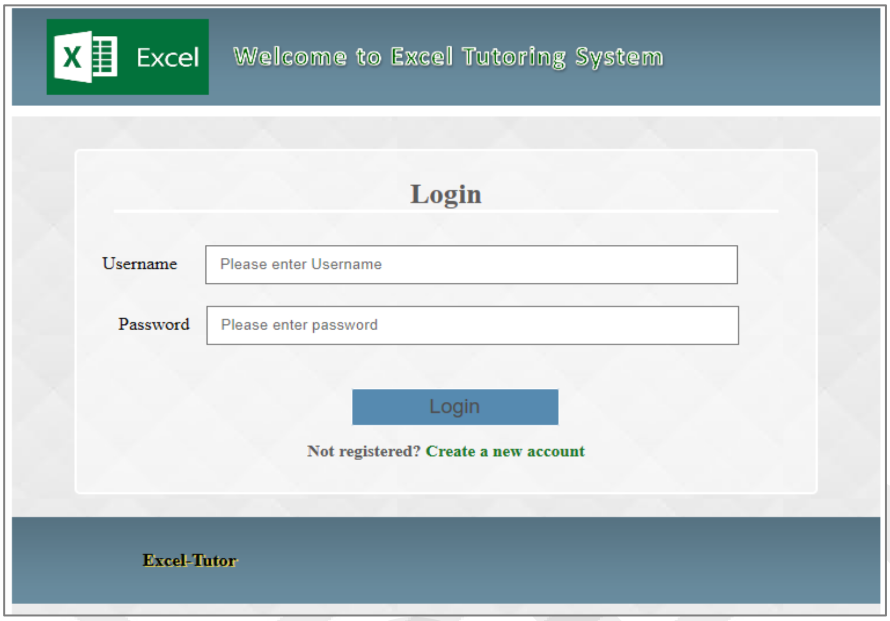


Figure 4.13 Login Page

When a student logs into the system for the first time, she/he is required to complete a pre-test to determine her/his prior knowledge of Excel. The pre-test consists of 22 multiple choice questions, as shown in Figure 4.14. It is possible for the student not to answer any questions if she/he has no relevant knowledge.

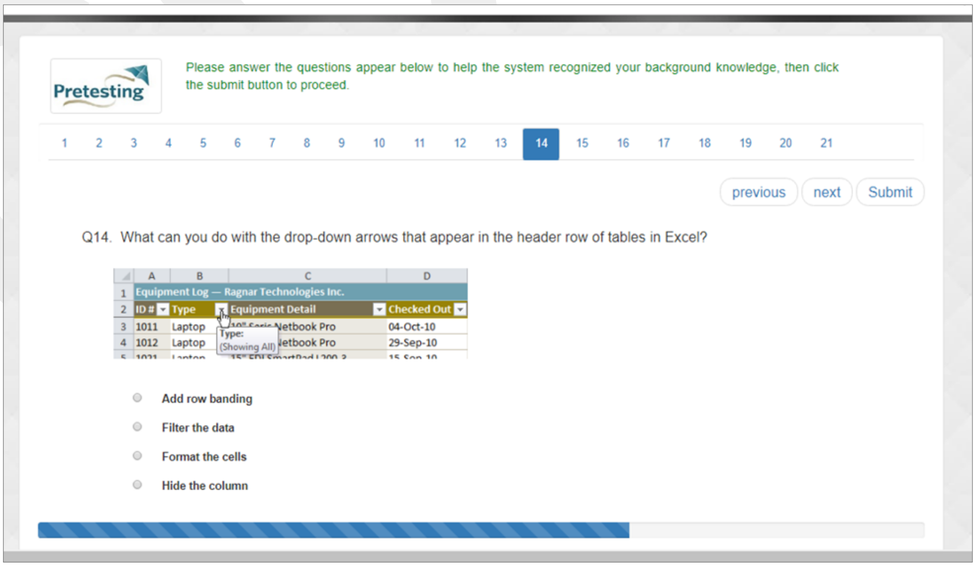


Figure 4.14 Pre-test page

The home page of the system appears after finishing the pre-test as shown in Figure 4.15. In this page, a student can navigate the course materials from the left dropdown menu.

For example, the learning content of Topic-1 "Working with Excel Environment" will appear as shown in Figure 4.16. The lesson content is displayed as text and images. Furthermore, the system provides a video lecture to help a student understand the topic with further explanation which meets the student's preferences. Furthermore, it provides an assessment task, as shown in Figure 4.17.

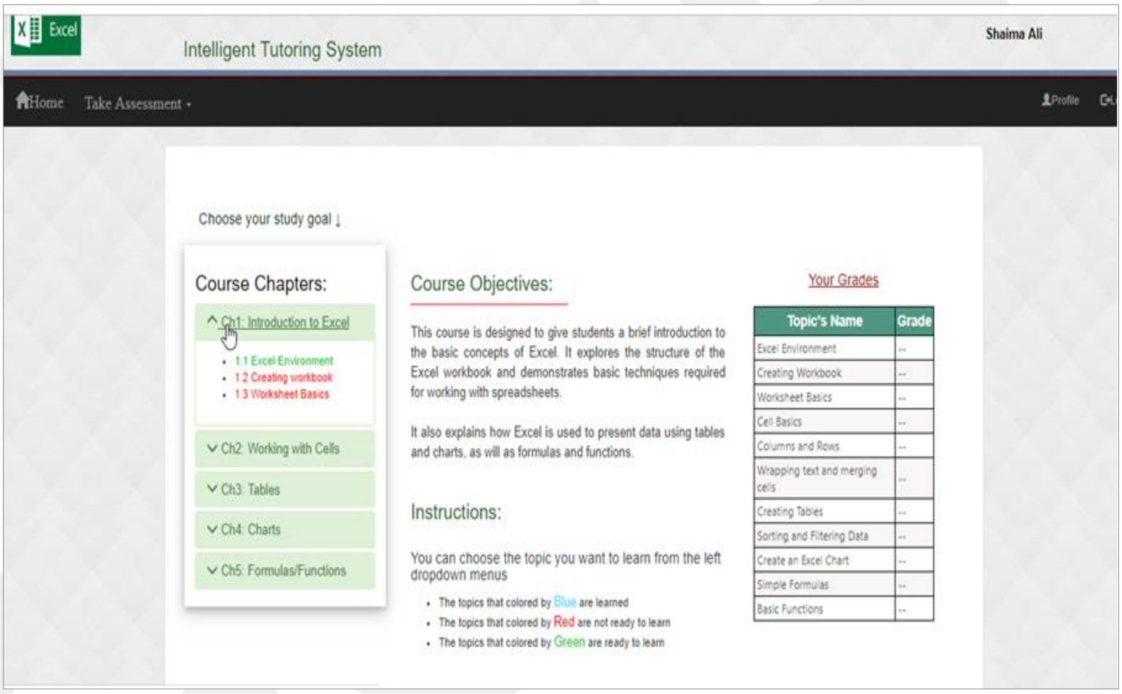


Figure 4.15 System home page

Figure 4.16 Learning topic page

After the student finishes reading the lesson, she/he has to answer the related test questions. Then the system will provide feedback according to the test score. If the student passes the test successfully, the system will inform her/him and allows the student to check her/his answers, as shown in Figure 4.18. Otherwise, the system advises the student to read the topic again and repeat the test. Figure 4.19 illustrates the system's feedback to the student when the student fails an exam.

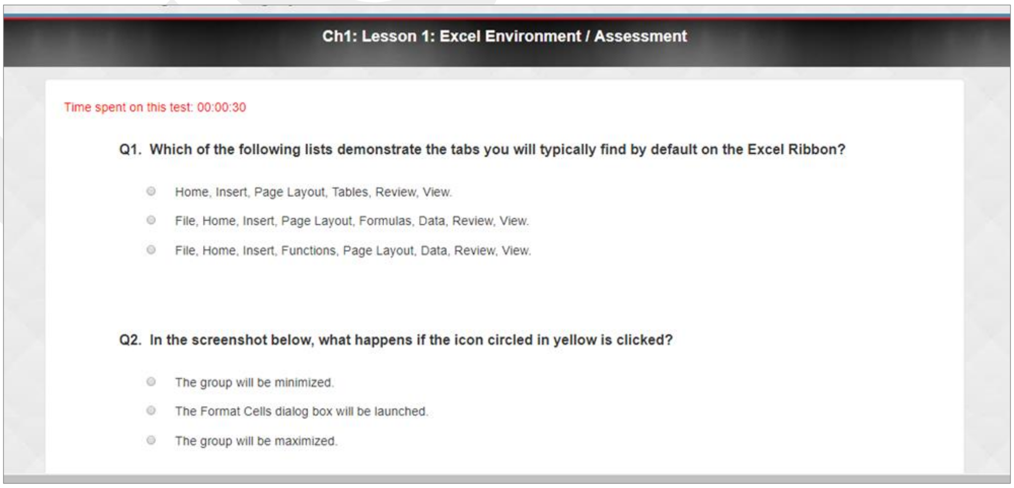


Figure 4.17 First topic test questions page

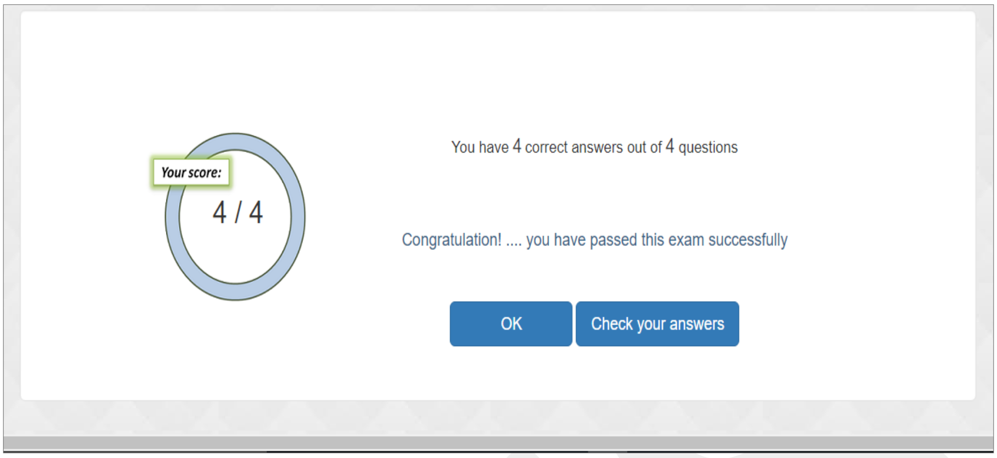


Figure 4.18 System feedback for a student passing the exam successfully

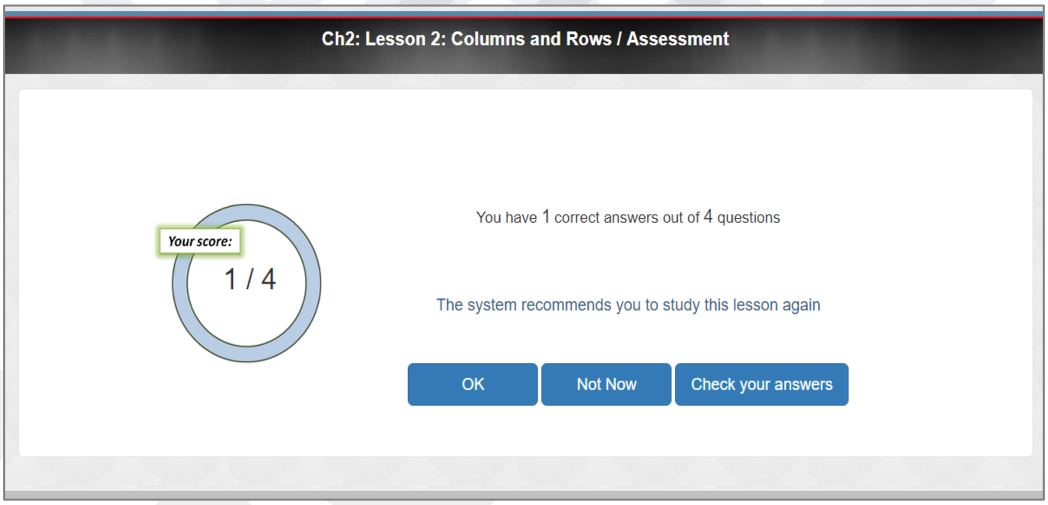


Figure 4.19 System feedback for a student not passing the exam

In addition, the system provides an alert message when the student selects the "not ready to learn" topic as shown in Figure 4.20. It also displays the alert message shown in Figure 4.21 when the student selects the "ready to learn topic" and he/she does not pass all the tests of the previous chapters

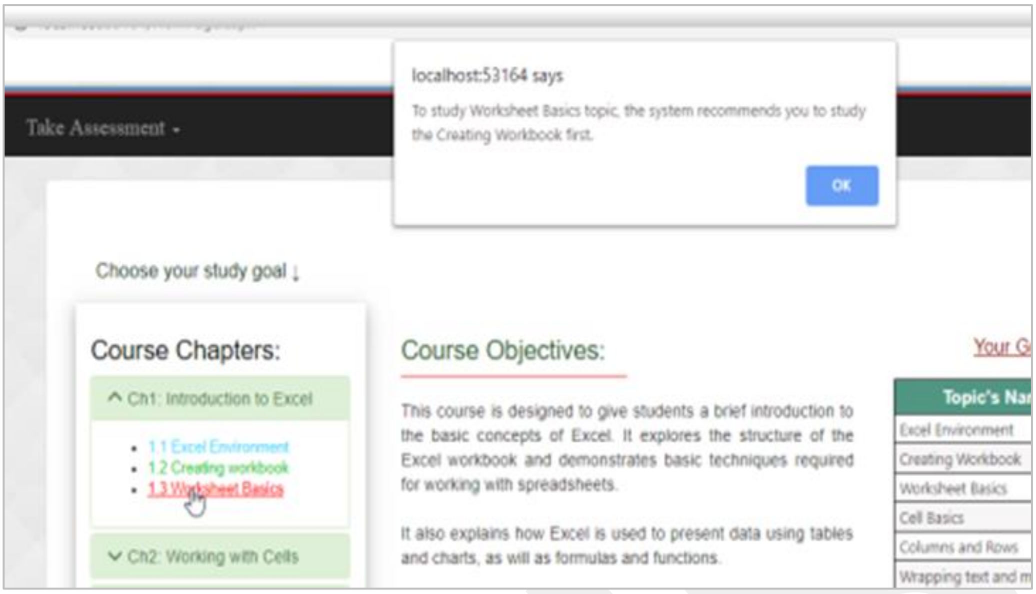


Figure 4.20 System feedback after selecting “not ready to learn” topic

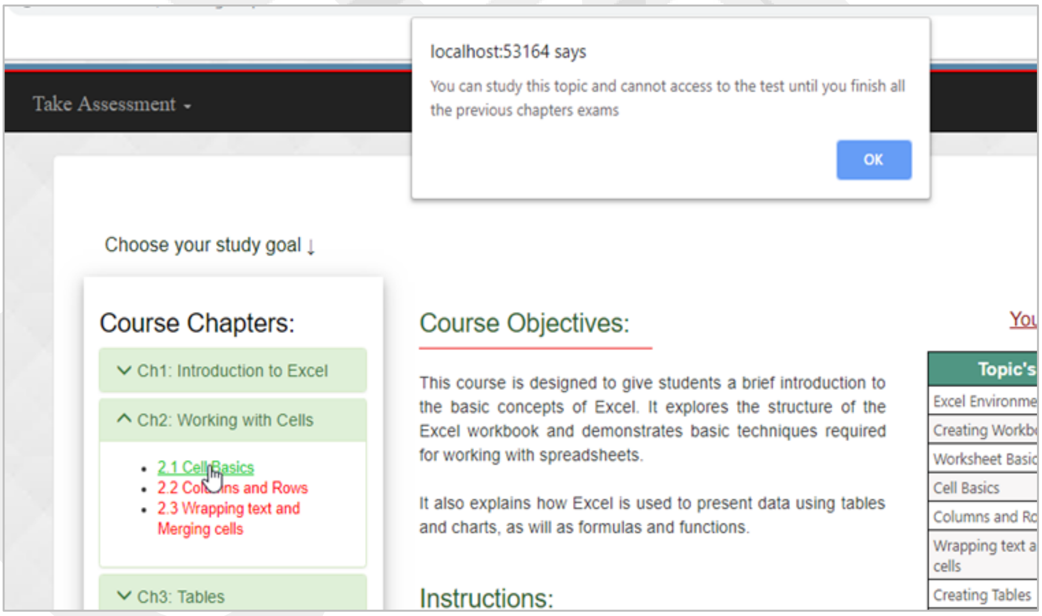


Figure 4.21 System feedback after choosing “ready to learn” topic

Moreover, after the student has finished the exam in a topic, the knowledge level of all related topics will be updated. The proposed ITS uses colors as an adaptive annotation technique which marks each topic with an appropriate color to indicate the student’s knowledge regarding these topics and helps the student to select appropriate instructional content for learning. If the topic is considered to be learned, then the system will highlight it in blue and if it is considered ready to be learned, then the system will highlight this topic in green. Otherwise, the topics will be highlighted in red, which means that these topics are not learned and are not ready to be learned.

In addition, at the top of most pages, the system displays a navigation bar, where the student can choose from several options. The student can go to her/his profile or logout from the system. The student can change the password from her/his profile. Moreover, from the navigation bar on the home page (see Figure 4.16), the student can choose (take an assessment) a button to conduct the test directly without studying the topic itself. Moreover, the student can return directly to the home page from any page in the system.

4.6 Summary

This chapter began with an introduction to FB-ITS explaining its main objectives. It presented the general architecture of FB-ITS and continued by discussing in detail all of its components. First, the knowledge domain module was discussed. Second, the student model, which consists of two layers, was presented. After that, the adaptation methods used in this system were discussed, followed finally by a presentation of the user interface of the system.

Since FB-ITS was designed as a research project to teach students Excel by incorporating the fuzzy logic and the Bayesian network techniques, the next chapter will present an experiment and a comparison of three versions of the system based on fuzzy logic, the Bayesian network and a combination of both techniques., It will also compare the system with a traditional e-learning system. As a conclusion, this chapter has successfully described the new hybrid method for the student model.

CHAPTER 5

SYSTEM EVALUATION

This chapter discusses how to evaluate FB-ITS to see whether it has achieved its objectives. It reviews the pilot study and how it was conducted. The chapter also explains how experiment conducted to evaluate the presented system are designed. The experimental results are discussed in this chapter which detail the comparison results of FB-ITS with the other two versions of the presented ITS, which has been designed separately based on fuzzy logic and Bayesian network. Moreover, this chapter discusses the comparison result of the FB-ITS with a traditional e-learning system. Finally, the summary of the chapter is presented.

The evaluation of e-learning systems is important to ensure that they meet learners' requirements, produce reliable and high quality services and enhance the learner-system interaction [27]. The evaluation includes identifying and clarifying the criteria selected to determine the effectiveness, usefulness, value and quality of the system [109]. FB-ITS was evaluated using an empirical method where the experiment was conducted with its own objectives and hypotheses to address various aspects including, students' academic performance and students' satisfaction in addition to system usability. Before starting the actual system evaluation experiments, a pilot study was conducted to determine the effectiveness of the system and data collection methods as discussed in the following section.

5.1 Pilot Study

To improve the execution of the experiment it was necessary to evaluate the proposed ITS, so a pilot study was conducted prior to the experiment with a few numbers of participants. The aim of this pilot study was to test the following issues:

- Data collection reliability

- Learning material content.
- Confusion and participants' questions.

In this small study, the experiment was carried out with 20 participants from undergraduate students attending the Introduction to Computers and Information Systems course (CMPE 105) at Atilim University in the 2018-2019 academic year. The sample of students was divided randomly into two groups so that the first group (control group) would be taught by the ITS designed using the Bayesian network and the second group (experimental group) would be taught by another version of the ITS that has been designed based on a combination of the Bayesian network and the fuzzy logic technique.

This study used the same data collection tools presented in Section 3.3. Cronbach's alpha coefficient was used to test the reliability of these tools. From the results, it was found that the reliability coefficient of student satisfaction and the system usability tools were 0.93 and 0.79, respectively, which mean that these scales are reliable and sufficient for further use.

Moreover, the pilot study conducted interviews with students after they finished learning using the system to evaluate the presented system according to technical problems that the student may have faced while interacting with the system. The results revealed positive opinions toward the use of the system with the exception of some software bugs such as the system failure when submitting exam answers encountered by a few students. The technical problems were solved and improved and some functions were added to the system based on student opinions, including displaying the correct answers of exam questions.

5.2 Experiment Design

The careful design of experiments, implementation, comprehensive analysis and reporting of results are important factors to consider when evaluating the effectiveness of e-learning systems [27]. This section describes the design of the experiment in testing the ability of FB-ITS to identify dynamically and update a student's level of knowledge. For the experimental study, three versions of ITS, including FB-ITS, were implemented to provide an educational program for Excel, based on the content of the CMPE105 course taught in several departments such as Art and Science, Management and Civil Aviation at Atılım University.

Pre-test/post-test designs are commonly used in experimental research for the purpose of comparing groups. A pre-test is a test that is given to participants prior to the experiment to assess their basic knowledge, while a post-test is similar to a pre-test and is given to participants after the completion of the experiment.

In the context of the experimental design presented in Figure 5.1, A total of 120 undergraduate students participated in this experiment, where firstly they were separated into two major groups: A and B. Group A contained 60 students and Group B contained 60. Secondly, the students in Group A separated into three groups: A1, A2, and A3, each of which contained 20 students. The participants in every group received the same content for learning Excel despite using different systems (ITS using Bayesian networks only, ITS using fuzzy logic only, FB-ITS, and a traditional e-learning system).

In the presented study, the experiment was conducted for a period of six weeks to validate the proposed system for practical use. It was designed to provide the answer to the research questions presented in Section 1.4.

In the first week of the experiment, every student joined the 60-minute session to become familiar with the systems (ITS and a traditional e-learning system). Following that, a pre-survey was presented to the students in order to collect preliminary information such as gender, department and GPA. They were then subjected to a pre-test which was distributed before dividing the participants sample into groups. After that, the students started studying the Excel topics. At the end of the experiment, they completed a post-test, followed by a student satisfaction and system usability questionnaire.

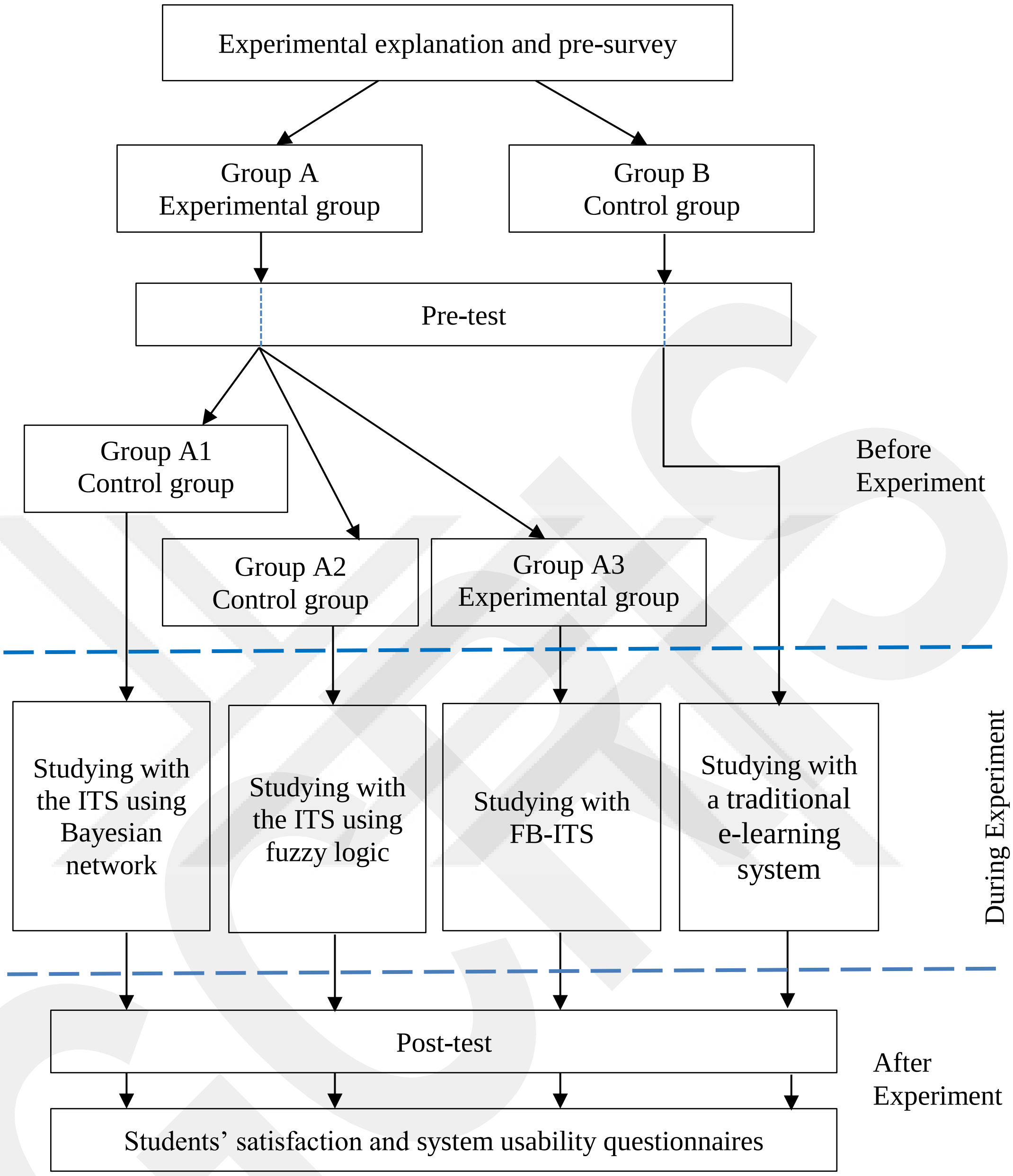


Figure 5.1 Experiment Design

At the end of the experiment and after collecting the data, every group of students was compared according to different aspects, including the students' academic performance, students' satisfaction, and system usability, which are as follows:

5.2.1 Comparison Group A3 and Group B

The students in the experimental group (Group A3) were taught using FB-ITS, whereas the students in the control group (Group B) were taught using a traditional e-learning system.

5.2.2 Comparison Groups A1, A2 and A3

The students within Groups A1, A2, and A3 studied using the ITS, but in different versions. At the same time, the students in Group A1 (control group 1) were taught by the ITS designed using the Bayesian network only and the students in Group A2 (control group 2) were taught by the ITS designed using fuzzy logic only, and the students in Group A3 (experimental group) were taught by FB-ITS.

For Groups A1, A2, and A3, the experiment was controlled in terms of department, gender, GPA and the time taken to perform the post-test, where these variables were measured and compared.

5.3 Results and Discussion

The analysis of the collected data focused on the educational impact on the students who used the system. The following sections describe how the data were analyzed to answer the research questions presented in Section 1.4.

5.3.1 Students' Academic Performance

This section is concerned with answering the research questions RQ1, RQ2, RQ3 and RQ4, which refer to the perceived level of the academic performance of students who had studied using different systems.

RQ1. Does the building of a student model using Bayesian networks based on fuzzy logic increase the performance of ITS in terms of students' academic performance compared to using fuzzy logic and Bayesian networks separately?

To answer this question, the following hypothesis was put forward:

H1: There is a statistically significant difference between the three groups (A1, A2 and A3) on students' academic performance in favor of Group A3.

Table 5.1 shows that group A3 had the highest mean value on students' academic performance (M = 82.95, SD = 18.59) while group A2 had the lowest mean value on students' academic performance (M = 69.77, SD = 22.81).

Table 5.1 Descriptive Statistics of groups A1, A2, and A3

Dependent Variable: Post-test			
Group	Mean	Std. Deviation	N
A1	79.09	21.39	20
A2	69.77	22.81	20
A3	82.95	18.59	20

In order to test hypothesis H1, the analysis of covariance (ANCOVA) was conducted to compare the students' academic performance in three different groups involved in the experiment. The independent variable was the type of e-learning system (Groups A1, A2 and A3), and the dependent variable consisted of scores on student academic performance administered after the experiment was completed. The participants' scores on the pre-test administration of the basic knowledge test were used as the covariate in this analysis. Preliminary checks were conducted to ensure that there was no violation of the assumptions of linearity, homogeneity of variances, homogeneity of regression slopes, and reliable measurement of the covariate. Levene's test for equality of variances was used for homogeneity of group variances. The assumption that variances were homogeneous was met, as shown in Table 5.2.

Table 5.2 Levene's test for homogeneity of the group variances

F	df1	df2	Sig.
0.555	2	57	0.575

Table 5.3 Tests of Between-Subjects Effects

Dependent Variable: Post-test						
Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	10032.096[a]	3	3344.032	11.047	.000	0.372
Intercept	28122.920	1	28122.920	92.906	.000	0.624
Pretest	8195.327	1	8195.327	27.074	.000	0.326
Group	7005.216	2	3502.608	11.571	.000	0.292
Error	16951.433	56	302.704			
Total	385244.339	60				
Corrected Total	26983.529	59				
a. R Squared = .372 (Adjusted R Squared = .338)						

Table 5.3 illustrated that, after adjusting for pre-test scores, there was significant difference between the three groups on post-test scores of the students, F (2, 56) = 11.571, $p < 0.001$, partial eta squared = 0.292, indicated a large effect size [110]. Also the results show that, there was a significant moderate effect of the pre-test scores on the post-test scores of the students (F=27.074, $p < 0.05$), as indicated by a partial eta squared value of 0.326.

The ANCOVA test indicated significant differences between the three groups (A1, A2, and A3). The results of this test did not show exactly where the significance between each two groups lies. As further analysis is needed, the groups between which there is a difference were evaluated by Pairwise Comparisons with Bonferroni adjustment for multiple comparisons.

The results shown in Table 5.4 indicated significant mean differences between the post-test scores of the group A3 and the group A1 at the 0.05 level (mean difference = 27.067), and between the post-test scores of the group A3 and the group A2 at the 0.05 level (mean difference = 30.110). There was no significant mean difference between groups A1 and A2. The average difference between the environment with A3 is higher than other environments (A1 and A2).

Table 5.4 Bonferroni Test (Pairwise Comparisons)

Dependent Variable: Post-test						
(I) Group	(J) Group	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference [b]	
					Lower Bound	Upper Bound
A1	A2	3.043	5.632	1.000	-10.858-	16.944
	A3	-27.067-*	7.082	.001	-44.545-	-9.588-
A2	A1	-3.043-	5.632	1.000	-16.944-	10.858
	A3	-30.110-*	6.392	.000	-45.885-	-14.335-
A3	A1	27.067*	7.082	.001	9.588	44.545
	A2	30.110*	6.392	.000	14.335	45.885
Based on estimated marginal means						
*. The mean difference is significant at the .05 level.						
b. Adjustment for multiple comparisons: Bonferroni.						

H1 is confirmed and it can be concluded that the students who used FB-ITS (A3) to learn Excel yield significantly better academic performance than students who studied with the ITS using the Bayesian network (A1) and fuzzy logic (A2).

RQ2. Do students who studied using FB-ITS have a higher academic performance than students who studied using the traditional e-learning system?

To answer this question, the following hypothesis was put forward:

H2: There is a statistically significant difference between the two groups (A3 and B) in student academic performance in favor of Group A3.

The descriptive statistics for Groups A3 (FB-ITS) and B (traditional e-learning system) are presented in Table 5.5. This table shows that Group A3 had a higher mean value in student academic performance ($M = 82.95$, $SD = 18.587$) than Group B ($M = 64.33$, $SD = 26.256$). In other words, it can be said that the students who used FB-ITS in learning performed better academically compared to students using the traditional e-learning system.

Table 5.5 Descriptive Statistics of groups A3 and B

Dependent Variable: Post-test			
Group	Mean	Std. Deviation	N
A3	82.95	18.587	20
B	64.33	26.256	60

To test hypothesis H2, a one-way between-groups analysis of covariance was conducted to compare the students' academic performance in two different groups. The independent variable was the type of e-learning system (A3 and B), and the dependent variable consisted of scores for the students' academic performance administered after the experiment was completed. The participants' scores on the pre-test administration of the basic knowledge test were used as the covariate in this analysis.

Preliminary checks were conducted to ensure that there was no violation of the assumptions of linearity, homogeneity of variances, homogeneity of regression slopes, and reliable measurement of the covariate.

Table 5.6 Tests of Between-Subjects Effects

Dependent Variable: Post-test						
Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	14834.302[a]	2	7417.151	15.188	.000	0.283
Intercept	74228.653	1	74228.653	151.992	.000	0.664
Pre-test	9633.084	1	9633.084	19.725	.000	0.204
Group	10300.490	1	10300.490	21.092	.000	0.215
Error	37604.599	77	488.371			
Total	433193.331	80				
Corrected Total	52438.900	79				
a. R Squared = .283 (Adjusted R Squared = .264)						

From Table 5.6, after adjusting for the pre-test scores, there was a significant difference between Groups A3 and B on the post-test scores of the students, $F(1, 77) = 21.092$, $p < 0.001$. The partial eta squared = 0.215 indicated a large effect size [110]. There was a weak relationship between the pre-test and post-test scores, as indicated by a partial eta squared value of 0.204.

H2 is confirmed and it can be concluded that the students who studied under FB-ITS (A3) have significantly better academic performance than students who studied using the traditional e-learning system (B).

RQ3. Are there any differences according to gender, department, and GPA in student academic performance?

To answer this question, three main hypotheses were put forward:

H3.1: There is statistically significant difference in student academic performance in Group A due to gender.

H3.2: There is a statistically significant difference in student academic performance in Group A due to department.

H3.3: There is a statistically significant difference in student academic performance in Group A due to GPA.

After testing hypothesis H3.1, there is a statistically significant difference in student academic performance in Group A due to gender.

As there was homogeneity of variance between the students' academic performance according to gender as assessed by Levene's test for equality of variances, $F = 0.896$, $p = 0.348$ with data normally distributed, an independent sample t-test was conducted to compare the students' academic performance in Group A for males and females using an alpha level (α) of 0.05.

Table 5.7 shows that female students scored a higher mean ($M = 77.84$, $SD = 18.608$) than males students ($M = 76.62$, $SD = 24.516$). The result of the independent sample t-test in Table 5.6 shows that there was no significant difference in scores for males and females, $t\ (58) = -.218$, $p = .828$ (> 0.001), two-tailed). The magnitude of the differences in the means (mean difference = −1.218, 95% CI: –12.386 to 9.950) was very small (eta squared = 0.0008).

Table 5.7 Independent-samples t-test for the difference between the averages of students' academic performance according to gender

Gender	N	Mean	Std. Deviation	t	Sig. (2-tailed)
Males	28	76.62	24.516	-.218-	0.828
Females	32	77.84	18.608		

H3.1 is therefore not confirmed. It can be inferred that there is no significant difference between male and female students in their academic performance.

Testing hypothesis **H3.2**, there is a statistically significant difference in students' academic performance in Group A due to their department.

Table 5.8 Descriptive Statistics of academic performance according to department.

Post-test								
Department	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Min.	Max.
					Lower Bound	Upper Bound		
Civil Aviation	9	74.24	23.837	7.946	55.92	92.57	18	91
Management	24	78.22	21.529	4.395	69.13	87.31	18	100
Arts and Sciences	27	77.44	21.188	4.078	69.06	85.82	18	100

Table 5.8 shows descriptive statistics of samples according to departments. The management group had the highest mean value (M = 78.22, SD = 21.529) while the Civil Aviation group had the lowest mean value (M = 74.24, SD = 23.837).

A one-way between-groups analysis of variance was conducted to explore the impact of students' specialty (department) on levels of students' academic performance in Group A, as measured by the post-test.

Table 5.9 ANOVA Test for academic performance according to department

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	104.836	2	52.418	0.111	0.895
Within Groups	26878.693	57	471.556		
Total	26983.529	59			

Table 5.9 shows that, there was no statistically significant difference at the $p < 0.05$ level in post-test scores for the three departments' groups: $F (2, 57) = 0.111$, $p = 0.895$.

Testing the hypothesis (**H3.3**), there is a statistically significant difference in students' academic performance in Group A due to GPA.

Table 5.10 Descriptive statistics of academic performance according to GPA

Post-test								
GPA	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Min.	Max.
					Lower Bound	Upper Bound		
0.0 to 2.0	13	79.37	20.963	5.814	66.70	92.04	18	100
2.1 to 3.0	29	77.12	24.220	4.498	67.90	86.33	18	100
3.1 to 4.0	18	76.01	17.487	4.122	67.31	84.71	41	100

Table 5.10 shows the descriptive statistics of the sample according to GPA. The GPA group (0.0 to 2.0) had the highest mean value ($M = 79.37$, $SD = 20.963$) while the GPA group (3.1 to 4.0) had the lowest mean value ($M = 76.27$, $SD = 21.386$).

A one-way between-groups analysis of variance was conducted to explore the impact of students' GPA on levels of students' academic performance in Group A as measured by the post-test.

Table 5.11 ANOVA Test for academic performance according to GPA.

Post-test					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	86.666	2	43.333	0.092	0.912
Within Groups	26896.863	57	471.875		
Total	26983.529	59			

Table 5.11 shows that there was no statistically significant difference at the $p < 0.05$ level in the post-test scores for the three GPAs' groups: $F(2, 57) = 0.092$, $p = 0.912$.

RQ4. Is there a difference in the time taken by students who studied with FB-ITS to perform the post-test compared to students who studied with ITS using fuzzy logic only, ITS using Bayesian networks only and traditional e-learning?

To answer this question, two main hypotheses were put forward:

H4.1: There is a statistically significant difference between Groups A1, A2 and A3 in the time taken to perform the post-test in favor of Group A3.

H4.2: There is a statistically significant difference between Group A3 and Group B in the time taken to perform the post-test in favor of Group A3.

Table 5.12 Descriptive statistics of Groups A1, A2 and A3 according to the time taken to perform the post-test

Time Taken to the post-test (minutes)								
Group	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Min.	Max.
					Lower Bound	Upper Bound		
A1	20	8.6145	6.03681	1.34987	5.7892	11.4398	.10	19.93
A2	20	10.6450	5.64528	1.26232	8.0029	13.2871	2.03	17.70
A3	20	7.8710	4.83915	1.08207	5.6062	10.1358	2.40	20.00

Table 5.12 shows descriptive statistics of the three groups. Group A2 had the highest mean time value ($M = 10.65$, $SD = 5.65$), while Group A3 had the lowest mean time value ($M = 7.87$, $SD = 4.84$).

To confirm hypothesis H4.1, a one-way between-groups analysis of variance (ANOVA) was conducted to explore the impact of three learning systems (Groups A1, A2 and A3) on levels of time taken to perform the post-test as measured in minutes. Table 5.13 shows that there was no statistically significant difference at the $p < 0.05$ level in time scores for the three groups: $F(2, 57) = 1.349$, $p = 0.268$.

Table 5.13 ANOVA test for Groups A1, A2 and A3 according to the time taken to perform the post-test

Time Taken to the post-test (minutes)					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	82.472	2	41.236	1.349	.268
Within Groups	1742.863	57	30.577		
Total	1825.335	59			

Testing the hypothesis (**H4.2**), there is a statistically significant difference between Group A3 and Group B in time taken to perform the post-test in favor of Group A3.

To confirm the hypothesis H4.2, an independent-samples t-test was conducted to compare the time taken to perform the post-test for Group A3 and Group B.

Table 5.14 Independent-samples t-test for comparison between Group A3 and Group B in time taken to perform the post-test

Group	N	Mean	Std. Deviation	t	Sig. (2-tailed)
A3	20	7.87	4.84	-4.526-	.000
B	60	13.86	5.90		

Table 5.14 shows that a lower mean value was observed in Group A3 (7.87 minutes) than in Group B (13.86 minutes). The result of the independent sample t-test illustrated in Table 5.13 shows that there was a significant difference in time scores for Group A3 ($M = 7.87$, $SD = 4.84$) and Group B ($M = 13.86$, $SD = 5.90$); $t(39.385) = -4.526$, $p = 0.000$ (< 0.001), two-tailed). The magnitude of the differences in the means (mean difference = −5.99, 95% CI: −8.66533 to −3.31367) was large (eta squared = 0.21).

H4.2 is therefore confirmed. It can be inferred that the students who used FB-ITS (A3) took significantly less time to perform the post-test than the students who used the traditional e-learning system (B).

5.3.2 Students' Satisfaction

This section is concerned with answering the research question RQ5, which refers to the perceived level of students' satisfaction with FB-ITS and the traditional e-learning system. The students' satisfaction level was tested using the ELS questionnaire mentioned in Section 3.3.

RQ5. Does adaptation based on the level of the student knowledge in FB-ITS lead to a high level of student satisfaction compared to a traditional e-learning system?

In order to answer this question, the following hypothesis was put forward:

H5: There is a statistically significant difference in students' satisfaction between students studying using FB-ITS (A3) and students studying using the traditional e-learning system (B) in favor of Group A3.

Before confirming H5, Cronbach's α [111] was used as a test for the internal consistency reliability of each scale of satisfaction questionnaire. Cronbach's $\alpha \geq 0.70$ is judged to be high in internal consistency [112]. In this study, Table 5.15 shows the reliability coefficients of the students' satisfaction and its components including learner interface, learning content and personalization.

Table 5.15 Reliability statistics of the students' satisfaction scale

Scales and Sub-scales	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
Satisfaction Scale	0.985	0.985	12
Learner interface	0.965	0.965	4
Learning content	0.968	0.968	4
Personalization	0.951	0.951	4

The satisfaction scale had a good reliability for the overall student satisfaction questionnaire, namely Cronbach's α = 0.985, which exceeds the recommended cut-off level of 0.70. Sub-scales of Cronbach's α ranged between 0.951 and 0.968. The results indicate that the scales and sub-scales can be used in the measurement of the indicated variables.

Table 5.16 Descriptive statistics of students' satisfaction

	N	Mean	Std. Deviation
Satisfaction	53	3.46	1.289
Satisfaction with Learner interface	53	3.42	1.297
The e-learning system is user-friendly.	53	3.38	1.390
The operation of the e-learning system is stable.	53	3.36	1.346
The e-learning system makes it easy for you to find the content you need.	53	3.51	1.382
The e-learning system is easy to use.	53	3.45	1.338
Satisfaction with Learning content	53	3.40	1.348
The e-learning system provides content that exactly fits your needs.	53	3.32	1.384
The e-learning system provides useful content.	53	3.42	1.460
The e-learning system provides sufficient content.	53	3.34	1.427
The e-learning system provides up-to-date content	53	3.51	1.368
Satisfaction with Personalization	53	3.55	1.305
The e-learning system enables you to control your learning progress.	53	3.47	1.409
The e-learning system records your learning progress and performance.	53	3.83	1.397
The e-learning system enables you to learn the content you need.	53	3.51	1.409
The e-learning system enables you to choose what you want to learn	53	3.38	1.376

Table 5.16 shows descriptive statistics of the satisfaction scale, subscales and items. The statistics for satisfaction were M = 3.46 and SD = 1.289. The sub-scale statistics were M = 3.42 and SD = 1.297 for satisfaction with the learner interface, M = 3.40 and SD = 1.348 for satisfaction with the learning content, and M = 3.55 and SD = 1.305 for satisfaction with personalization. In terms of items, the highest mean was awarded to the question "The e-learning system records your learning progress and

performance.” with M = 3.83 and SD = 1.397, while the lowest mean was awarded to the question “The e-learning system provides content that exactly fits your needs.” with M = 3.32 and SD = 1.384.

To test the hypothesis (H5**)**, an independent-samples t-test was conducted to compare the satisfaction scores for Group A3 and Group B. Table 5.17 shows group statistics and independent samples t-tests for the satisfaction scale and sub-scales for both Groups A3 and B. The highest mean value was observed in Group A3 in the satisfaction with personalization sub-scale (3.68), while the lowest mean value was also observed in Group A3 in satisfaction with the learning content sub-scale (3.34).

Furthermore, Table 5.17 shows that there is no significant difference in scores for Group A3 (M = 3.49, SD = 1.48) and Group B (M = 3.44, SD = 1.18; t (51) = .137, p = .891, two-tailed). The magnitude of the differences in the means (mean difference = .05, 95% CI: −0.68994 to 0.79120) was very small (eta squared = 0.0004). No significant differences in scores for the satisfaction sub-scales were observed, either.

Table 5.17 Independent-samples t-test for students’ satisfaction

	Group	N	Mean	Std. Deviation	t	Sig. (2-tailed)
Satisfaction	A3	20	3.49	1.48	0.137	0.891
	B	33	3.44	1.18		
Satisfaction with Learner interface	A3	20	3.45	1.46	0.110	0.913
	B	33	3.41	1.21		
Satisfaction with Learning content	A3	20	3.34	1.56	-0.245-	0.808
	B	33	3.43	1.23		
Satisfaction with Personalization	A3	20	3.68	1.51	0.552	0.584
	B	33	3.47	1.18		

An evaluation of FB-ITS has revealed reasonably acceptable results in terms of student satisfaction. H5 is therefore not confirmed. It can be inferred that there is no significant difference between FB-ITS and the traditional e-learning system in terms of student satisfaction.

5.3.3 System Usability

This section is concerned with answering the research question RQ6, which refers to the perceived level of usability of FB-ITS and the traditional e-learning system. System usability was tested using the SUS questionnaire mentioned in Section 3.3.

RQ6. Does a user interface of FB-ITS have a high level of system usability compared to a traditional e-learning system?

In order to answer this question, the following hypothesis was put forward:

H6: There is a statistically significant difference in system usability between FB-ITS (Group A3) and the traditional e-learning system (Group B) in favor of Group A3.

Before confirming H6, Cronbach's α [111] was used as a test for the internal consistency reliability of the system usability questionnaire. The system usability scale had a good reliability, Cronbach's $\alpha = 0.909$. Results indicate that the scales can be used in measurement of the indicated variables.

Table 5.18 Descriptive Statistics of system usability scale

	N	Mean	Std. Deviation
System Usability	45	3.03	.972
I think that I would like to use this system frequently	45	2.96	1.445
I found the system unnecessarily complex	45	3.38	1.302
I thought the system was easy to use	45	3.16	1.364
I think that I would need the support of a technical person to be able to use this system	45	3.04	1.331
I found the various functions in this system were well integrated	45	3.02	1.138
I thought there was too much inconsistency in this system	45	2.80	1.217
I would imagine that most people would learn to use this system very quickly	45	3.11	1.301
I found the system very cumbersome to use	45	2.91	1.379
I felt very confident using the system	45	3.04	1.261
I needed to learn a lot of things before I could get going with this system	45	2.87	1.358

Table 5.18 shows descriptive statistics of system usability scale. Statistics for system usability were (M = 3.03, SD = 0.972). The item ‘I thought there was too much inconsistency in this system.’ recorded the lowest mean value (M = 2.80, SD = 1.217).

To test the hypothesis (H6), an independent-samples t-test was conducted to compare the system usability scores for Group A3 and Group B. Table 5.19 shows that a higher mean value was observed in Group A3 (3.09) than in Group B (2.99).

Table 5.19 Independent-samples t-test for system usability

	Group	N	Mean	Std. Deviation	t	Sig. (2-tailed)
System Usability	A3	18	3.0889	1.12191	0.335	0.739
	B	27	2.9889	0.87808		

Also Table 5.19 shows that there was no significant difference in scores for Group A3 (M = 3.09, SD = 1.12) and Group B (M = 2.99, SD = .878; t (43) = 0.335, p = 0.739, two-tailed). The magnitude of the differences in the means (mean difference = 0.10, 95% CI: -.50246 to 70246) was very small (eta squared = 0.003).

H6 is therefore not confirmed. It can be inferred that, there is no significant difference between FB-ITS and the traditional e-learning system in terms of system usability.

5.4 Summary

This chapter was concerned with the evaluation of the effectiveness of FB-ITS. The evaluation of FB-ITS was based on the comparison with other versions of the ITS that were implemented using the Bayesian network and fuzzy logic separately and the traditional e-learning system. Additionally, this chapter described the experiment and the results obtained. Three variables include student academic performance, student satisfaction, and system usability, which were used to collect the data. Similarly, the experiment was controlled in terms of department, gender, GPA and the time taken for the post-test, as these variables were measured and compared.

The evaluation of the proposed system showed significantly satisfactory results and positive effects in terms of students' academic performance, where the results revealed that the students who used FB-ITS to learn Excel had higher academic performance than students who studied Excel with the ITS using Bayesian network and fuzzy logic separately.

Furthermore, in comparison with the performance of the traditional e-learning system in terms of academic performance, the results indicate that the students who studied with FB-ITS had higher academic performance than students using the traditional e-learning system. The students who used the presented ITS needed less time on average to perform the post-test than the students who used the traditional e-learning system.

In conclusion, the evaluation of the system showed satisfactory results and positive effects in terms of academic performance as well as moderate results in terms of student satisfaction and usability.

CHAPTER 6

CONCLUSION AND FUTURE WORKS

This chapter presents the summary of this research and research discussion. In addition, it lists the research publications resulted from this study. Finally, it provides some suggestions for future work.

6.1 Summary of the Study

This study began with an analysis of the related existing literature including adaptive e-learning, intelligent tutoring systems, and artificial intelligence techniques such as fuzzy logic and Bayesian networks, which have been used to develop ITSs. Furthermore, the usability issues of adaptive e-learning systems was reviewed.

In order to improve adaptive intelligent e-learning systems, this research studied the usage of AI techniques to build the student model which is a core component of intelligent tutoring systems. A web-based intelligent tutoring system called FB-ITS was designed and implemented by taking into account systems and models in related published research. It contains the major components of ITS needed to provide adaptation, including the knowledge domain model, the learner model, user interface model and the adaptation model.

The major aim of this thesis was to create a novel hybrid method that combines Bayesian network and fuzzy logic techniques to offer adaptive instruction and personalized support in web-based intelligent tutoring systems. The presented system provides adaptation of course content for each individual student based on their knowledge level. In particular, the system identifies and updates the knowledge level of each student. Thus, it allows each individual student to finish an online course at his/her own pace.

Moreover, it makes decisions about the topics of the learning material, which topic should be delivered, which topic needs revision and which topic is learned. It highlighted each topic with an appropriate color, indicating the student's knowledge level regarding these topics to help a student select the appropriate topic to study. In this manner, the system helps the student to save time and effort during the learning process.

An experiment involving 120 undergraduate students from Atılım University, Turkey in the 2019-2020 academic year was conducted to evaluate the efficiency of the proposed system (FB-ITS). This work compared the effectiveness of the FB-ITS which provides knowledge to each student in an adaptive manner against two versions of ITSs that were developed and implemented using fuzzy logic and the Bayesian network separately. Moreover, the efficiency of the presented system was evaluated by comparison with a traditional e-learning system. Three dependent variables were utilized to evaluate the effectiveness of the proposed system, including the students' academic performance, student satisfaction, and system usability. Similarly, the experiment was controlled in terms of department, gender, GPA and the time taken for the post-test as these variables were measured and compared. The findings of this experiment are reported in Chapter 5 and discussed in the following section.

6.2 Research Discussions

This study applied AI techniques including the Bayesian network and fuzzy logic to create a novel hybrid student model in order to offer adaptive instruction and personalized support in a web-based intelligent tutoring system. A web-based intelligent tutoring system called FB-ITS was designed and implemented in the present study.

The effectiveness of the proposed system was evaluated by comparing it with other systems based on three dependent variables including students' academic performance, students' satisfaction, and system usability. The experiment results revealed that the students who used FB-ITS to learn Excel had higher mean values in terms of academic performance (82.95) than students who studied Excel with the ITS using Bayesian network (79.09) and fuzzy logic (69.77) separately. Moreover, in terms of the amount of time taken to perform the post-test, FB-ITS recorded the lowest mean time value (7.87 minutes) compared with the other two versions.

By comparing the performance of the presented system with traditional e-learning, it was concluded that the students who studied with FB-ITS had a higher mean value on academic performance (82.95) than students who studied using the traditional e-learning system (64.33). The results of the present work support the results of other studies that used AI techniques to develop intelligent educational systems [1], [11], [76], [78]. Moreover, in terms of time taken to perform the post-test, the students who used the FB-ITS needed less time (7.87 minutes) on average than the students who used the traditional e-learning system (13.86 minutes). Moreover, the results of the independent-samples t-test can lead us to conclude that the students who used the FB-ITS took significantly less time to perform the post-test than the students who used the traditional e-learning system. In a similar study [44], the adaptive intelligent system performed well compared with another traditional educational system in terms of the time needed to read each domain concept.

Additionally, the results concluded that there was no statistically significant difference in students' academic performance due to gender, GPA or department. In terms of the influence of gender on the students' academic performance, this result is in parallel with those reported by [113], [114]. On the other hand, there is another study that proved the opposite such that the academic performance of students being affected by gender saw females scoring higher than males [115].

An evaluation of the FB-ITS has revealed reasonably acceptable results in terms of student satisfaction. Student satisfaction levels were tested using the ELS questionnaire, and the responses were analyzed using an independent-samples t-test. The results revealed that the level of satisfaction among students in the FB-ITS group was similar to the level of the student satisfaction in the traditional e-learning group. Furthermore, the evaluation of the system showed moderate results in terms of system usability.

6.3 List of Publications

A number of research publications resulting from this study are listed below:

- M. Eryılmaz, A. M. Adabashi, and A. Yazıcı, “Artificial Intelligence Methods in E-Learning,” in Handbook of Research on Faculty Development for Digital Teaching and Learning, IGI-global, 2019, pp. 287–307.
- A. Adabashi and M. Eryılmaz, “Bayesian Network Based on Fuzzy Logic in Educational Intelligent Systems,” *Int. Educ. Res. J.*, vol. 5, pp. 24–26, 2019.
- M. Eryılmaz, A. M. Adabashi, “How Artificial Intelligence Technologies Shape e-Learning?”, International Conference on Research in Education and Science (ICRES), Çeşme, Turkey, 2019.

6.4 Future Work

While this research has shown that it has achieved its aims with reasonable results, improvements are needed and must be considered to achieve a better level of performance. This section presents an interesting issue to be explored in future works.

The proposed ITS framework can be used as a reference model to develop instances of intelligent tutoring systems by focussing on different views of the domain model and also the adaptation model. In the context of the domain model, where the Bayesian network in the FB-ITS is implemented by MSBNx, a component-based Windows application, the Excel topics network can be easily modified to address another learning domain. In addition, since developing an intelligent tutoring system for each specific course is tiring and undesirable due to the cost of new development, the framework within which FB-ITS was developed is reusable. In the future, FB-ITS can be extended to other courses such as PowerPoint and Access.

Another potential improvement is that the adaptation of the course materials can be based on learning style in addition to knowledge level. Finally, the evaluation of the system can be performed with different dependent variables.

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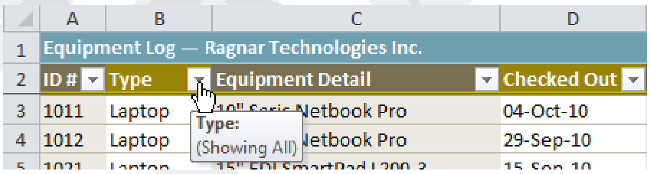
APPENDIX A

A SAMPLE OF THE PRE-TEST AND POST-TEST QUESTIONS

A sample of the pre-test and post-test questions.

- Which of the following is NOT a group on the default Excel Ribbon under the Home tab?
  a) The Formulas group
  b) The Clipboard group.
  c) The Alignment group.
  d) The Editing group.

- What can you do with the drop-down arrows that appear in the header row of tables in Excel?



  a) Add row banding
  b) Filter the data
  c) Format the cells
  d) Hide the column

- Study the highlighted cells in the image below and identify which of the following represents the correct cell address for these cells:
  a) The cell reference for the selected cells is B:21, C:28, D:22, E:26 and F:25.
  b) The cell reference for the selected cells is row 15, column F
  c) The cell reference for the selected cells is F4:F5
  d) The cell reference for the selected cells is B15:F15

	A	B	C	D	E	F
7	Total sales	50000	78200	89500	91250	308950
8	Cost of sales	25000	42050	59450	60450	186950
9	Gross profit	25000	36150	30050	30800	122000
10						
11	Overhead	7500	7520	5620	3520	24160
12	Marketing	7000	6630	4500	3200	21330
13		14500	14150	10120	6720	45490
14	Net profit	10500	22000	19930	24080	76510
15	Profit %	21	28	22	26	25
16						

- When you click on a cell to activate it, the cell address appears in:
  a) The formula bar.
  b) The name box.
  c) The cell.
  d) None of above.

APPENDIX B

STUDENT SATISFACTION QUESTIONNAIRE

The items of the e-learner satisfaction (ELS) tool [104].

Component	No.	Question
Learner interface	1.	The e-learning system is user-friendly.
	2.	The operation of the e-learning system is stable.
	3.	The e-learning system makes it easy for you to find the content you need.
	4.	The e-learning system is easy to use.
Learning content	5.	The e-learning system provides content that exactly fits your needs.
	6.	The e-learning system provides useful content.
	7.	The e-learning system provides sufficient content.
	8.	The e-learning system provides up-to-date content
Personalization	9.	The e-learning system enables you to control your learning progress.
	10.	The e-learning system records your learning progress and performance.
	11.	The e-learning system enables you to learn the content you need.
	12.	The e-learning system enables you to choose what you want to learn

APPENDIX C

SYSTEM USABILITY QUESTIONNAIRE

The items of the System Usability Scale [101]

No.	Question
1	I think that I would like to use this system frequently
2	I found the system unnecessarily complex
3	I thought the system was easy to use
4	I think that I would need the support of a technical person to be able to use this system
5	I found the various functions in this system were well integrated
6	I thought there was too much inconsistency in this system
7	I would imagine that most people would learn to use this system very quickly
8	I found the system very cumbersome to use
9	I felt very confident using the system
10	I needed to learn a lot of things before I could get going with this system

APPENDIX D

CONDITIONAL PROBABILITY DISTRIBUTION TABLES

Conditional Probability Distribution (CPD) tables for each node in Bayesian network model.

P(Excel_Environment)

Excel_Environment	
Learned	notLearned
0.735	0.265

P(Creating_workbook/Excel_Environmen)

Parent Node	**Creating_workbook**	
Excel_Environment	Learned	notLearned
Learned	0.78	0.22
notLearned	0.29	0.71

P(Worksheet_Basics/Creating_workbook)

Parent Node	**Worksheet_Basics**	
Creating_workbook	Learned	notLearned
Learned	0.75	0.25
notLearned	0.37	0.63

P(Cell Basics / Creating_workbook)

Parent Node	**Cell Basics**	
Creating_workbook	Learned	notLearned
Learned	0.69	0.31
notLearned	0.35	0.65

P(Columns_and_Rows / Cell Basics)

Parent Node	**Columns_and_Rows**	
Cell Basics	Learned	notLearned
Learned	0.74	0.26
notLearned	0.3	0.7

P(WrapText_and_MergCells /Cell Basics)

Parent Node	**WrapText_and_MergCells**	
Cell Basics	Learned	notLearned
Learned	0.65	0.35
notLearned	0.226	0.774

P(Creating_Tables/Columns_and_Rows)

Parent Node	**Creating_Tables**	
Columns_and_Rows	Learned	notLearned
Learned	0.736	0.264
notLearned	0.366	0.634

P(Sorting_and_Filtering /Columns_and_Rows)

Parent Node	**Sorting_and_Filtering**	
Columns_and_Rows	Learned	notLearned
Learned	0.58	0.42
notLearned	0.4	0.6

P(Creating_Chart / Creating_Table)

Parent Node	**Creating_Chart**	
Creating_Table	Learned	NotLearned
Learned	0.6	0.4
notLearned	0.364	0.636

P(Simple_Formulas/Cell Basics)

Parent Node	**Simple_Formulas**	
Cell Basics	Learned	notLearned
Learned	0.61	0.39
notLearned	0.322	0.678

P(Basic_Functions / Simple_Formulas)

Parent Node	**Basic_Functions**	
Simple_Formulas	Learned	notLearned
Learned	0.68	0.32
notLearned	0.34	0.66