# Type-2 Fuzzy Logic based Systems for Adaptive Learning and Teaching within Intelligent E-Learning Environments

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A thesis submitted for the degree of Doctor of Philosophy in Computer Science

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July 2016

# Abstract

The recent years have witnessed an increased interest in e-learning platforms that incorporate adaptive learning and teaching systems that enable the creation of adaptive learning environments to suit individual student needs. The efficiency of these adaptive educational systems relies on the methodology used to accurately gather and examine information pertaining to the characteristics and needs of students and relies on the way that information is processed to form an adaptive learning context. The vast majority of existing adaptive educational systems do not learn from the users' behaviours to create white-box models to handle the high level of uncertainty and that could be easily read and analysed by the lay user. The data generated from interactions, such as teacher–learner or learner–system interactions within asynchronous environments, provide great opportunities to realise more adaptive and intelligent e-learning platforms rather than propose prescribed pedagogy that depends on the idea of a few designers and experts.

Another limitation of current adaptive educational systems is that most of the existing systems ignore gauging the students' engagements levels and mapping them to suitable delivery needs which match the students' knowledge and preferred learning styles. It is necessary to estimate the degree of students' engagement with the course contents. Such feedback is highly important and useful for assessing the teaching quality and adjusting the teaching delivery in small and large-scale online learning platforms. Furthermore, most of the current adaptive educational systems are used within asynchronous e-learning contexts as self-paced e-learning products in which learners can study in their own time and at their own speed, totally ignorant of synchronous e-learning settings of teacher-led delivery of the learning material over a communication tool in real time.

This thesis presents novel theoretical and practical architectures based on computationally lightweight T2FLSs for lifelong learning and adaptation of learners' and teachers' behaviours in small- and large-scale asynchronous and synchronous e-learning platforms. In small-scale asynchronous and synchronous e-learning platforms, the presented architecture augments an engagement estimate system using a noncontact, low-cost, and multiuser support 3D sensor Kinect (v2). This is able to capture reliable features including head pose direction and hybrid features of facial expression to enable convenient and robust estimation of engagement in small-scale online and onsite learning in an unconstrained and natural environment in which users are allowed to act freely and move without restrictions. We will present unique real-world experiments in large and small-scale e-learning platforms carried out by 1,916 users from King Abdul-Aziz and Essex universities in Saudi Arabia and the UK over the course of teaching Excel and PowerPoint in which the type 2 system is learnt and adapted to student and teacher behaviour. The type-2 fuzzy system will be subjected to extended and varied knowledge, engagement, needs, and a high level of uncertainty variation in e-learning environments outperforming the type 1 fuzzy system and non-adaptive version of the system by producing better performance in terms of improved learning, completion rates, and better user engagements.

# Acknowledgements

First, let me express my gratitude to Almighty God for all the mercy He showered me throughout the entire period of this work by providing me with the strength and perseverance to accomplish this work.

My gratitude also goes to my supervisor, Prof. Hani Hagras, for the relentless guidance and advice he provided me during the entire course of the work. Not to be forgotten are the students and staff members of the School of Computer Science and Electronic Engineering of Essex University in the United Kingdom as well as those of the King Abdul-Aziz University in Saudi Arabia. The cooperation they showed me will never be forgotten. I am really grateful to all of them. I am also extending my special thanks to a very special friend, Bo Yao, who worked with me in proposing the engagement systems and the test bed environment in the intelligent classroom within the Essex University and Abdulkareem, who cooperated and worked with me during the period of developing the test bed environment for King Abdul-Aziz University.

Special appreciation goes to my wife, Rihab, my daughter, Dana, and my son, Alwaleed, for the patience, support, motivation, and encouragement they provided me during the study. This appreciation also extends to my family members, especially my mother, my sisters, and my brothers, whose support and prayers sustained me throughout these trying moments. I really appreciate the help of everyone who saw to it that everything came to a successful conclusion.

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# List of Acronyms

| | |
|---|---|
| FL | Fuzzy Logic |
| FLS | Fuzzy Logic System |
| 2D | Two-dimensional |
| 3D | Three-dimensional |
| IT2FS | Interval type-2 fuzzy logic system |
| UMF | Upper Membership Function |
| LMF | Lower Membership Function |
| FOU | Footprint of Uncertainty |
| MIMO | Multiple Input Multiple Output |
| MISO | Multiple Input Single Output |
| MF | Membership Function |
| RGB | Red Green Blue |
| RGB-D | Red Green Blue-Depth |
| iClassroom | Intelligent Classroom |
| AI | Artificial Intelligence |

# List of Publications

1. **K. Almohammadi**, H. Hagras, D.Alghazzawi, G. Aldabbagh “A survey of the Artificial Intelligence Techniques Employed for Adaptive Educational Systems,” Journal of Artificial Intelligence and Soft Computing Research, 2016. (Accepted for publication)

2. **K. Almohammadi**, H. Hagras, D.Alghazzawi, G. Aldabbagh “zSlices-Based Type-2 Fuzzy-Logic System for Users-Centric Adaptive Learning in Large Scale E-Learning Platforms,” submitted to Journal of Soft Computing, 2016.

3. **K. Almohammadi**, H. Hagras, D.Alghazzawi, G. Aldabbagh “Users-Centric Adaptive Learning System Based on Interval Type-2 Fuzzy Logic for Massively Crowded E-learning Platforms,” Journal of Artificial Intelligence and Soft Computing Research, vol.6, pp. 81-101, March 2016.

4. **K. Almohammadi**, H. Hagras, B. Yao, A. Alzahrani, D.Alghazzawi, G. Aldabbagh, “A Type-2 Fuzzy Logic Recommendation System for Adaptive Teaching” Journal of Soft Computing, Springer Berlin Heidelberg, pp. 1-15, August 2015.

5. **K. Almohammadi**, B. Yao, A. Alzahrani, H. Hagras, D. Alghazawi, “An Interval Type-2 Fuzzy Logic Based System for Improved Instruction within Intelligent E-Learning Platforms”, Proceedings of the 2015 IEEE International Conference on Fuzzy Systems, Istanbul, Turkey, August 2015.

6. **K. Almohammadi**, B. Yao , H. Hagras “ An Interval Type-2 Fuzzy Logic Based System with User Engagement Feedback for Customized Knowledge Delivery within Intelligent E-Learning Platforms”, Proceedings of the 2014 IEEE International Conference on Fuzzy Systems, Beijing, China, July 2014.

7. **K. Almohammadi** and H. Hagras, “An Interval Type-2 Fuzzy Logic Based System for Customised Knowledge Delivery within Pervasive E-Learning Platforms", Proceedings of the 2013 IEEE International Conference on Systems, Man and Cybernetics, Manchester, UK, October 2013.

8. **K. Almohammadi** and H. Hagras, “An Adaptive Fuzzy Logic Based System for Improved Knowledge Delivery within Intelligent ELearning Platforms,” Proceedings of the 2013 IEEE International Conference on Fuzzy Systems, Hyderabad, India, 2013.

# Chapter 1: Introduction

The enhancement of student learning performance and satisfaction represents one of the main objectives of educational systems. In order to be able to tailor the teaching process according to the needs and preferences of each student, teachers have to conduct accurate evaluations of the different competencies of students, which can naturally differ in terms of level of knowledge, interest, social background, and level of motivation [James 2012], [Ohle 2015]. An expert teacher in the classroom environment is aware of the differentiated characteristics and learning abilities of the students. However, there are limits to the degree to which any teacher can adjust the learning environment to optimally educate every student simultaneously due to classroom size and the accuracy of the evaluation process conducted by the teacher [James 2012]. Therefore, the accuracy of learning and analysing such characteristics can be facilitated by a smaller class size, which would allow teachers to focus on the needs and preferences of each individual student [James 2012]. Studies have shown that, in contrast to group education, one-to-one teaching is more likely to generate a higher student learning performance [Bloom 1984],[ Kid 2010], [Vandewaetere 2011]. However, it might be difficult to provide such attention and teaching in traditional classrooms.

The Internet has become a central core to the educative environment experienced by learners, thus facilitating learning at any location and at any time [Zhao 2006]. Allen and Seaman [Allen 2008] claimed that in 2008, nearly a quarter of all students in post-secondary and further education in the USA were taking courses delivered exclusively online. By 2009, Ambient Insight Research reported that 44%

of post-secondary students in the USA were taking at least some of their courses online and projected that penetration would increase to 81% by 2014 [Ambient Insight Research 2009]. Thus, developed economies have been the principle market for self-paced e-learning products in recent times [Adkins 2013]. However, developing economies are now enthusiastically embracing e learning due to the huge increase in suppliers [Adkins 2013]. A global e-learning system is beginning to define itself. In 2011, the market for self-paced e-learning reached a total of $35.6 billion worldwide and has a five-year compound growth rate of 7.6% [Adkins 2013]. By 2016, revenues will be as high as $51.5 billion [Adkins 2013]. Such findings across the world, and in the USA in particular, reflect the global rapid adoption of e-learning, from an emergent alternative to traditional course delivery. It is rapidly entering mainstream and becoming the predominant method of delivering post-secondary education [Ambient Insight Research 2009], [Ryan 2012].

## 1.1 E-Learning and its methods of delivery

E-learning is a system of electronic learning whereby instructions are devised or formatted to support learning and then delivered to the intended beneficiaries through digital devices that normally come in the form of computers or mobile devices [Clark 2011]. E-learning may be designed in two forms. One form of e-learning is designed as an instructor-led type of learning known as synchronous e-learning, while the other is designed in a format that is a self-paced individual study, known as asynchronous e learning [Clark 2011]. In asynchronous e-learning, when the learners take up a course study that utilises spoken or printed texts that come in the form of illustrations, photos, animation, or video as learning materials, and with which evaluations are made, the learners are then given the opportunity to control the time and place as well as the pace at which they want to undertake their own learning

[Beetham 2013], [Clark 2011]. The other e-learning format, known as synchronous e-learning, is real-time instructor-led training that is designed for instructions on the learning to be delivered or facilitated by an instructor to take place in real time [Clark 2011], [Selvakumarasamy 2013]. Generally, different communication tools are utilised for this type of e-learning format, which is usually delivered in real time, mostly over the Internet. Students undertaking the training usually log on at a scheduled time and establish communications directly with the instructors [Selvakumarasamy 2013]. Unfortunately, it appears that these e learning environments, which could be asynchronous learning environments or synchronous learning environments, have the same problems raised in normal classrooms due to the lack of interaction, which means that the diagnosing process cannot be fully applied between the teachers and students. In addition, the e-learning courses are offered and designed for all students, without considering the individual students' unique needs and abilities [Ciloglugil 2012], [Essalmi 2010].

## 1.2 Adaptive educational systems

It is important that the learner characteristics are monitored by the adaptive educational systems and the instructional milieu is appropriately adjusted to offer support and to make improvements to the learning process [Oxman 2014], [Shute 2012]. Such systems are receiving much interest as a result of their ability to deliver instructional content and analysis by actively adapting to the individual student requirements and needs [Adaptive Learning 2012], [Shute 2012]. Adaptive educational systems contain three different models. The learner profile or model is used as means to infer and diagnose student abilities and characteristics, the second model is the taught content representation to be learnt, and the third model is instructional model which is used to convey and match how the content is suggested to the learner in adaptive and dynamic contexts [Oxman 2014]. The efficiency of adaptive educational systems depends on the methodology employed to collect and diagnose information regarding the learning needs and characteristics of students as well as how this information is processed to develop an adaptive and intelligent learning context [Shute 2012]. Student needs and characteristics in the teaching environment can be classified based on many variables, such as current student knowledge, learning styles, affective states, personality traits, and student goals [Ciloglugil 2012]. The main objective of considering these variables is to allow students to better achieve their learning goals and objectives [Martins 2008]. Course content could be adapted to each learner through feedback, content sequencing, and the presentation of materials in different teaching style approaches [Shute 2012].

The aim of adaptive educational systems is to tailor the overall learning approach in order to fulfil the needs of students [Essalmi 2010]. Hence, it is essential that the profiles of students be created accurately with consideration for the examination of their affective states, levels of knowledge, skills, and personality traits. The information required then needs to be utilised and developed in order to improve the adaptive learning environment [Essalmi 2010]. Acquiring those learning data models then can be used in two ways, prescribed pedagogy proposed by the experts and the designers of the adaptive educational system or by the dynamically learning suited the pedagogy from the teachers or amateurs student's behaviours. This learning capabilities will ensure the improvements of the learner and the system over life-long learning mode. Relying on designer or expert knowledge for guiding the pedagogy of the adaptive educational system may be considered time-consuming and costly. Furthermore, it may even be impossible to tackle the varied characteristics of learners in some cases due to incomplete knowledge about what constitutes effective instruction. In proposing a pedagogy, automatic learning from learner behaviors can make the design of adaptive e-learning and teaching system more convenient and effective, which saves the effort and time of experts and designers. Even more, it will give them insight into what makes online instruction effective. The learning models generated from student behaviors can be easily edited and modified in a lifelong learning model.

### 1.2.1 Overview on some AI techniques that are employed for adaptive educational systems

AI approaches are regarded as valuable tools, as they have the ability to develop and replicate the decision-making process adopted by people [Frias-Martinez 2004]. There are various AI techniques that have been used in adaptive educational systems, such as fuzzy logic (FL), Bayesian networks, neural networks, and hidden Markov models. There are various ways through which AI approaches are used in adaptive educational systems. For example, in some systems, the core focus is to examine and assess student characteristics to generate profiles of the students with the intention of evaluating their overall level of knowledge to be used as basis for prescribed software pedagogy [Yadav 2014], [Yildiz 2014], [Millán 2013], [Chen 2013], [Sripan 2010], [Chika 2009], [Saleh 2009], [Bai 2008], [Venkatesan 2008], [Yannibelli 2006], [Yeh 2005], [Gamboa 2001], [Gertner 2000], [Stathacopoulou 1999], [Martin 1995]. The AI approaches are also used to facilitate the diagnostic process completion so that course content can be adjusted to cater to the needs of every student, and some of them are used to learn from the student behaviours to adjust the prescribed software pedagogy [Cha 2006], [Gutierrez-Santos 2010], [Idris 2009], [Moreno 2005], [Seridi-Bouchelaghem 2005], [Xu 2002], [Azough 2010], [Huang 2007], [ Huang 2008], [Kavčič 2004], [Hsieh 2012].

However, most of the existing adaptive educational systems do not learn from student behaviours. Adaptive educational systems that depend on the ideas of a few experts or designers that are used in tackling student behaviour might be characterised by various sources of uncertainty about the learner response evaluation with an adaptive educational system, linked to learner reception of instruction. Various sources of uncertainty can occur in e-learning environments, resulting from examining student variables, such as assessments or the engagement level. In addition, needed instructional action outcomes, such as what concept should be studied in accordance with this assessment and engagement, combine in a suitable form of proposed environment targets to recognise ideal learning activities. This form of learning-teaching decision is often needed to deal with information that is uncertain (we are not sure that the available information is absolutely true) and/or imprecise (the values handled are not completely defined) [Brusilovsky 2007]. An example of a rule that we need to deal with would be: 'if the student knowledge in Excel is very low and in PowerPoint is high, then he/she should study moderate Excel materials'. We are not sure that this rule and each antecedent and consequent is absolutely true for the target learners. Therefore, how do we ensure high accuracy in assessing the individual's knowledge level, learning style, and other needs in order to provide the best and correct individual adaptive action? This question is quite critical, due to several sources of uncertainties in how accurately student responses are actually assessed by adaptive educational methods as well as the corresponding uncertainties associated with how the resulting instruction to the student is actually understood and received.

In e-learning environments, there are high levels of linguistic uncertainties, where the individual students can differ greatly in how the same terms, words, or methods (e.g., course difficulty or length of study time) are received and comprehended, which can vary according to student motivation, knowledge, and future plans about learning a given subject in an e-learning environment. The AI techniques, such as FL, neural networks, genetic algorithms, and Markov models, can manage the inherent uncertainty that human decision making has, and they are innovative approaches that are tolerant of impression, uncertainty, and partial truth. In this respect, these AI techniques are useful for several reasons, including that they are capable of developing and imitating the human decision-making process [Ahmad 2004].

Thus, developing adaptive educational systems based on the knowledge of how learners interact with the learning environment in readable and interpretable white box models is critical in the guidance of the adaptation approach for learner needs as well as understanding the way learning is achieved. Nevertheless, the majority of the employed adaptive educational systems do not learn from user behaviours (learns to adapt) to create easily read and understood white box models that could handle high levels of uncertainties and are easily understood and checked by the lay user. However, in the case of the majority of the used techniques (e.g., Bayesian networks, hidden Markov models, and neural networks), there is an issue with knowledge representation, which means that such AI techniques cannot create transparent models of human behaviour. Thus, it is not possible to rely on the black box characteristics of these AI techniques, as they pose significant challenges to users regarding interpretation [Stathacopoulou 2007]. Another potential limitation of such black box model-based techniques is that they need to repeat time-consuming iterative learning procedures in order to adapt their models as a result of the dynamic and constantly changing nature of the e-learning process.

### 1.2.2 Overview on the application of fuzzy logic systems in education and e-learning platforms

Fuzzy logic systems (FLSs) are well known for their abilities to generate white box models that can handle high levels of uncertainties. However, the vast majority of FLSs employ type 1 FLSs, which handle the encountered uncertainties based on precise type 1 fuzzy sets [Mendel 2001]. In contrast, interval type 2 FLSs can handle the uncertainties faced through interval type 2 fuzzy sets, which are characterised by a footprint of uncertainty (FOU), which provides an extra degree of freedom that enables handling high uncertainty levels [Mendel 2001]. Additionally, during the even distribution of uncertainty by interval type 2 fuzzy sets across the FOU, it is usual to cipate improvement regarding modelling precision and performance when using general type 2 fuzzy sets, thus allowing for an unbalanced distribution within applications in areas that have uneven distributions of uncertainty when information regarding this kind of distribution is available [Wagner 2010].

A framework geared towards user-modelling, based on the FLS, induces simplified reasoning for both users and designers, which therefore assists in terms of amendments and comprehension [Ahmad 2004], [Jameson 1996], [Kavčič 2003]. Furthermore, FLSs are commonly utilised in order to examine and assess learning- and knowledge-related outcomes [Prokhorov 2015],[Yadav 2014],[ Yildiz 2014],[ Chen 2013], [Sripan 2010],[ Saleh 2009],[ Bai 2008], [Venkatesan 2008], [Nykänen 2006], [Weon 2001], [Ma 2000], [Chen 1999], [Chang 1993]. The FLS are also used to facilitate the diagnostic process completion, so that course content can be adjusted to cater to the needs of every student. In relation to Xu [Xu 2002], a profiling system adopting a multi-agent approach has been presented, whereby the creation of fuzzy models for content and students was based on a dynamic plan formally defined ahead of time for one individual. This framework was obtained through profile abstraction, which is recognised as comprising student-centred learning tasks, such as the topic at hand and the time spent on the topic. Furthermore, the content framework was devised and created with fuzzy links between the subjects, and the knowledge of the individuals (referred to as prerequisite relations) were established to be utilised in order to formally determine the learning adaptation (i.e., the order of issues to be examined by the individual) [Xu 2002]. The work of [Kavčič 2004] employs FL to model user knowledge of domain concepts. The work represents the dependencies between domain concepts in order to cycle graph, as some concepts have essential or supportive perquisites between them, and they use fixed rules to accomplish dynamic updating of user knowledge regarding the concepts. Through these procedures, the right concepts are adapted to the students. Similarly, the work of [Chrysafiadi 2015], who developed and use of fuzzy knowledge state define FuzKSD module. He defines this module in a way that points out the alterations on the state of a student's level of knowledge. Chrysafiadi also used Fuzzy Cognitive map which collaborates with FuzKSD and represent the relationship between the domain concepts. When changes regarding to the learners' level of knowledge on domain concepts arises, FuzKSD tries to point out the learners' knowledge, updates it both in this concept and also in all other concepts that are related to it, considering the learner updated knowledge as well the dependences in FCM for the domain concepts.

Additionally, Hsieh (2012), in his work, he propose a system which use fuzzy inference helps to analysis the learners' linguistic ability, something through accumulated learner profile which helps them to select the best article that is to be read next. Once the learner has gone through the article, he/she is challenged through vocabulary tests which involve words that he/she has encountered while reading that article [Hsieh 2012]. Thereafter, the learners profile is updated in relation to their performance in the test as well as their linguistic ability which are recalculated and analysed and finally a new article is chosen for delivery [Hsieh 2012].

Nevertheless, in previous research, the behaviours of the students are re-formed through criterion links between student knowledge and topics with the individual behaviour being restricted by establishing a dynamically grounded study plan for the student. However, the needs of the student in previous studies were not learnt automatically through the large data set obtained from various students, as was the case with the system discussed in this thesis. Moreover, the systems considered in previous studies did not adapt in a lifelong learning approach to ensure that the generated models adapt to the students' changing needs and expanding knowledge. Moreover, to the best of our knowledge, the adoption of type 2 fuzzy approaches in the context of an adaptive learning educational environment has not been examined yet in the literature.

### 1.2.3 Considering the students' degree of engagement in adaptive educational systems

Currently, e-learning is confronted by a significant limitation, in that student engagement is not considered by adaptive learning and teaching systems to be used as the basis of the adaptation process, and the systems do not map delivery needs in terms of the appropriated instructional approach and content taught. Estimating the engagement degree of the users robustly and automatically is a key procedure for various applications and research topics and has been widely studied in different laboratories and semi-constrained environments. Thus, automatic and continuous learning of what content is suitable for a learner when he/she has lower or higher engagement is an important factor for achieving higher student learning outcomes, engagement, and satisfaction. In order for students to obtain knowledge from the course, they need to engage with it, regardless of how the course is delivered [Clark 2011]. The more a student engages with the content of the course, the more information they will absorb [Clark 2011]; hence, if a course can be better tailored to student engagement, the students will inevitably learn more in asynchronous and synchronous learning environments. In addition, it is unreasonable to expect the teacher in a synchronous learning environment to track each individual learner, especially in online learning, where the number of students is high. Therefore, automatically gauging and analysing the objective feedback from the attendees is a key step in the procedures of education so that adaptive education is delivered.

A conventional non-contact method to estimate the engagement degree is to analyse eye gaze features. In the work of Mayberry [Mayberry 2014], eye gaze direction is calculated based on two-dimensional (2D) video data, using a low-cost embedded hardware platform to determine the engagement and reaction of the users in gameplay so that feedback can be provided to the gaming user interface and gameplay logic [Mayberry 2014]. In the work of Ye [Ye 2012], the learner engagement level was estimated and classified based on an image for the application scenarios of human-computer interaction by a webcam using the features extracted from 2D user images, including head pose, eye gaze, eyebrow and head movements, mouth opening statuses, etc. In the work of Hardy [Hardy 2013], user engagement levels were estimated by 2D camera images based on the extracted facial features, and the output results were labelled into four different levels of engagement. However, the 2D image-based methods are inadequate for returning robust features to complex vision applications, such as eye gaze recognition. Therefore, higher-level systems using multiple hybrid sensors are studied.

Different from the non-contact method, in other studies [Mello 2009], [Mota 2003], wearable sensors were embedded into glasses facing users' eyes, which were used to analyse the eye gaze and interests of the users. In another study [Amershi 2006], a skin conductance sensor was employed to recognise the connection between the biological degree of skin conductance and emotional experiences in a training session of training and learning systems. Similarly, in [Corcoran 2012] research, a particular chair utilising pressure sensors was developed to understand the regular body actions to relate a child's interest level in the procedure of conducting an education session on a computer. This system was also utilised by [Asteriadis 2009] to observe signals of the student body gestures for recognising student emotions in a learning session. In the work of [Hernandez 2013], a system based on hybrid wearable sensors sensing the real-time data of skin conductance, heart rate, and EMG was proposed, and this system used an unsupervised feature selection algorithm to measure learner engagement. However, wearable electronic devices are intrusive and uncomfortable for the users, especially those electronic devices required to be deployed near sensitive parts, such as the eyes.

In another study [Ishii 2014], an engagement estimation system based on a particular eye gaze tracking device was proposed. This system is able to robustly measure the user's engagement based on the orientation of the eye gaze captured by a particular non-contact device. However, the main disadvantage is due to the high expense (around $2000 USD per piece) of this type of sensor, which can be only used for a single user within a relatively short distance (60 centimetres). A similar method was reported by [Mello 2012], where an engagement analysis system based on an eye tracker was proposed, and this system is able to label the student as not engaged if the student looks away from the screen.

Besides the engagement analysis methods using various sensors, the literature reports systems based on sensor-free methods for estimating student engagement. In [Baker 2012], Baker developed an engagement and emotion analysis system based on machine learning to detect user emotional states, such as boredom, engagement, confusion, frustration, etc. The system employs data mining techniques, analysing the log data, which covers the information of student activities, such as the length of time the student spends on finishing the question, the difficulty level of the question, and the accuracy of the answer given by the student, etc. However, these methods are not substantially better, especially when subject to stringent cross-validation processes [Baker 2012]. A similar engagement detection method was presented by Badge [Badge 2012] based on academic activities and log information of learners performed on a social network.

Importantly, the main focus of the adaptive learning technology and environments was on the asynchronous learning environment, completely ignoring synchronous online learning environments and models that could be built to model adaptive teaching and training that could enable teachers to learn the behaviours of expert teachers in tackling different student engagement in accordance with variables of the course content in dynamic environments.

## 1.3 Aims and Objectives of this Research

This research aims to contribute towards realising and creating effective intelligent adaptive online learning small and large scale platforms, which could more precisely model and correlate the student variables (such as knowledge level, background, prior knowledge, learning style, and motivation level) with needed instructional and pedagogical variables (such as situated difficulty level, pace of study, and suitable teaching instructional approach) in easily readable white box models. These learnt models will then enable the learning environment to be automatically, intelligently, pervasively, and continuously adapted to given student needs in order to deliver the best context and content (learning practice) of education that adheres to such needs and preferences.

As an important phase to begin to achieve this aim, we employed self-learning type-1 and an interval type 2 Fuzzy systems, which enable the generation of FL-based models from the data. These type-1 and type-2 fuzzy models are generated from data representing various student characteristics, capabilities, and engagement degrees according to their desired learning needs. These learnt FL-based models are then used to improve the instruction to the various students based on their individual characteristics. In addition, the proposed systems are continuously adapting in a lifelong learning mode to make sure that the generated models adapt to the individual student needs. These presented theoretical and practical environments deal with different challenges that are encountered as discussed earlier in this chapter. The steps and processes for achieving the main aim are as follows.

In the first stage of the work, a theoretical and practical environment was developed based on type-1 FL. Learning-teaching behaviour is represented in a human readable and linguistically interpretable manner by the fuzzy rules. Their transparency makes them perfect for quick assessment to explain the reason and method of certain combinations of inputs actuating specific rules, where a certain set of output conclusions has been yielded. The proposed environment employs a self-learning mechanism that generates a FL-based model from the data. We incorporated and gauged the student engagement levels, and we mapped them to suitable delivery needs, which match the knowledge and preferred learning styles of the students. The resulting practical and theoretical environments incorporate a novel system for gauging the student engagement levels based on utilising visual information to automatically calculate the engagement degree of the students. This differs from traditional methods that usually employ expensive and invasive sensors. Our approach only uses a low-cost Red Green Blue-Depth (RGB-D) video camera (Microsoft Kinect) operating in a non-intrusive mode, whereby the users are allowed to act and move without restrictions. This fuzzy model is generated from data representing various student capabilities and their desired learning needs. The learnt FL-based model is then used to improve the knowledge delivery to the various students based on their individual characteristics. The proposed environment is adaptive, where it is continuously adapting in a lifelong learning mode to ensure that the generated models adapt to the individual student preferences. This employed approach was not computationally demanding and generated easily read and analysed white box models, which can be checked by the lay user, which is mainly suitable for adapting the dynamic nature of the e-learning process.

In this stage of the work, we extended the original practical and theoretical environment to use interval type 2 FLSs which employ the type-2 membership functions (MFs) which can handle the faced uncertainties. The learnt type 2 MFs minimise and handle high levels of linguistic uncertainties in the e-learning environment, whereby students can interpret and act on the same terms, words, or methods (e.g., course difficulty, length of study time, or preferred learning style) in various ways according to their level engagement, knowledge, and future plans. This environment was superior in facilitating the online adaptation of the rules, while being robust to the high level of linguistic uncertainties that exist in such an environment.

In the second stage of the work, we presented a method based on type-2 FL utilising visual RGB-D features, including head pose direction and facial expressions captured from Kinect (v2), a low-cost but robust 3D camera, to measure the engagement degree of students in both remote and onsite education for small-scale e-learning platforms. This system augments another self-learning type-2 FLS that helps teachers with recommendations of how to adaptively vary their teaching methods to suit the level of students and enhance their instruction delivery. This proposed dynamic e-learning environment integrates both onsite and distance students as well as teachers who instruct both groups of students. The rules are learnt from the student and teacher learning/teaching behaviours, and the system is continuously updated to give the teacher the ability to adapt the delivery approach to varied learner engagement levels. The efficiency of the proposed system has been tested through various real-world experiments in the University of Essex intelligent classroom (iClassroom) among a group of 30 students and six teachers. These experiments demonstrated the capabilities—compared to type 1 fuzzy systems and non-adaptive systems—of the proposed interval type 2 FL-based system to handle uncertainties and improve the average learner motivation to engage during learning.

In the final phase, a novel, theoretical, and practical environment based on a "zslice-based type-2 FL-based" system that can learn student-preferred knowledge delivery needs based on their characteristics and current levels of knowledge in order to generate an adaptive learning environment for large-scale e-learning platforms. Over another categorisation of student backgrounds, the system can handle further uncertainty and adapt the resulting rules and MFs in a novel learning mode, accommodating further uncertainties arising from background changes in the e-learning environment and the associated changing user behaviour. We will present large-scale, real-world experiments involving 1,871 students from the King Abdul-Aziz University over the course of teaching Excel and PowerPoint in which the type-2 Fuzzy system learnt and adapted to student behaviour, while subjected to extending knowledge and a high level of linguistic uncertainty variation in e-learning environments, which combine various students. In addition, we will show how our zslice type 2 FL-based system generated by the one-pass learning technique was able to deal with the high level of uncertainties in the adaptive e-learning environment and outperform those generated by interval type 2 FL, type 1 fuzzy systems, adaptive, instructor-led systems, and non-adaptive systems.

## 1.4 Significance of this Research

This work will advance knowledge in multidisciplinary fields, such as pedagogy of online education and adaptive learning landscapes. Attaining a comprehensive and more adequate understanding of the correlation of learner characteristics, prior knowledge, engagement, and their needs according to the authoring, instructing, and delivering online teaching content as delivered and comprehend by the learners is a pivotal area of research and has not yet been investigated well in online learning environments (OLEs). When the student has lower satisfaction, performance, and engagement with the online learning system, most providers of current online learning platforms will end with lower completion rates and reputations. According to Onah [Onah 2014], there are high dropout rates in the number of students who enrolled within massive open online courses, and the completion rates in those courses are less than 13%. Therefore, it is worthwhile for service providers to learn to adapt to the learners needs and preferences in a manner that grips their engagement, speeds up their performance, and gains their satisfaction in easily and readable white box models, which can be checked in real time, edited, and understood easily. Adaptive learning systems are an important enabler for achieving and realising such aims. Thus, finding the correlation between learner characteristics, prior knowledge, engagement, and their needs according to the authoring and delivering online teaching content, from the perspectives of the learners is a significant first step towards realising more effective and intelligent adaptive learning systems that serve such a goal. The transparency of the proposed model based on the type 2 FLS can give insight into how the learning within e-learning platform is realised. In addition, it can be used to further verify the kinds of learning and teaching behaviours to be emphasised or rejected in the future. It is important to focus on developing explanatory models to produce interpretable insight. Such insight advances the understanding of learning and produces recommendations for improved educational practices. In addition, the proposed models will be flexible so that many learner attributes could be mapped to it and will correlate to more instructional variables to achieve more intelligent learning context, and it can be used to test a practical hypothesis regarding the learning-teaching behaviour.

## 1.5 Novelty

It is clear from the studies that exist in the literature that adaptive learning environments must be realised, most previous studies do not learn from user behaviours to create more easily read and understood white box models that could handle high levels of uncertainties. Therefore, when considering some of these approaches (namely Bayesian networks, hidden Markov models, and neural networks), there is a problem in terms of knowledge representation, meaning that such AI approaches are not able to establish transparent human behaviour frameworks [Stathacopoulou 2007]. One further restriction of such approaches is that they require the repetition of time-consuming iterative learning methods to fulfil framework amendments following the dynamic nature of the e-learning process. The FLSs are well known for their abilities to generate white box models that can handle high levels of uncertainties. However, the vast majority of FLSs employ type 1 FLSs, which handle the encountered uncertainties based on precise type 1 fuzzy sets [Mendel 2001]. In contrast, interval type 2 FLSs can handle the uncertainties faced through interval type 2 fuzzy sets, which are characterised by a FOU, which provides an extra degree of freedom that enables handling high uncertainty levels [Mendel 2001]. Therefore, the main contribution of this research is to provide a novel type-2 FLS that can overcome the high level of linguistics and numerical uncertainty that may hinder the development of an efficient learning context and investigate the implications of using easily read and understood white box models for modelling such environments.

To address these problems that are related to the degree of ignoring learner engagement degree as adaptation and evaluation variable. It is obvious that incorporating learner engagements as a learner personalisation variable enriches the learning environments with a highly crucial pedagogical dimension. In this thesis, we introduce and utilise an engagement estimate system using non-contact, low-cost, and multi-user support 3D sensor Kinect (v2), which is able to capture reliable features, including head pose direction and hybrid features of facia; expression, enabling the convenient and robust estimation of engagement based on interval type 2 FLS in large-scale online and onsite learning in an unconstrained and natural environment, where users are allowed to act freely and move without restrictions.

In addition, to the best of our knowledge, no previous studies have been proposed to learn the teaching behaviour process according to the varied onsite and distance learners' levels of engagement in their respective small and large scale learning environments to then be used as an aiding tool to improve the varied average level of engagement in a balanced and improved way.

## 1.6 The Structure of the Thesis

The rest of the thesis is organised as follows. Chapters 2 gives an overview on type-1 FLSs and type-2 FLSs, respectively. This chapter is very important, as it describe type-1 FLSs and type-2 FLSs theory, which have been utilised as the main components in building the proposed theoretical and practical environments.

Chapter 3 presents our proposed interval type 2 FL-based system with user engagement feedback for customised knowledge delivery within small-scale intelligent e-learning platforms. Chapter 4 presents our proposed type 2 FL recommendation system for adaptive teaching in small-scale e-learning platforms. In the fifth chapter, we proposed a zSlice-based type 2 FLS for adaptive learning within large-scale e-learning environments, where we have evaluated the proposed environments within large-scale e-learning platforms. Finally, we present our conclusions and our future work plans in Chapter 6.

# Chapter 2: An Overview of Type-1 and Type-2 Fuzzy Logic Based Systems

The main goal of the proposal of fuzzy systems is to develop the means and solutions to model, quantify, and handle the uncertainty in complex systems [Dutt 2013]. Within adaptive e-learning environments, there are high levels of uncertainty, vagueness, and imprecision in modelling the data and information related to learners, such as their capabilities, characteristics, and needs and interactions linked with taught content that could facilitate developing a model to meet the needs of an educational setting. Therefore, it is impossible to quantify and measure their relations with the use of conventional models of mathematics. FLSs offer some useful capabilities to represent and reason with vagueness and impressions to imitate the human approach of reasoning [Ahmad 2004]. This reasoning may be for the learner whose abilities, characteristics, and needs are being diagnosed and modelled, or it may be that of modelling the expert or learners whose knowledge constitutes the foundation for the system's reasoning and adaptation [Ahmad 2004].

Within the adaptive learning environment, these correlated models can be used to deliver content that matches the user's needs and preferences in a dynamic way, which will result in improved engagement, better completion rate, and enhanced student performance when dealing with the uncertainties related to real e-learning environments. Also, in our proposed synchronous adaptive teaching environment, when learning correlated models that describe the best pedagogical decisions based on the content difficulty level as well as the average level of student engagement and the variation between engagements in a dynamic real online teaching environment. This learned model is used to enhance teaching performance by informing the teacher about the best teaching approaches in order to gain an enhanced average level of learner engagement [Almohammadi 2015a],[Almohammadi 2015b]. Teaching-learning behaviour modelling based on FL facilitates reasoning for designers and users to understand and modify [Jameson 1996], [Kavčič 2003], because the information produced by the system can be represented in transparent and flexible human-readable models.

A new category and extension of fuzzy systems can be defined as type-2 FLSs, where type-2 fuzzy sets are used to convey numeric and linguistic uncertainty [Mendel 2001], [Mendel 2014]. This type-2 fuzzy system can be proposed to directly model and reduce the effects of uncertainties [Mendel 2001], [Mendel 2014]. An extended part of type-1 FL, known as type-2 FL, can be minimised to type-1 FL with a complete disappearance of uncertainty [Mendel 2001], [Mendel 2014]. There are more degrees of freedom in a type-2 FLS (in the footprint of uncertainty and the third dimensions of type-2 fuzzy sets) compared to the type-1 FLSs. This is indicative of the type-2 FLSs' having the position of exceeding the performance of type-1 FLSs due to its large number of degrees of freedom in its design [Mendel 2001], [Mendel 2014]. Type-2 FLSs provide a methodology for tackling different sources of numeric and linguistic uncertainty that exist in e learning environments.

The rest of this chapter will provide the following information: Section 2.1 of this chapter will concisely introduce an overview of FL theory along with the description of type-1 FLSs which will be in Section 2.2. A brief introduction of type-2 fuzzy sets as the methodology of managing uncertainties and extending the capabilities of the type-1 fuzzy sets will be presented in Section 2.3. Section 2.4

discuss the description of type-2 FL systems. The zSlice-based type-2 FLSs will be introduced in Section 2.5. Finally, Section 2.6 will outline the discussions.

## 2.1 Overview of Fuzzy Logic Theory

In this section, we will outline the extenuation from crisp sets to fuzzy sets.

### 2.1.1 Crisp Sets

The elements x ⊂ A are identified to define a crisp set A within the universe of discourse X [Mendel 2001]. It can be realized by determining one condition or many that makes x ⊂ A [Mendel 2001], [Mendel 2014]. Therefore, the definition of A will be: A={x | x meets some condition(s)}. In other words, this leads to the introduction of a zero-one MF (it can be called a discrimination, indictor, or characteristic function), which may also represent it with respect to A [Mendel 2014]. In addition, $\mu_A(x)$ has been denoted as follows [Mendel 2001]:

$$\mathrm{A} \Rightarrow \mu_A(x) = \begin{cases} 1 & if\ x \in A \\ 0 & if\ x \notin A \end{cases} \quad . \tag{2.1}$$

Figure 2.1 demonstrates an instance of a crisp set that models the crisp set of a very low knowledge level in comprehending a concept. It demonstrates that if the current knowledge of the learner is less than or equal to 30, then the learner's knowledge of the concept is very low, and its related MF is one. When the knowledge degree is greater than 30, it does not fit the criteria for very low crisp sets, and its related MF will be zero. Nevertheless, it is actually complex to determine whether the learner's knowledge is zero compared to the condition in which the learner's knowledge is 30. An additional dilemma is that the sharp position between the perception of very low and low is 30, which is not accurate for all people whose knowledge is appraised; several persons regard 20 as the sharp position between two perceptions, whereas others could describe 45 as that sharp mark. Hence, this type of set cannot be precise or deal with the basis of uncertainty that emerges from these vague descriptions, which are extremely common in real-world complex environments. Fuzzy sets are able to consider these shortcomings, and will be introduced in the next section.

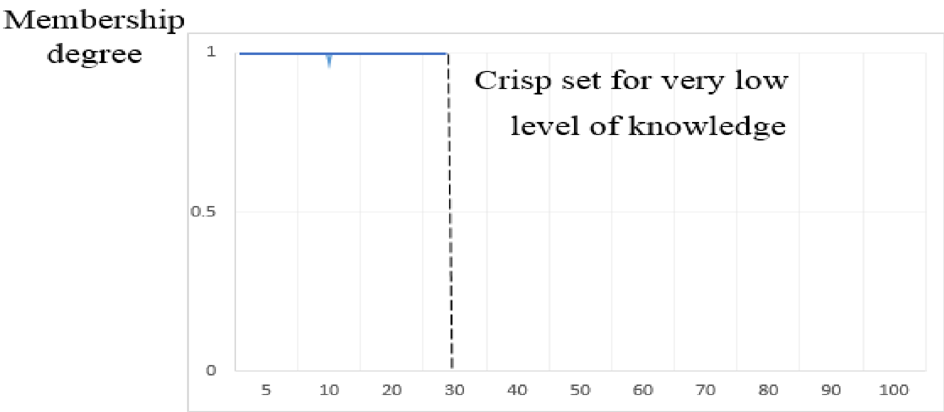



Figure 2.1: An example of a crisp set for a very low level of knowledge.

## 2.1.2 Fuzzy Sets

A crisp set is generalised by a fuzzy set. In the universe of discourse X, it gets recognition, and the MF $\mu_A(x)$ characterises it. The values are in the interval [0, 1]. The degree of similarity is provided by the MF for an element in X in the fuzzy set F, and F can also be considered a subset of X [Mendel 2001], [Mendel 2014]. An element of X can have both a partial and complete membership in the fuzzy set; thus, the element can be seen in more than one fuzzy set to different degrees of similarity [Mendel 2001]. One can exhibit a fuzzy set F in X form as a set of order pairs of a generic element x along with its grade of MF $\mu_F(x)$ [Mendel 2001], [Mendel 2014]:

$$F = \{(x, \mu_F(x)) \mid x \in X\}. \tag{2.2}$$

Thus, the form of MF for fuzzy set F will be:

$$(x, \mu_F(x)) \qquad \forall\, x \in U. \tag{2.3}$$

Here, the grade of the MF is denoted by $\mu_F(x)$ [Mendel 2001]. Nevertheless, $\mu_F(x)$ is represented as an MF, which is a common practice [Mendel 2001]. When $X$ is continuous (such as for real numbers), the representation of $F$ will be as follows [Mendel 2001], [Mendel 2014]:

$$F = \int_X \mu_F(x)/x. \tag{2.4}$$

Here, the collection of all points $x \in X$ in association with MF, $\mu_F(x)$, are denoted by the integral sign of Equation 2.4 [Mendel 2001], [Mendel 2014].

### 2.1.3 Linguistic Variables

As Zadeh [1975] asserted, while pulling back from the surface of overpowering complication, the application named linguistic variables is naturally explored, and these variables comprise the values of words and sentences, not numbers. What drives one to use words or sentences instead of numbers is the linguistic characterization that is not generally specific in the same way numerical characterizations are. The general tendency of humans is to try to express the complicated world through words and sentences in a less particular way than using mathematical approaches or numbers. Thus, information in FL is elucidated by words represented by labels and linguistic variables representing words, which are related to fuzzy sets [Doctor 2006].

Hence, a linguistic variable for the average knowledge level or student engagement level within the domain that covers certain value ranges can be defined as $u$, and $x$ denotes the numerical measured values of $u$ with $x \in X$, where $x$ and $u$ can be used interchangeably. Further decomposition of the linguistic variable $U$ can be done in the form of a set of terms $T(u)$ constituting fuzzy granularisation of the linguistic variable into fuzzy sets, defined over its universe of discourse [Mendel 2001], [Mendel 2014].

As a result, decomposition of the linguistic variable $u$ that represents such characteristics as the level of student knowledge can be done in the form of a number of labels or terms, such as very high, high, medium, low, and very low. Fuzzy numbers are expressed through these labels, of which the semantic and perceptual amalgamation ultimately constitutes fuzzy granules. Each label is formed by a fuzzy set, which is described mathematically by choosing a particular MF type.

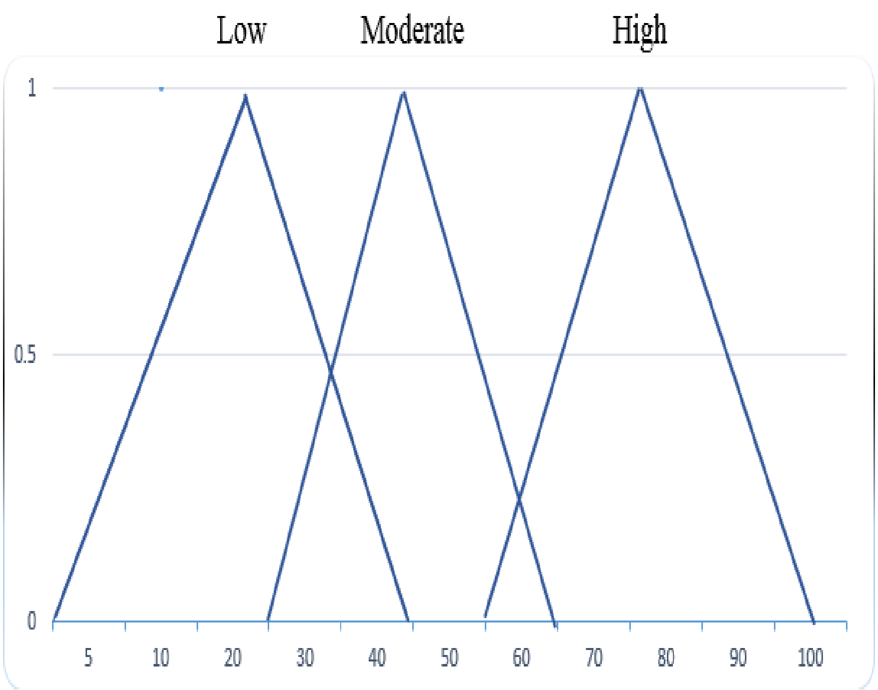



Figure 2.2: Triangular MFs representing fuzzy sets for student engagement level.

The fundamental characteristics of singleton (type-1) FLSs are explained in detail in the next section.

## 2.2 Type-1 Fuzzy Logic Systems

Fuzzy logic can be seen as an extension of traditional set theory, as statements can be partial truths that fall between absolute truth and absolute falsity [Mendel 1995]. The FLS comprises four stages (as Figure 2.3 shows): fuzzifier, rule base, inference engine, and defuzzifier [Mendel 1995]. Rules can be extracted from numerical data or supplied by experts. Upon establishing the rules, an FLS may be considered a mapping from crisp inputs to crisp outputs, and such a mapping may be articulated numerically as $y = f(x)$ [Mendel 1995].

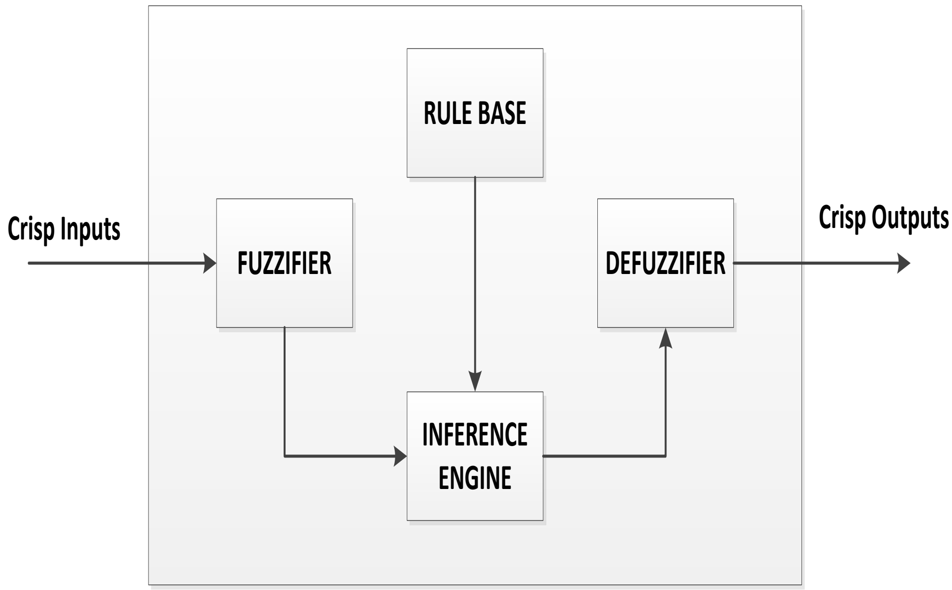



Figure 2.3: Overview of a fuzzy logic system [Mendel 2001].

### 2.2.1 Fuzzification

A crisp point input vector, including p inputs $x = (x_1,\ldots,x_p)^T \in X_1 \times X_2, \ldots, X_p \equiv \mathrm{X}$ within a fuzzy set, $A_X$ in X is measured by the fuzzifier [Mendel 2001]. The singleton fuzzifier is popular among fuzzifiers, and it will be applied for the environment we have proposed. There is solely a single nonzero membership point in the input fuzzy set of the singleton fuzzification [Mendel 2001].

This means that the fuzzy set $A_x$ can be defined as a fuzzy singleton supported by $x'$ if $\mu_{A_x}(x)$ =1 for x=$x'$ and $\mu_{A_X}(x)$ =0 for $x \neq x'$ in regards to all other $x \in X$. Thus, its meaning can be interpreted as every distinct component of $\mu_{A_x}(x)$ being a fuzzy singleton. It indicates that we must assume $\mu_{x_i}(x_i') = 1$ for $x_i$=$x'$ and $\mu_{x_i}(x') = 0$ for $\forall\, x_i \in X_i \; and \; x \neq x_i'$ [Mendel 2001].

## 2.2.2 Rule Base

A type-1 fuzzy system with *p* inputs $x_1 \in X_1, \dots, x_p \in X_p$ and *k* outputs $y_1 \in Y_1, \dots, y_k \in Y_k$ will be considered by our study [Mendel 2001]. Thus, the formulation of the rule base for this Multiple Input Multiple Output- (MIMO) FLS carrying M rules will be as follows [Doctor 2006]:

$$R = \{R^1_{MIMO}, R^2_{MIMO}, \dots \dots .., R^M_{MIMO}\}. \tag{2.5}$$

Here, the form of the $l^{th}$ rule is:

$$R^l_{MIMO}: if\ x_1\ is\ F^l_1\ and\ \dots and\ x_m\ is\ F^l_m\ Then\ y_1\ is\ G^l_1, \dots, y_K\ is\ G^l_K\ l = 1, \dots, M. \tag{2.6}$$

Lee [1990] proffered outcomes that assert that the rule base of MIMO can be taken in terms of a group of Multi-Input Single-Output (MISO) rule bases, as follows [Doctor 2006]:

$$R = \{RB_{1\,MISO}, RB_{2\,MISO}, \dots \dots .., RB_{k\,MISO}\}. \tag{2.7}$$

Here, the rule base of the multiple $p$ inputs and the $c^{lh}$ single output (MISO) $RB_{c\,MISO}$ is present with c = 1,…, k and k is the total number of outputs of the type-1 FLS; M rules are contained within the rule base [Doctor 2006].

## 2.2.3 Fuzzy Inference Engine

The functionality inference engine block in the FLS in Figure 2.7 is to map input fuzzy sets to output fuzzy sets [Mendel 2001]. The following is formulated from every rule in a MISO fuzzy rule base with M, which is the total number of rules, $l = 1,2,3, \ldots, M$ with $p$ inputs $u_1 \in U_1, \ldots, u_n \in U_p$ and one output $v \in G_c^l$ [Kassem 2012], [Mendel 2001]:

$$R_{C\,MISO}^{l}\text{: If } u_1 \text{ } is \text{ } F_1^l \text{ and } u_p \text{ } is \text{ } F_p^l\text{, then } v \text{ } is \text{ } G_c^l \quad l = 1, \ldots, M, \tag{2.8}$$

where $F_1^l, F_2^l, \ldots, F_p^l$ are fuzzy sets in $U_1, U_2, \ldots, U_p$ and $G_c^l$ are fuzzy sets in $V$. The inference engine employs these if-then rules to map input fuzzy sets in $U = U_1 \times U_2, \ldots, U_m$ to output fuzzy sets in $V$. Every rule is interpreted as a fuzzy implication [Mendel 2001], and in FL, there are numerous means where a fuzzy implication could be described [Lee 1990]. The popular implications of engineering applications are Mamdani implications, and our proposed system will apply these implications.

Let $F_1^l \times, \ldots, \times F_p^l$ be $A$ and $G_c^l$ be $B$, so that the rule demonstrated in Equation (2.8) is construed by the inference engine as $A \rightarrow B$. The mapping is completed from $\mu_A(u)$ to $\mu_B(\text{v})$, in which $u \in U$ and $v \in \text{V}$. Moreover, $u$ and $v$ are linguistic variables, and their arithmetic values are *x* and *y*, where $x \in U$ and $v \in \text{V}$ [Kassem 2012]. By taking *x* and *y* into account, the interpretation performed by the inference engine can be written as

$$\mu_{R^l}(x, y) = \mu_{A\rightarrow B}(x, y). \qquad (2.9)$$

To calculate the firing strength degree $f^l(x)$ of the $l^{th}$ rule $R^l$, the computation is demonstrated in the subsequent equation in which $\star$ is the selected t-norm:

$$f^l(x) = \mu_{x_1}(x_1) \star \ldots \ldots \star \mu_{x_p}(x_p). \qquad (2.10)$$

Following the computation of the firing degree $f^l(x)$ for every rule $R^l$, we can find the output fuzzy set $B^l$. The final output fuzzy set is established by merging the output fuzzy set for every rule by means of a t-conorm operator [Kassem 2012].

### 2.2.4 Defuzzification

The functionality of the defuzzifier is to calculate a crisp output for the type-1 FLS from the fuzzy sets that existed at the output of the inference engine. I have used one type of defuzzification method, the centre set defuzzification approach [Karnik 1998], [Sugeno 1993], in which each rule's consequent is replaced by a singleton placed at its centroid, whose amplitude equals the firing level. Then the centroid composed of these singletons can be found [Mendel 2001]. The formula for obtaining the output is:

$$y_{cos}(x)_c = \frac{\sum_{l=1}^{M} ce_c^l \; T_{i=1}^{p} \mu_{F_i^l}\ (x_i\,)}{\sum_{l=1}^{M} \; T_{i=1}^{p} \mu_{F_i^l}\ (x_i\,)}, \qquad (2.11)$$

Where $ce_c^l$ is the centroid of the $l^{th}$ rule and $T_{i=1}^{p}\mu_{F_i^l}\ (x_i\,)$ is the firing strength level [Mendel 2001].

## 2.3 Type-2 Fuzzy Sets

Modelling numeric and linguistic uncertainties is possible through type-2 fuzzy sets because their MFs are fuzzy as well [Mendel 2002]. The linguistic and numeric uncertainties faced by e-learning environments can be managed by type-2 fuzzy sets to acquire improved teaching-learning behaviour models. As shown in Figure 2.4a, the points on the triangle can be shifted either right or left, and the amounts do not have to be equal, as can be seen in Figure. 2.4b. Thus، blurring type-2 fuzzy sets can be assumed accordingly [Mendel 2014]. Therefore, no single value remains for the MF ($u$') at a particular value of $x$, say $x$', or any value of points intersected by the vertical line with the blurred area in Figure. 2.4c. The weight of those values is not required to be the same, so an amplitude distribution can be assigned to each of these points. A 3D MF is created to realise this distribution for all $x \in X$, where a type-2 fuzzy set is characterised by a type-2 MF [Mendel 2001], [Mendel 2014]. Conventionally, a type-2 MF $\mu_{\tilde{A}}(x, u)$ denotes a type-2 fuzzy $\widetilde{A}$ set [Mendel 2001], [Mendel 2014], where, $x \in X$ and $u \in J_x \subseteq [0,1]$, which means [Mendel 2001]:

$$\tilde{A} = \{((x, u), \mu_{\tilde{A}}(x, u)) | \; \forall \, x \in X \,, \forall \, u \; \in J_x \; \subseteq [0,1] \,\} \qquad (2.12)$$

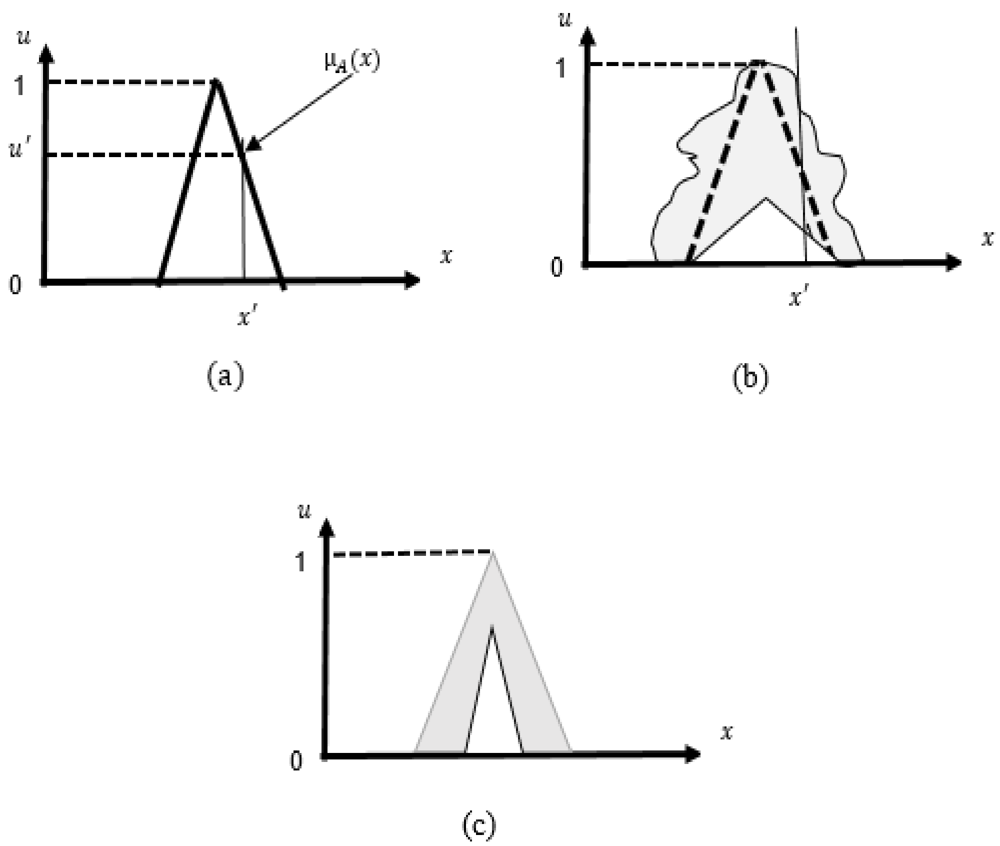



Figure 2.4: (a) Type-1 MF and (b) blurred type-1 MF (c) FOU [Mendel 2001].

## 2.3.1 Interval Type-2 Fuzzy Logic Sets

Formally, let $\tilde{A}$ be an interval type-2 fuzzy set (IT2 FS), as shown in Figure 2.5 a, which is characterized as follows [Mendel 2006a]:

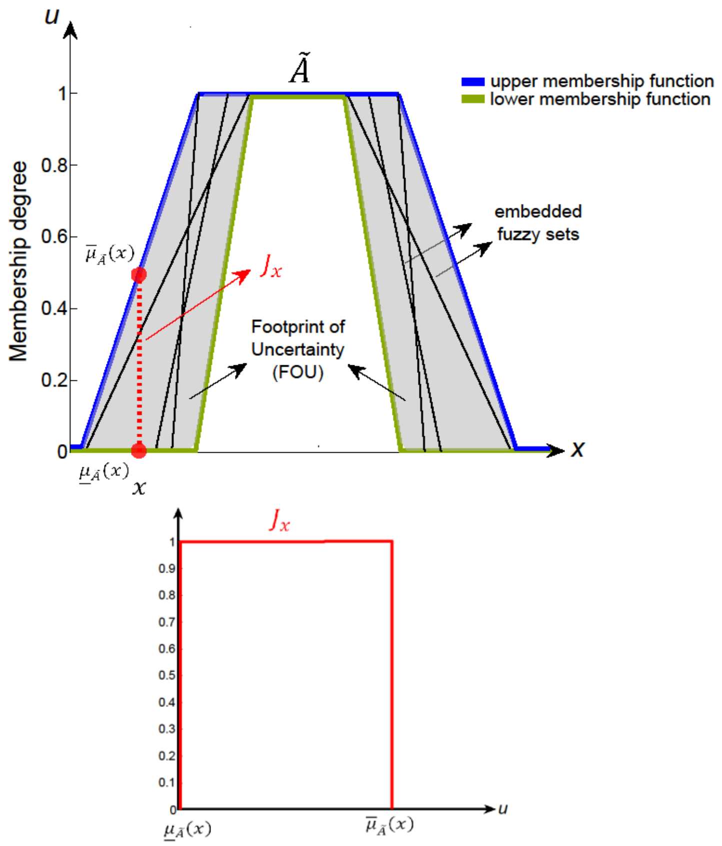
$$\tilde{A} = \int_{x\in X}\int_{u\in J_x} 1/(x,u) \; = \; \int_{x\in X}\left[\int_{u\in J_x} 1/u\right]/x \tag{2.13}$$

where $x$, the *primary variable*, has domain $X$; $u \in U$, the *secondary variable*, has domain $J_x$ at each $x \in X$; $J_x$ is called the *primary membership* of $x$ and is defined in Equation (2.14) and the *secondary grades* of $\tilde{A}$ all equal 1 [Mendel 2006a].

$$J_x = \left\{(x,u)\colon u \in \left[\underline{\mu}_{\tilde{A}}(x), \overline{\mu}_{\tilde{A}}(x)\right]\right\} \tag{2.14}$$

Moreover, uncertainty about $\tilde{A}$ is conveyed by the union of all the primary memberships, which is called the *footprint of uncertainty* (FOU) of $\tilde{A}$, and is formalized as:

$$FOU(\tilde{A}) = \cup_{\forall x \in X} J_x = \{(x,u): u \in J_x \subseteq [0,1]\} \tag{2.15}$$




(a) (b)

Figure 2.5: (a) FOU of an IT2 FS and its primary membership with its associated (b) secondary MF.

The *upper membership function* (UMF), as shown in blue in Figure 2.5 a, and the *lower membership function* (LMF), as shown in green in Figure 2.5 a, of $\tilde{A}$ are two type-1 MFs that bound the FOU. The UMF is associated with the upper bound of

$FOU(\tilde{A})$ and is denoted by $\overline{\mu}_{\tilde{A}}(x)$, $\forall x \in X$, and the LMF is associated with the lower bound of $FOU(\tilde{A})$ and is denoted by $\underline{\mu}_{\tilde{A}}(x)$, $\forall x \in X$, i.e.

$$\overline{\mu}_{\tilde{A}}(x) \equiv \overline{FOU(\tilde{A})} \quad \forall x \in X \tag{2.16}$$

$$\underline{\mu}_{\tilde{A}}(x) \equiv \underline{FOU(\tilde{A})} \quad \forall x \in X \tag{2.17}$$

As the name suggests, IT2 fuzzy sets are based on the idea of an interval for the additional degree of freedom of a type-2 fuzzy set, which is the third dimension represented by the secondary membership function, as illustrated in Figure 2.5 b. According to [John 2007], the reason for the popularity of interval techniques is that in a case where the secondary membership function is non interval, computation becomes much more difficult. Hence, until recently, IT2 fuzzy sets have been the subject of a larger focus and greater use in terms of applications and research.

Within the literature, interval type-2 fuzzy sets have been extensively used in a wide range of applications, including control of mobile robots [Hagras 2004], forecasting of time series [Karnik 1999b], decision making [Ozen 2004a], [Ozen 2004b], and additional situations outlined in [Mendel 2002] and [Hagras 2012]. The main reason for this proliferation of applications is that type-2 fuzzy sets can respond to the shortcomings of type-1 [Greenfield 2009] because they can better (with respect to type-1 fuzzy sets) model the uncertainty associated with the available information, measurements, etc. [Karnik 1999a]. More important, type-2 FSs provide ways to handle the linguistic uncertainty that is emphasized by the adage ‘words mean different things to different people’ [Mendel 1999]. However, IT2 FSs are also prone to generate a number of incompatible statements as pointed out by Greenfield and

John, who suggest the use of general type-2 FSs to achieve consistency in modelling statements [Greenfield 2009].

The next subsection introduces the general type-2 FL, where the secondary membership function is non interval [John 2007] and can be modelled.

### 2.3.2 General Type-2 Fuzzy Logic Sets

As noted in Figure 2.6, which displays the historical development of type-2 fuzzy logic, the full definition of type-2 fuzzy logic systems, including general type-2 fuzzy logic, took place in the 2000s. This step forward also embodies the establishment of the connection between type-1 and type-2 fuzzy logic as it follows the definition of the type of reduction introduced in [Karnik 1999a]. With the significant progress in interval type-2 fuzzy logic, the complexity of the general type-2 fuzzy logic has become more approachable. Recently, the introduction of zSlices [Wagner 2010] and alpha-planes [Mendel 2009], [Mendel 2010] has helped bridge the gap caused by the complexity of the design and implementation of general type-2 fuzzy sets, especially for real-world applications.

Formally, a general type-2 fuzzy set $\tilde{G}$ is defined as follows [Mendel 2001a]:

$$\tilde{G} = \int_{x \in X} \int_{u \in J_x} \mu_{\tilde{G}}(x, u)/(x, u) \tag{2.18}$$

Where $0 \leq \mu_{\tilde{G}}(x, u) \leq 1$ and the integral denote union over all admissible values of $x$ and $u$.

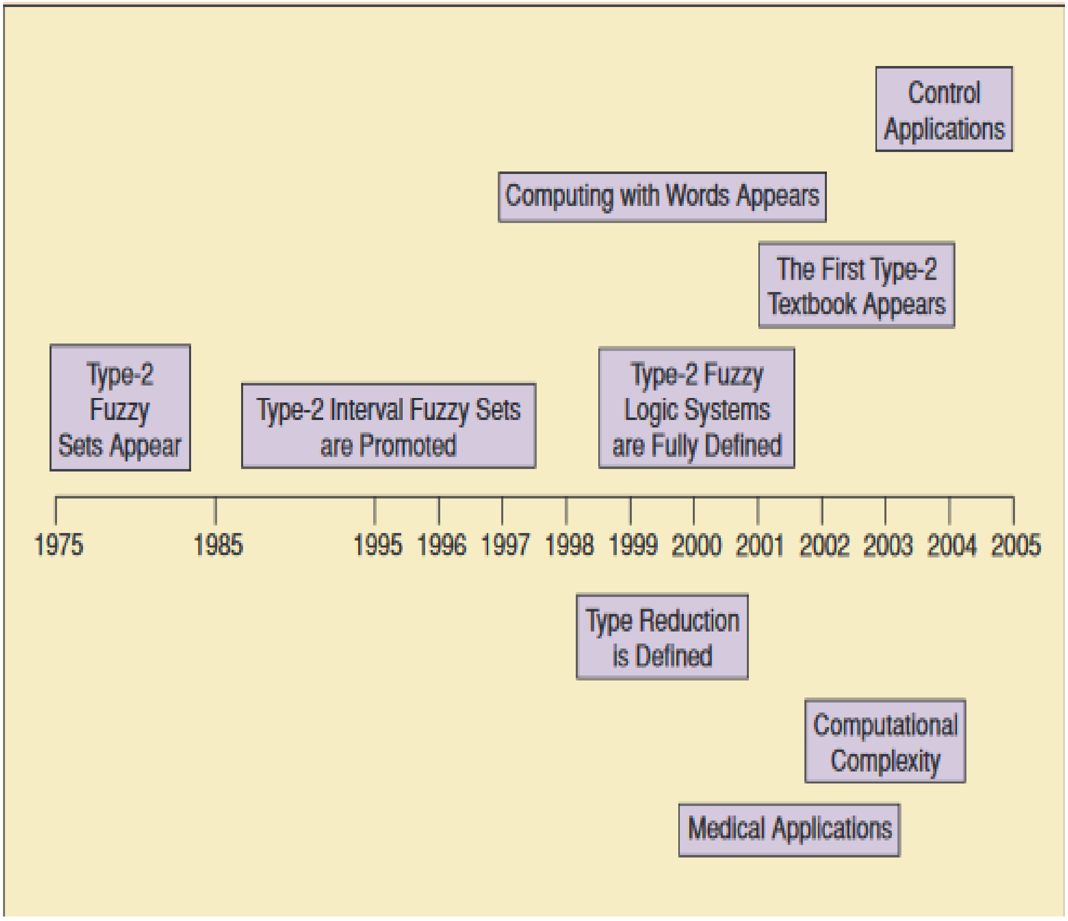



Figure 2.6: A timeline depicting the historical development of type-2 fuzzy logic [John 2007].

A *vertical slice* of $\mu_{\tilde{G}}(x,u)$ at $x = x'$, which is a 2-D plane whose axes are $u$ and $\mu_{\tilde{G}}(x',u)$, can be represented as follows [Mendel 2001]:

$$\mu_{\tilde{G}}(x = x', u) = \int_{u \in J_{x'}} f_{x'}(u)/u \quad J_{x'} \subseteq [0,1] \tag{2.19}$$

Where $0 \leq f_{x'}(u) \leq 1$.

Hence, a general type-2 fuzzy set $\tilde{G}$ can be re-expressed in the union of all vertical slices as shown in Equation (2.20) [Mendel 2001]:

$$\tilde{G} = \int_{x \in X} \left[ \int_{u \in J_x} f_x(u)/u \right] /x \quad J_x \subseteq [0,1 \tag{2.20}$$

As has been noted before, type-2 fuzzy logic allows for better (in comparison to type-1 fuzzy logic) modelling of uncertainty because type-2 fuzzy sets encompass an FOU, which gives more degrees of freedom to type-2 fuzzy sets in terms of their third dimension [Wagner 2010]. Figure 2.7 shows the secondary membership functions (the third dimension) of type-1 FSs (Figure 2.7 A), IT2 FSs (Figure 2.7 B) and GT2 FSs (Figure 2.7 C). As seen in Figure 2.7 A, the secondary MF in type-1 fuzzy sets has only one value in its domain ('a' in Figure 2.7 A) corresponding to the primary membership value at which the secondary grade is 1 [Wagner 2010]. Hence, in type-1 FSs, for each x value, there is no uncertainty associated with the primary membership value [Wagner 2010]. However, it can be observed in Figure 2.7 B that there is maximum uncertainty represented in the secondary MF of an IT2 FS because the primary membership takes in values in the interval [a, b], where each point in the interval has an associated secondary membership that is always 1 [Wagner 2010]. In GT2 FSs, the uncertainty (represented in the secondary MF) can be modelled with any degree between type-1 and IT2 fuzzy sets, for example by the triangular secondary MF shown in Figure 2.7 C [Wagner 2010]. Hence, GT2 fuzzy sets can model the uncertainty in the third dimension precisely, from nearly no uncertainty (i.e. type-1) to maximum (i.e. IT2, where the uncertainty is equally spread in the third dimension) [Wagner 2010].

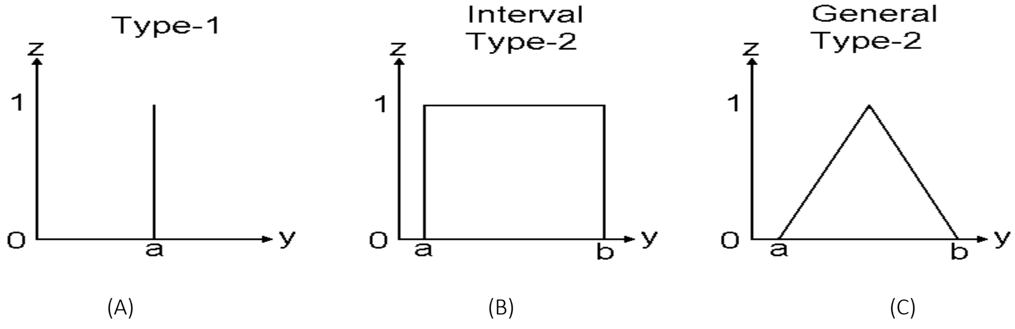



Figure 2.7: Views of the secondary membership functions (third dimensions) of (a) type-1 fuzzy sets, (b) interval type-2 fuzzy sets, and (c) general type-2 fuzzy sets [Wagner 2010].

## 2.4 Type-2 Fuzzy Logic Systems

The need for a type-2 FLS stems mainly from the uncertainty inherent in the knowledge that is used to construct the rules of an FLS [Mendel 2000]. According to Mendel [Mendel 2000], there are three ways in which such uncertainty can occur: the words that are used in antecedents and consequents of rules can mean different things to different people, consequents obtained by polling a group of experts will often be different for the same rule as experts will not necessarily be in agreement, and only noisy training data are available. These aforementioned sources of uncertainty translate into uncertain antecedents or consequent membership functions within the FLS [Karnik 1999a]. Several studies in the literature put forward that type-1 FLSs, whose membership functions are type-1 fuzzy sets, are unable to handle rule uncertainties directly [Mendel 2000] and therefore are inappropriate for certain types of real-world applications. Meanwhile, type-2 FLSs, which use type-2 fuzzy sets, have the potential to provide better performance than type-1 FLSs [Mendel 2006b]. Due to the computational complexity of using a GT2 FS, most people only use IT2 FSs in a T2 FLS, the result being an IT2 FLS [Mendel 2006b]. Within the literature, T2 FLSs (especially IT2) have found their way into many engineering applications and are also known as fuzzy logic controllers (FLCs) or fuzzy expert systems [Mendel 2006a].

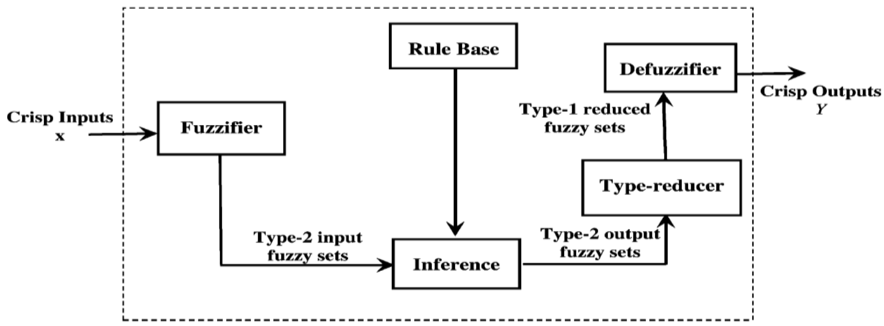



Figure 2.8 Type-2 fuzzy logic system [Hagras 2004].

The architecture of a type-2 FLS is illustrated in Figure 2.8 where the interconnection of the five components (fuzzifier, rules, inference engine, type-reducer and defuzzifier) is shown. As can be seen, the structure of a type-2 FLS is very similar to that of the type-1 FLS shown in Figure 2.8. Different from type-1 FLSs, type-2 FLSs have the additional block labelled as type-reducer, which is an extension of a type-1 defuzzification procedure and represents a mapping of a type-2 fuzzy set into a type-1 fuzzy set [Mendel 2001]. In a type-2 FLS, the steps taken to form type-2 fuzzy output sets are similar to those of a type-1 FLS with the distinction that one of the antecedent or consequent fuzzy sets are of type-2 [Mendel 2006b].

## 2.4.1 Fuzzifier

In the same fashion as a type-1 FLS, the fuzzifier maps the crisp inputs into fuzzy sets. Again, there are two types of fuzzification techniques available (singleton and non-singleton), which were mentioned in Section 2.2.1 and will not be repeated here.

## 2.4.2 Rule Base

The distinction between the type-1 FLS and type-2 FLS is associated with the nature of the membership functions, which is not important while forming rules. Hence, the structure of the rules remains exactly the same in the type-2 FLS, the only difference being that now some, or all, of the sets involved are type-2 [Karnik 1999a]. However, the formal representation of the $l^{\text{th}}$ fuzzy rule in a type-2 FLS with $M$ rules can be restated as follows [Mendel 2001]:

$$R^l : IF\ x_1 is\ \widetilde{F_1^l}\ and\ x_2\ is\ \widetilde{F_2^l}\ and\ \dots and\ x_p\ is\ \widetilde{F_p^l}, THEN\ y\ is\ \widetilde{G^l}\quad l = 1,..,M \quad (2.21)$$

Where $x_i$ are inputs; $\widetilde{F}_i^l$s are antecedent sets $(i = 1, \dots, p)$; $y$ is the output; and $\widetilde{G}_l$ are consequent sets. In the case of multiple consequents in the FLS, the rules can be regarded as a group of multiple-input, single-output formats as in Equation (2.21).

### 2.4.3 Inference Engine

The inference process in a type-2 FLS is also quite similar to the inference process of a type-1 FLS [Karnik 1999a]. Formally, the inference engine combines rules and gives a mapping from input type-2 fuzzy sets to output type-2 fuzzy sets [Karnik 1999a]. In detail, multiple antecedents in rules are connected by the t-norm (corresponding to the intersection of sets) [Karnik 1999a]. The membership grades in the input sets are combined with those in the output sets using the sup-star composition [Karnik 1999a]. Multiple rules may be combined using the t-conorm operation (corresponding to union of sets) [Karnik 1999a].

### 2.4.4 Type Reduction

The output of the inference engine in a type-2 FLS is different from that in a type-1 FLS. As noted in Figure 3.5, the inference engine of a type-2 FLS outputs type-2 fuzzy sets, which then go into the type-reducer block to be fed into the defuzzifier component of the system. In this case, one uses extended versions of type-1 defuzzification methods that give a type-1 fuzzy set, which is also referred to as a 'type-reduced set' [Karnik 1999a]. The methods include centroid, centre-of-sums, height, modified height, and centre-of-sets type reduction [Mendel 2001]. As pointed out by Mendel [Mendel 2001], [Liang 2000], centre-of-sets type reduction has reasonable computational complexity that lies between computationally expensive centroid-type reduction and the simple height- and modified-height-type reductions, which have problems when only one rule fires. Furthermore, a centre-of-sets type reduction allows for real-time operation if the rule base is small [Hagras 2004].

Type reduction for arbitrary type-2 fuzzy sets can be computationally very costly [Mendel 2001]. The computation of meet and join for interval type-2 sets is comparatively more straightforward. The formalization for a type-reduced set using the centre-of-sets type reduction for IT2 FLS is given in Equation (2.22) below [Mendel 2001]:

$$Y_{cos}(x) = [y_l, y_r]$$

$$= \int_{y^1 \in [y_l^1, y_r^1]} \cdots \int_{y^M \in [y_l^M, y_r^M]} \int_{f^1 \in [\underline{f}^1, \overline{f}^1]} \cdots \int_{f^M \in [\underline{f}^M, \overline{f}^M]} 1 \Big/ \frac{\sum_{i=1}^{M} f^i y^i}{\sum_{i=1}^{M} f^i} \tag{2.22}$$

where $Y_{cos}(x)$ is an interval set determined by its leftmost point $y_l$ and its rightmost point $y_r$, $i = 1 \cdots M$ and $M$ is the number of rules. $y^i$ corresponds to the centroid of the type-2 interval consequent set of the $i^{th}$ rule and is a pre-computed type-1 interval fuzzy set determined by its leftmost point $y_l^i$ and its rightmost point $y_r^i$ [Mendel 2001a]. $f^i$ denotes the firing strength (degree of firing) of the $i^{th}$ rule, which is an interval type-1 set determined by its leftmost point $\underline{f}^i$ and rightmost point $\overline{f}^i$ [Hagras 2004].

In the operation of an IT2 FLS in a real-world application, the calculation of the type-reduced sets can be divided into two stages. The first stage is the ahead-of-time calculation of centroids of the type-2 interval consequent sets of each rule, and the second stage is the calculation of the type-reduced sets that are to be defuzzified after each inference process [Hagras 2004]. The procedures for both stages are detailed in [Mendel 2001], [Hagras 2004], [Karnik 1999a] [Mendel 2006a] and [Mendel 2006b].

### 2.4.5 Defuzzifier

To get a crisp output from a type-2 FLS, the type-reduced set that is a type-1 fuzzy set needs to be defuzzified. According to Mendel [Mendel 2001], the most natural way to defuzzify the type-1 reduced set is to find its centroid, but there are other ways, such as choosing the highest membership point in the type-reduced set [Karnik 1999a]. For an IT2 FLS, the crisp output $y(\boldsymbol{x})$ of the system is the average of the end points of the type-reduced set $Y_{cos}(x)$ as follows [Mendel 2001]:

$$y(\boldsymbol{x}) = \frac{y_l + y_r}{2} \tag{2.23}$$

Most of the calculations above have been formulated using IT2 fuzzy sets because they provide simplicity over GT2 fuzzy sets. Until recently, the high complexity associated with GT2 FS design and their computational requirements have made them appear unsuitable for real-world use. However, the introduction of zSlices [Wagner 2010] and alpha-planes [Mendel 2009] has helped bridge the gap caused by the complexity of the design and implementation of GT2 fuzzy sets, especially for real-world applications. It has been proven that alpha-plane and zSlice representations are equivalent [Zhai 2012]; hence, the choice of representation for GT2 FSs can be considered a design decision. This thesis was use zSlice representation, so the next section will briefly introduce zSlices and present their use to implement GT2 FSs in real-world applications.

## 2.5 Introduction to zSlices

A zSlice is formed by slicing a general type-2 fuzzy set in the third dimension ($z$) at level $z_i$ [Wagner 2010]. The result of this slicing action is an interval set in the third dimension with height $z_i$. In other words, a zSlice $\tilde{Z}_i$ is equivalent to an interval type-2 fuzzy set with the exception that its membership grade $\mu_{\tilde{Z}_i(x,u)}$ in the third dimension is not fixed to 1; instead is equal to $z_i$ where $0 \leq z_i \leq 1$. Thus, the zSlice $\tilde{Z}_i$ can be written as follows [Wagner 2010]:

$$\tilde{Z}_i = \int_{x \in X} \int_{u_i \in J_{i_x}} z_i/(x, u_i) \tag{2.24}$$

where at each $x$ value (as shown in Figure 2.9 A), zSlicing creates an interval set with height $z_i$ and domain $J_{i_x}$ which ranges from $l_i$ to $r_i$ as shown in Figure 2.9 B, $1 \leq i \leq I$, where $I$ is the number of zSlices (excluding $\tilde{Z}_0$) and $z_i = i/I$.

Thus, Equation (2.24) can be written as follows [Wagner 2010]:

$$\tilde{Z}_i = \int_{x \in X} \int_{u_i \in [l_i, r_i]} z_i/(x, u_i) \tag{2.25}$$

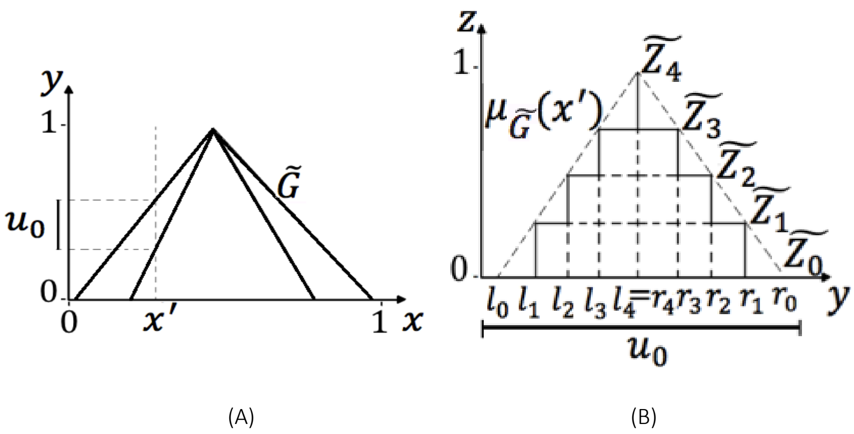



Figure 2.9 (a) A front view of a general type-2 set $\tilde{\boldsymbol{G}}$ and (b) A third dimension at x' of a zSlice-based general type-2 fuzzy set (Adapted from [Wagner 2010])

Additionally, $\tilde{Z}_0$ is regarded as a special case with $z = 0$, as shown in Equation (2.26) [Wagner 2010]. Hence, it has been noted to consider that $1 \leq i \leq I$ as $\tilde{Z}_0$ will not contribute to the crisp output of the zSlice-based GT2 FLS and it can be omitted with no effects [Wagner 2010].

$$\tilde{Z}_0 = \int_{x \in X} \int_{u \in J_x} 0/(x, u) \tag{2.26}$$

## 2.5.1 zSlices-Based General Type-2 Fuzzy Sets

A general type-2 fuzzy set $\tilde{G}$ could be seen as equivalent to the collection of an infinite number of zSlices:

$$\tilde{G} = \int_{0 \leq i \leq I} \tilde{Z}_i \ , \ \ I \to \infty \tag{2.27}$$

In a discrete universe of discourse, Equation (2.27) can be rewritten as follows:

$$\tilde{G} = \sum_{i=1}^{I} \tilde{Z}_i \tag{2.28}$$

In real-world implementation of GT2 FSs, the discrete version will be used as shown in Equation (2.28) where the summation sign does not denote arithmetic addition, but rather the union set theoretic operation [Wagner 2010]. Using the max operation to represent the union, the membership function $\mu_{\tilde{G}}(x')$ at $x'$ of the zSlice-based general type-2 fuzzy set $\tilde{G}$ can be expressed as follows:

$$\mu_{\tilde{G}}(x') = \sum_{u_i \in J_{x'}} max(z_i)/u \, , \, J_{x'} \subseteq [0,1] \tag{2.29}$$

Where $0 \leq i \leq I$. It is worth noting that at $x'$, $\mu_{\tilde{G}}(x')$ is a type-1 fuzzy set.

The operations on zSlice-based GT2 fuzzy sets, namely the intersection and union operations implemented through the meet and join operations, have been described in detail in [Wagner 2010]. Accordingly, the join and meet operations between two zSlice-based GT2 fuzzy sets are reduced to the computation of the join and meet operation between each corresponding zSlices in both sets, successively [Wagner 2010]. Because each zSlice is a special IT2 FS, the computations that were considered to be complex for GT2 FSs have been simplified and therefore made practical to be implemented in real-world applications. Hence, zSlice representation has enabled GT2 FSs to be considered suitable to employ within applications that require more complex uncertainty modelling. The various steps involved in the processing of a zSlice-based GT2 FLS is described and outlined by Wagner [Wagner 2010], [Wagner 2009].

## 2.6 Discussion

In this chapter, we firstly provided a brief overview of type-1 fuzzy logic systems to establish the case for their application in handling the uncertain and imprecise information in real e-learning environments. A nonlinear mapping of an input set that is acquired from varied student characteristics, knowledge levels, and engagement levels to a set of outputs that are related to student needs and preferences can be achieved via tailored adaptive learning content. The type-1 FLS rule base will have a collection of independent MIMO systems that facilitate this mapping, which directly models the user behaviours in the environment [Doctor 2006]. Learning these rules is possible as part of an intelligent system from data acquired by monitoring learner behaviour in the e-learning environment and representing it as a set of if-then statements that describes the current state of the learner and the associated student needs in an adaptive intelligent learning system, as Figures 2.10 and 2.11 show.

*IF* **Student-Age** *is* **Teen** *AND* **Student-Gender** *is* **Female** *AND* **Secondary-Grade** *is* **Excellent** *AND* **Method-of-Providing-Higher-Education** *is* **Full-Time** *AND* **the Secondary-Section** *is* **Science** *AND* **Average-Knowledge-in-Excel** *is* **Very Low** *AND* **Average-Knowledge-in-PowerPoint is Low,** *then the* **Suited-Excel-Difficulty-Level** is **Easy** *AND* **Needed-Time-to-Study-Excel** *is* **Very Long** *AND* **Suited-PowerPoint-Difficulty-Level** *is* **Moderate** *AND* **Needed-Time-to-Study-PowerPoint** *is* **Short.**

Figure 2.10: One example of an extracted rule from the produced rules.

*IF* **the learners' average level of engagements** *is* **Low** *AND* the **learners' average standard deviation level of engagements** *is* **Moderate** *AND* **the difficulty level of the current lesson** *is* **Hard** THEN **the recommendation to use the "asking questions" teaching approach** *is* **High** *AND* **the recommendation to use the "practical explanation (demo)" approach** *is* **Low** *AND* **the recommendation to use the "teaching with cases (problem solving)" approach** *is* **Moderate** ***AND*** **the recommendation to use the "PowerPoint slides" teaching approach** *is* **Low**

Figure 2.11: An example of one of the extracted fuzzy rules.

The acquired user behaviours can be represented clearly and flexibly by providing the fuzzy rules, which ultimately enhances an approach based on behaviour to express the decisions learned from the system [Brooks 1991], [Doctor 2006]. The rules describe particular situations or states of the e-learning environment according to learner needs under specific conditions. This approach to handling the embodied systems is more appropriate than traditional AI techniques, in which acquired information is inclined to be unpredictable, partial, and influenced by the environment and a perfect and full solution is far from being predefined [Doctor 2006], [Sharples 1999]. These advantages increase the strength of FLSs with respect to their easy adaptability and improved suitability during real-time processing [Callaghan 2001], [Doctor 2006].

Learning–teaching behaviour is represented in a human-readable and linguistically interpretable manner by the fuzzy rules. Their transparency makes them able to be assessed quickly so one can explain the reason for and method of certain combinations of input-actuated specific rules where a certain set of output conclusions has been yielded. There is an association with linguistic labels appearing in the consequent and antecedent of rules grouped as input and output values in the system. Adapting the fuzzy sets of an FLS is possible from the data yielded from the system. There many other options for soft computing techniques, as discussed in the introduction, such as neural networks and genetic algorithms for learning both rules and MFs of FLSs [Doctor 2006].

Most of the FL-based systems developed for e-learning environment applications have used type-1 FL for handling uncertainty and imprecisions [Chrysafiadi 2015], [Prokhorov 2015], [Yadav 2014], [Yildiz 2014], [Chen 2013], [Hsieh 2012], [Sripan 2010], [ Saleh 2009], [Bai 2008], [Venkatesan 2008], [Nykänen 2006], [Kavčič 2004], [Xu 2002]. Type-1 FLSs, however, have a common problem in that they cannot fully handle or accommodate all uncertainties because they use precise type-1 fuzzy sets [Mendel 2001], [Mendel 2014]. Type-1 fuzzy sets handle uncertainties associated with inputs and outputs using precise and crisp MFs that the user believes captures the uncertainties [Mendel 2001], [Mendel 2014]. Once the type-1 MFs have been chosen, all the uncertainties disappear, because type-1 MFs are precise [Mendel 2001], [Mendel 2014]. Type-1 fuzzy sets are chosen or generated under specific parameter ranges from the input and output variables and thereafter model the user behaviour under specific learning-teaching conditions. The number of users existing in the e-learning environment with their different backgrounds and characteristics will cause a high level of linguistic uncertainty whereby user interpretations and responses to their levels of knowledge, difficulty of the content, time needed, and other needs are different and varied according to their plans, cognition, preknowledge, and motivation levels. These uncertainties translate to the fuzzy set MFs [Mendel 2002]. The effectiveness of type-1 FLSs is limited by their use of precise type-1 fuzzy sets, which handle only the uncertainties associated with the specific user view under which the MFs were generated. The mentioned linguistic uncertainties would cause the values of fuzzy set MFs associated with linguistic labels to change. The specific type-1 MFs would therefore no longer be effective enough at modelling the user behaviours under the new conditions and would, therefore, not be able to handle the associated linguistic uncertainties.

This chapter has also considered the introduction of type-2 fuzzy systems where type 2 fuzzy sets with the direct ability of modelling linguistic uncertainties have been presented. Accordingly, they also have the ability of reducing their effects on the design of the adaptive learning and teaching system. Consequently, type-2 fuzzy sets based on FLSs will be potent enough to yield an improved performance compared to type-1 FLSs that will have their effects reflected in facilitated student performance and improved student engagement and achievement rates.

A big number of type-1 fuzzy sets, having been embedded inside the FOUs of the type 2 fuzzy sets, constitute every input and output in type-2 FLSs. The input and output variables are described using a big number of type-1 fuzzy sets, which permits the acquisition of higher perfection while recording the user behaviour within the educational environments. Its reflection will be seen in facilitated student performance and improved student engagement and achievement rates. An example of such encountered uncertainties in e-learning environments is the acquired rules from user behaviours, which define their learning-teaching behaviours and target those users within e-learning environments. The number of users who could be students or experts, a number we used in obtaining the consequent of rules, makes their agreement difficult regarding the same consequents to tackle learners' needs. Another issue is that the meaning of the words and fuzzy sets used to describe the learner and instructional variables (inputs and outputs), such as their behaviour, within the e learning environment means different things to different people. We will show an example of how we used the type-2 fuzzy systems to model and reduce the uncertainties that exist within the e-learning environments.

In the next three chapters, we will introduce the proposed empirical theoretical and practical environments based on T2FLS.

# Chapter 3: The Proposed IT2FLS with User Engagement Feedback for Adaptive Learning within Small-Scale Intelligent E-Learning Platforms

## 3.1 Introduction

The recent years have witnessed an expansion in realising adaptive educational systems for intelligent e-learning platforms. Such platforms permit the development of customised learning contexts adapted to the requirements of every student by correlating the students' characteristics with instructional variables. However, the vast majority of the existing adaptive educational systems do not learn from the users' behaviours to create white box models that can handle the linguistic uncertainties and be easily read and analysed by the lay user. Moreover, most of the existing systems ignore gauging the students' engagement levels and mapping them to suitable delivery needs that match the students' knowledge and preferred learning styles. This chapter presents a novel interval type-2 fuzzy logic–based system that can learn the user's preferred knowledge delivery needs and learning style based on the students' characteristics, capabilities and engagement levels to generate a customised learning environment.

Within the e-learning platforms, there are high levels of uncertainties associated with the precision in evaluating the individual's knowledge delivery needs, the preferred style of learning and other requirements for provision of the adaptive knowledge delivery. This uncertainty is quite critical due to several sources of uncertainties in how accurately students' responses are actually assessed by adaptive educational methods, as well as the corresponding uncertainties associated with how the resulting instruction to the student is actually understood and received. In e-learning environments, there are high levels of linguistic uncertainties where the students can differ greatly in how the same terms, words, or methods (e.g. course difficulty, length of study time, preferred learning style) are received and comprehended. This varies according to the students' levels of engagement, knowledge and future plans. To tackle the uncertainty that may inhibit the advancement of an efficient learning context, it is suggested that any adaptive educational system should incorporate flexible AI methods [Ahamed 2004]. Fuzzy logic systems are well known for their ability to generate white box models that can handle high levels of uncertainties. However, the vast majority of fuzzy logic systems employ type-1 fuzzy logic systems which handle the encountered uncertainties based on precise type-1 fuzzy sets [Mendel 2001]. In contrast, interval type-2 fuzzy logic systems can handle the faced uncertainties through interval type-2 fuzzy sets which are characterized by a footprint of uncertainty (FOU), which provides an extra degree of freedom to enable handling high uncertainty levels [Mendel 2001].

This chapter presents theoretical and practical environments based on IT2FLS and T1FLS for adaptive knowledge delivery within small-scale intelligent e-learning platforms. This proposed theoretical and practical environment can learn the users' knowledge delivery needs and suited learning style based on the students' characteristics, capabilities and average engagement degree during learning activities to generate an adaptive e-learning environment. For measuring students' engagement, the chapter presents a novel system for gauging the students' engagement levels based on utilising visual information to calculate automatically the engagement degree of students. This differs from traditional methods, which usually employ expensive and invasive sensors. Our approach uses only a low-cost RGB-D video camera (Kinect, Microsoft) operating in a non-intrusive mode where the users are allowed to act and move without restrictions. The interval type-2 fuzzy logic and type-1 fuzzy logic models are created from data collected from a number of students with differing capabilities, levels of engagement and needs. The learnt type-2 fuzzy-based and type-1 fuzzy-based models are then used to improve the knowledge delivery to the various students based on their individual characteristics, capabilities and engagement levels. We will show how the presented system enables the adaptation within the learning environments to improve individualised knowledge delivery to students, which can result in enhancing the students' performance and increasing their engagement and motivation. The proposed system is continuously able to respond and adapt to students' needs on a highly individualised basis. Thus, online courses can be structured to deliver customised education to the student based on various criteria of individual needs and characteristics. The FLSs have been tested through various experiments with the participation of 15 students. These experiments indicate that the proposed IT2FLS have the ability to handle linguistic uncertainties to produce better performance, which includes better learning performance and engagement that outperforms that of the T1FLS and non-adaptive systems.

This chapter will describe the proposed theoretical and practical environment-based IT2FLS for knowledge delivery customisation within intelligent e-learning platforms in section 3.2. Section 3.3 presents the experiments and results, while the discussions are presented in Section 3.4.

## 3.2 The Proposed IT2FLS-Based Environment Components

Our system aims to adapt and customise the knowledge delivery within intelligent e-learning platforms according to students' individual knowledge needs. Figure 3.1 shows an overview of the proposed system, whereby the data are gathered through assessing students' knowledge delivery needs, as held by students, according to their characteristics, capabilities variables and engagement levels in the online learning environment, which is subsequently examined and analysed based on the extracted fuzzy logic membership functions related to inputs and outputs. The employed type-2 fuzzy sets generation approach is based on Liu (2007), which is a method centred on creating type-2 fuzzy sets via the gathering of type-1 fuzzy sets information from participants [Liu 2007]. The type-1 fuzzy sets derived are combined, thus resulting in the FOU, which accordingly induces a type-2 fuzzy set, which is seen to signify a word. Furthermore, an unsupervised one-pass approach, as motivated through [Mendel 2001], [Wang 2003], [Hagras 2007], is used by our system with the aim of extracting the rules from the data collected, which will help to describe the knowledge delivery needs of students according to their current characteristics, capabilities variables and engagement levels. This information will be used to build a model that learns the behaviour of the students.

The students' learned behaviours will be taken into account and will subsequently create an output in consideration of the current state of inputs. Accordingly, this type-2 FLS will make changes to the online learning environment in relation to the learned behaviours of the students and will further enable the online adaptation and enhancement of rules. This facilitates long-term learning owing to the changing of the students' performance, engagement levels and delivery needs.

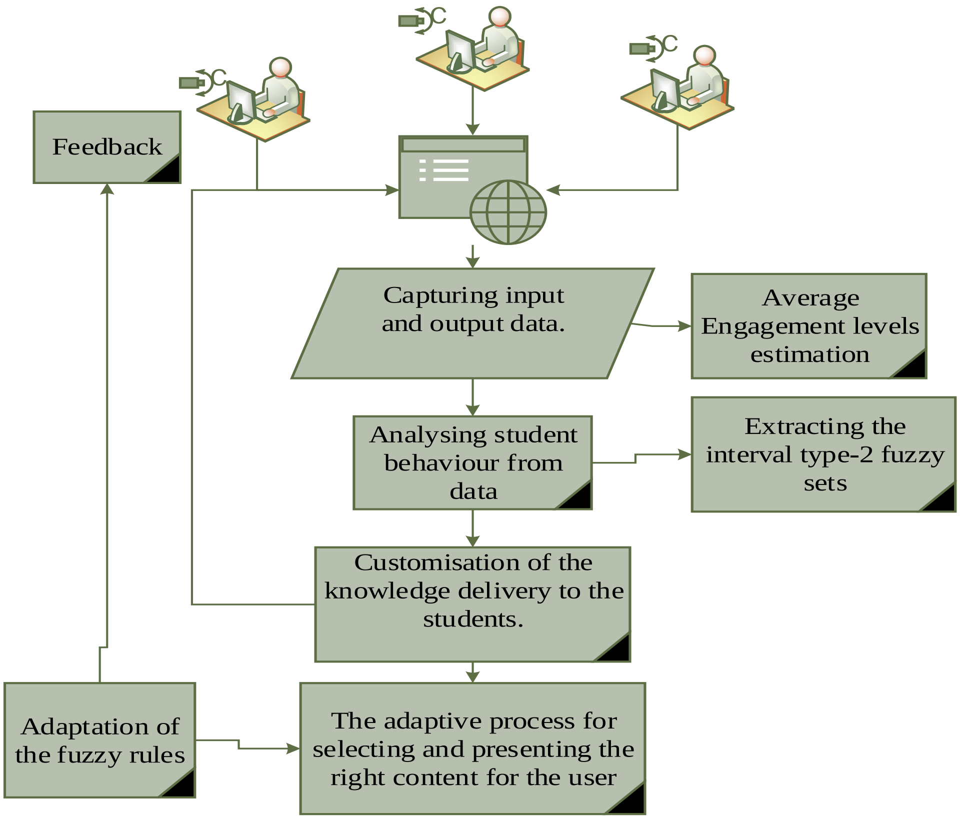



Figure 3.1: An overview on the proposed type-2 fuzzy logic–based systems for improved knowledge delivery within intelligent e-learning platforms.

The proposed system comprises five phases, as shown in Figure 3.1, which will be discussed in detail in the following subsections.

### 3.2.1 Capturing the Inputs and Outputs Data

Initially, our system gathers and captures the students' data through assessing the students' knowledge delivery needs with the preferred instructional style, along with their characteristics, capabilities and engagements levels within the online learning environment. Importantly, upon the change in an individual student's knowledge delivery needs, characteristics, or engagement levels, the system will actively record the data (both current inputs and outputs). Thus, our system creates and learns a descriptive model of the students' knowledge delivery needs according to their characteristics, capabilities and engagement levels; this is achieved through the data gathered, generating a set of multi-input and output data pairs, which take the following form [Mendel 2001], [Wang 2003], [Hagras 2007]:

$$x^{(t)}; y^{(t)} \qquad (t = 1,2,\ldots,N), \tag{3.1}$$

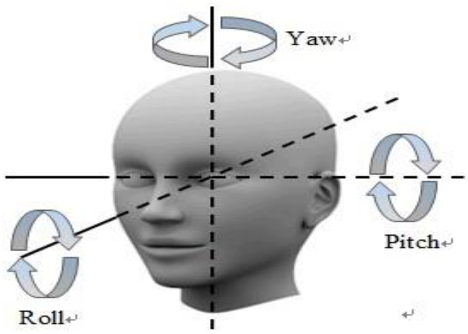
Where $N$ is recognized as the number of data instances, $x^{(t)} \in R^n$ and $y^{(t)} \in R^k$, our system extracts rules that explain how the $k$ output knowledge delivery needs variables $y = (y_1, \ldots, y_k)^T$ are affected by the input variables $x = (x_1, \ldots, x_n)^T$, including their characteristics, capabilities and engagement level. Six input variables were captured during the usage of the system: the scores for fuzzy logic, mathematics and Java; average engagement degree; and the age and gender of each student. Afterwards, the scores and results were revealed to the students so they could determine their needs and preferences and the right content for their level with their preferred learning style. Hence, the system recorded the students' needs for knowledge delivery with 12 outputs related to the preferred difficulty level and the time needed to study for the three subjects (Java, math and fuzzy logic). In addition, six dimensions of the Felder-Silverman learning style model (visual/verbal, sensing/intuitive and active/reflective), as indicated in Table 3.1, were used to obtain and capture the percentage of student strengths and preferences for each one of them [Dung 2012]. A model mapping inputs to outputs is achieved by the established fuzzy rules without requiring a mathematical model. Therefore, individual rules can be adapted online, affecting only certain aspects of the descriptive model created and learned by the proposed system.

### 3.2.1.1 The Proposed Method for Capturing the Engagement Degree

In the proposed system for capturing the engagement degree, first we compute the head pose by using the Kinect camera using the Kinect for Windows SDK, as shown in Figure 3.2 a. Then we calculate the deviation degrees of the current head orientation away from the monitor to measure the extent of distraction. Finally, we select the largest distraction extent degree to estimate the engagement degree of the student. More details are discussed in this subsection.

#### 3.2.1.1.1 Head Pose Estimation

Recently, head pose estimation has received major attention as an important procedure for human behaviour recognition. With depth cameras such as Microsoft Kinect, Panasonic D-Imager, and PrimeSense 3D Sensors available at reasonable prices, the research focus of head pose estimation has shifted from 2D video analysis to 3D (RGB-Depth) information analysis and has shown better accuracy and performance than 2D methods [Murphy-Chutorian 2009], [Fanelli 2011], [Murphy-Chutorian 2010]. The Microsoft Kinect supports the capture of the 2D RGB video stream and the 3D depth stream at the real-time speed of 30 frames per second, using advanced techniques of infrared projection and light coding. However, the depth information captured from Kinect is not as accurate and robust as the data acquired by other expensive devices, such as laser sensors. To address this problem and improve the accuracy of the estimation results, the method reported in [Cai 2010] was employed. The algorithm is based on a regularised maximum likelihood deformable model fitting (DMF) approach to reduce the impact of noise factors in the depth channel. Because this approach was done in the latest version of Kinect Windows SDK (as shown in Figure 3.2 a), we used the module directly to perform head pose estimation on the student (user) in e-learning environments, as shown in Figure 3.3. The Kinect SDK provides and describes the head pose relating to the Kinect camera by three angles, pitch, roll and yaw, as demonstrated in Figure 3.2 b. The three angles are illustrated in degrees ranging from -90 to +90 degrees.


(a) (b)

Figure 3.2: (a) The used Kinect camera (b) Head pose angles (yaw, pitch and roll)


Figure 3.3: Head pose estimation

#### 3.2.1.1.2 Engagement Degree Estimation

Because the head pose can perform a continuous state on all the three degrees of freedom based on which engagement estimation is performed, we will consider the following assumptions describing the relation between the head pose angles and engagement degree:

- Facing front/towards the monitor—the user is engaged in the online learning.
- Facing down—the student is sleepy or probably playing with a tablet/smartphone.
- Facing to the left/right—the user is distracted from the learning and interacting with another student nearby.
- Looking around—the student is thinking about other matters and is not concentrating.

Based on the assumptions above, the engagement degree of the student can be calculated and modelled by the deviation between the current head orientation and the optimum engaged head pose (facing towards the screen/monitor), as shown in the following equations.

$$\mathrm{Engagmentdegree} = 1 - \{\mathrm{Max}(\mathrm{Deviation_p}, \mathrm{Deviation_r}, \mathrm{Deviation_p})\} \quad (3.2)$$

$$Deviation_p = 1 - \frac{|\, Pitch_c - Pitch_o \,|}{Pitch_{max}} \quad (3.3)$$

$$Deviation_r = 1 - \frac{|\, Roll_c - Roll_o \,|}{Roll_{max}} \quad (3.4)$$

$$Deviation_y = 1 - \frac{|Yaw_c - Yaw_o|}{Yaw_{max}} \tag{3.5}$$

Where $\text{Pitch}_c$, $\text{Roll}_{c,}$ $\text{Yaw}_c$ are the three angles (pitch, roll, and yaw) of the current head pose obtained by the algorithm of Kinect head pose estimation. $\text{Pitch}_o$,$\text{Roll}_o$, $\text{Yaw}_o$ are the angles describing the optimum engaged head pose that are recorded in the initialisation stage of the system. $\text{Pitch}_{max}$, $\text{Roll}_{max}$, $\text{Yaw}_{max}$ are the maximum angles defined in the Kinect SDK.

### 3.2.2 Extracting the Interval Type-2 Fuzzy Sets

It is essential that the gathered students' input/output data be categorized via the relevant fuzzy membership functions. This provides quantification of the raw input and output values, changing them into linguistic labels, for instance, very low/low and high/very high. The approach detailed in [Liu 2007] is implemented, which creates a type-2 fuzzy set, the FOU of which embeds the numerous type-1 fuzzy sets seen to signify each student's individual view concerning a particular linguistic label explaining the student characteristics, capabilities, engagement level and knowledge delivery needs. Accordingly, for the type-2 fuzzy sets, the generated FOU will combine the various perspectives of students relating to modelling such words and will handle the uncertainties. In the employed approach, the data are gathered through questioning the participants on their views relating to particular linguistic labels, which will generate type-1 fuzzy sets. Following this stage, using the approach of [Liu 2007], the type-2 fuzzy sets are constructed where the type-1fuzzy sets representing the students individual view are combined, resulting in the FOU of the type-2 fuzzy set that represents the given word. Through application of the representation theorem [Mendel 2001] and [Liu 2007], each of the interval type-2 fuzzy sets $\tilde{A}_s$can be calculated as follows:

$$\tilde{A}_s = \cup_{i=1}^{n} A^i \tag{3.6}$$

Where $A^i$is referred to as the $i^{th}$ embedded type-1 fuzzy set and $\cup$ is an aggregation operation [Liu 2007]. The process of generating $\tilde{A}$ *is* based on approximating the upper MF $\overline{\mu}_{\tilde{A}}(x)$ and the lower MF $\underline{\mu}_{\tilde{A}}(x)$ of $\tilde{A}_s$. This will depend on the shape of the embedded type-1 fuzzy sets and the FOU model that is to be generated for $\tilde{A}_s$. In our system we use interior FOU models, right and left shoulder MFs (shown in Figure 3.4 a, b and c) for the upper and lower MF parameters from all the embedded non-symmetric triangle type-1 MFs. As shown in Figure 3.4 a, the resulting interior interval type-2 fuzzy set is described by parameters $\underline{a}_{MF}$, $\underline{c}_{MF}$, $\overline{c}_{MF}$and $\overline{b}_{MF}$ denoting a trapezoidal upper MF and the parameters $\overline{a}_{MF}$and $\underline{b}_{MF}$for a non-symmetric triangular lower MF, with an intersection point $(p, \mu_p)$ [Liu 2007].The procedures for calculating these parameters are now described as follows:

Given the parameters for the triangle type-1 MFs generated for each of the *i* students [ $a_{MF}^i$,$b_{MF}^i$], the procedure for approximating the FOU model for interior FOUs is as follows [Liu 2007]: For the upper MF $\overline{\mu}_{\tilde{A}}(x)$, we need to follow these steps:

1) For $\mu(x) = 0$, , find $\underline{a}_{MF}$ to be equal to the minimum $a_{MF}^{min}$ of all left-end points $a_{MF}^i$ and $\overline{b}_{MF}$to be equal to the maximum $b_{MF}^{max}$of all right-end points $b_{MF}^i$ [Liu 2007].
2) For $\mu(x) = 1$, find $\underline{c}_{MF}, \overline{c}_{MF}$ which correspond to the minimum and the maximum of the centres of the type-1 MFs.

3) Approximate the upper MF $\overline{\mu}_{\tilde{A}}(x)$by connecting the following points with straight lines:$(\underline{a}_{MF}, 0)$, $(\underline{c}_{MF}, 1)$, $(\overline{c}_{MF}, 1)$and $(\overline{b}_{MF}, 0)$. The result is a trapezoidal upper MF as depicted in Figure 3.4 a.

The steps to approximate the lower MF $\underline{\mu}_{\tilde{A}}(x)$ are as follows:

1) For $\mu(x) = 0$, determine $\overline{a}_{MF}$ to be equal to the maximum $a_{MF}^{max}$ of all left-end points $a_{MF}^{i}$ and $\overline{b}_{MF}$ to be equal to the minimum $b_{MF}^{min}$ of all right-end points $b_{MF}^{i}$ [Liu 2007].
2) Compute the intersection point $(p, \mu_p)$ by the following equations [Liu 2007]:

$$p = \frac{\underline{b}_{MF}(\overline{c}_{MF} - \overline{a}_{MF}) + \overline{a}_{MF}(\underline{b}_{MF} - \underline{c}_{MF})}{(\overline{c}_{MF} - \overline{a}_{MF}) + (\underline{b}_{MF} - \underline{c}_{MF})} \tag{3.7}$$

$$\mu_p = (\underline{b}_{MF} - p)/(\underline{b}_{MF} - \underline{c}_{MF}) \tag{3.8}$$

3) Approximating the lower MF $\underline{\mu}_{\tilde{A}_s}(x)$ by joining the following points with straight lines: $(\underline{a}_{MF}, 0)$,$(\overline{a}_{MF}, 0)$,$(p, \mu(p))$, $(\underline{b}_{MF}, 0)$ and $(\overline{b}_{MF}, 0)$. The result according to Figure 3.4 a) is a triangle lower MF.

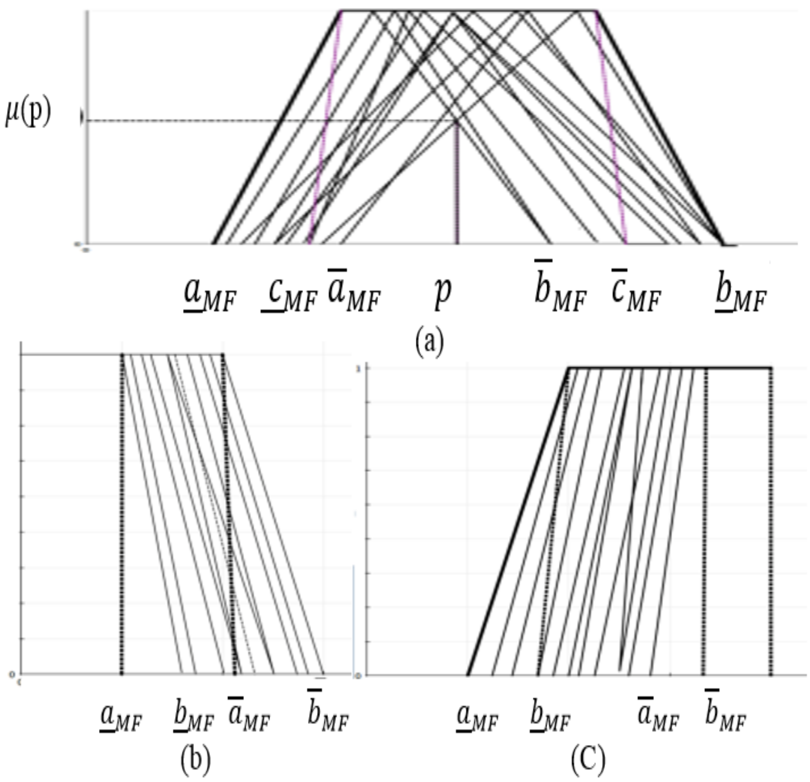



Figure 3.4: (a) An interior type-2 MF embedding the different type-1 fuzzy sets, (b) left shoulder type-2 MF embedding the different type-1 fuzzy sets. (c) Right shoulder type-2 MF embedding the different type-1 fuzzy sets [Liu 2007].

### 3.2.3 Extracting the type-2 Fuzzy Rules from the Collected Data

The generated interval type-2 fuzzy sets are mixed with the data of accumulated user input/output with the aim of extracting the rules explaining the behaviours of the students. The rule extraction method employed in this chapter is based on an improved form of the Wang-Mendel approach for the type-1fuzzy logic system and the interval type-2 fuzzy logic systems [Wang 1992], [Mendel 2001], [Wang 2003], [Doctor 2004], [Doctor 2005a], [Doctor 2005b], [Hagras 2007].

For extracting the type-1 fuzzy rules, we employed method that is acknowledged as being a one-pass approach centred on garnering fuzzy rules from data under examination. The rules' antecedent and consequent fuzzy sets divide the output and input spaces into fuzzy areas.

MIMO rules are extracted by the system, which accordingly highlights the relationship between $x = (x_1, \ldots, x_n)^T$ and $y = (y_1, \ldots, y_k)^T$. Notably, the following form is adopted [Wang 1992], [Wang 2003], [Doctor 2004], [Doctor 2005a], [Almohammadi 2013b]:

$$\text{If } x_1 \text{is } A_1^{(l)} \text{and ... and } x_n \text{ is } A_n^{(l)} \text{ Then } y_1 is\ B_1^{(l)} \text{and... and } y_k \text{ is } B_k^{(l)} \quad (3.9)$$

Where l=1, 2...M, and M is recognized as the number of rules, whilst l is the rules index. There are V fuzzy sets defined for each input $x_s$ with $A_s^q, q = 1, \ldots, V$. There are W fuzzy sets $B_c^h, h = 1, \ldots, W$ defined for each output $y_c$.

In an attempt to simplify the subsequent notation, the approach in regard to single-output rules is highlighted owing to the technique being relatively simply expanded to rules with various outputs [Doctor 2004], [Doctor 2005a], [Almohammadi 2013b]. The following are the different steps involved in the extraction of rules:

**Step 1:**

In regard to a fixed pair of input-output $(x^{(t)}; y^{(t)})$ in the dataset (1) $(t = 1,2, \ldots, N)$, the membership values are computed $\mu_{A_s^q}(x_s^{(t)})$ for each membership function $q = 1, \ldots, V$, and each input variable $s$ $(s = 1, \ldots, n)$, find $q^* \in \{1, \ldots, V\}$ as can be seen in [Wang 1992], [Wang 2003], [Doctor 2004], [Doctor 2005a], [Almohammadi 2013b]:

$$\mu_{A_s^{q*}}(x_s^{(t)}) \geq \mu_{A_s^q}(x_s^{(t)}) \tag{3.10}$$

For all q = 1,...,V .

The following rule may be referred to as generated by $(x^{(t)}; y^{(t)})$[Wang 1992], [Wang 2003], [Doctor 2004], [Doctor 2005a], [Almohammadi 2013b]:

If $x_1^t$ is $A_1^{q^*}$ and ... and $x_n^t$ $is$ $A_n^{q^*}$ Then $y$ $is$ centerd at $y^{(t)}$ (3.11)

In regard to each of the input variables $x_s$, there are fuzzy sets $A_s^q, q =, 1, \dots V$ that characterise it, thus facilitating the generation of the greatest possible number of rules ($V^n$), where *n* is the total number of input variables. However, considering the dataset, rules will only be generated amongst the $V^n$ possibilities comprising a dominant region with at least one point of data. Accordingly, as a result of following Step 1, one rule is generated on the basis of each data pair of input-output; for each input, the fuzzy set that achieves the greater membership value in the IF part of the rule is selected. This can be seen in Equation (3.10) and Equation (3.11).

However, this is not the final rule; this will be established in the subsequent stage. Nevertheless, the rule's weight can be calculated as follows [Wang 2003], [Wang 1992], [Doctor 2005]:

$$w^{(t)} = \prod_{s=1}^{n} \mu_{A_s^q}(x_s(t)) \tag{3.12}$$

The rule weight $w^{(t)}$ is centred on establishing the points' strength $x^{(t)}$ in regard to the fuzzy region fitting the rule.

**Step 2:**

For all the t data points from 1 to N, Step 1 is repeated in an attempt to establish the N data–generated rules through Equation (3.11). Because the number of data points is significant, this will imply the generation of numerous rules through the application of Step 1, all of which share the same IF part and which are further acknowledged as contradictory, i.e. rules comprising the same antecedent membership functions but dissimilar consequent values. Through this stage, those rules seen to have the same IF element are brought together into a single rule.

Accordingly, the *N* rules are broken down into groups, with the same IF part seen across all rules within the same group. If it is considered that there are M groups where Group *l* will encompass $N_l$, the rules are as follows [Wang 1992], [Wang 2003], [Doctor 2004], [Doctor 2005a], [Almohammadi 2013b]:

$$\text{if } x_1 \text{ is } A_1^{(q^l)} \text{and}\ldots\text{and } x_n \text{ is } A_n^{(q^l)} \text{ Then y is centred at } y^{(t_u^l)} \quad (3.13)$$

Where $N_l$ and $t_u^l$ is the data points index in regard to Group. The rules' weighted average in the conflict group is then calculated as follows [Wang 1992],[Wang 2003],[Doctor 2004], [Doctor 2005a], [Almohammadi 2013b]:

$$av^{(l)} = \frac{\sum_{u=1}^{N_l} y^{(t_u^l)}\, w^{(t_u^l)}}{\sum_{u=1}^{N_l} w^{(t_u^l)}} \quad (3.14)$$

Accordingly, the $N_l$ rules are then combined into a single rule, adopting the following configuration [Wang 1992], [Wang 2003], [Doctor 2004], [Doctor 2005 a], [Almohammadi 2013b]:

$$\text{If } x_1 \text{ is } A_1^{(l)} \text{and} \ldots \text{ and } x_n\ is\ A_n^{(l)} \text{ Then } y \text{ is } B^{(l)} \quad (3.15)$$

Where the output fuzzy set $B^l$ is selected in regard to the following, where among the W output fuzzy sets $B^1$...$B^w$, find the $B^{h*}$ such that [Wang 1992], [Wang 2003], [Doctor 2004], [Doctor 2005a], [Almohammadi 2013b]:

$$\mu_{B^{h*}}(\,av^{(l)}) \geq \mu_{B^h}\ (\,av^{(l)}) \tag{3.16}$$

For $h = 1,2,\ldots,W$, $B$ is chosen as $B^{h^*}$.

As can be seen from the above, data pairs of input-output comprising multiple outputs are handled by our system. Step 1 is recognized as being distinct in regard to the number of outputs associated with each rule; on the other hand, Step 2 provides straightforward expansion with the aim of enabling rules to encompass multiple outputs; for each output, the calculations detailed in Equation (3.14) and Equation (3.16) are repeated.

The type-2 fuzzy system considered in this chapter extracts various multiple-input–multiple-output rules, which are known to explain the relation between $x = (x_1,\ldots,x_n)^T$ and $y = (y_1,\ldots,y_k)^T$ and adopt the following form:

$$\text{IF } x_1 \text{ is } \tilde{A}_1^l \ldots \text{and } x_n \text{ is } \tilde{A}_n^l \text{ THEN } \ y_1\ is\ \tilde{B}_1^l \ldots and\ y_k\ is\ \tilde{B}_k^l \tag{3.17}$$

$l = 1,2,\ldots.,M$, where $M$ is the number of rules and $l$ is the index of the rules.

Notably, there are $V_i$ interval type-2 fuzzy sets $\tilde{A}_s^q$ , $q = 1,\ldots,V_i$ explained for each input $x_s$where $s = 1,2,\ldots.,n$. There are $V_o$ interval type-2 fuzzy sets $\tilde{B}_c^h$ , $h = 1,\ldots,V_o$, explained for each output $y_c$where $c = 1,2,\ldots.,k$, the $V_i$ input interval type-2 fuzzy sets.

In an attempt to explain and abridge the subsequent representation, the approach for those rules comprising a single output is demonstrated because the method is relatively simple to expand in regards to rules involving numerous outputs. The various stages involved in this rule extraction are shown below.

**Stage 1**: In regard to a fixed input–output pair, $(x^{(t)}; y^{(t)})$ in the dataset $(t = 1,2,\ldots,N)$, the upper and lower membership values are computed $\overline{\mu}_{\tilde{A}_s^q}\left(x_s^{(t)}\right)$ and $\underline{\mu}_{\tilde{A}_s^q}\left(x_s^{(t)}\right)$ for each of the fuzzy set $\tilde{A}_s^q$ , $q = 1, \ldots, V_i$, as well as for each input variable $(s = 1,\ldots,n)$. Find $q^* \in \{1, \ldots, V_i\}$ such that [Mendel 2001], [Wang 2003], [Doctor 2005b], [Hagras 2007]:

$$\mu_{\tilde{A}_s^{q*}}^{cg}\left(x_s^{(t)}\right) \geq \mu_{\tilde{A}_s^q}^{cg}\left(x_s^{(t)}\right) \tag{3.18}$$

For all q = 1,...,$V_i$. Notably, $\mu_{\tilde{A}_s^q}^{cg}\left(x_s^{(t)}\right)$ is the centre of gravity of the interval membership of $\tilde{A}_s^q$ at $x_s^{(t)}$, as can be seen below [Mendel 2001], [Wang 2003], [Doctor 2005b], [Hagras 2007]:

$$\mu_{\tilde{A}_s^q}^{cg}\left(x_s^{(t)}\right) = \frac{1}{2}\left[\overline{\mu}_{\tilde{A}_s^q}\left(x_s^{(t)}\right) + \underline{\mu}_{\tilde{A}_s^q}\left(x_s^{(t)}\right)\right] \tag{3.19}$$

The following rule will be referred to as the rule generated by $(x^{(t)}; y^{(t)})$ [Mendel 2001], [Wang 2003], [Doctor 2005 b], [Hagras 2007]:

$$\text{IF } x_1 \text{is } \tilde{A}_1^{q^{*}(t)} \ldots \text{and } x_n \text{ is } \tilde{A}_n^{q^{*}(t)} \text{THEN } y \text{ is centered at } y^{(t)} \tag{3.20}$$

For all of the input variables $x_s$ there are $V_i$ type-2 fuzzy sets $\tilde{A}_s^q$, which enables the greater amount of potential rules equal to $V_i^n$. Nevertheless, when considering the dataset, there will be the generation of those rules amongst the $V_i^n$ possibilities that show a dominant region comprising a minimum of one data point.

In the first stage, there is the creation of one rule for each respective input–output data pair, with the fuzzy set selected being that which is seen to achieve the greater value of membership at the data point, and notably selected as the one in the rule's *IF* element. Nevertheless, this is not the finalised version of the rule, which will be calculated in the subsequent step. Notably, the computation of the rule weight is carried out as follows [Mendel 2001], [Wang 2003], [Doctor 2005b], [Hagras 2007]:

$$wi^{(t)} = \prod_{s=1}^{n} \mu_{\tilde{A}_s^q}^{cg}(x_s(t)) \tag{3.21}$$

A rule $wi^{(t)}$ weight is a measure of the strength of the points $x^{(t)}$ belonging to the fuzzy region that the entire rule encompasses.

**Stage 2**: The first stage for all of the data points from 1 to *N* is repeated; this helps to obtain *N* data–generated rules in the form of Equation (3.20). Because there is a significant number of data points comprising numerous similar instances, Stage 1 witnesses the creation of multiple rules, all of which have the same IF part in common but which are all conflicting. During this stage, those rules seen to have the same IF part are amalgamated to form a single rule. Accordingly, the rules *N* are divided into groups, with rules in each of the groups seen to have the same IF part. If it is considered that such groups amount to M, it may also be stated that the group has $N_l$ rules, thus [Mendel 2001], [Wang 2003], [Doctor 2005b], [Hagras 2007]:

$$\text{IF } x_1 \text{is } \tilde{A}_1^l \text{ ... and } x_n \text{is } \tilde{A}_n^l \text{ THEN y is centered } at\ y^{(t_u^l)} \tag{3.22}$$

Where $u = 1, \dots, N_l$ and $t_u^l$ is the data points index of Group $l$. The weighted average of all rules involved in the conflict group is subsequently calculated as shown below:

$$av^{(l)} = \frac{\sum_{u=1}^{N_l} y^{(t_u^l)} wi^{(t_u^l)}}{\sum_{u=1}^{N_l} wi^{(t_u^l)}} \quad (3.23)$$

These $N_l$ rules are combined into a single rule, utilising the following format [Mendel 2001], [Wang 2003], [Doctor 2005b], [Hagras 2007]:

$$\text{IF } x_1 \text{is } \tilde{A}_1^l \dots \text{and } x_n \text{is } \tilde{A}_n^l \text{ THEN } y \text{ is } \tilde{B}^l \quad (3.24)$$

Where there is the selection of the output fuzzy set $\tilde{B}^l$ based on the following: amongst the $V_o$ output interval type-2 fuzzy sets $\tilde{B}^l, \dots, \tilde{B}^{V_o}$ find the $B^{h*}$ such that [Mendel 2001], [Wang 2003], [Doctor 2005b], [Hagras 2007]:

$$\mu_{\tilde{B}^{h*}}^{cg}\left(av^{(l)}\right) \geq \mu_{\tilde{B}^{h}}^{cg}\left(av^{(l)}\right) \qquad \text{for } h = 1{,}2 \dots, V_o \quad (3.25)$$

$\tilde{B}^l$ is selected owing to the fact that $B^{h*}$, where $\mu_{\tilde{B}^h}^{cg}$ is the center of gravity of the interval membership of $\tilde{B}^h$ at $av^{(l)}$as in Equation (3.19).

As can be seen from the above, data pairs of input-output, comprising multiple outputs, are handled by our system. Step 1 is recognized as being distinct in regard to the number of outputs associated with each rule; on the other hand, Step 2 provides straightforward expansion with the aim of enabling rules to encompass multiple outputs; for each output, the calculations detailed in Equations (3.23)- (3.25) are repeated.

### 3.2.4 The Customization of Knowledge Delivery to Students

The fuzzy rules generated through the input and output data of students and the extracted membership functions facilitate the proposed system in terms of establishing and learning the characteristics and requirements of knowledge delivery to students. As such, the system is then in a position to make changes to the online learning environment with particular consideration to the requirements of students. The system's actions are initiated through the examination and monitoring of student variables, which cause an impact to be felt by the online instructional environment, especially in regard to the learned approximation of students' individual needs. The type-2 fuzzy adaptive educational system considered in this chapter works as follows:

- The crisp inputs that encompass the characteristics, capabilities and average level of engagement of the student, detailed in the e-learning environment, are fuzzified into the input interval type-2 fuzzy sets (singleton fuzzification).
- The inference engine and rule base are activated, which creates the outputs (student needs) type-2 fuzzy sets.
- The inference engine outputs are processed by type reduction to produce type-reduced sets.
- The type-reduced type-1 fuzzy outputs are then de-fuzzified to create crisp outputs
- The crisp outputs are then fed to the outputs as explained in chapter 3.

For T1FLS, within this system we employ the centre of sets defuzzification, product implication and singleton fuzzification [Mendel 2001], [Doctor 2006]. A crisp input vector can be correlated with a crisp output vector $y = f(x)$ using the following formula:

$$y(x) = f_s(x) = \frac{\sum_{l=1}^{M} y^{-l} \prod_{i=1}^{n} \mu F_i^l\,(x_i)}{\sum_{l=1}^{M} \prod_{i=1}^{n} \mu F_i^l\,(x_i)} \tag{3.26}$$

Where *M* is the number of rules in the rule base, $y^{-l}$ is the centroid of the *lth* output fuzzy set $B^l$ , $\prod_{i=1}^{n} \mu F_i^l\,(x_i)$ is the product of the membership values of each rule's inputs. When considering multiple outputs, this equation is repeated for each output parameter.

### 3.2.5 The Adaptive Process for Selecting and Presenting the Right Content for the User

The proposed system must be able to adjust to the changing requirements (knowledge delivery needs), constantly expand the knowledge level and hold the various student engagement levels by providing the students with the ability to modify their learning needs. The system will change its rules or apply new ones accordingly. In case of a given input, no rules fire from the rule base (i.e. the rule's firing strength in Equation (3.21) $wi^{(t)} = 0$), and the system will capture the system input and user-preferred delivery needs to create a rule that can cover this uncovered input status. Thus, the system will incorporate new rules when the state of the online learning environment monitored at that time is indeterminate, according to the present rules in the rules base (i.e. where none of the present rules are fired). In such an instance, new rules will be devised and added by the system, whereby the antecedent sets highlight the online environment's present input states, with the consequent fuzzy sets reliant on the current state of knowledge delivery needs. For all of the input parameters $x_s$, the fuzzy sets that provide membership values, where $\mu_{\tilde{A}_c^h}^{cg}(\, x_s^{(t')}) > 0$ are identified. As a result, this creates a number of identified fuzzy sets in a grid for each input parameter. From such a grid, new rules are constructed based on all individual combinations of successive input fuzzy sets. The consequent fuzzy sets that provide the greatest value of membership to the student-defined knowledge delivery needs ($y_c$) are accordingly chosen to act as the generated rule consequent. The resulting fuzzy sets can be established through conducting a calculation of the output interval memberships' centre of gravity [Hagras 2007].

$$\mu^{cg}_{\tilde{B}^{h^*}_c}(y_c) \geq \mu^{cg}_{\tilde{B}^{h}_c}(y_c) \tag{3.27}$$

For $h = 1, \ldots, W$ the $\tilde{B}_c$ is chosen as $\tilde{B}^{h^*}_c$ where $c = 1, \ldots, k$. This enables the gradual addition of new rules.

In case the user indicates a change of preference and need for the knowledge delivery at a given input status, the fired rules will be identified, and the rule consequents will be changed if more than two users signal the same knowledge delivery needs, as indicated by Equation (3.27). Thus, the fired rules are adapted to reflect more appropriately the updated knowledge delivery requirements of the students, considering the present state of the online learning environment.

The system proposed in this chapter will adopt life-long learning through facilitating the adaptation of rules according to the knowledge delivery needs of students, which notably change over time, and in regard to the state of the online learning environment. Owing to the system's flexibility, the fuzzy logic model learned initially may be effortlessly expanded to make changes to both new and existing rules.

## 3.3 Experiment and Results

Various experiments were conducted on a sample of 15 students from Essex University. The experiments involved knowledge delivery for an online course of fuzzy logic and its associated areas in which each student should be skilled, such as mathematics and programming. The experiments commenced by giving all students the non-adaptive version of the system to study for half an hour, after which their level of knowledge of Java programming, fuzzy logic and mathematics was examined. Six input variables were captured during the usage of the system: the scores for fuzzy logic, mathematics and Java; average engagement degree; and the age and gender of each student. We measured the average engagement degree for each student using the Kinect camera, as shown in Figure 3.5 and as explained in section 3.2.1.1. Afterwards, the scores and results were revealed to the students so they could determine their needs and preferences and the right content for their level with their preferred learning style. Hence, the system recorded the students' needs for knowledge delivery with 12 outputs related to the preferred difficulty level and the time needed to study for the three subjects (Java, math and fuzzy logic). In addition, six dimensions of the Felder-Silverman learning style model (visual/verbal, sensing/intuitive and active/reflective), as indicated in Table 3.1, were used to obtain and capture the percentage of student strengths and preferences for each one of them [Dung 2012].

After the students' inputs and outputs had been obtained, the students were divided into three five-member groups. The groups were equally divided based on the students' previous knowledge and average degree of engagement to overcome the possibility of the effect of external factors on the evaluations of the systems, such as placing students with poor performance and low motivation in one group or vice versa.

The first group studied the non-adaptive version of the system, the second studied a knowledge delivery system based on type-1 fuzzy logic and the third studied the knowledge delivery system based on the applied interval type-2 fuzzy logic system.

| **Learning Styles** | **Application in Online Courses** |
| --- | --- |
| Visual | Visual learners prefer to acquire knowledge by using images, graphics, charts, animation and videos. |
| Verbal | Verbal learners prefer to acquire knowledge by using texts and audio. |
| Active | Active learners prefer to acquire knowledge by using self-assessment exercises and multiple-choice exercises. |
| Reflective | Reflective learners prefer to acquire knowledge by using examples, outlines and looking at results pages. |
| Sensing | Sensing learners prefer to acquire knowledge by using examples, explanation, facts and practical materials |
| Intuitive | Intuitive learners prefer to acquire knowledge by using definitions and algorithms. |

**Table 3.1: Learning styles categories [Dung 2012]**

Once the groups were equally divided and the type-1 and type-2 groups' input and output data were obtained in this phase, the type-2 fuzzy logic and type-1 models were constructed for each group using the linguistic variables and rules, as explained in Section 3.2.2 and 3.2.3 (See Figure 3.6 for one of the extracted interval type-2 fuzzy logic sets and Appendix A for the extracted fuzzy sets.) The type-2 fuzzy sets were obtained to capture the uncertainty that signifies students' individual views concerning a particular linguistic label explaining the characteristics, preferences and requirements, while the type-1 fuzzy logic system uses a type-1 fuzzy set shown in yellow dashed lines in Figure 3.6.

Figure 3.5 : Various participants with GUI of the vision engagement system.

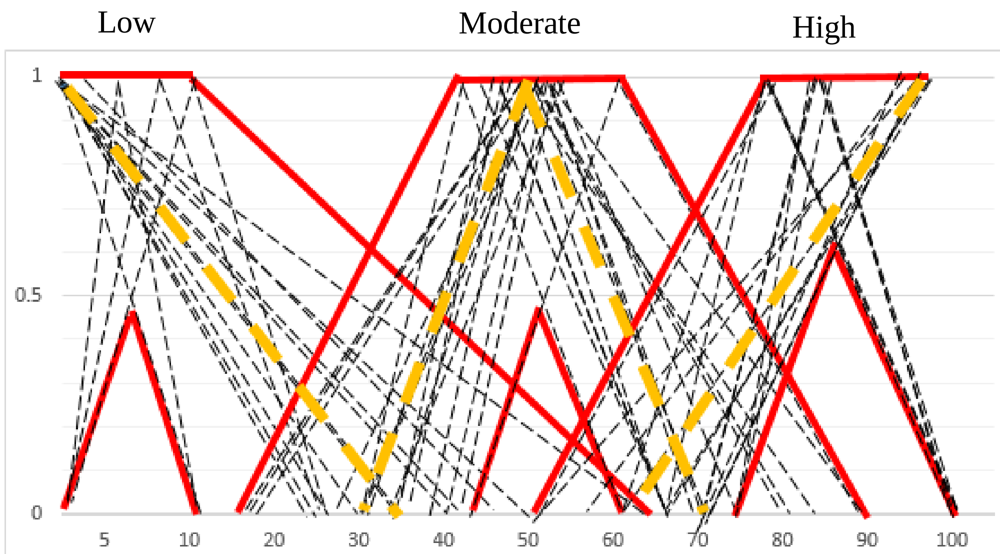



Figure 3.6: The generated interval type-2 fuzzy sets of the average engagement level

In the second phase, the course contents of the three subjects (Java, math and fuzzy logic) were delivered as required for the second group that used the system based on type-1 fuzzy logic and the third group that used the system based on the applied interval type-2 fuzzy logic system. Meanwhile, the first group continued to study a non-adaptive version of the system. Thus, the second and the third groups were presented with individually tailored learning content matched to their needs and preferences according to the rule base learnt from various similar system users. Users were presented with learning objects (LOs) according to their knowledge delivery needs. Each LO unit, such as arrays in Java, is associated with three linguistic variables corresponding to the difficulty of Java content and whether the user prefers to spend more time studying Java topics and its learning style type. There were more than 600 LOs for the three subjects (Java, math and fuzzy logic) that ranged from very easy to very difficult content, and they covered all the learning styles categories that are theoretically described in Table 3.1 (see Figure 3.7) [Dung 2012]. Once this phase was complete, students from the three groups were asked—after sufficient study time—to retake the previous tests with the aim of measuring the suggested system's overall efficiency in terms of improved learning outcomes and average degree of engagement which was measured using the Kinect camera (as shown in Figure 3.5 and as explained in section 3.2.1.1) during student learning in the three groups.

# Java Study Topics

| | | | | | |
|---|---|---|---|---|---|
| * Arrays | Examples | Summary | Quiz | Practical Exercise | Video Tutorial |
| * Datae & Time | Examples | Summary | Quiz | Practical Exercise | Video Tutorial |
| * Regular Experssions | Video Tutorial | | | | |
| * Methods | Examples | Summary | Quiz | Practical Exercise | Video Tutorial |
| * File and I/O | Examples | Summary | Quiz | Practical Exercise | Video Tutorial |
| * Exceptions | Examples | Summary | Quiz | Practical Exercise | Video Tutorial |

# Java Array Quiz

## Please Answer These Questions:

### Question one :

The array stores a fixed-size sequential collection of elements of different type

- ◯True
- ◯False

### Question Two :

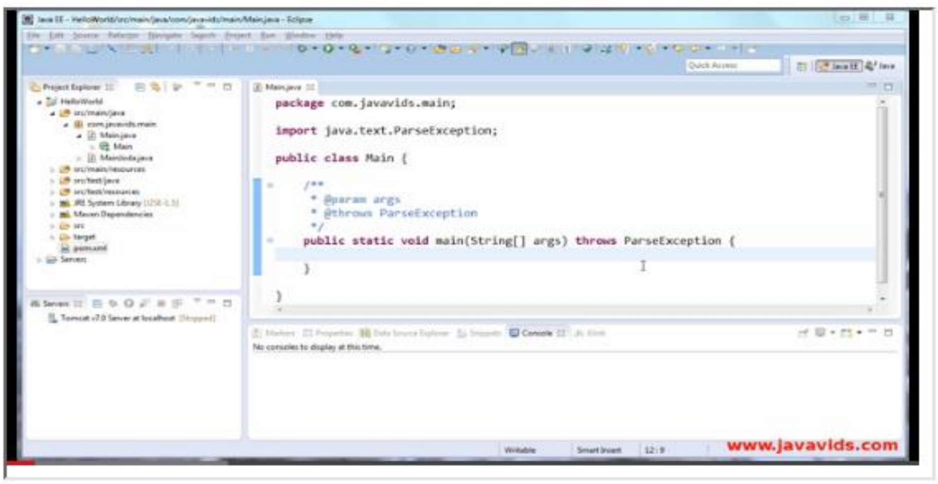
The result of the following code will be _______

```
double[] myList = {1.9, 2.9, 3.4, 3.5};
for (int i = 0; i < myList.length; i++) {
    System.out.println(myList[i] + " ");
}
```

- ◯1.9, 2.9, 3.4, 3.5

# Java date and time Tutorial videos

## *First Tutorial*



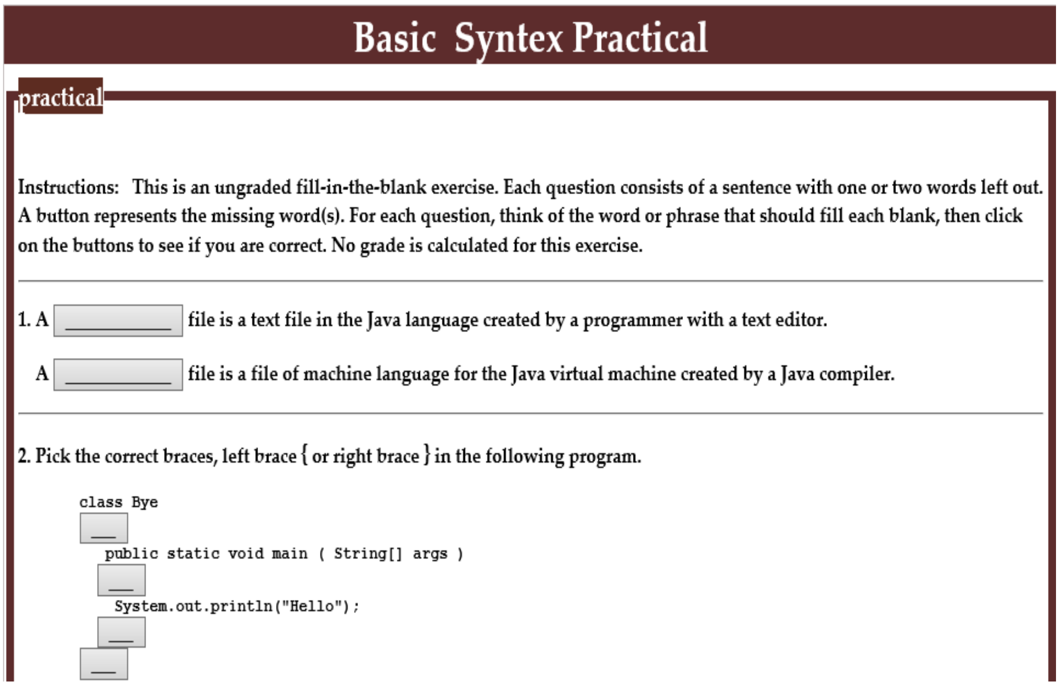



Figure 3.7: Screenshots of various java study masteries

The results from the knowledge delivery system based on the applied interval type-2 fuzzy logic system were compared with those from the knowledge delivery system based on type-1 fuzzy logic and with those obtained from using the same knowledge delivery for all users, the non-adaptive version. Figure 3.8 shows the improvements of the average scores obtained by each of the three different groups' students in the three tested subjects (Java, math and fuzzy logic) prior to and after the application of the system using type-1 and type-2 fuzzy logic techniques and the non-adaptive version. As clearly shown in Figure 3.8, there is a significant increase in fuzzy logic, Java and mathematics average scores due to the employment of the type-2 fuzzy logic system, which resulted in a 6% better average learning improvements than did the type-1 fuzzy logic system and a 13% better gain than the non-adaptive system gave.

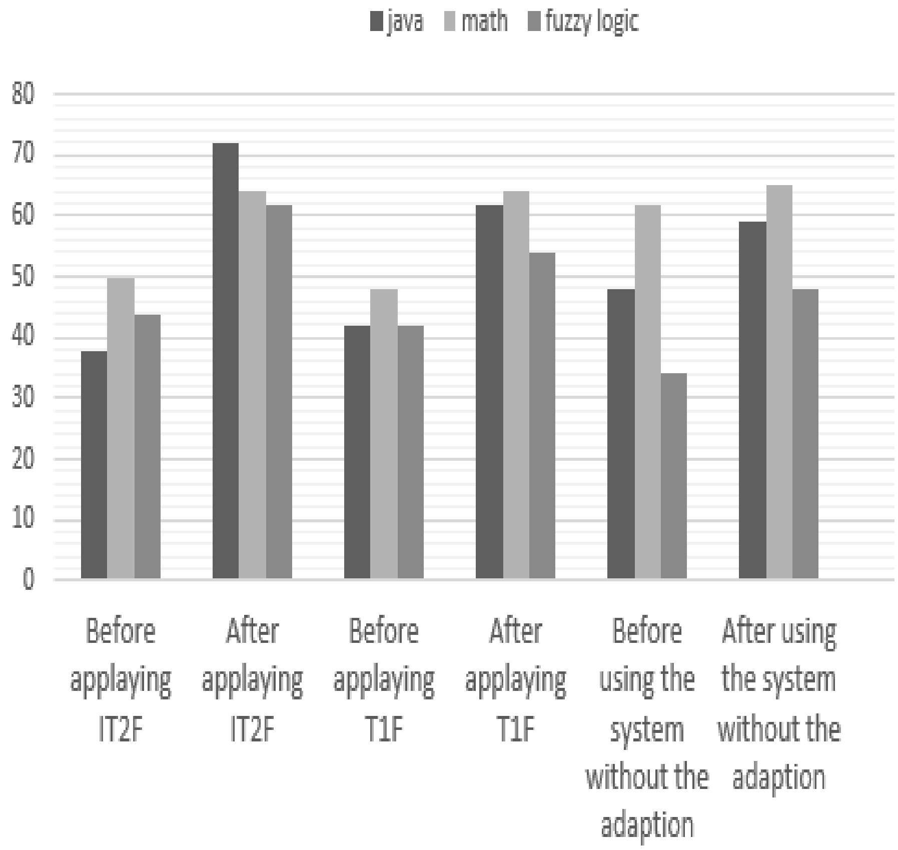



Figure 3.8: The improvements of the average scores

In addition, as shown in Figure 3.9, the average engagement degree obtained for the three groups indicated that the students engage more with the interval type-2 adaptive educational system than they do with the type-1 fuzzy system and the non-adaptive system. The improvements in the students' learning outcomes and average engagement degree evidence the effectiveness of the proposed interval type-2 adaptive educational systems compared to the type-1 fuzzy system and the non-adaptive based system.

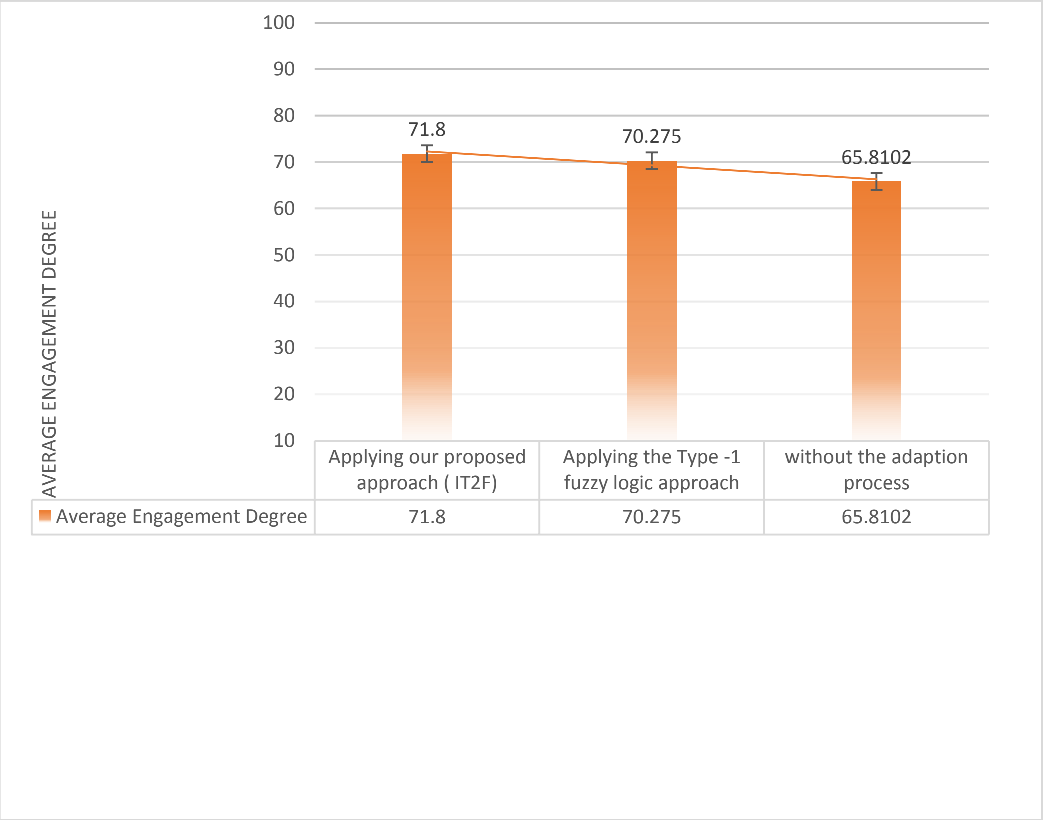



Figure 3.9: the improvements of the engagements level.

Table 3.2 shows the average error and standard deviation for some of the system outputs obtained regarding the students' learned data. These results demonstrate that the type-2 fuzzy logic system produces a lower average and standard deviation of errors than the type-1 fuzzy logic system between the system output and the user desired output. This means that the type-2 system is more effective at capturing student behaviour.

| | IT2FLs | | T1FLs | |
|---|---|---|---|---|
| Output Name | Average error | Standard Deviation | Average error | Standard Deviation |
| Level of difficulty for studying Java | 1.71 | 1.27 | 2.43 | 1.95 |
| Needed time for studying Java materials | 2.42 | 1.79 | 2.04 | 1.67 |
| Level of difficulty for studying Math | 1.58 | 1.24 | 2.61 | 2.04 |
| Needed time for studying Math materials | 2.00 | 1.26 | 2.29 | 2.07 |
| Level of difficulty for studying Fuzzy logic | 1.45 | 1.14 | 2.65 | 2.59 |
| Needed time for studying Fuzzy Logic materials | 2.26 | 1.11 | 2.31 | 2.20 |
| Preference strength for Visual materials | 2.70 | 1.51 | 1.93 | 1.66 |
| Preference strength for Verbal materials | 2.64 | 1.27 | 2.33 | 1.83 |
| Preference strength for Active materials | 2.15 | 1.57 | 2.30 | 1.83 |
| Preference strength for reflective materials | 2.09 | 1.45 | 2.38 | 1.85 |
| Preference strength for Sensing materials | 2.77 | 1.34 | 1.97 | 1.36 |
| Preference strength for Intuitive materials | 2.07 | 1.35 | 2.11 | 1.74 |

Table 3.2: Average error and standard deviations of some of the systems outputs

## 3.4 Discussion

This chapter presented an interval type-2 fuzzy logic–based system that can learn users' preferred knowledge delivery needs and learning style based on students' characteristics and engagement levels to generate a customised learning environment, resulting in enhanced student performance and engagement. For capturing the engagement levels of students, we proposed a method to use visual information to calculate the engagement degree automatically. This differs from traditional methods which usually employ expensive and invasive sensors. The presented type-2 fuzzy model was first created from data acquired from a number of students of differing capabilities and learning needs. The model was subsequently used to enhance knowledge delivery to the individuals based on their characteristics and engagement levels. The proposed system is able to adapt and respond to the requirements of students continuously and on an individualised basis. Furthermore, the type-2 fuzzy logic–based model created is a white box model that can be easily read and interpreted.

The effectiveness of the proposed system has been actualised through several real-world experiments with 15 students participating. The experiments revealed the ability of the proposed type-2 based system to handle the linguistic uncertainties, resulting in enhanced performance in terms of better user engagement and improved learning compared to type-1– based fuzzy systems and non-adaptive systems.

In the next chapter, we will extend the proposed theoretical and practical environments to be used in synchronous e-learning settings with the aim of customising instructional delivery to improve and increase the engagement and satisfaction of different learners.

# Chapter 4: A T2FLS Based Recommendation Approach for Adaptive Teaching within Small-Scale eLearning Platforms

## 4.1 Introduction

Recently, the teacher's role has moved from one where they know everything to one where teachers must be continuously learning and reflective on their skills [Mergler 2012].The teacher's role in the learning environment has been found to be the most influential aspect in improving student satisfaction, outcomes, and engagements [Hattie 2003], [Lovat 2007].Thus, most teachers aim to improve their teaching skills, which have been acquired through their pre-service teaching qualification, training, and career expertise [Mergler 2012]. However, our understanding of what constitutes quality teaching has changed over time, and the definition has become more challenging [Lovat 2007]. Thus, it is difficult to get definite feedback about the best instructional approaches that teachers can follow to promote different learners' engagement, outcomes, and satisfaction due to several issues associated with teachers, learners, and technology-mediated learning and their interactions in the teaching-learning process [Almohammadi 2015a], [Almohammadi 2015b]. First is the issue of teacher expertise in evaluating various learners' engagements as well as the best instructional approaches and teaching actions to maintain the various learners' engagement in a balanced and improved way. Even if teachers profess to have high learner engagement, they will, under normal circumstances, receive no feedback about the engagement of remote learners. Moreover, the total size of remote and on-site students makes it difficult for teachers to diagnose students' interests and discover the best instructional actions to motivate them regarding the learning objectives [Almohammadi 2015a], [Almohammadi 2015b].

Similarly, beginning teachers step into an unknown world, working under the obligation to teach learners with different needs and levels of engagement, and this variable can cause them apprehension [Smith 2005]. This is because there is no smooth initiation into teaching and many teachers struggle to progress from pre-service training to professional practice [Smith 2005]. Importantly, new teachers are usually required to teach like experienced teachers, and thus face the multiple tasks of being students, instructors, and scientists [Öztürk 2013]. Although novices do not have the qualities of experienced teachers, they are still required to meet similar requirements as soon as they enter the field. Furthermore, the most difficult or irksome teaching assignments are often dumped on newly qualified teachers and junior staff members [Öztürk 2013]. The immense stress resulting from these factors results in the situation whereby new teachers leave the teaching job at higher rates than new workers in other fields [Wonacott 2002].

High teacher stress and turnover affects student learning in terms of achievement, engagement, and, ultimately, the outcomes that comprise the end result of the education system. Recently, with advances in educational technology, adaptive educational systems have emerged, and, despite being intended for use by individual students in asynchronous learning contexts, such systems can be used to tailor instructional content to the needs of each student, thus promoting improved learning performance [Shute 2012], [Intelligent Adaptive Learning 2012]. Drawing on the ideas underpinning these adaptive systems that learn and adapted what works best for students, we extend a synchronous system to adaptive teaching and training that enables teachers to learn the behaviors of expert teachers in tackling different students' engagement in accordance with variables of the course content. This process will open opportunities for professional growth for teachers and enhance instruction, which will lead to better student achievement and promote student engagement.

A higher level of engagement with the course content and teaching instructions enables students to acquire more knowledge, therefore improving their learning performance [Clark 2011]. As such, maintaining and increasing the learning engagement of different students requires ongoing learning in the context of the instructions established by experienced teachers. Given these considerations, the purpose of this chapter is to identify the instructional approaches that experienced teachers, in light of general course characteristics and different student engagement levels, deem to be the most effective. Subsequently, this learned behavior can be applied in the training of new teachers to improve their teaching approaches and thus promote better learning.

The effectiveness of any adaptive and intelligent teaching framework depends on the approach used to accurately accumulate data about the best instructional approaches, and also the ability of how and when this information is processed to prepare an effective instruction context [Shute 2012]. The important question arises, then, of how one can ensure precision in evaluating and choosing the appropriate teaching approach that will best promote and improve learner engagement. This question is quite critical because of uncertainties about how accurately teacher decisions about instructional approaches are actually categorized by the learning system—as well as the corresponding uncertainties associated with how the resulting instruction is actually decided and administered according to the varied levels of learner engagement.

In synchronized teaching environments, there are high levels of linguistic uncertainties whereby teachers can interpret and act on the same terms, words, or methods (e.g., pertaining to lesson difficulty, appropriate teaching style, and approach) in various ways, according to their pupils' varied levels of engagement, knowledge, and expertise in their subject. The integration of flexible Artificial Intelligence (AI) techniques within adaptive e-learning contexts could help to handle the uncertainties that may negatively affect the development of an environment which encourage learning and teaching [Ahmad 2004].

To the best of our knowledge, no previous studies have been proposed to learn the teaching behavior process according to the varied on-site and distance learners' levels of engagement in their respective learning environments.

This chapter presents an IT2FLS capable of understanding various teachers' behaviors, involving their instructional decisions in accordance with various varied learners' average engagement levels and the difficulty level of the content in dynamic teaching environments. The type-2 fuzzy model is first created from data collected from a number of teaching sessions with different teaching approaches conducted by different qualified teachers. The learned type-2 fuzzy-based model is then used to improve instructional delivery approaches that can be used as supplemental tools to aid the teaching profession and enhance the learning process. We will show how the proposed system enables the customization of instructional delivery to improve and increase different learners' engagement. Furthermore, the proposed system is flexible enough to allow constant updating in accordance with the level of student engagement. A number of experiments have been conducted within the iClassroom at the University of Essex among a group of thirty students and six teachers to assess the efficiency of the proposed system. The results of the experiments indicate that, in comparison to type-1 fuzzy systems and non-adaptive systems, the proposed system based on interval type-2 fuzzy logic has greater capacity for managing ambiguities and stimulating student engagement and satisfaction.

## 4.2 The Proposed Environments Components

Throughout the proposed e-learning framework, knowledge acquisitions would be transformed based on the teacher's instructional approaches and tutorial actions aimed at fulfilling and prompting the current feedback regarding the varied levels of engagement of the remote and on-site learners. Figure 4.1 shows the conceptual model of the proposed environment whereby the data about the appropriate instructional approach are recorded by the tutor according to the distance and on-site learners' varied engagement levels and the lesson's difficulty level (for the three teaching sessions in the case of the carried out experiments) in the observer component. In this component, the data from the e-learning framework are monitored and captured at whatever point the teacher alter his or her instructional approach. Accordingly, these gathered data will be used in the fuzzy learning component. This component will initially enable the system to generate the type-2 fuzzy sets as per the methodology described in [Liu 2007], [Almohammadi 2014], [Almohammadi 2013a].

This method centers on producing type-2 fuzzy sets via the gathering of type-1 fuzzy sets from various instructors. These type-1 fuzzy sets are combined, resulting in the FOU, which appropriately induces a type-2 fuzzy set, which is seen to signify a word. Furthermore, this component implements an unsupervised one-pass approach, as inspired by [Wang 2003], [Hagras 2007], [Almohammadi 2015a], [Almohammadi 2015b], and obtains the rules from the acquired data; this is the main goal of this component. In the IT2FLS adaptation rules component, these learned rules trigger the best instructional methodologies based on the current state of inputs. This adaptation model component also considers the new teacher-learned actions that are subject to the existing input parameters from the e-learning environment that are already monitored in the observer component, and subsequently creates an output in consideration of the current state of inputs. This further enables the online adaptation and enhancement of rules and ultimately facilitates life-long learning owing to the dynamic quality of teaching and learning process interactions.

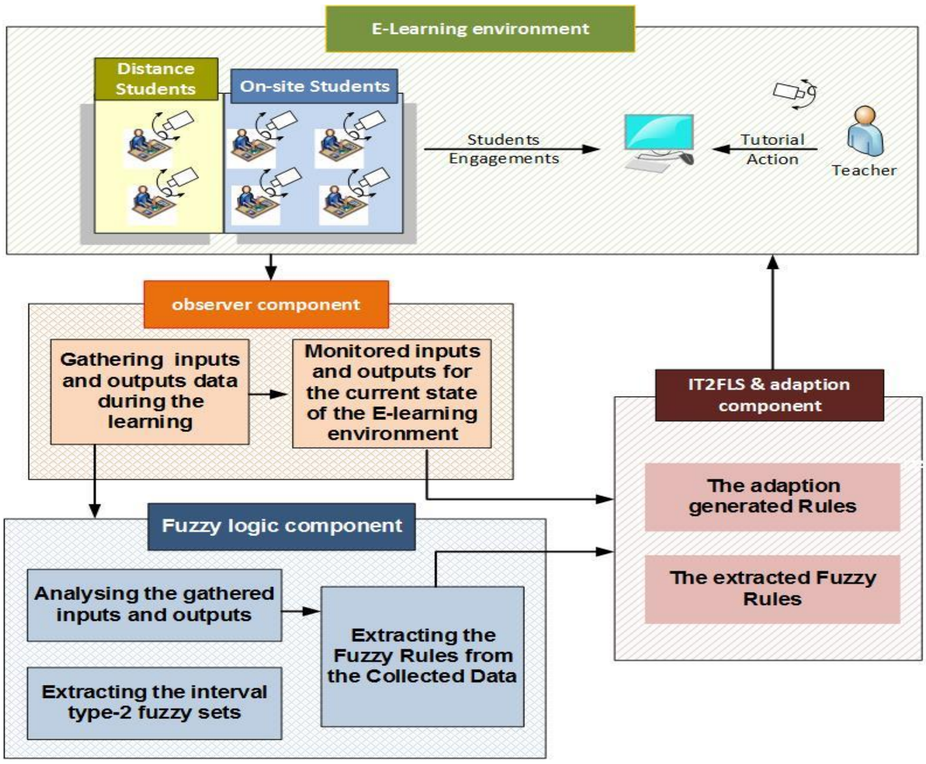



Figure 4.1: An overview on the proposed Type-2 Fuzzy Logic Based recommendation approach for Adaptive Teaching across Interactive E-learning Environments.

As demonstrated in Figure 4.1, there would be three components in the proposed system which are the observer component, the fuzzy logic component and the IT2FLS and adaptation components. These three components will be discussed in detail in the following subsections.

## 4.2.1 The Observer Component

Primarily, the proposed system gathers and captures the data through collecting the appropriate instructional approach as recorded by the teacher, according to the distance learners' varied average level of engagement and the difficulty level of the current lesson taught within the online learning environment. It is noteworthy that the data (both current inputs and outputs) would be actively recorded by the system if there was any change in the appropriate instructional approach (as indicated by the teachers) in accordance with the current state of the e-learning environment. Thus, our system creates and learns a descriptive model of the best instructional teachers' methodologies used in tackling and promoting the varied levels of engagement of distance learners in a balanced way; this is achieved through the data gathered, generating a set of multi-input and multi-output data pairs, which take the following form [Wang 2003],[Hagras 2007], [Almohammadi 2015a] :

$$x^{(t)}; y^{(t)} \qquad (t = 1,2,\dots,N), \tag{4.1}$$

Where $N$ is referred to as the total of data instances, $x^{(t)} \in R^n$ , and $y^{(t)} \in R^k$. Rules are basically mined by our system, which explains how the $k$ output, which is the best instructional approach variables $y = (y_1, \ldots, y_k)^T$ are affected by the input variables $x = (x_1, \ldots, x_n)^T$. A model mapping inputs to outputs is achieved using the established fuzzy rules without requiring a mathematical model. Therefore, individual rules can be adapted online, affecting only certain aspects of the descriptive model created and learned by the proposed system.

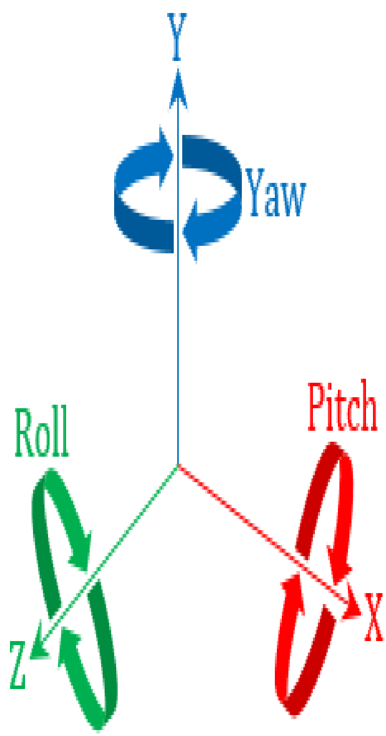
#### 4.2.1.1 The Proposed Method for Engagement Degree Estimation

The first step is to calculate the head pose orientation and the face emotion using the SDK of Kinect v2. After that, the deviation degrees of the current head orientation away from the expected direction (towards the whiteboard or screen) are calculated to measure the extent of distraction. And then we select the largest distraction extent degree to estimate the engagement degree of the student. Finally, based on the deviation and the face emotion, the engagement degree can be computed.

##### 4.2.1.1.1 Head Pose Estimation

To robustly estimate the head pose orientation and improve the accuracy of the results, the method based on a regularized maximum likelihood Deformable Model Fitting (DMF) reported in [Cai 2010] which is robust against the impact of noise factors in the depth channel. As this method has been developed in the latest version v1409 of Kinect v2 Windows SDK, in our experiments we utilize the module directly to obtain the 3D head pose orientation of the student in E-Learning environments. In our experiments, we use the latest model Kinect v2 as shown in Figure 4.2 a) which is more robust than the previous model [Almohammadi 2014]. The SDK of Kinect v2 provides and describes head pose relating to the Kinect camera by three angles: pitch, roll and yaw, as demonstrated in Figure 4.2 b).


(a)




(b)

Figure 4.2: (a) The used Kinect v2. (b) Head pose angles.

#### 4.2.1.1.2 Engagement Degree Estimation

Based on the visual features including head pose together with the face emotion returned by the 3D sensor, in our experiments, we will consider the following assumptions describing the relation between the input visual features and the output engagement degree:

- Facing the whiteboard (or computer screen in case of remote learning) – the student is engaged in the class.
- Facing down – the student is sleepy or probably playing a tablet/smartphone.
- Facing to the left/right – the user is distracted from the learning and interacting with another student nearby.

- Looking around/away – The student is thinking about irrelevant problems and is not concentrated.
- Face emotion – One eye is not open or both of the two eyes are closed (*falling-asleep*), and other face emotion for example, mouth open and close (*speaking*), facial expression is *happy*, face emotion is *engaged*, etc.

Based on the assumptions above, the engagement degree of the student can be calculated and modelled by the face emotion of the student and the deviation between the current head orientation and the optimum engaged head pose (facing towards the whiteboard) which are shown in the following equations.

$$\textit{Engagement Degree} = (1\text{-}\textit{Deviation}) \times \textit{Emotion Modifier} \tag{4.2}$$

Where Emotion Modifier is decided by the facial emotion including falling-asleep, speaking, happy, engaged. In this experiment we mainly consider the factor falling-asleep for face expression analysis:

$$\textit{EmotionModifier} = \begin{cases} 1 & \textit{Two eyes are open} \\ \text{OEC Modifier} \quad \textit{if} & \textit{One eye is closed} \\ 0 & \textit{Two eyes are closed} \end{cases} \tag{4.3}$$

Where *OEC Modifier* is in the range of 0 and 1, and can be determined by the actual application scenario.

$$Deviation = max\{D_{pitch}, D_{roll}, D_{yaw}\} \tag{4.4}$$

$$D_{pitch} = \frac{|Pitch_c - Pitch_o|}{Pitch_{max}} \tag{4.5}$$

$$D_{roll} = \frac{|Roll_c - Roll_o|}{Roll_{max}} \tag{4.6}$$

$$D_{yaw} = \frac{|Yaw_c - Yaw_o|}{Yaw_{max}} \tag{4.7}$$

Where $Pitch_c$, $Roll_c$, $Yaw_c$ are the three angles (pitch, roll and yaw) of the current head pose obtained by the Kinect v2. $Pitch_o$, $Roll_o$, $Yaw_o$ are the angles describing the optimum engaged head pose orientation which are recorded in the training stage. $Pitch_{max}$,$Roll_{max}$, $Yaw_{max}$ are the maximum angles defined and returned by the Kinect v2 SDK.

## 4.2.2 Fuzzy Logic Component

### 4.2.2.1 Extracting the Interval Type-2 Fuzzy Sets

Classification of the acquired teaching–learning behavior input/output data through the relevant fuzzy membership functions is a vital step in this component layer. The raw input and output values are ultimately quantified through this process, which leads them into linguistic labels such as *low/moderate* and *high* for the average level of engagement. The type-2 fuzzy set extraction approach used is indicated in [Liu 2007], [Almohammadi 2014], and [Almohammadi 2013a], by which a type-2 fuzzy set is developed and its FOU embeds the numerous type-1 fuzzy sets, so that each teacher's individual interpretation can be specified regarding a particular linguistic label that justifies the appropriate instructional approach and various varied learners' average engagement levels. Therefore, the teachers' diverse views with regard to modeling these words would be integrated by the FOU produced, and the uncertainties would also be handled for the type-2 fuzzy sets. In this method, data are gathered by questioning the teachers regarding their specific linguistic labels through which type-1 fuzzy sets would be produced. Subsequent to this step, the type-2 fuzzy sets are produced, while the type-1 fuzzy sets (demonstrating the teachers' individual views) are integrated, through which the FOU of the type-2 fuzzy set is delivered to represent the given word. Through the application of the Representation Theorem [Mendel 2001], [Liu 2007], each of the interval type-2 fuzzy sets $\tilde{A}_s$ can be calculated as follows:

$$\tilde{A}_s = \cup_{i=1}^{n} A^i \tag{4.8}$$

In this equation, $\cup$ is an aggregation operation and $A^i$ is referred to as the $i^{th}$ embedded type-1 fuzzy set [Liu 2007]. Reckoning the upper MF $\overline{\mu}_{\tilde{A}}(x)$ and the lower MF $\underline{\mu}_{\tilde{A}}(x)$ of $\tilde{A}_s$ can deliver the process of $\tilde{A}$ production. The embedded type-1 fuzzy sets and the upcoming FOU model for $\tilde{A}_s$ would collectively decide the occurrence of this mechanism. For the upper and lower MF parameters, interior FOU models, right and left shoulder MFs (shown in Figure 4.3 a, b and c) are to be applied in our system. According to Figure 4.3 a, the parameters: $\underline{a}_{MF}, \underline{c}_{MF}, \overline{c}_{MF}$ and $\overline{b}_{MF}$ denoting a trapezoidal upper MF and the parameters: $\bar{a}_{MF}$ and $\underline{b}_{MF}$ for a symmetric triangular lower MF, with an intersection point $(p, \mu_p)$ are most likely to describe the resulting interior interval type-2 fuzzy set [Liu 2007]. We describe below the procedures for calculating these parameters:

The type-1 MFs for each of the $i$ teachers is described according to the parameters $[a_{MF}^i, b_{MF}^i]$. For interior FOUs, we provide below the procedure for assessing the FOU model [Liu 2007]: We should follow the given steps for the upper MF $\overline{\mu}_{\tilde{A}}(x)$,

1) For $\mu(x) = 0$ , determine $\underline{a}_{MF}$ to be equal to the minimum $a_{MF}^{min}$ of all left-end points $a_{MF}^{i}$ and $\overline{b}_{MF}$ to be equal to the maximum $b_{MF}^{max}$ of all right-end points $b_{MF}^{i}$ [Liu 2007].
2) For $\mu(x) = 1$, calculate $\underline{c}_{MF}, \overline{c}_{MF}$ which correlate to the minimum and the maximum of the centres of the type-1 MFs.
3) Approach the upper MF $\overline{\mu}_{\tilde{A}}(x)$ by joining the following points with straight lines: $(\underline{a}_{MF}, 0)$,$(\underline{c}_{MF}, 1)$,$(\overline{c}_{MF}, 1)$and $(\overline{b}_{MF}, 0)$. Figure 4.3 a) illustrates the result, which is a trapezoidal upper MF.

Following are the steps to estimate the lower MF$\underline{\mu}_{\tilde{A}}(x)$:

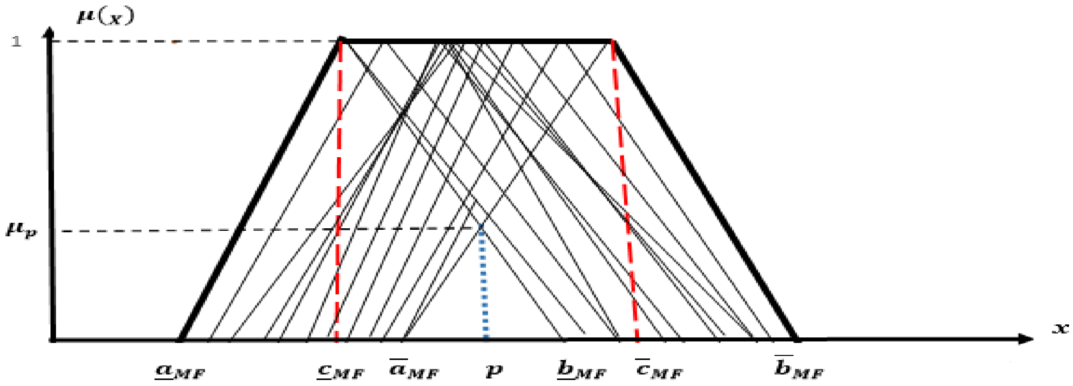
1) For $\mu(x) = 0$, determine $\overline{a}_{MF}$ to be equal to the maximum $a_{MF}^{max}$ of all left-end points $a_{MF}^{i}$ and $\overline{b}_{MF}$ to be equal to the minimum $b_{MF}^{min}$ of all right-end points $b_{MF}^{i}$ [Liu 2007].
2) By using the following equations, compute the intersection point $(p, \mu_p)$ [Liu 2007]:

$$p = \frac{\underline{b}_{MF}(\overline{c}_{MF} - \overline{a}_{MF}) + \overline{a}_{MF}(\underline{b}_{MF} - \underline{c}_{MF})}{(\overline{c}_{MF} - \overline{a}_{MF}) + (\underline{b}_{MF} - \underline{c}_{MF})} \tag{4.9}$$

$$\mu_p = \frac{(\underline{b}_{MF} - p)}{(\underline{b}_{MF} - \underline{c}_{MF})} \tag{4.10}$$

3) Approximating the lower MF $\underline{\mu}_{\tilde{A}_s}(x)$ by joining the following points with straight lines :$(\underline{a}_{MF}, 0)$,$(\overline{a}_{MF}, 0)$,$(p, \mu(p))$, $(\underline{b}_{MF}, 0)$and $(\overline{b}_{MF}, 0)$.The result according to Figure 4.3 a) is a triangle lower MF.

The method adopted for computing the FOU for the right and left shoulder is similar to that described in [Liu 2007]. To compute the upper MF $\overline{\mu}_{\tilde{A}}(x)$ for the left shoulder (as shown in Figure 4.3 b), points $(0,1)$,$(\overline{a}_{MF}, 1)$ and $(\overline{b}_{MF}, 0)$ should be joined with straight lines. To compute the lower MF$\underline{\mu}_{\tilde{A}}(x)$, points $(0,1)$,$(\underline{a}_{MF}, 1)$,$(\underline{b}_{MF}, 0)$, and $(\overline{b}_{MF}, 0)$ should be connected with straight lines. Similarly, as shown in Figure 4.3 c), to estimate MF $\overline{\mu}_{\tilde{A}}(x)$ for the right shoulder, points $(\underline{a}_{MF}, 0)$,$(\underline{b}_{MF}, 1)$ and $(M, 1)$ should be joined with straight lines. To approximate the lower MF$\underline{\mu}_{\tilde{A}}(x)$, points $(\underline{a}_{MF}, 0)$,$(\overline{a}_{MF}, 0)$, $(\overline{b}_{MF}, 1)$ and $(M, 1)$ should be joined with straight lines [Liu 2007].




(a)

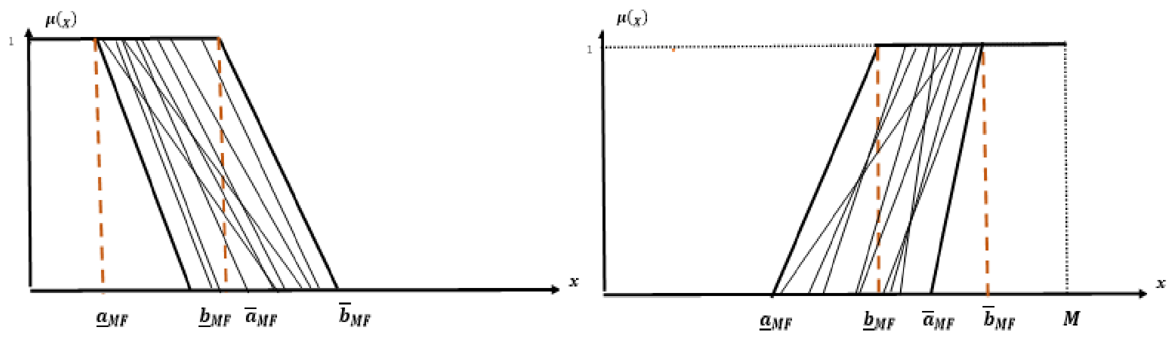



Figure 4.3: (a) An interior type-2 MF embedding the different type-1 fuzzy sets, (b) left shoulder type-2 MF embedding the different type-1 fuzzy sets (c) Right shoulder type-2 MF embedding the different type-1 fuzzy sets [Liu 2007].

#### 4.2.2.2 Extracting the Fuzzy Rule from the Collected Data

The data collected from the e-learning environment (input/output) are combined with the extracted type-2 fuzzy sets so that the rules describing the actions of teachers can be extracted. An enhanced form of the Wang–Mendel technique is used to drive the rule extraction method employed in this chapter [Wang 2003], [Hagras 2007]. This method was explained in the previous chapter in section 3.2.3. An example of the extracted rule with multiple inputs-outputs is shown in Figure 4.4.

> *IF* **the learners' average level of engagements** *is* **Low** *AND* the **learners' average standard deviation level of engagements** *is* **Moderate** *AND* **the difficulty level of the current lesson** *is* **Hard** THEN **the recommendation to use the "asking questions" teaching approach** *is* **High** *AND* **the recommendation to use the "practical explanation (demo)" approach** *is* **Low** *AND* **the recommendation to use the "teaching with cases (problem solving)" approach** *is* **Moderate** ***AND*** **the recommendation to use the "PowerPoint slides" teaching approach** *is* **Low**

Figure 4.4: An example of one of the extracted fuzzy rules

### 4.2.3 The IT2FLS and adaption component

The generated type-2 fuzzy sets and the fuzzy rules extracted from the input and output gathered data of learners enables the proposed system to learn and obtain the best instructional approaches in accordance to the varied level of engagement of the learners and the difficulty level of the taught content. The system is consequently able to notify the teachers to re-adjust the online learning environment with specific consideration to appropriate instructional approach. The system actions are triggered through the examination and monitoring of various learners' varied levels of engagement and the lesson difficulty, which subsequently affects the online instructional environment, with a particular consideration of the learned approximation of best tutorial actions that could be followed by the teachers. The following are the functionalities of the proposed type-2 fuzzy adaptive system:

- As specified in the e-learning environment, the crisp inputs including the learners' variables are fuzzified (via singleton fuzzification) into the input interval type-2 fuzzy sets.
- The outputs (instructional approaches) type-2 fuzzy sets are generated by the activation of inference engine and rule base.

The proposed system must have the ability to be fine-tuned with respect to the dynamic and diverse varied learners' engagements and various difficulties of the taught lessons' states by continuously enabling teachers to modify their instructional approaches. Subsequently, the system will re-adjust its procedures or it would apply new ones. If no rules arouse from the rule base (i.e. the rule's firing strength in Equation (3.21) in section 3.2.3 in chapter 3 ( $wi^{(t)} = 0$) in a given input, subsequently the system input would be captured by the system. To create a rule covering this uncovered input status, it will capture the appropriated teaching approaches. Therefore, new rules would be integrated in the system while there is an undefined state of the online learning environment at that moment as per the existing rules in the rules base (i.e. where none of the present rules are fired). The new rules will be generated and the system integrates them in such an instance, in which the online learning environment's current input states are specified by the antecedents besides the consequent fuzzy sets that are dependent on the current state of the instructional approach. The fuzzy sets that have membership values, where $\mu^{cg}_{\tilde{A}^h_c}(x_s^{(t')}) > 0$, are identified for all of the input parameters $x_s$. Consequently, for each input parameter, numerous identified fuzzy set(s) are generated in the form of a grid from which new rules are generated based on all individual combinations of successive input fuzzy sets. The consequent fuzzy set that provides the greatest value of membership to the teacher defines the appropriate instructional approach $(y_c)$ so that it can operate as the generated rule consequent. After performing a calculation of the output interval memberships' center of gravity, we can establish the fuzzy sets [Wang 2003], [Hagras 2007],[Almohammadi 2013a]:

$$\mu^{cg}_{\tilde{B}^{h^*}_c}(y_c) \geq \mu^{cg}_{\tilde{B}^h_c}(y_c) \tag{4.20}$$

For $h = 1,\ldots,W$ the $\tilde{B}_c$ is chosen as $\tilde{B}^{h^*}_c$, where $c = 1,\ldots,k$. Consequently, new and upcoming rules can be progressively added.

In case the teacher needs to change the suited instructional approaches at a given input status, the fired rules will be identified and the rule consequents will be changed (if more than two teachers signal the same modifications for the teaching approaches), as indicated by Equation (4.20). Therefore, the fired rules are modified so that the updated suited instruction approaches for the students could be reflected in a desirable way, while taking into account the existing state of the online learning environment. The system proposed in this chapter adopts life-long learning through facilitating the adaptation of rules according to the optimized instruction delivery approaches by teachers, which notably change over time based on students varying levels of engagements and in regard to the state of the online learning environment. Owing to the system flexibility, the fuzzy logic model learned initially may be effortlessly expanded in order to make changes to both new and existing rules. These fuzzy rules enable a large range of values for all parameters (input and output) to be captured, which in turn enables the continuation of the generation of rules, even when the online learning environment gradually changes. On the other hand, if notable changes occur in terms of the students' varied average level of engagements or in the environment (which may not be captured by the present rules, as highlighted above), the new rules will be automatically generated, which ultimately satisfy present conditions. Accordingly, the inconspicuous system will expand its actions and may be adapted in order to improve the instruction delivery.

## 4.3 Experiment and Results

Various real-world experiments were performed in the iClassroom of the University of Essex to compare the effectiveness of the proposed Interval Type-2 Fuzzy Logic based System (IT2FLS) with the Type-1 Fuzzy Logic based counterpart system (T1FLS) and the non-adaptive version of the system in regards of enhancing the quality of instruction to promote better student engagement and satisfaction. To perform the experiments, 20 lessons from a Microsoft Excel course were selected and categorized according to level of difficulty (i.e. very hard, hard, moderate, easy and very easy). Furthermore, we examined four teaching approaches, namely teaching: using PowerPoint slides, practical explanation (demo), teaching with cases (problem solving) and asking questions. These approaches were recommended by different expert teachers to be used in the systems.

Real-world experiments were conducted with a sample of 30 students and six teachers from the University of Essex. The experiments began by training the system. Three groups were formed from the 15 students, each of which was randomly assigned five distance learners. An expert teacher was assigned to each group to teach 20 lessons using the four teaching approaches.

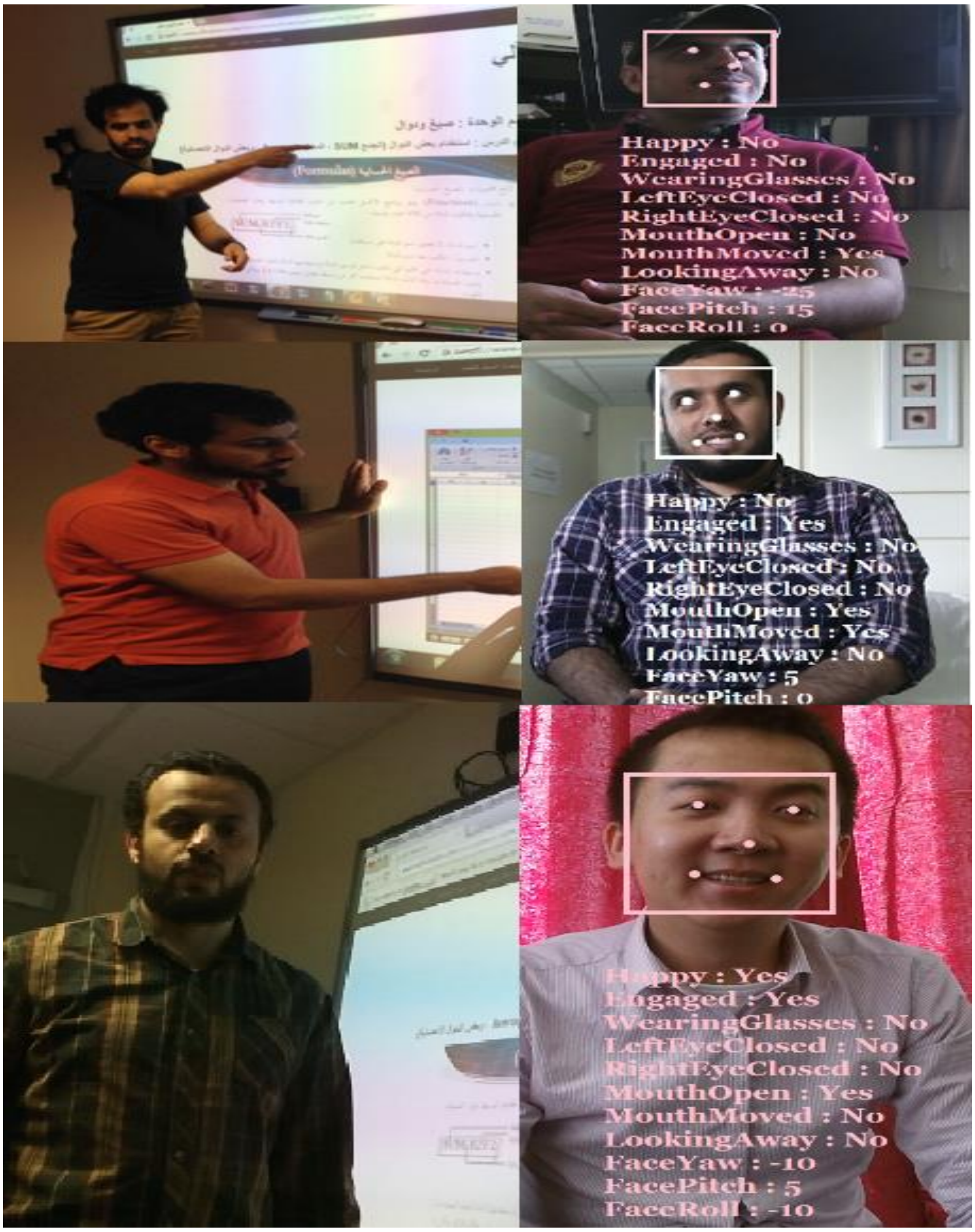



Figure 4.5: Teachers are shown on the left side photographs while they are teaching different lessons with different teaching approaches. On the right side photographs, the students' engagement feedback are shown in the teachers' user interface

During the teaching sessions, the learners' average level of engagements and the average standard deviation level were measured and accumulated every five seconds, as well as the difficulty level of the current lesson being presented in the teacher-user interface; both were used as input variables. When the teacher decided to change the teaching approach, he/she should rank and prioritize these teaching approaches from zero (not beneficial in the current situation) to ten (absolutely beneficial in the current situation); this ranking was used as the output. The teacher recorded the inputs and their related outputs in the system's database. These inputs/outputs were captured by the observer component whenever the teacher changed or recorded the appropriated instructional approach. The left hand side of Figure 4.5 shows the teachers teaching the lessons while the right hand side shows the students' engagement degree recognized by the teacher user interface. The average engagement degree for each student was measured using the Kinect camera (as shown in Figure 4.5 and as explained in section 4.2.1.1).

It should be noted that the calculation of the average learners' engagement and the standard deviation was taken from the beginning of teaching a lesson in one of the four teaching approaches until teaching another lesson that differed in difficulty level or until changing the teaching approach.

After collecting sufficient datasets, we started the testing phase. Here, three five-member groups were taught by three different teachers (i.e. one teacher assigned to each group). The teacher in the first group used a system applying T1FLS, while the second group's teacher used applied IT2FLs recommendations. The third group did not use any technological system and served as the control group for the experiment. After dividing the three groups equally and the input and output data for type-1 and type-2 groups were obtained. Then, by using the linguistic variables and rules, the fuzzy logic models for both the type-1 and type-2 were constructed. The type-2 fuzzy sets (shown in thick line in Figure 4.6) were obtained to capture the uncertainty that represents teachers' views regarding a particular linguistic label explaining the average of students' engagement, their standard deviation and the teaching approach, while the type-1 fuzzy logic system uses a type-1 fuzzy set (shown in dashed lines and sample from the extracted fuzzy sets can be found in Appendix B) as it shown in Figure 4.6 .In addition, examples of the generated rule is shown in Figure 4.4.

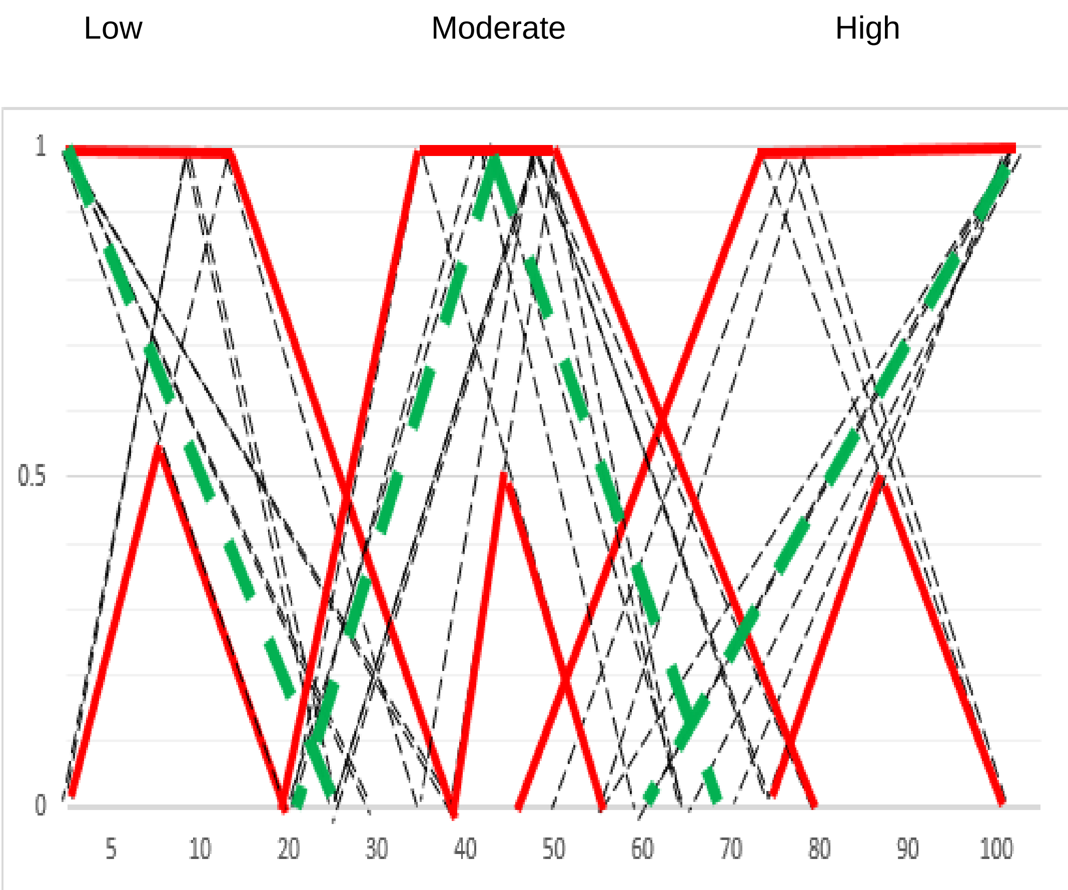



Figure 4.6: The generated interval type-2 fuzzy sets of the average engagement level (think solid lines) and the type-1 fuzzy sets (thick dashed lines).

As soon as the teachers in the first and second groups started introducing the first lesson, the observer component started calculating the average engagement and the standard deviation. Simultaneously, the observer component tried finding the matched rule(s) with the current monitored inputs. When the system found the matched rule(s), it would be presented in the teacher user interface thus, he/she could know what the best teaching approach in that situation was given the output of the IT2FLS. The teacher could ignore this output and the system would learn from his/her decision of re-prioritizing and re-ranking the teaching approaches based on the current given data. Hence, if the teacher determined to continue teaching the lesson (or any lesson in the same difficulty level) without changing the teaching approach, the observer component will continue calculating the average engagement and the standard deviation. In contrast, if the teacher changed the teaching approach or taught a lesson that differed from the previous one, the observer component would modify its action accordingly and adapt the corresponding rules.

The notification frequency is determined by changes in the monitored inputs (the eLearning environment state), modified by the average level of engagement, the average standard deviation of learners engagements, or the difficulty level of the lesson. We have noticed that these inputs do not sharply change, so the notifications should not affect the instructor mode of teaching. Through the experiments, it has been shown that 66% of the suggested teaching approaches were followed by the teacher, whereas 34% divided between the edited ones and the recommendation that affects the instructor mode of teaching. It is important to note that teachers might need some time to switch from one teaching approach to another, so they might in some cases ignore the recommended approach.

Finally, for evaluation purposes the teacher learned data was collected to compare the type-2 and type-1 fuzzy logic system to know the average error and standard deviation of the teachers' preferred output and the system outputs. In addition, the comparison between the three groups in terms of the average engagements and standard deviations involved comparing them based on the data gathered by the observer component (during the whole teaching session for every group) and based on the students' views which tracked by their questionnaire responses.

| Output Name | Type-2 Fuzzy Logic | | Type-1 Fuzzy Logic | |
|---|---|---|---|---|
| | Average error | Standard deviation | Average error | Standard deviation |
| Asking questions approach | 2.60 | 1.43 | 2.73 | 1.88 |
| Practical explanation (demo) approach | 1.90 | 1.28 | 2.78 | 1.67 |
| teaching with cases (problem solving) approach | 2.09 | 1.32 | 2.88 | 1.79 |
| Using PowerPoint slides | 2.31 | 1.71 | 2.97 | 1.95 |

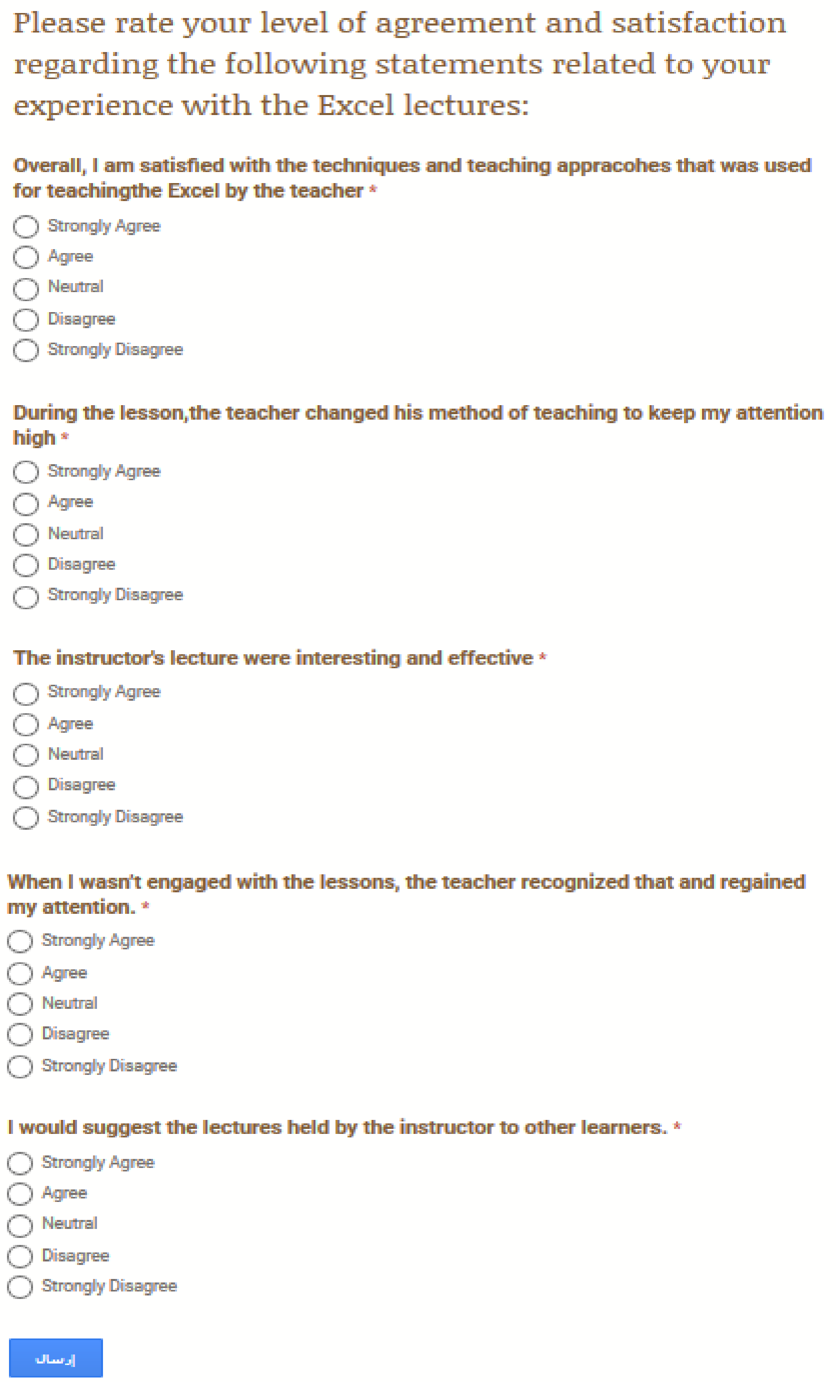
Table 4.1: Average error and statndard deviation of the system outputs

Firstly, based on the teachers' learned data, Table 4.1. shows the average error and standard deviation to compare the teacher preferred output and the system outputs in both systems IT2FLS and T1FLS. These results clearly show that IT2FLS has less average error and standard deviation. Even for the least improvements in the "Asking questions Approach", the IT2FLS produced almost 5% better performance when compared to T1FLS in terms of lower average error between the system output "asking question approach" and the preferred teacher learned output "asking question approach." In addition, the IT2FLS produced better spread of the errors by having 23% less standard deviation when compared to T1FLS. Consequently, IT2FLS appears to be more effective than type-1 fuzzy logic system in recording teachers' tutorial actions.

On the other hand, according to data gathered by the observer component, the results indicated that the use of IT2FLS makes students more engaged and brings them closer to each other in terms of their degree of engagement. Accordingly, there was little dispersion of the set of engagement data for the IT2FLS group, with an average engagement degree of 68.75% and 10% average standard deviation, compared to an average engagement degree of 64.23% and 16% average standard deviation for the type-1 fuzzy logic system (T1FLS)—and a 44.34% average engagement degree and 20% average standard deviation for the control group.

Furthermore, we analyzed the participants' satisfactions in the questionnaire (see Figure 4.7) using ANOVA to compare the responses from the groups at a significance level of 0.05. The analysis revealed that there is a significant statistical difference between the various groups ($p << 0.05$). We also carried out Tukey comparison test to see which pair of groups has the difference. We observed that group

3 (IT2FLS) and Group 1 (control group) were the most significantly different groups as compared to other pairings, as shown in Figure 4.8



Please rate your level of agreement and satisfaction regarding the following statements related to your experience with the Excel lectures:

**Overall, I am satisfied with the techniques and teaching appracohes that was used for teachingthe Excel by the teacher** *

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

**During the lesson,the teacher changed his method of teaching to keep my attention high** *

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

**The instructor's lecture were interesting and effective** *

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

**When I wasn't engaged with the lessons, the teacher recognized that and regained my attention.** *

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

**I would suggest the lectures held by the instructor to other learners.** *

- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

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Figure 4.7: the designed questionnaire for measuring participants' satisfactions

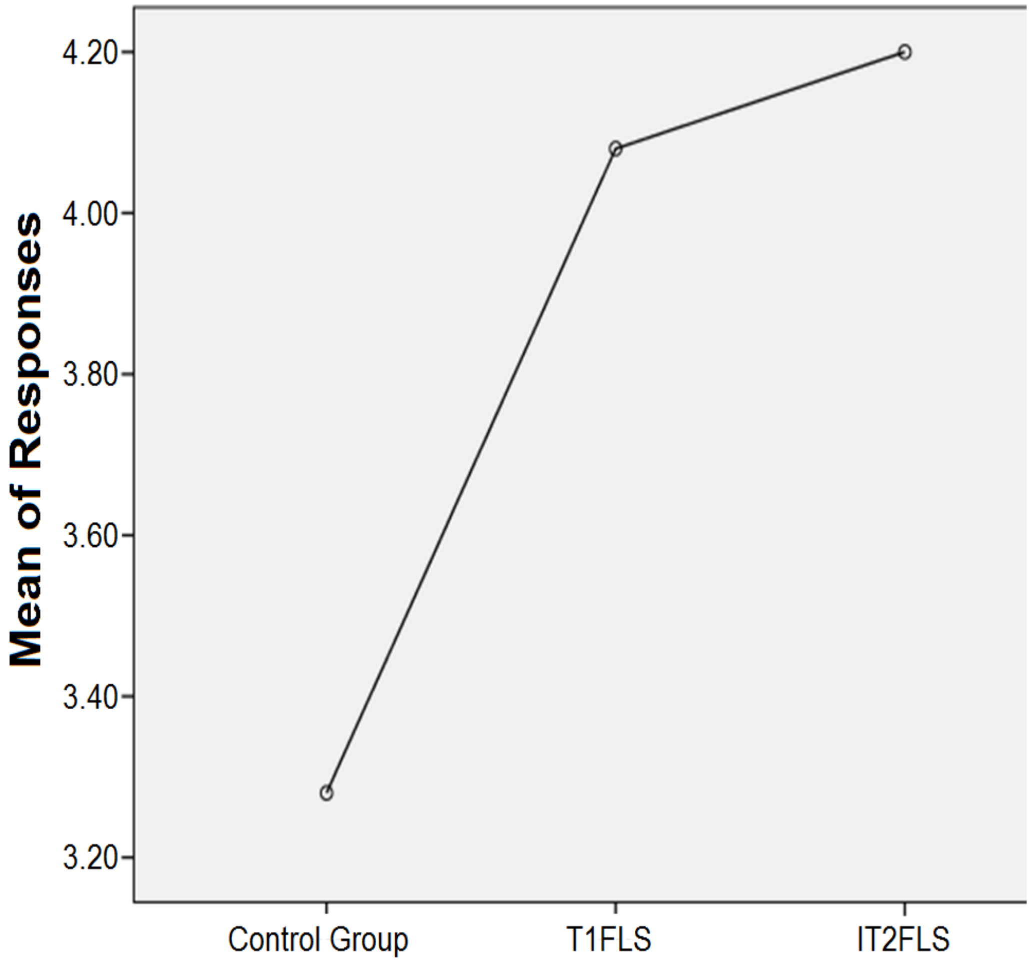


Figure 4.8: Plot for group means comparison using Tukey.

## 4.4 Discussion

E-learning platforms facilitate the interaction between students and instructors while mitigating temporal or spatial constraints. Nevertheless, such platforms require measuring the degree of students' engagement with the delivered course content and teaching style. Such information is highly valuable for evaluating the quality of the teaching and altering the teaching delivery style in massively crowded online learning platforms. When the number of learners is high, it is essential to attain overall engagement and feedback, yet doing so is highly challenging due to the high levels of uncertainties related to students and the learning context. To handle these uncertainties more robustly, we have presented a method based on type-2 fuzzy logic utilizing visual RGB-D features, including head pose direction and facial expressions captured from Kinect v2, a low-cost but robust 3D camera, to measure the engagement degree of students in both remote and on-site education. This system augments 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 students and enhance their instruction delivery. This proposed dynamic e-learning environment integrates both on-site and distance students as well as teachers who instruct both groups of students. The rules are learned from the students' and teachers' learning/teaching behaviors, and the system is continuously updated to give the teacher the ability to adapt the delivery approach to varied learners' engagement levels.

The IT2FLS has been tested and compared with the T1FLS and with a non-adaptive system within a small-scale elearning platform. The experiments were conducted with a population of six teachers and 30 students at Essex University. The results revealed that IT2FLS was better able to handle uncertainties where IT2FLS produced lower average errors and standard deviation compared to T1FLS between the system outputs and the preferred teacher outputs. This has resulted in increasing the average level of engagement over the T1FLS group by 7%; the engagement level improved over the control group by 55%. Furthermore, the use of the IT2FLS system brought the students' engagement levels closer together, yielding an average standard deviation improvement of about 37.5% over the T1FLS group and about 50% over the control group. Using ANOVA and Tukey tests, we found that the satisfaction level of the participants in the IT2FLS differed significantly from the satisfaction level of students in the control group ($p < 0.05$).

Thus, these promising results from the proposed system has facilitated the instruction with better delivery to the learners more than the type 1 fuzzy systems and the non-adaptive version.

It should be noted that the proposed system can be scalable and is designed for a large number of remote students. In addition, the system can be extended in terms of the relations between more varied student input variables and more teaching methods outputs to be tested. In the future, we intend to carry experiments with large size classes.

In the next chapter, we aim to employ the general new zSlices-based type-2-fuzzy-logic-based system to better handle uncertainties in the model and extend the flexibilities of the proposed models. We also conduct various large-scale, real-world experiments involving 1,871 students from King Abdul-Aziz University to test the proposed zSlices-based type-2-fuzzy-logic-based system with the IT2FLS. Unfortunately, we could not utilize the engagement system within the employed experiments because of the large number of distance learners and the inability to require them to buy the Kinect v2 camera.

# Chapter 5: zSlices-Based T2FLs for Users-Centric Adaptive Learning in Large Scale E-Learning Platforms

## 5.1 Introduction

Previous experiments and chapters for small-scale e-learning platforms have proven that interval type-2 FLSs are capable of providing better performance compared to type-1 FLSs as type-2 FLSs can be considered as groups of uncountable embedded type-1 FLSs [Mendel 2001]. The interval type-2 fuzzy sets assume the even distribution of uncertainty by interval type-2 fuzzy sets across the FOU. However, better performance can expected through the use of general type-2 fuzzy sets as general type-2 fuzzy sets can allow for an unbalanced distribution within applications in areas that have uneven distributions of uncertainty when information regarding this kind of distribution is available [Wagner 2010]. In adaptive e-learning environments that could learn the learners behaviour, there are multi learners where their behaviours can be extracted from various characteristics such as their pervious education; an example is the secondary school education level. In Saudi Arabia, there are two secondary education sections which are the humanities section and scientific secondary section. We will show how we utilise the third dimension to manage more the raised uncertainty using zSlices based general type-2 fuzzy sets.

This chapter presents a new zSlices-based general type-2 fuzzy-logic-based system that can learn students' preferred knowledge delivery needs based on their characteristics and current levels of knowledge to generate an adaptive learning environment. We have evaluated the proposed system's efficiency through various large-scale, real-world experiments involving 1871 students from King Abdulaziz University. These experiments demonstrate the proposed zSlices general type-2 fuzzy-logic-based system's capability for handling linguistic uncertainties to produce better performance, particularly in terms of enhanced student performance and improved success rates compared with interval type-2 fuzzy logic, type-1 fuzzy systems, adaptive, instructor-led systems, and non-adaptive systems.

## 5.2 The zSlices-based General T2FLS for users-centric adaptive learning in large scale e-learning platforms

Our proposed theoretical and practical environment based on zSlices general type-2 fuzzy logic aims to correlate and learn various needed instructional variables like the suited current level of content difficulty and the time needed for the taught content that can tackle the current state of various learner variables, such as current levels of knowledge and characteristics. Figure 5.1 shows an overview of the proposed environment where interactions occur between various learners and the e-learning environments in the application layer. The main objective of this layer is first to specify needed instructional variables to be learned (the outputs) in the learning environment according to the learners' variables, which are the inputs. Secondly, this layer will enable the system to gather and monitor these specified data related to evaluating students' understanding of their knowledge delivery needs according to their characteristics variables in the online learning environment, which is subsequently examined and analyzed in the learning fuzzy rules layer.

The learning fuzzy rules' functionality generates the system learned rules. The objective of the first component of this layer is to extract the zSlices general type-2 fuzzy sets for the system input and output, which are based on a method that centers on creating type-2 fuzzy sets [Liu 2007], [Almohammadi 2014], [Almohammadi 2013a], [Almohammadi 2015a] gathered from a sample of participants (n=30 students in the conducted experiments) to handle the internal uncertainties for two groups of students. After acquiring the fuzzy sets and collecting data (which took one week in the conducted experiments), the system is able to generate the fuzzy rules that describe the best needed instructional actions that satisfy the current state of students' capabilities and characteristics. The proposed zSlices system utilizes an unsupervised one-pass technique (inspired by previous studies [Bilgin 2012], [Wang 2003], [Hagras 2007], [Almohammadi 2013a]) for extracting the rules from the collected data in this extracting fuzzy rule component.

Finally, the adaptation layer is used when it takes the students' learning current input states and gives them suitable outputs to accomplish their learning tasks. Our proposed environment in this layer further enables the online adaption and enhancement of rules and facilitates long-term learning due to changes in performance and capabilities, delivery instructional needs. The proposed environment comprises the three following layers (as shown in Figure 5.1), which with their sub-components are discussed in detail in the following subsections.

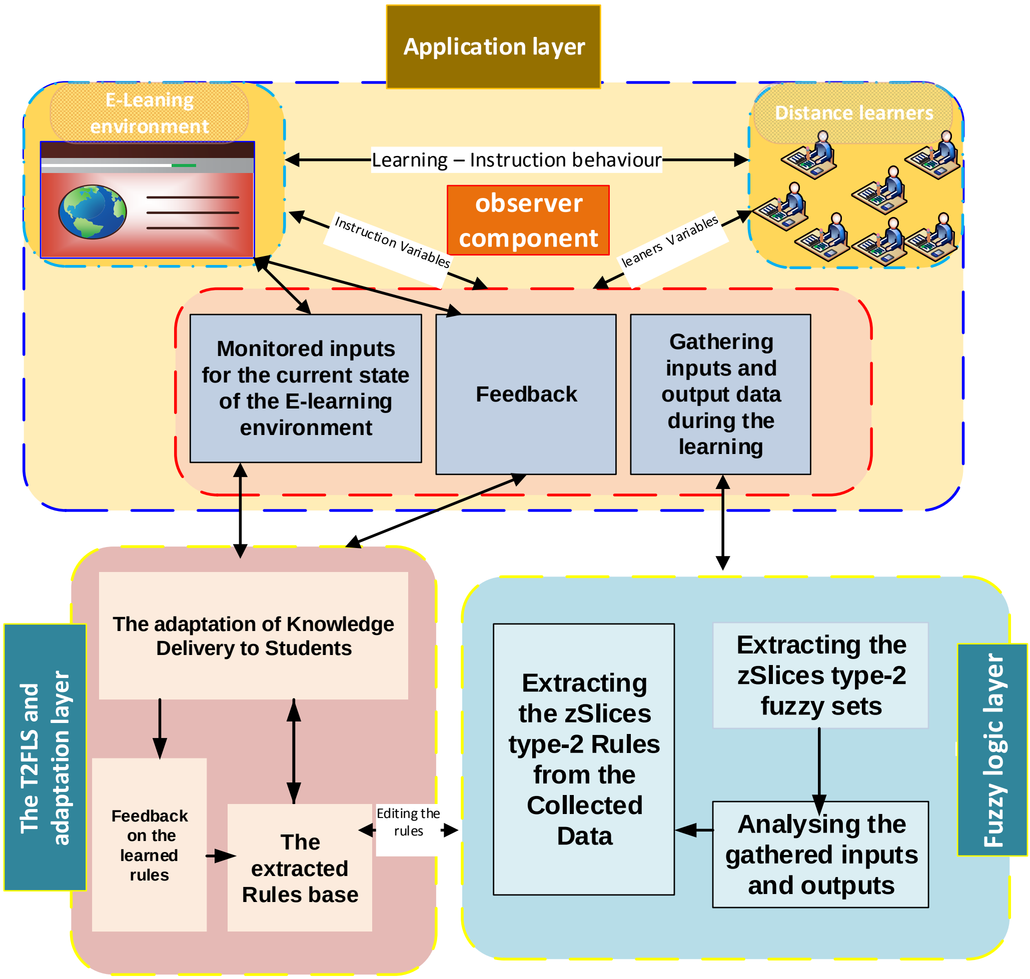


Figure 5.1 :An overview on the proposed zSlices based on type-2 fuzzy logic for users-centric adaptive learning system in large scale e-learning platforms

## 5.2.1 Application Layer

The main purpose of this layer is to first specify the learners' variables, which are the inputs according to the system outputs; these are related to the content or instructional variables to be learned. Instructional variables could be the suitable learning content difficulty level and time needed, along with the preferred learning style and method of knowledge acquisition. These variables promote the student learning level that matches the current learner variables, which include the student's current level of knowledge and other personal characteristics related to the adaptation process, making it more personalized.

#### 5.2.1.1 The Observer Component

The objective of this component in the proposed system is to record and monitor the system inputs and outputs. The data are captured via the collection and assessment of various student knowledge delivery requirements (outputs for the fuzzy system) according to their characteristics and capabilities (inputs for the fuzzy system) within the application layer. It is noteworthy that this component is also responsible for actively recording data (both current inputs and outputs) to see if there is any change in the student instructional needs in accordance with the current state of the e-learning environment [Hagras 2007], [Almohammadi 2013a]. Therefore, the observer component enables proposed environments to create and learn a descriptive model of the appropriate student instructional needs used in handling and promoting the students' current levels of knowledge and capability; this is accomplished via this process of data gathering, which generates a set of multi-input and multi-output data pairs, which will be formed as follows [Bilgin 2012], [Wang 2003], [Hagras 2007]:

$$x^{(t)}; y^{(t)} \qquad (t = 1,2,\dots,N), \tag{5-1}$$

Where $N$ is the total number of data instances, $x^{(t)} \in R^n$ , and $y^{(t)} \in R^k$. The rules generated by the proposed system are basically explaining how the $k$ output, which is the students' instructional needs variables $y = (y_1, \dots, y_k)^T$, are affected by the input variables $x = (x_1,\dots,x_n)^T$, which are the student characteristics and capabilities. A correlating model for inputs to outputs is constructed using the established fuzzy rules without requiring a mathematical model. Thus, individual rules can be adapted online, affecting only certain aspects of the descriptive model created and learned by the proposed system.

## 5.2.2 The Fuzzy Rules Learning Layer

### 5.2.2.1 Extracting the zSlice based general type-2 fuzzy sets

Categorization of the gathered learning-instruction behavior input/output data via the relevant fuzzy membership functions is an important step in the fuzzy rule learning layer. This component enables the system to quantify the raw input and output values by changing them into linguistic labels such as *very low*, *low*, *moderate*, *high*, and *very high* for the average level of knowledge in the current learning subject. A zSlice is formed by slicing a general type-2 fuzzy sets in the third dimension (z) at level $z_i$[Wagner 2009], [Wagner 2010]. The result of this slicing action is an interval set in the third dimension with height $z_l$. In other words, a zSlice $\tilde{Z}_i$ is equivalent to an interval type-2 fuzzy set with the exception that its membership grade $\mu_{\tilde{Z}_i(x,u)}$ in the third dimension is not fixed to 1; instead it is equal to $z_l$, where $0 \leq z_i \leq$ 1[Wagner 2010]. Thus, the zSlice $\tilde{Z}_l$ can be written as [Wagner 2010]:

$$\tilde{Z}_i = \int_{x \in X} \int_{u_i \in J_{i_x}} z_i/(x, u_i) \tag{5-2}$$

Interval type-2 fuzzy sets with the height $z_l$ extraction approach that produce a type-2 fuzzy set are detailed in [Liu 2007], [Almohammadi 2014], [Almohammadi 2013a], [Almohammadi 2015a]. Their FOU integrates the numerous type-1 fuzzy sets that describe the interpretation of each students' views regarding a particular linguistic label that justifies the learned instructional and learner variables (inputs-outputs) related to the learning environment. Accordingly, the learners' various perspectives regarding modeling these words would be embedded by the generated FOU to handle uncertainties for the type-2 fuzzy sets. In this approach, the data are collected by asking the students for their views regarding their specific linguistic labels through which type-1 fuzzy sets would be generated. Following this step, the type-2 fuzzy sets are extracted while the type-1 fuzzy sets representing the learners' individual views are combined, resulting in the FOU of the type-2 fuzzy sets being delivered that represent the given word [Liu 2007], [Almohammadi 2014], [Almohammadi 2013a], [Almohammadi 2015a]. Through the application of the Representation Theorem, each of the interval type-2 fuzzy sets $\tilde{A}_s$ can be computed as follows:

$$\tilde{A}_s = \cup_{i=1}^{n} A^i \tag{5-3}$$

Where $A^i$ is referred to as the $i^{th}$ combined type-1 fuzzy set and $\cup$ is an aggregation operation. Reckoning the upper membership function (MF) $\overline{\mu}_{\tilde{A}}(x)$ and the lower MF $\underline{\mu}_{\tilde{A}}(x)$ of $\tilde{A}_s$ can deliver the process of $\tilde{A}$ production [Liu 2007], [Almohammadi 2014], [Almohammadi 2013a], [Almohammadi 2015a]. This depends on the shape of the embedded type-1 fuzzy sets and the FOU model to be generated for $\tilde{A}_s$. In our system, we use the interior FOU models and the right and left shoulder MFs for the upper and lower MF parameters, as shown in Figure (5.2) a, Figure (5.2) b and Figure (5.2) c . As is shown in Figure (5.2) a, the resulting interior interval type-2 fuzzy set is constructed by the parameters $\underline{a}_{MF}$, $\underline{c}_{MF}$, $\overline{c}_{MF}$ and $\overline{b}_{MF}$ denoting a trapezoidal upper MF and the parameters $\overline{a}_{MF}$ and $\underline{b}_{MF}$ for a symmetric triangular lower MF, with an intersection point $(p, \mu_p)$. We describe the procedures for calculating these parameters below.

Given the parameters for the symmetric triangle type-1 MFs generated for each of the i students [$a^i_{MF}$,$b^i_{MF}$], for interior FOUs, we provide the procedure for calculating the FOU model below [Liu 2007], [Almohammadi 2014], [Almohammadi 2013a], [Almohammadi 2015a] .

For the upper MF $\overline{\mu}_{\tilde{A}}(x)$, we need to follow these three steps:

1. For $\mu(x) = 0$ , find $\underline{a}_{MF}$ to be equal to the minimum $a_{MF}^{min}$ of all left-end points $a_{MF}^{i}$ and $\overline{b}_{MF}$ to be equal to the maximum $b_{MF}^{max}$ of all right-end points $b_{MF}^{i}$ For $\mu(x) = 1$, find $\underline{c}_{MF}, \overline{c}_{MF}$ that correspond to the minimum and the maximum of the centers of the type-1 MFs .

2. Approximate the upper MF$\overline{\mu}_{\tilde{A}}(x)$ by connecting the following points with straight lines: $(\underline{a}_{MF}, 0)$,$(\underline{c}_{MF}, 1)$,$(\overline{c}_{MF}, 1)$and $(\overline{b}_{MF}, 0)$.

Figure (5.2) a shows the result, which is a trapezoidal upper MF. For the lower MF$\underline{\mu}_{\tilde{A}}(x)$ we need to follow these three steps [Liu 2007], [Almohammadi 2014], [Almohammadi 2013a], [Almohammadi 2015a]:

1. For $\mu(x) = 0$, find $\overline{a}_{MF}$ to be equal to the maximum $a_{MF}^{max}$ of all left-end points $a_{MF}^{i}$ and $\overline{b}_{MF}$ to be equal to the minimum $b_{MF}^{min}$ of all right-end points $b_{MF}^{i}$

2. Compute the intersection point $(p, \mu_p)$ by using the following equations

$$p = \frac{\underline{b}_{MF}(\overline{c}_{MF} - \overline{a}_{MF}) + \overline{a}_{MF}(\underline{b}_{MF} - \underline{c}_{MF})}{(\overline{c}_{MF} - \overline{a}_{MF}) + (\underline{b}_{MF} - \underline{c}_{MF})} \quad (5\text{-}4)$$

$$\mu_p = \frac{(\underline{b}_{MF} - p)}{(\underline{b}_{MF} - \underline{c}_{MF})} \quad (5\text{-}5)$$

3. Approximate the lower MF $\underline{\mu}_{\tilde{A}_s}(x)$ by connecting the following points with straight lines: $(\underline{a}_{MF}, 0)$,$(\overline{a}_{MF}, 0)$,$(p, \mu(p))$, $(\underline{b}_{MF}, 0)$and $(\overline{b}_{MF}, 0)$.

The result, as it is illustrated in Figure (5.2) a, is a triangle lower MF.

The method adopted for computing the FOU for the right and left shoulder is similar to that described in [Liu 2007], [Almohammadi 2014], [Almohammadi 2013a], [Almohammadi 2015a]. To compute the upper MF $\overline{\mu}_{\tilde{A}}(x)$ for the left shoulder (as shown in Figure (5.2)b), points $(0,1)$, $(\overline{a}_{MF}, 1)$ and $(\overline{b}_{MF}, 0)$ should be joined with straight lines. To compute the lower MF$\underline{\mu}_{\tilde{A}}(x)$, points $(0,1)$, $(\underline{a}_{MF}, 1)$, $(\underline{b}_{MF}, 0)$, and $(\overline{b}_{MF}, 0)$ should be connected with straight lines. Similarly, as shown in Figure (5.2) c, to estimate MF $\overline{\mu}_{\tilde{A}}(x)$ for the right shoulder, points $(\underline{a}_{MF}, 0)$,$(\underline{b}_{MF}, 1)$ and $(M, 1)$ should be joined with straight lines. To approximate the lower MF$\underline{\mu}_{\tilde{A}}(x)$, points $(\underline{a}_{MF}, 0)$,$(\overline{a}_{MF}, 0)$, $(\overline{b}_{MF}, 1)$ and $(M, 1)$ should be joined with straight lines [Liu 2007], [Almohammadi 2014], [Almohammadi 2013a], [Almohammadi 2015a].

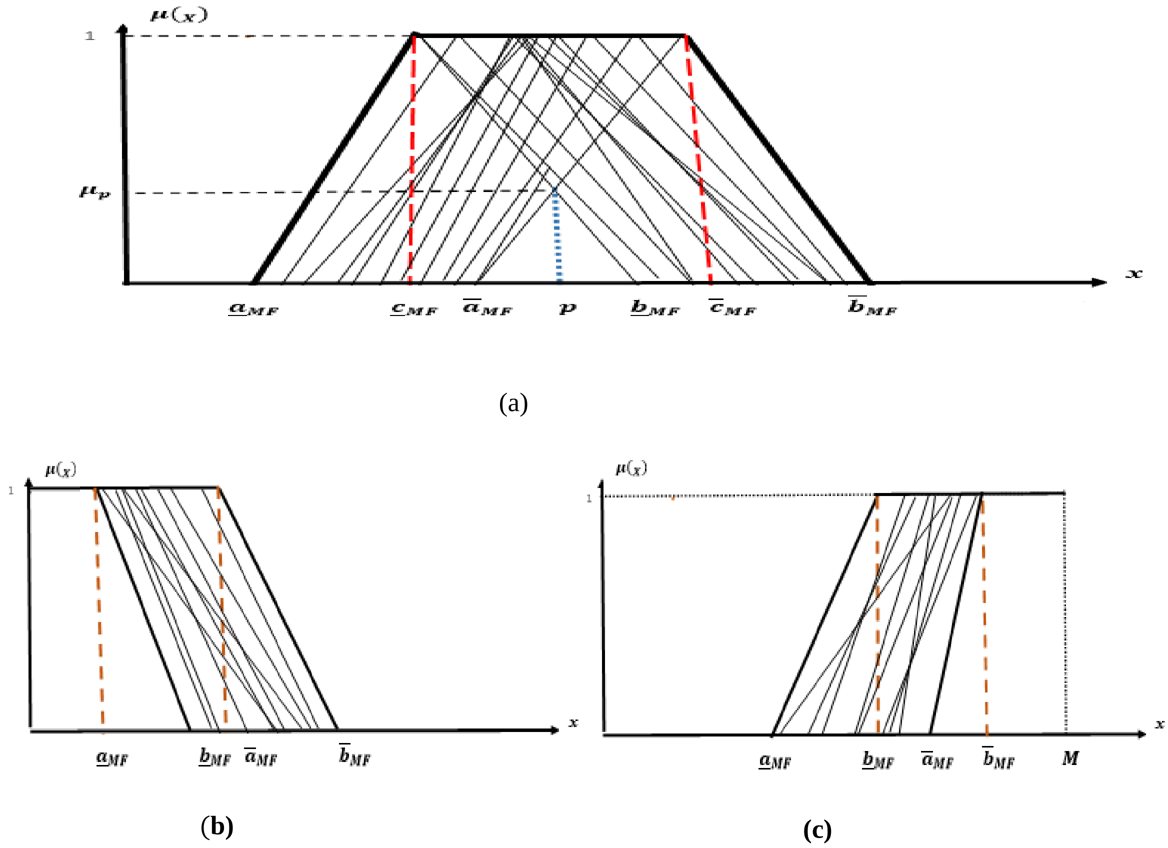


Figure 5.2: (a) An interior type-2 MF embedding the different type-1 fuzzy sets, (b) left shoulder type-2 MF embedding the different type-1 fuzzy sets, (c) right shoulder type-2 MF embedding the different type-1 fuzzy sets [Liu 2007], [Almohammadi 2014], [Almohammadi 2013a], [Almohammadi 2015a] .

The experiments section describes and draws the zSlices general type-2 fuzzy set combining two interval type-2 fuzzy sets with height $\boldsymbol{z_2}$ from two categorized participant groups.

### 5.2.2.2 Extracting the fuzzy rules

The extracted fuzzy set is amalgamated with the collected input/output user data with the aim of obtaining those rules known to define student behaviors. Our system's method of learning the rules from the data is based on an extended and further developed version of the Mendal-Wang approach [Bilgin 2012], [Wang 2003], [Hagras 2007], [Almohammadi 2013a]. This is a one-pass technique for extracting fuzzy rules from the accumulated data. The fuzzy sets for the antecedents and consequents of the rules divide the input and output space into fuzzy regions. Several multi-input/multi-output rules are extracted using the type-2 fuzzy system, through which the association between $x = (x_1, \ldots, x_n)^T$ and $y = (y_1, \ldots, y_k)^T$ can be explained such that:

$$IF\ x_1 \text{ is } \tilde{A}_1^l \ldots \text{and } x_n \text{ is } \tilde{A}_n^l \text{ THEN } y_1\ is\ \tilde{B}_1^l \ldots..and\ \ \mathrm{y_k}\ is\ \tilde{B}_\mathrm{k}^l \quad (5\text{-}6)$$

$l = 1,2, \ldots., M$, where $l$ is the index of the rules and $M$ is the number of rules.

Specifically, for each input $x_s$ where $s = 1,2, \ldots., n$, there are $V_i$ type-2 fuzzy sets $\tilde{A}_s^q$ , $q = 1, \ldots, V_i$, and each one of them has defined $I$ zSlices $\widetilde{Z_l A_s^q}$ where $l = 1, \ldots., l$. Similarly, for each output $y_c$, there are $V_o$ type-2 fuzzy sets $\tilde{B}_c^h$ , $h = 1, \ldots, V_o$, where $c = 1,2, \ldots., k$ and each set has defined $I$ zSlices $\widetilde{Z_l B_c^h}$, where $l = 1, \ldots., l$. It is worth noting that the total number of zSlices is the same for all the $V_i$ input sets and $V_o$ output sets, which are generated according to the various students' views, as indicated in the previous section.

To clarify and summarize the following representation, an approach comprising a single output is illustrated because of the method's simplicity for upgrading the rules involving multiple outputs. We note the several phases included in this rule extraction below.

**Phase 1:** The upper and lower membership values are calculated as $\overline{\mu}_{\tilde{A}_s^q}\left(x_s^{(t)}\right)$ and $\underline{\mu}_{\tilde{A}_s^q}\left(x_s^{(t)}\right)$ for each zSlice $\widetilde{Z_l A_s^q}$ where $l = 1, \dots., l$, for each of the fuzzy set $\widetilde{A}_s^q$ , $q = 1, \dots, V_i$ , and for each input variable $s$ $(s = 1, \dots, n)$ regarding a fixed input–output pair $(x^{(t)}; y^{(t)})$ in the dataset $(t = 1,2, \dots, N)$ by finding $q^* \in \{1, \dots, V_i\}$ such that [Bilgin 2012], [Wang 2003], [Hagras 2007], [Almohammadi 2013a] :

$$\mu_{\tilde{A}_s^{q^*}}^{zcg}\left(x_s^{(t)}\right) \geq \mu_{\tilde{A}_s^q}^{zcg}\left(x_s^{(t)}\right) \tag{5-7}$$

For all $q$ = 1,...,$V_i$, where $\mu_{\tilde{A}_s^q}^{zcg}\left(x_s^{(t)}\right)$ is the z-weighted center of gravity of the membership of $\tilde{A}_s^q$ at $x_s^{(t)}$, which can be seen below [Bilgin 2012], [Wang 2003], [Hagras 2007], [Almohammadi 2013a] :

$$\mu_{\tilde{A}_s^q}^{zcg}\left(x_s^{(t)}\right) = \frac{1}{2}\left[\frac{\sum_l^I \overline{\mu}_{\widetilde{Z_l A_s^q}}\left(x_s^{(t)}\right) * z_l}{\sum_l^I z_l} + \frac{\sum_l^I \underline{\mu}_{\widetilde{Z_l A_s^q}}\left(x_s^{(t)}\right) * z_l}{\sum_l^I z_l}\right] \tag{5-8}$$

Where $z_l = l/I$ and $1 \leq l \leq I$ .The rule given below is generated by $(x^{(t)}; y^{(t)})$ [Bilgin 2012], [Wang 2003], [Hagras 2007], [Almohammadi 2013a]:

$$IF x_1 \text{is } \tilde{A}_1^{q^{*(t)}} \text{ and } x_n \text{ is } \tilde{A}_n^{q^{*(t)}} THEN \text{ centered } at\ y^{(t_u^l)} \tag{5-9}$$

For all of the input variables $x_s$, there are $V_i$ type-2 fuzzy sets $\tilde{A}_s^q$, which makes the greater amount of possible rules equal to $V_i^n$. However, when considering the dataset, there will be the generation of those rules among the $V_i^n$ possibilities that show a dominant region comprising a minimum of one data point.

In the first phase, there is the generation of one rule for each particular input/output data pair, with the selected fuzzy set being that which is seen to obtain the greatest value of membership at the data point and particularly selected as the one in the rule's IF element. However, this is not the final version of the rule, which is computed in the following step. The calculation of the rule weight is accomplished as follows [Bilgin 2012], [Wang 2003], [Hagras 2007], and [Almohammadi 2013a]:

$$wi^{(t)} = \prod_{s=1}^{n} \mu_{\tilde{A}_s^{q^*}}^{zcg}\left(x_s^{(t)}\right) \tag{5-10}$$

A rule $wi^{(t)}$ weight is a degree of the strength of the points $x^{(t)}$ regarding the fuzzy region covered by the entire rule.

**Phase 2:** For all of the data points from 1 to *N*, the first phase is repeated. With the help of this practice, *N* rules extracted from the data are taken in the form of Equation (5-9). Phase 1 witnesses the generation of multiple rules, all of which have the same IF part in common yet are all conflicting. During this phase, those rules that have the same IF part are amalgamated to form a single rule. Subsequently, the rules *N* are divided into groups, with rules in each group seem to have the same IF part. If such groups amount to *M* and it may also be stated that the group has $N_l$ rules, then [Bilgin 2012], [Wang 2003], [Hagras 2007], [Almohammadi 2013a]:

$$IF\ x_1 \text{is } \tilde{A}_1^l \ldots \text{and } x_n \text{is } \tilde{A}_n^l \text{ THEN } y \text{ is centered } at\ y^{(t_u^l)} \tag{5-11}$$

Where $u = 1, \dots, N$ and $t_u^l$ are the data points index of Group $l$. The equation given below shows how to calculate the weighted average of all rules involved in the conflict group:

$$av^{(l)} = \frac{\sum_{u=1}^{N_l} y^{\left(t_u^l\right)} wi^{\left(t_u^l\right)}}{\sum_{u=1}^{N_l} wi^{\left(t_u^l\right)}} \tag{5-12}$$

Subsequently, a single rule is formed by integrating these $N_l$ rules, resulting in the following form [Bilgin 2012], [Wang 2003], [Hagras 2007], and [Almohammadi 2013a]:

$$IF\ x_1 \text{is } \tilde{A}_1^l \dots \text{and } x_n \text{is } \tilde{A}_n^l \text{ THEN } y \text{ is } \tilde{B}^l \tag{5-13}$$

where there is the selection of the output fuzzy set $\tilde{B}^l$ on the basis of the following: we compute the lower and the upper membership values $\underline{\mu}_{\widetilde{Z_l\tilde{B}_c^h}}\left(av^{(l)}\right)$ and $\overline{\mu}_{\widetilde{Z_l\tilde{B}_c^h}}\left(av^{(l)}\right)$ for each zSlice $\widetilde{ZB}_c^h$, where $l = 1, \dots., I$ for each fuzzy output $\tilde{B}^l, \dots, \tilde{B}^{V_o}$; calculate $B^{h*}$ such that [Bilgin 2012], [Wang 2003], [Hagras 2007], [Almohammadi 2013a] :

$$\mu_{\tilde{B}_c^{h^*}}^{zcg}\left(av^{(l)}\right) \geq \mu_{\tilde{B}_c^h}^{zcg}\left(av^{(l)}\right) \quad \text{for all h } = 1, \dots \dots, V_o \tag{5-14}$$

$\tilde{B}^l$ is chosen due to the $B^{h*}$, where $\mu_{\tilde{B}_c^h}^{zcg}\left(av^{(l)}\right)$ is the z-weighted center of gravity of the membership of $\tilde{B}^h$ at $av^{(l)}$ as illustrated also in Equation (5-8):

$$\mu_{\tilde{B}_c^h}^{zcg}\left(av^{(l)}\right) = \frac{1}{2}\left[\frac{\sum_l^I \overline{\mu}_{\widetilde{Z_l\tilde{B}_c^h}}\left(av^{(l)}\right) * z_l}{\sum_l^I z_l} + \frac{\sum_l^I \underline{\mu}_{\widetilde{Z_l\tilde{B}_c^h}}\left(av^{(l)}\right) * z_l}{\sum_l^I z_l}\right] \tag{5-15}$$

The proposed system can effectively handle the input/output data pairs, including multiple outputs as per the work presented above. Phase 1 is recognized as being distinct with regard to the number of outputs associated with each rule. In contrast, Phase 2 provides a straightforward expansion with the aim of enabling rules to encompass multiple outputs; for each output, the calculations detailed in Equations ((5-12)–(5-14)) are repeated.

## 5.2.3 The online adaption and lifelong learning layer

### 5.2.3.1 The customization of knowledge delivery to students

The generated type-2 fuzzy sets and the fuzzy rules extracted from the input and output gathered learner data enables the proposed system to learn and obtain the best instructional actions in accordance with the current learners. The system is consequently able to notify the system to re-adjust the online learning environment with specific consideration of the appropriate instructional actions. The system actions are triggered through the examination and monitoring of various learners' variables, which subsequently affects the online instructional environment, with particular consideration of the learned approximation of best instruction actions that will be generated for the learners. The followed architecture and functionality of the adaptive zSlices system, including type-reduction and defuzzification processes, are naturally inherited from the structure of a zSlices-based general type-2 FLS, as described in [Wagner 2010]. At the end of these calculations, the crisp output reflecting the users' need and preference is presented to the users within the online learning environment.

### 5.2.3.2 Adaptive online life-long learning mechanism for dynamically updating selection and presentation of appropriate content

It is important for the proposed system to have the ability to be adjustable with respect to the dynamic and changing learners' needs and to constantly expand the students' knowledge levels by continuously enabling them to modify their instructional and learning needs. According to these modifications, the system will readjust its rules or apply new ones. In a given input state, if no rules fire from the rule base (i.e., the rule's firing strength in Equation (5-10) $wi^{(t)} = 0$), the proposed system will actively record these inputs and the outputs (the instructional needs) to create a rule covering this uncovered input status. Thus, new rules would be added in the system when the state of the monitored online learning environment at that time is indeterminate per the existing rules in the rules base (i.e., when none of the present rules are fired). In such cases, the new rules will be extracted and the system will incorporate them, whereby the antecedent sets highlight the online environment's present input states with the consequent fuzzy sets reliant on the current state of instructional needs.

For all of the input parameters $x_s$, the fuzzy sets that have membership values, where $\mu_{\tilde{A}_c^h}^{cg}( x_s^{(t')}) > 0$ are identified. As a result, for each input parameter, a number of identified fuzzy set(s) are generated in the form of a grid, from which new rules are generated based on all individual combinations of successive input fuzzy sets. The resulting fuzzy set that provides the greatest value of membership to the student defines the needed instructional variable ($y_c$) so that it can act as the extracted rule consequent. The resulting fuzzy sets can be established by conducting a calculation of the output memberships' center of gravity [Hagras 2007]:

$$\mu^{zcg}_{\tilde{B}^{h^*}_c}(y_c) \geq \mu^{zcg}_{\tilde{B}^{h}_c}(y_c) \quad (5\text{-}16)$$

For $h = 1, \ldots, W$ the $\tilde{B}_c$ is chosen as $\tilde{B}^{h^*}_c$, where $c = 1, \ldots, k$. Consequently, new and upcoming rules can be progressively added.

In case the user needs to change the suited instructional requirement at a given input status, the fired rules will be identified, and the rule consequents will be changed (if more than two students signal the same modifications for the instructional needed variables), as indicated by Equation (5-16). Therefore, the fired rules are modified so that the updated suited instruction needs for the students could be reflected in a desirable way while considering the present state of the online learning environment.

This component enables the system proposed to adopt lifelong learning by facilitating the adaptation of rules according to the students' instructional needs, which notably change over time according to their capabilities and characteristics. Owing to the system's flexibility, the fuzzy logic model learned initially may be effortlessly expanded to make changes to both new and existing rules. These fuzzy rules enable a large range of values for all parameters (input and output) to be captured, which in turn enables the continuation of the generation of rules, even when the online learning environment gradually changes. Meanwhile, if notable changes occur in terms of the students' knowledge level (which may not be captured by the present rules, as highlighted above), the new rules will be automatically generated, which ultimately satisfy present conditions. Accordingly, the inconspicuous system will expand its actions and may be adapted to improve the instruction delivery by adhering to the students' needs.

## 5.3 Experiments and Results

We performed various real-world experiments at King Abdulaziz University in Saudi Arabia using a large-scale e-learning platform comprising 1871 students. We conducted these experiments using the fully developed e-learning platform to deliver PowerPoint and Microsoft Excel modules as the University permitted. The e-learning platform facilitated the examination of all adaptive proposed systems, which included a total of twenty-one learning units consisting of twelve units for Excel and nine for PowerPoint. Each unit combined of various numbers of lessons, all of which offered training in different aspects of the Microsoft programs. Figure 5.3 and 5.4 demonstrate a full explanation of each of these learning units based on the approved course structure and contents from King Abdulziz University.


Figure 5.3: The main interface of the designed online learning platform.

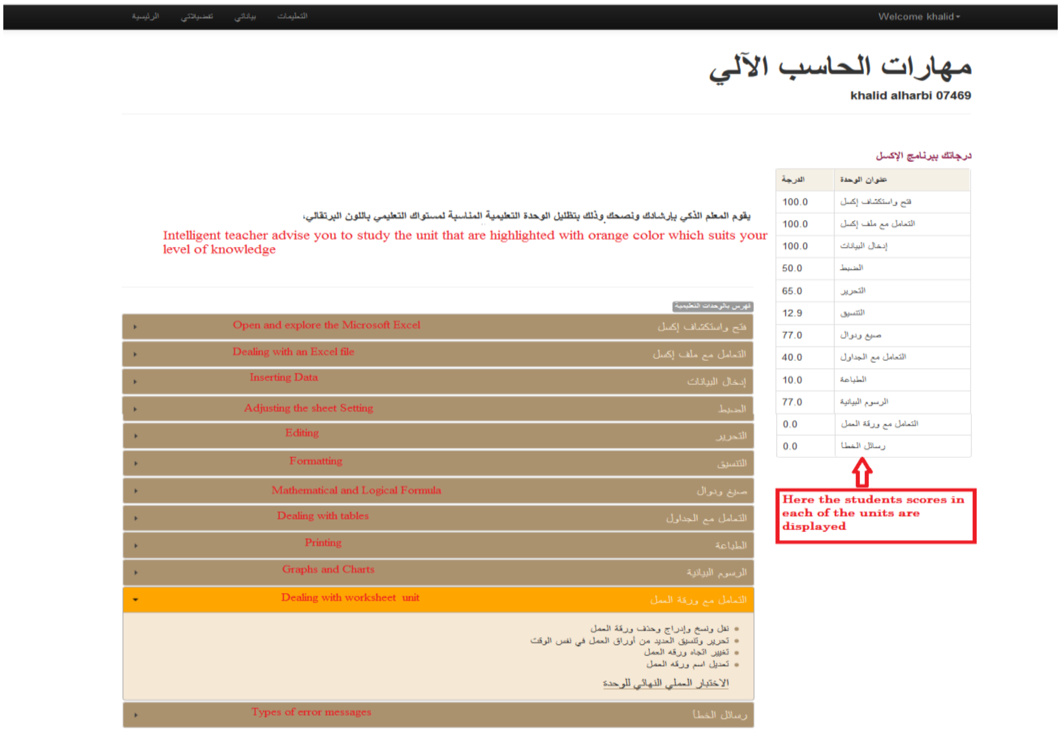


Figure 5.4: The learning units designed for both Excel and PowerPoint.

As Figure 5.5 illustrates, each lesson comprised five key components: PowerPoint slides explaining the lesson, a practical demonstration of the lesson, practical exercises, a video lecture explaining the lesson, and a final assessment task. An overview of these features using screenshots follows.


Figure 5.5: The main lesson interface.

1. The student views a text-based explanation of the module on PowerPoint slides. For instance, Figure (5.6) shows how this lesson teaches students how to create line charts and pie charts.

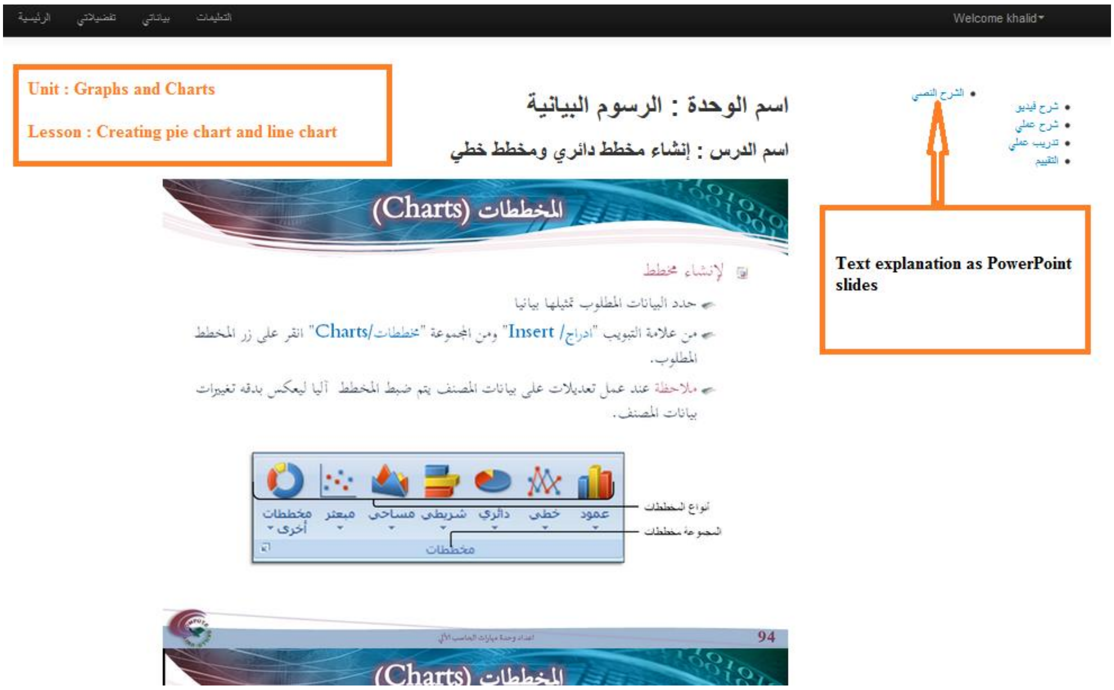


Figure 5.6: Text-based explanation interface for the pie chart creation lesson.

2. A demonstration shows learners how to apply their new knowledge in practice, as Figure (5.7) illustrates. For example, the lesson on creating a pie chart first directs students to select a range of cells and instructs them to click on the insert tab in the Charts group to select Pie and choose the most appropriate pie chart (Figure 5.7).

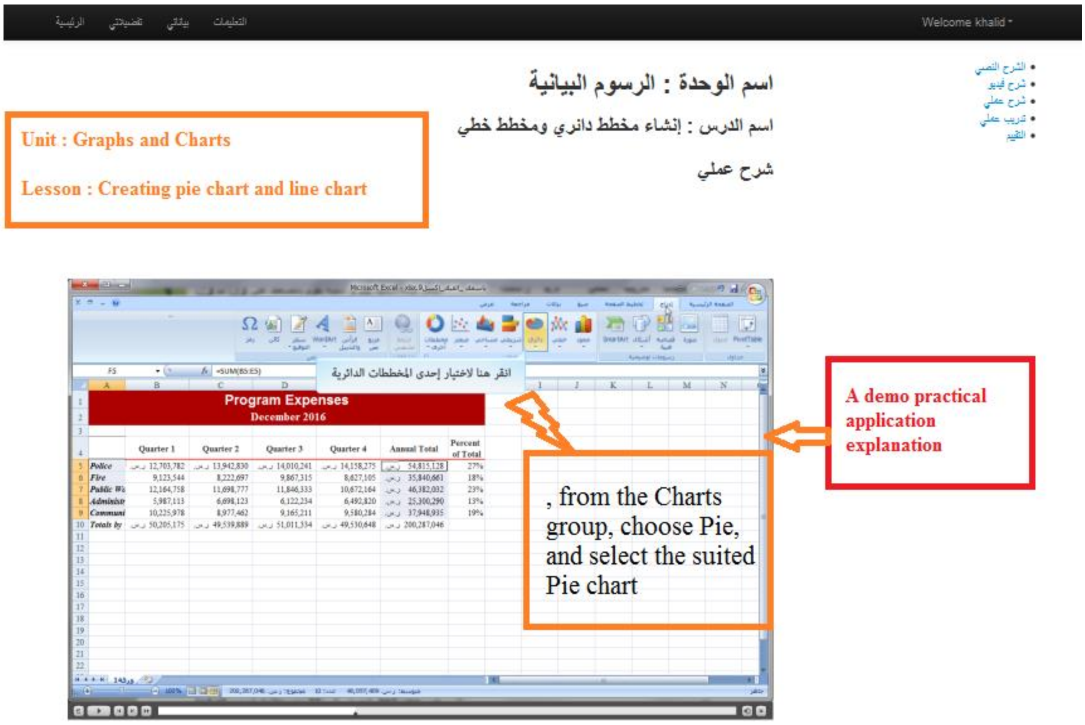


Figure 5.7: Practical demonstration on how to create a pie chart.

3. The module provides relevant practical exercises for the students to complete to reinforce their abilities. If a student submits an incorrect answer, the system offers a hint. For instance, for the lesson “Changing the Sheet Direction,” students must determine how to switch the orientation of the page from left to right. To do so, they are required to select the Page Layout tab. If they click on a different tab, the system offers a hint to assist them in making the correct choice by using a red triangle to guide them toward the correct tab (Figure (5.8)). Students can make three

attempts for each step of the task. If the student successfully makes a correct move—for instance, if he or she clicks on the Sheet Right-to-Left button in the sheet options—the system offers positive feedback and congratulates the student for making the correct choice (Figure (5.9)).

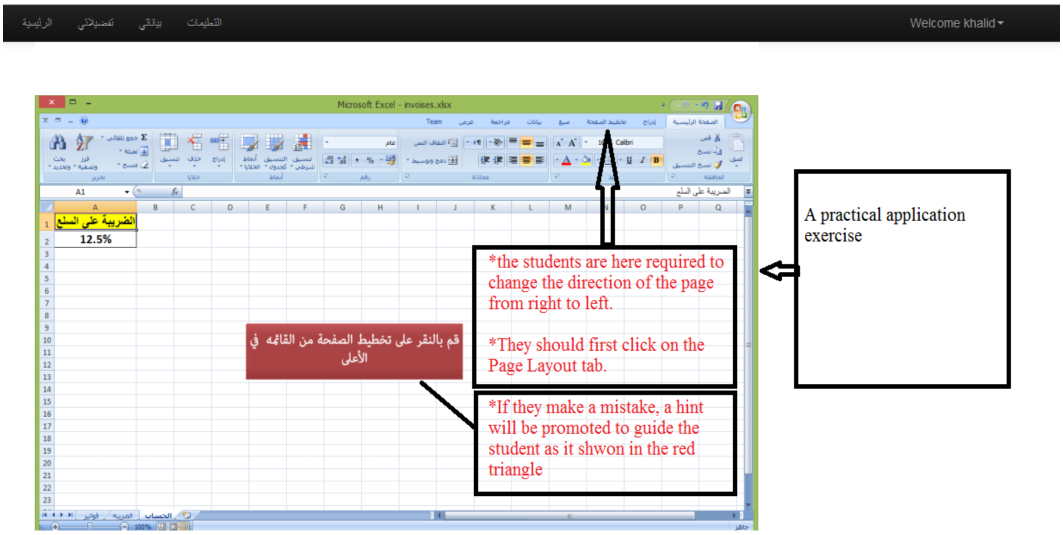


Figure 5.8: Practical exercise showing the steps for changing the chart direction (when students respond incorrectly).

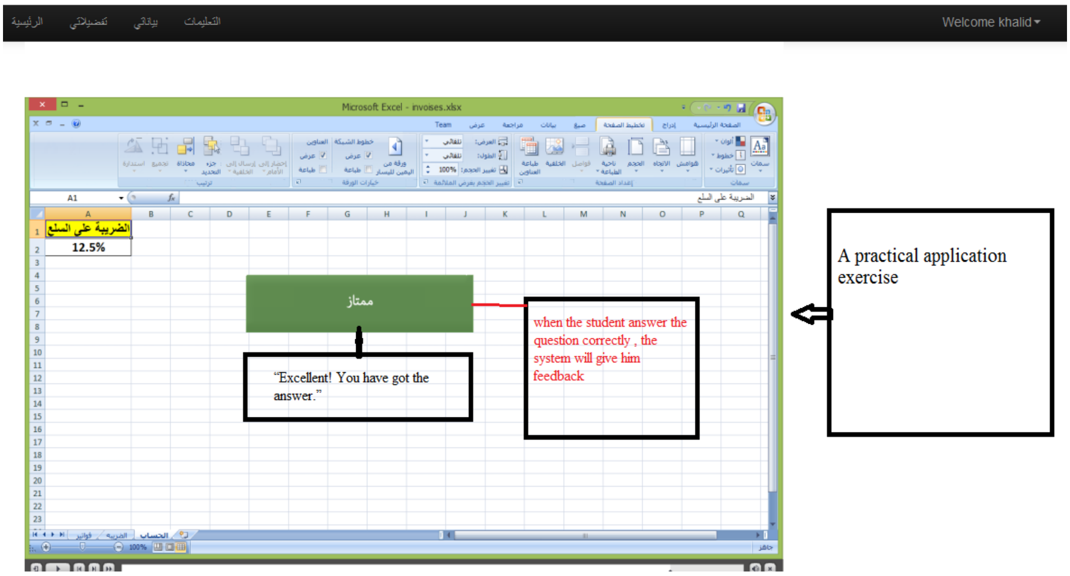


Figure 5.9: Practical exercise showing the steps for changing the chart direction (when students respond correctly).

4. Figure (5.10) presents a video featuring a lecturer discussing the lesson on creating pie charts and line charts.

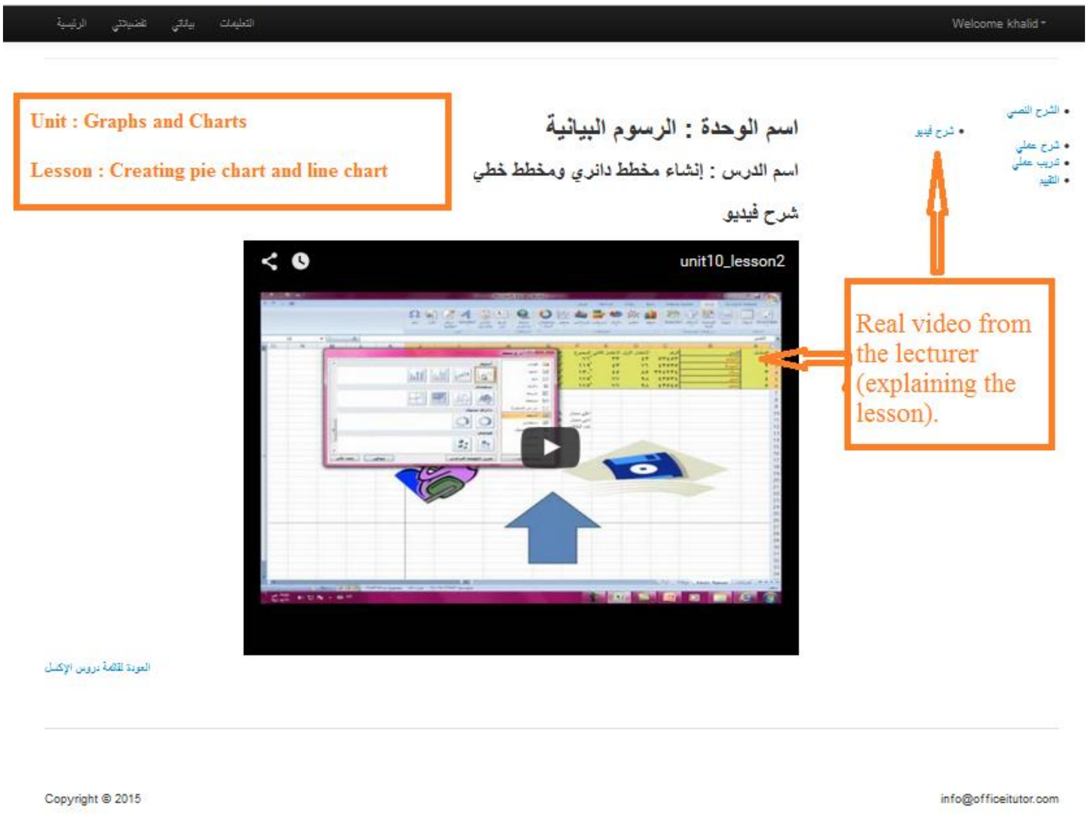


Figure 5.10: Lecturer video interface for creating the pie chart lesson.

5. The final lesson component is an assessment exercise that provides feedback to students, enabling them to see whether their answer is correct. This assessment differs from the earlier practical exercises, which offered only hints to guide the students. The user can make only one attempt at this exercise and receives feedback about whether the answer is correct (see Figure (5.11)).

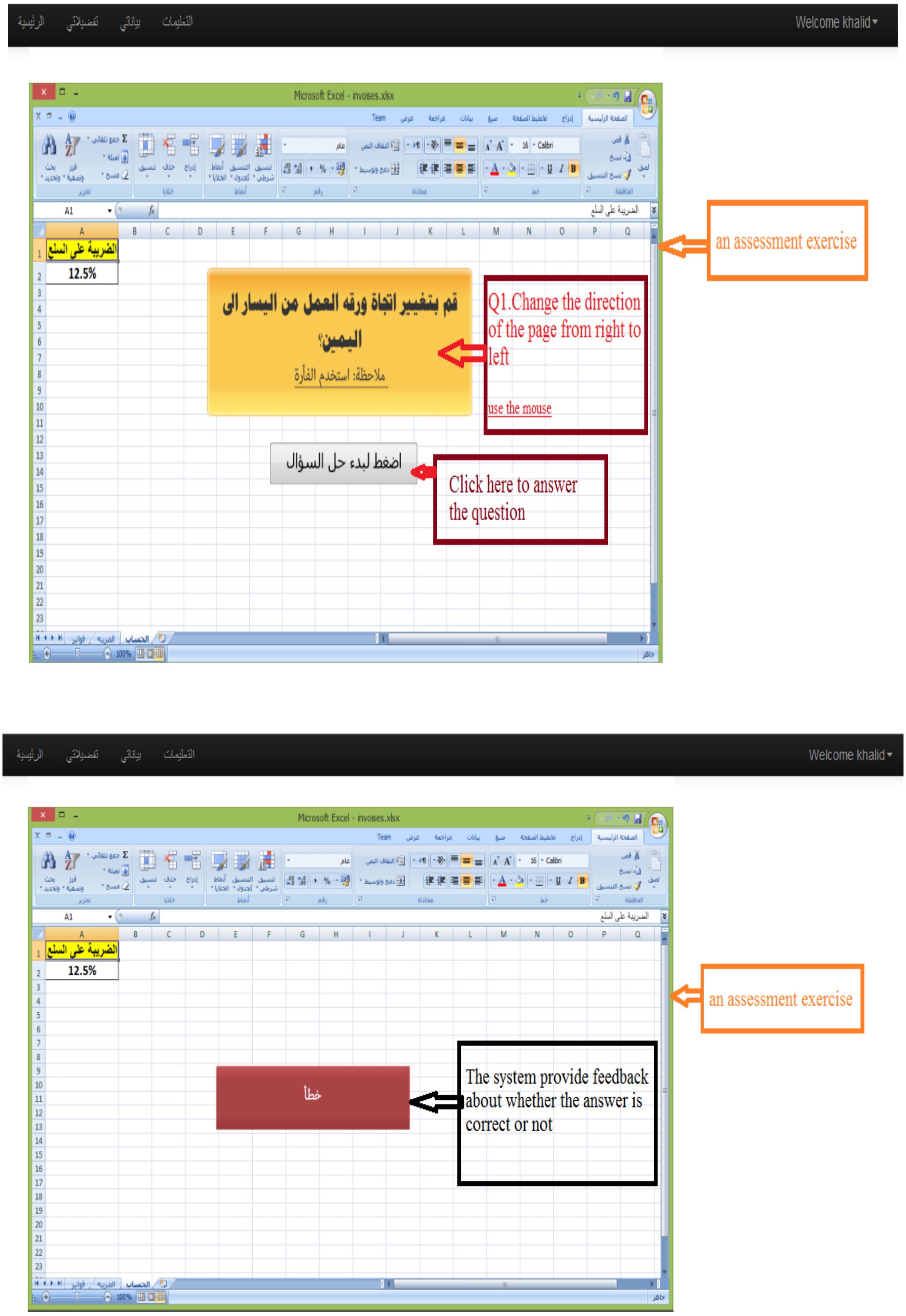


Figure 5.11: Assessment exercise interfaces (with system feedback about whether the answer is correct).

The main aim of the experiment was to determine the relative performance of the zSlices-based general type-2 fuzzy system (zSlices-based general T2FS) compared to the IT2FLS), the T1FLS, the instructor-led adaptive system, and the non-adaptive version, for the purposes of increasing instruction quality, bettering student performance, and enhancing overall students success rates. At the start of this study, a total of 1871 students were involved to participate with equal numbers of randomly-chosen e-learners assigned to each group. The monitoring phase of the study required the students to register for the course and complete a cohesive pre-assessment to determine their existing knowledge of PowerPoint and Excel.

We collected the average scores for these two pre-assessment tests along with the students' gender, age, secondary school grade, status as full- or part-time status, and secondary school course of study to form the ***seven inputs for the fuzzy systems***. Subsequently, we deliberately revealed the average assessment results to the students so they could determine the appropriate content for their level and preference. **Four outputs** were collected from the students: the difficulty level they needed for Excel and PowerPoint, time needed for Excel, and time needed for PowerPoint.

Once we collected the inputs and outputs for the proposed model, we constructed the zSlices-based general T2FS, IT2FLS, and T1FLS using the fuzzy sets to generate rules (see Figure (5.12)), as explained in section 5.2.2. We used these fuzzy sets to analyze and manage the uncertainties associated with perceptions about modeling a particular linguistic label to determine learner characteristics and instructional needs. Figure (5.13) shows the interval type-2 fuzzy sets; dashed yellow lines indicate the type-1 fuzzy sets. A total of 30 students participated in constructing interval type-2 fuzzy sets; we required them to discuss their opinions on how such fuzzy sets should be modeled. On the other hand, two user groups contributed toward the construction of two interval type-2 fuzzy sets in the zSlice-based general T2FS; one group was drawn from the humanities section and the other from the scientific secondary section. The scientific section (high z=1) was assigned more weight in the third dimension than the humanities section (high z=0.5), as approximately 60% of the users were drawn from the scientific section and were more likely to study courses in Saudi Arabia.

*IF* **Student-Age** *is* **Teen** *AND* **Student-Gender** *is* **Female** *AND* **Secondary-Grade** *is* **Excellent** *AND* **Method-of-Providing-Higher-Education** *is* **Full-Time** *AND* **the Secondary-Section** *is* **Science** *AND* **Average-Knowledge-in-Excel** *is* **Very Low** *AND* **Average-Knowledge-in-PowerPoint is Low,** *then the* **Suited-Excel-Difficulty-Level** is **Easy** *AND* **Needed-Time-to-Study-Excel** *is* **Very Long** *AND* **Suited-PowerPoint-Difficulty-Level** *is* **Moderate** *AND* **Needed-Time-to-Study-PowerPoint** *is* **Short.**

Figure 5.12: One example of an extracted rule from the produced rules

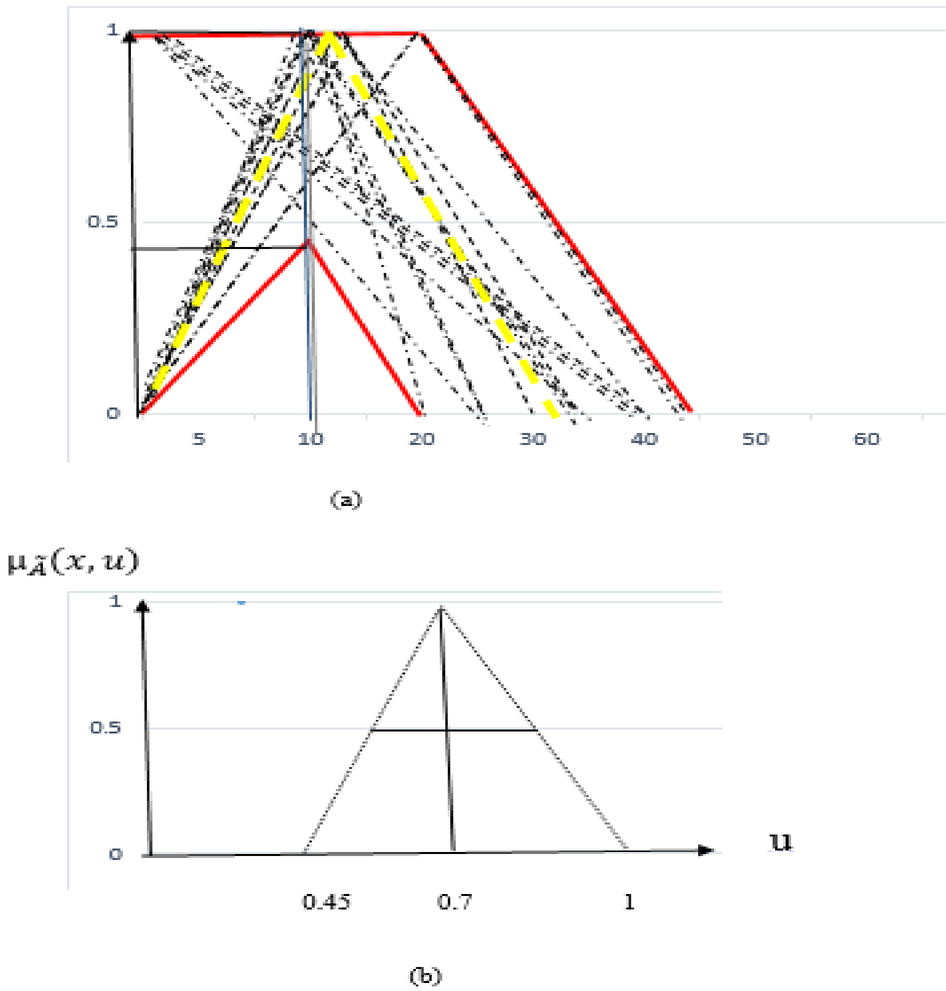


Figure 5.13: (a) An example of the extracted interval type-2 fuzzy set (very easy) of the suitable required difficulty level (thick solid lines) and the type-1 fuzzy sets (thick dashed lines).(b) Third dimension of x=10 of the the zSlice based type-2 fuzzy set

The second phase of the experiment process provided adaptive course content on both Excel and PowerPoint to the third, fourth, and fifth user groups, who used a type-1-fuzzy-logic-based system (T1FLS), an applied interval type-2 fuzzy logic system (IT2FLS), and an applied zSlice-based general type-2 fuzzy system, respectively. At the same time, the first group proceeded with the module using the non-adaptive system version, whereas the second group employed the instructor-led adaption model that came with fixed rules devised based on expert knowledge. A more customizable module was given to students in the third, fourth, and fifth groups, who used an adaptive learning system that could be modified based on the user's unique learning needs. The rules in this case were generated based on different system users. A series of learning objects (LOs) were given to the users based on their chosen learning needs. In each lesson, all LOs were linked to two linguistic values correlated with the Excel and PowerPoint material's level of difficulty and the tendency for students to take longer learning PowerPoint and Excel topics. All 63 lessons across both modules were characterized by these features as the difficulty of the content fluctuated from very easy to more advanced, with different topics taking longer to complete. Following this stage in the experiment, we assessed the findings in order to evaluate the students' performance at the end of the semester.

We comparatively analyzed the results we obtained from the applied zSlice-based general T2FS environment, IT2FLS environment, T1FLS environment, fixed rule system, and non-adaptive version. Figure (5.14) illustrates the extent to which students improved their performance based on their assessment scores before and after using the e-learning system. Based on the figures we present, the average scores of students using the zSlices-based general T2FS rose markedly by 26.45%, indicating that this system yielded the most positive performance. We found that student scores increased by 26.04% using I2TFLS and 23.78% using the T1FLS system, whereas the instructor-led adaptive system generated an increase of 20.48%, and the non-adaptive version generated an increase of 19.06% among the control group.

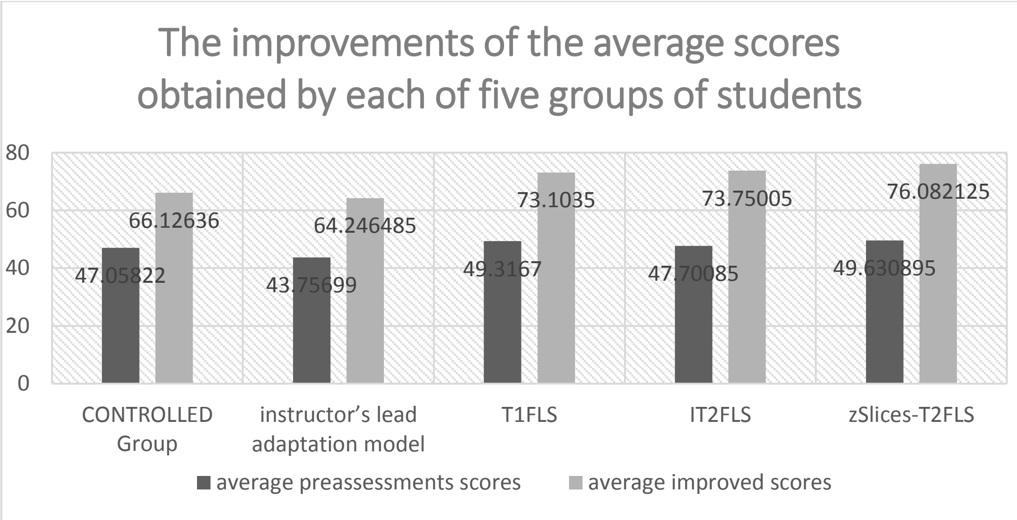


Figure 5.14: The improvement in the average scores obtained from each of the five study groups before and after each system's application.

In addition, we analyzed the groups' mean of learning improvements from the pretests to the posttests using ANOVA for comparison at a significance level of 0.05. The analysis revealed a significant statistical difference between the various groups ($p < .05$). We also carried out Tukey HSD and LSD comparison tests to see which pair of groups had the greatest difference. We observed that Group 5 (zSlices T2FLS with M=26.4512 and SD=26.25757) and Group 1 (controlled group with M=19.0681 and SD=23.51329) were the most significantly different groups as compared to other pairings, as shown in Figure 5.15. Moreover, Group 5 (zSlices T2FLS) was significantly different from Group 2, which was the instructor-led adaptation model (with M=20.4895 and SD=26.14493), and a notable difference existed between the zSlices T2FLS and T1FLS groups (with M=23.7866 and SD=25.37530). The least significantly different groups, according to the results, were zSlices T2FLS and IT2FLS (with M=26.0491 and SD=26.58322).

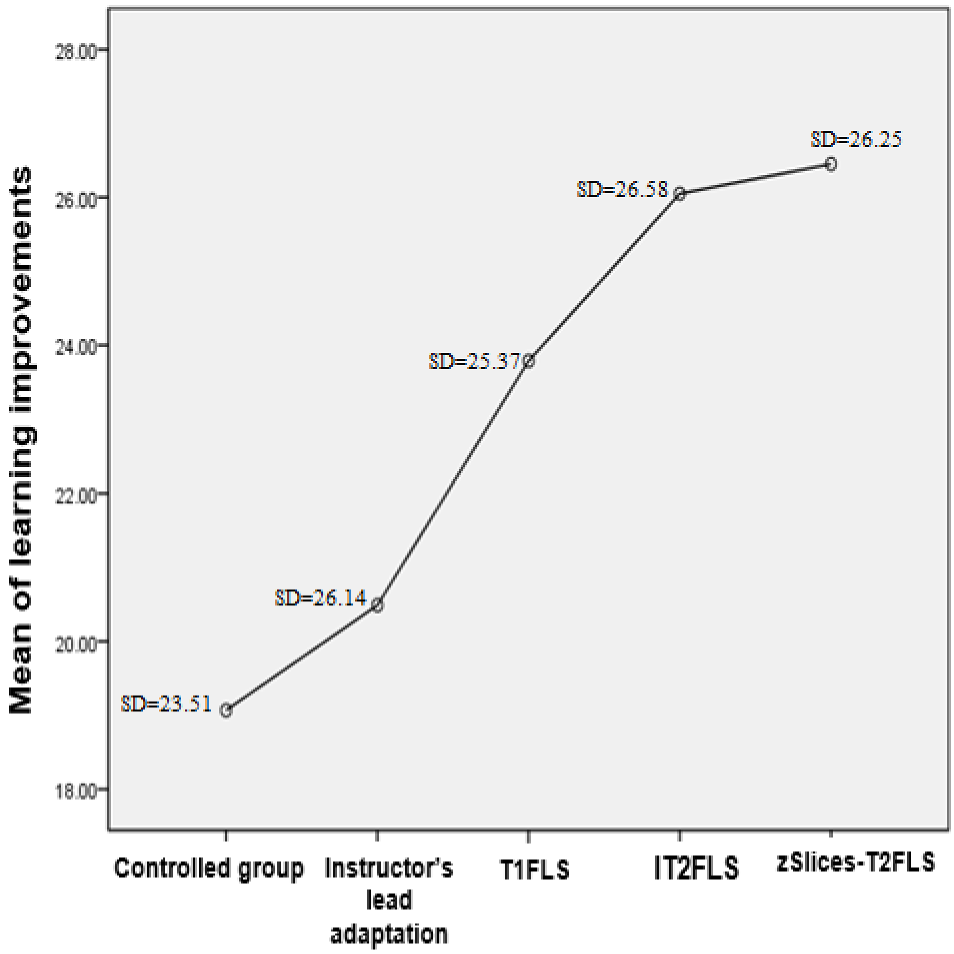


Figure 5.15: Means plots for the groups' learning improvement

Additionally, we analyzed the rate of completion for all five groups, as Figure (5.16) shows, finding that the total number of students who completed at least 90% of the lessons with the zSlices-based general type-2 adaptive educational system exceeded the students in the other groups to realise 6.61% improvement over those in the interval type-2 adaptive educational group, 8.23% over those in T1FLS, 16.09% over the instructor-led adaptive system group, and 17.26% over the non-adoptive-based system's group. The improvement in the students' learning performance and completion rates indicates the effectiveness of the proposed zSlices-based general T2FS adaptive educational system compared with the other methods.

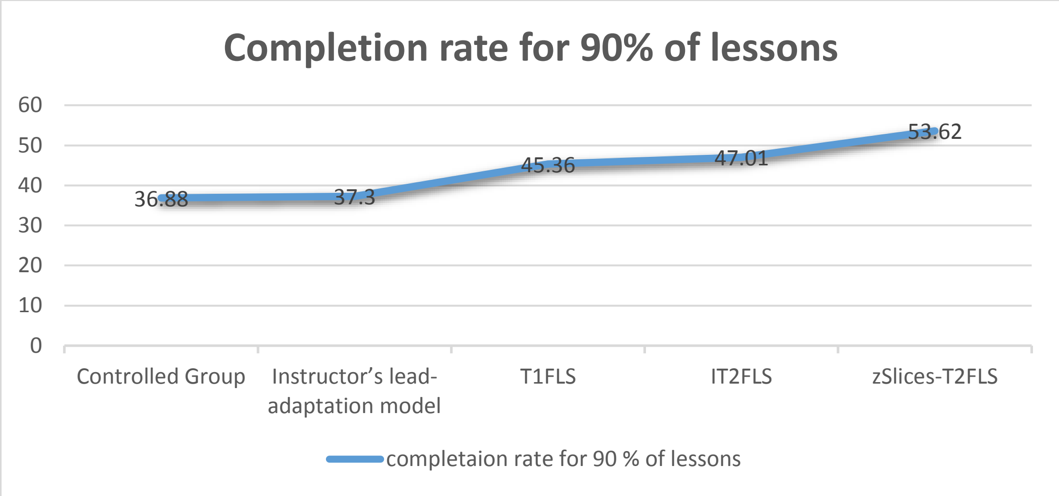


Figure 5.15: the completion rate obtained by each of the five groups of students in the two study subjects after each system's application.

Furthermore, Table 5.1 presents the average error and standard deviation of the system outputs compared to the desired learner outputs. The collective data set contained a total of 960 instances, 672 of which were classified as training data and 288 of which were classified as testing data. These results demonstrate that the zSlices-based general T2FLS produces a lower average error rate and standard error deviation than the ITFLS and T1FLS systems when the system outputs are compared to the student-desired outputs. As an example of the improvements in the 'level of difficulty needed for studying Excel', the zSlices-based general T2FLS produced 8.3% and 3.5% better performance when compared to IT2FLS and T1FLS, respectively, in terms of lower average error between the system output and the students' learned output. In addition, the zSlices-based general T2FLS produced a better spread of the errors by having 0.2% and 13% less standard deviation than IT2FLS and T1FLS, respectively. In other words, the zSlices-based general T2FLS captures student behaviour more effectively.

| Output | T1FLS | | T2FLS | | zSlices-T2FLS | |
|---|---|---|---|---|---|---|
| | AE | SD | AE | SD | AE | SD |
| Level of difficulty needed for studying Excel | 30.104 | 23.424 | 28.589 | 20.291 | 27.585 | 20.237 |
| Needed time for studying Excel | 32.130 | 26.131 | 28.758 | 21.831 | 28.14 | 21.64 |
| Level of difficulty needed for studying PowerPoint | 29.638 | 23.372 | 28.761 | 20.724 | 28.00 | 20.61 |
| Needed time for studying PowerPoint | 31.520 | 25.740 | 29.358 | 22.732 | 29.02 | 23.18 |

Table 5.1: Average error (AE) and statndard deviation (SD) of the system outputs.

## 5.4 Discussion

In this chapter we have proposed a novel zSlices-based general type-2 fuzzy logic system that can determine different users' pedagogical needs and preferences in a dynamic online environment based on both their knowledge level and characteristics. This system's purpose is to improve student performance and increase completion rates of lessons by presenting students with tailored, adaptive content that matches their needs. This chapter tested the zSlice-based general T2FS in comparison with the IT2FLS, the T1FLS, the instructor-led adaptive system, and the non-adaptive system. A large-scale e-learning platform in which 1871 King Abdul-Aziz University students participated facilitated the testing process.

The results revealed that IT2FLS was better able to handle uncertainties, producing lower average errors and standard deviation. This resulted in an increased completion rate over the T1FLS group by 1.62%, over the instructor's lead adaption model by 9.48%, and over the controlled group by 10.65%. In addition, this improved students' performance for the IT2FLS group was over the performance improvement achieved by T1FLS group by 2.26% and over the instructor's lead adaption model by 5.56%, and over the controlled group by 6.98% .

In addition, the findings indicate that the zSlice-based general T2FS is more effective at managing uncertainty, lowering average errors and standard deviation, and increasing the overall completion rate by 6.61%, 8.23%, 16.09% and 17.26% compared with the IT2FLS, T1FLS, instructor-led adaption, and control groups respectively. Furthermore, the zSlice-based general T2FS system achieved an improvement in student performance that was higher than that of the IT2FLS by 0.40%, and higher than that of the T1FLS, instructor-led adaption, and control groups by 2.66 %, 5.96%, and 7.38%, respectively.

These results clearly demonstrate that the proposed zSlice-based general T2FS and IT2FLS can more effectively provide adaptive content to students. In the next chapter, we presents the conclusions and the future work of the thesis.

# Chapter 6: Conclusions and Future Work

This thesis began with the introduction in Chapter 1, which presented the background of adaptive educational systems and their related significance as well as the motivation for providing tailored learning experiences within intelligent e-learning platforms. Such e-learning platforms enable the creation of automatic adaptive learning environments to suit the students' individual requirements and needs. Adaptive educational systems are used to capture, analyze, and model important information regarding the behaviour of students and to provide dynamic, tailored learning experiences. Furthermore, we provided an explanation of the problems associated with the vast majority of existing adaptive educational systems, noting that many do not learn from the users' behaviours to create white-box models to handle the high level of uncertainty and that could be easily read and analysed by the lay user. The data generated from interactions, such as teacher–learner or learner–system interactions within asynchronous environments, provide great opportunities to realize more adaptive and intelligent e-learning platforms. Another shortcoming of current adaptive educational systems is that they do not detect learner engagement during activities and map it to learners' pedagogical delivery needs. In addition, most current adaptive educational systems are used within asynchronous e-learning contexts that are totally ignorant of synchronous e-learning settings.

We then presented the application of fuzzy logic and other artificial intelligence (AI) techniques, which have been used to handle uncertainty and achieve robust modelling and adaption within the e-learning environment along with applications of engagement feedback to achieve and realize more effective and adaptive e-learning contexts. We then introduced the objectives, the novelty and significance, and the structure of this thesis along with the discussion.

In Chapters 2, we described the theoretical background of this project. To start, Chapter 2 introduced the basic concepts and theory of fuzzy logic, its extension from crisp logic, and other relevant concepts, including the type-1 fuzzy set and linguistic variables. Furthermore, we provided an explanation for the singleton (type-1) fuzzy logic system's basic characteristics, including its working procedures and components. We also discussed and provided an explanation of fuzzy logic's benefits as an AI-based model for encoding and developing the context for teaching and learning with the imprecise information that is generated within real e-learning platforms. The learned user behaviours can be formed flexibly and clearly through the provisioning of fuzzy rules that can improve a behaviour-based approach to express the information learned from the system. Particular states and situations related to e-learning environments are described by the rules that correspond to a specific learner's characteristics and needs. The representation of learning–teaching behaviour, as it relates to fuzzy logic, is done in a manner that is readable by humans and linguistically interpretable. These rules are perfect for quick assessments because of their transparency, which is done in an attempt to explain the method and purpose of certain combinations of inputs that yield a certain set of output conclusions. We also discussed how type-1 fuzzy logic is not robust enough to handle the high level of uncertainty associated with real e-learning environments. Thus, we concluded that there is a need for a system that is capable of robustly, adaptively, and automatically dealing with and minimizing uncertainty within e-learning environments.

The type-2 fuzzy logic concept, as well as the zSlices-based type-2 fuzzy sets and interval type-2 fuzzy sets were introduced in Chapter 2. Subsequently, the chapter provided an explanation of the interval and the zSlices-based type-2 fuzzy logic systems, including their working procedures. We also discussed how these type-2 fuzzy logic categories are more robust than type-1 fuzzy logic-based systems for handling the high level of uncertainty associated with real-world e-learning environments. Having been implanted inside the type-2 fuzzy sets' footprints of uncertainty (FOUs), many type-1 fuzzy sets are part of every type-2 fuzzy logic system's input and output. Interval type-2 fuzzy logic systems can manage the raised uncertainties by encoding them via FOUs. These FOUs give more choices and degrees of freedom to be utilized when dealing with high uncertainty levels. Furthermore, an IT2FLS has an even distribution of uncertainty because of the deployment of interval type-2 fuzzy sets. However, using general type-2 fuzzy sets such as zSlices allows an uneven distribution of uncertainty in modelling the teaching-learning behaviour. This kind of distribution is better suited to handling the encountered uncertainties in comparison to an interval type-2 fuzzy logic system, which Chapter 5 demonstrated. Hence, we concluded that type-2 fuzzy logic systems have the ability to deal with these uncertainties automatically and adaptively, outperforming type-1 fuzzy logic systems.

## 6.1 Summary of Achievements and contributions

We highlighted the first asynchronous theoretical and practical environments based on a type-1 fuzzy logic system and an integrated type-2 fuzzy logic system for adaptive knowledge delivery within small-scale intelligent e-learning platforms in Chapter 3. The users' pedagogical needs as along with the appropriate instructional approach, which is based on the student's degree of average engagement, capabilities, and characteristics during learning activities, can be determined through the proposed theoretical and practical environments to generate an adaptive e-learning environment. The chapter presented a novel system for measuring students' engagement levels based on an automatic calculation of the students' degree of engagement using visual information. This is different from traditional approaches that normally use expensive, invasive sensors. Our method utilized only an affordable RGB-D video camera (Kinect, Microsoft) in a nonintrusive operation mode with no restrictions pertaining to user movements and actions. The data collected from students with different abilities, characteristics, needs, and engagement levels were used to create type-1 and interval type-2 fuzzy logic models, which were then used to improve the delivery of knowledge to various students based on their individual characteristics and engagement levels.

Different experiments involving fifteen students were used to test the efficiency of the proposed environments. We compared the results of our systems, which delivered knowledge to each student in a customized fashion using type-1 fuzzy logic and interval type-2 fuzzy logic systems, against a system that had not been customized for the users. The results indicated that there is a considerable increase in the average java, fuzzy logic, and mathematics scores when utilizing an interval type-2 fuzzy logic system. Specifically, average scores increased by 13%, and utilizing a nonadaptive system resulted in average scores increasing by 6% compared to an adaptive type-1 fuzzy logic system. Furthermore, average student engagement with the interval type-2 adaptive educational system was 2% higher than that of students engaging with the type-1 system and 7% higher when compared to a nonadaptive system, according to the average degree of engagement obtained for the three groups. The results obtained for the system outputs regarding the students' learned data show that the mean error and standard deviation related to type-2 fuzzy logic systems are lower than those related to type-1 systems, meaning that the type-2 system captured student behaviour better. Thus, the proposed system in this chapter resulted in a better learner behaviour model and improved delivery of knowledge to students, thus increasing students' outcomes and average learner engagements.

In Chapter 4, we extended the proposed theoretical and practical environments to be used in synchronous e-learning contexts with the aim of giving teachers the ability to adapt their instructional approaches to improve and increase the engagement and satisfaction of different learners within small scale e-learning platforms. This new model, based on an integrated type-2 fuzzy logic system, was capable of learning different teachers' pedagogical decisions based on the content difficulty level as well as the students' average levels of engagement and the variation between the engagements in a dynamic, online teaching environment. The type-2 fuzzy-based model was applied to enhance the teaching performance by informing the teacher of the best teaching approaches to increase the average learners' engagement. Moreover, we presented a method based on type-2 fuzzy logic systems that utilized visual RGB-D features, including head pose and facial expressions captured from a low-cost but capable 3D camera (Kinect v2) to estimate the students' degree of engagement in both remote and onsite education environments. In addition, the proposed system was flexible enough to allow constant updating in accordance with the level of student engagement.

Through various real-world experiments, the evaluation of the proposed system's effectiveness was tested in the University of Essex iClassroom on a sample that consisted of six teachers and thirty students. The experiment showed that the proposed interval type-2 fuzzy logic system produced a lower standard deviation and average errors compared to the type-1 fuzzy logic system between the preferred teacher outputs and the system outputs. Therefore, it was confirmed that the interval type-2 fuzzy logic system was better at handling uncertainty and capturing teacher behaviour. The deployments of the proposed interval type-2 system led to a 7% increase in the average engagement level over the type-1 system group as well as a 55% improvement in engagement level over the control group. Moreover, the use of the interval type-2 fuzzy logic system brought individual students' engagement levels closer together and yielded an average standard deviation improvement of about 50% over the control group and about 37.5% over the type-1 fuzzy logic system group. The participants' satisfaction levels were tested using a questionnaire, and the responses were analyzed using ANOVA and Tukey tests. The tests revealed that the level of satisfaction among participants in the interval type-2 group was quite different from the level of the students' satisfaction in the control group. Thus, the promising results from the proposed system have facilitated an instructional style with better knowledge delivery to learners in comparison to the type-1 fuzzy logic and nonadaptive systems.

Chapter 5 presented an extended and novel zSlices-based environment based on the type-2 fuzzy logic system to better handle uncertainties in the previous environments and extend the flexibility of the proposed models in large-scale e-learning platforms. We tackled the shortcomings and limitations of the small number of students involved in testing the integrated type-2 fuzzy logic system in Chapter 3 by conducting a large-scale evaluation of the proposed system via real-world experiments on 1,871 students within a massively crowded e-learning platform from King Abdul-Aziz University. Because of the large number of distance learners and their inability to purchase the Kinect v2 camera, we could not use the engagement system in the experiments.

This chapter presented a new zSlices-based type-2 fuzzy logic system that is capable of identifying and learning students' preferred knowledge delivery needs based on their characteristics and current levels of knowledge to generate an adaptive learning environment. We evaluated the proposed system's efficiency through various large-scale, real-world experiments involving 1,871 students from King Abdul-Aziz University. Such evaluations showed that the proposed zSlices-based type-2 fuzzy logic system's ability to handle uncertainty resulted in superior completion rates, success rates, and overall learning compared with interval type-2 fuzzy logic, type-1 fuzzy logic, adaptive, instructor-led, and nonadaptive systems.

The results indicated that the interval type-2 fuzzy logic system was better able to handle uncertainty, resulting in lower average errors and standard deviation. This resulted in a 1.62% increase in completion rate over the type-1 fuzzy logic system group, a 9.48% increase over the instructor-led adaption model, and a 10.65% increase over the control group. In addition, students' average performance rates within the interval type-2 fuzzy logic system group were 2.26% higher than the type-1 system group's rates, 6.98% higher than the control group's rates, and 5.56% higher than the instructor-led adaption model group's rates.

Moreover, the findings revealed that the zSlices-based general T2FS is more efficient at handling uncertainty, lowering average errors and standard deviation, and expanding the overall completion rate by 6.61%, 8.23%, 16.09%, and 17.26% compared with the interval type-2 fuzzy logic, type-1 fuzzy logic, instructor-led, and control groups, respectively. Furthermore, the zSlices-based general T2FS system achieved an improvement in student performance that was 0.40% higher than that of the interval type-2 fuzzy logic system, 2.66% higher than the type-1 fuzzy logic system, 5.96% higher than the teacher-led adaption model, and 7.38% higher than the control group.

## 6.2 Future work

In the future, we aim to employ general type-2 fuzzy logic systems that are better at handling uncertainty in the model. We also aim to deploy the proposed system for more e-learning courses with more inputs and outputs that will include thousands of students. We will explore adding more complex learner inputs and teaching outputs in both synchronous and asynchronous e-learning settings. The proposed model was built to be easily read, checked, and analyzed by the lay user, which makes it more valuable, and we can make these rules available for teachers to edit , verify and delete when needed. To optimize the rules and the extracted fuzzy sets, we aim to employ a Big Bang–Big Crunch–based optimization algorithm to fine-tune the parameters of the fuzzy logic system to encourage more robust learning and teaching behaviour-based models.

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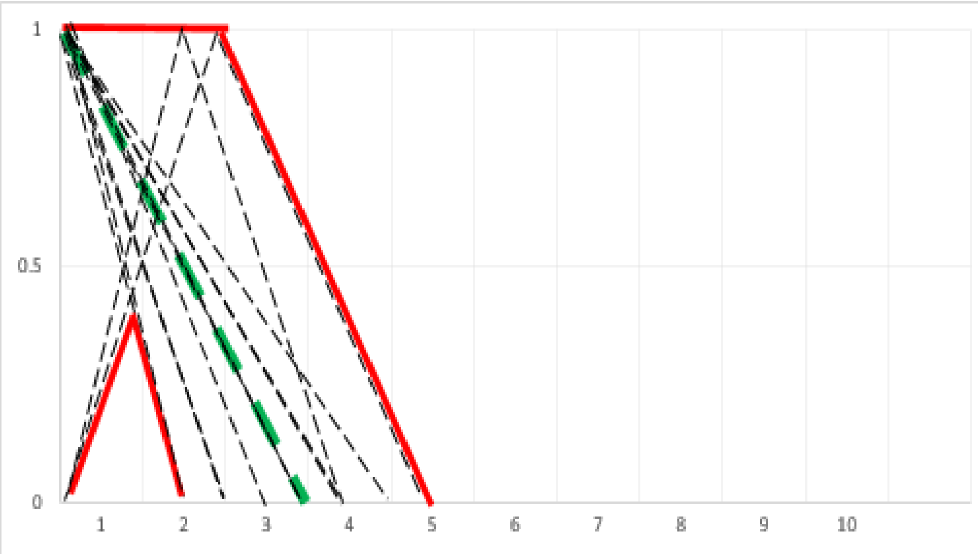
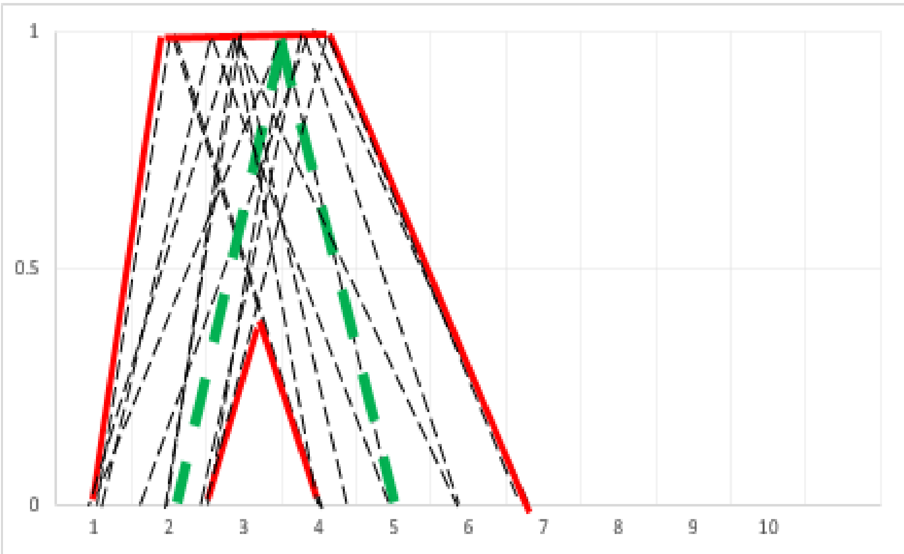
# Appendices

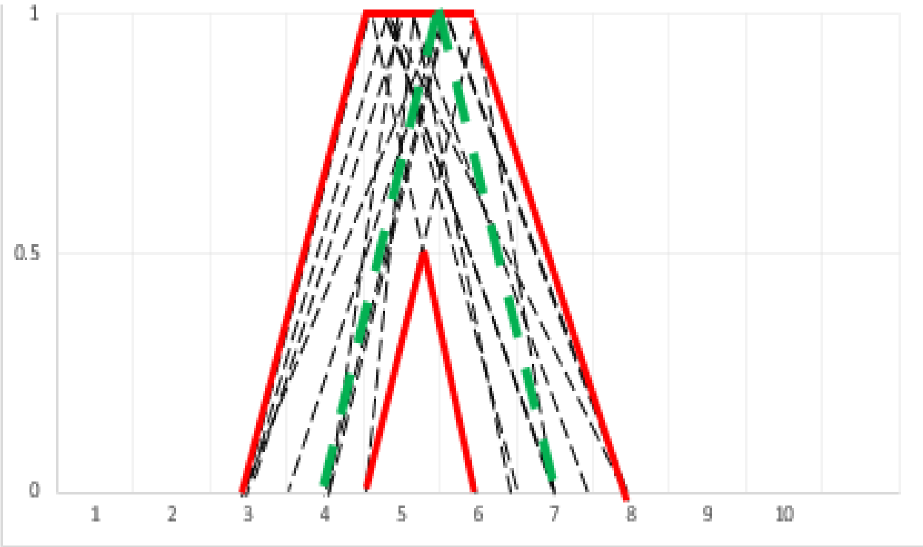
## Appendix A: Chapter 3: The extracted MFs



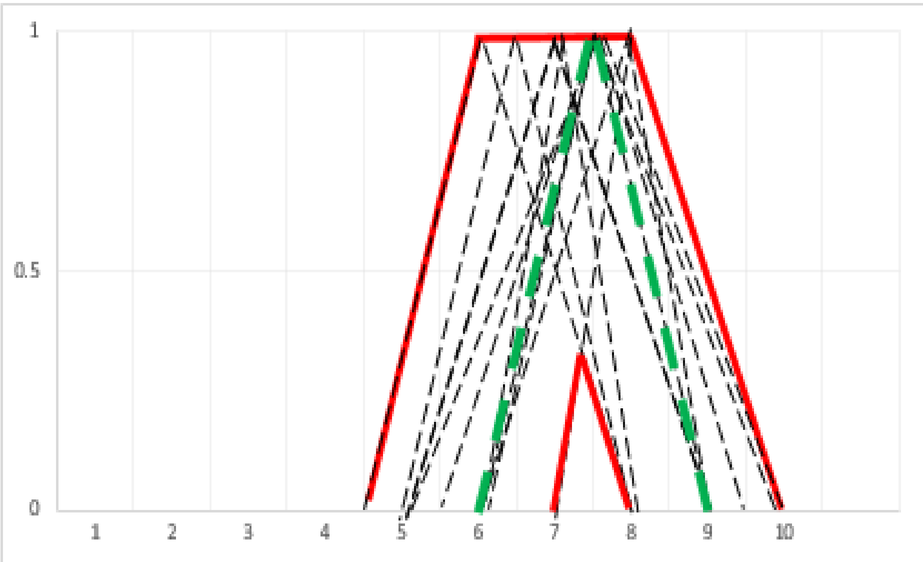

The generated "very low" interval type-2 fuzzy sets of the knowledge level



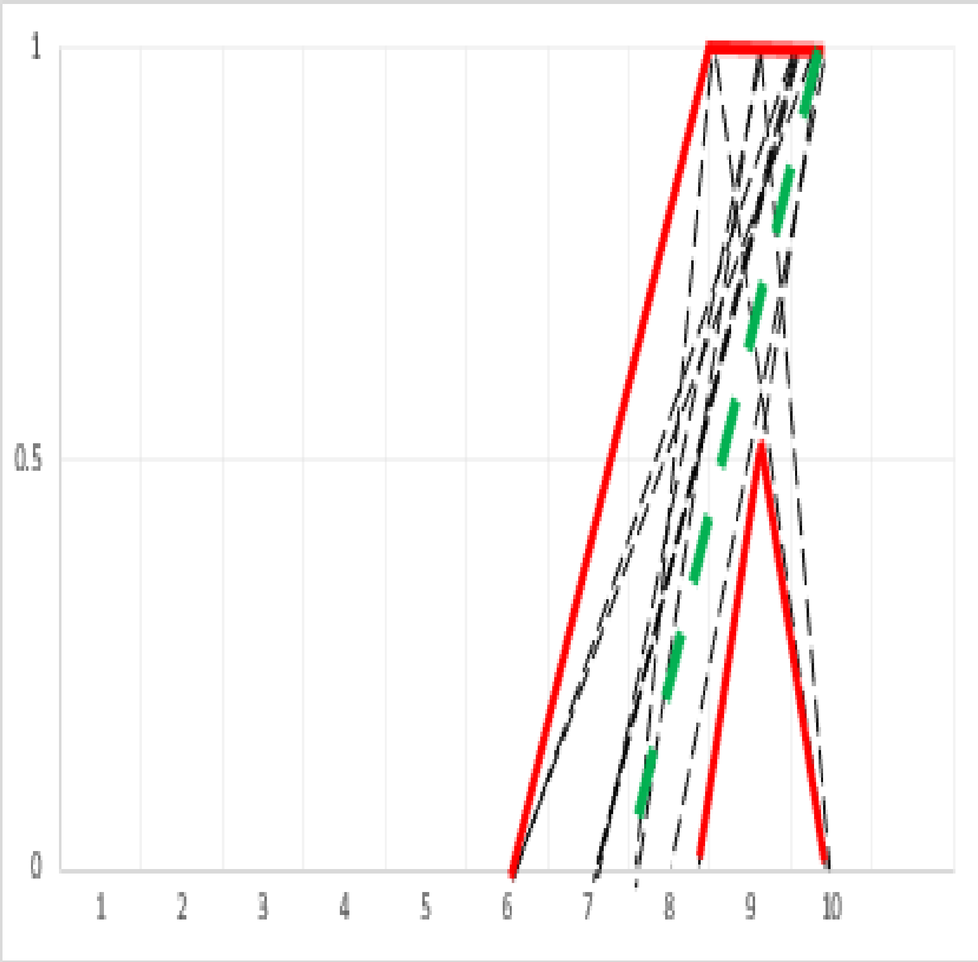

The generated "low" interval type-2 fuzzy sets of the knowledge level



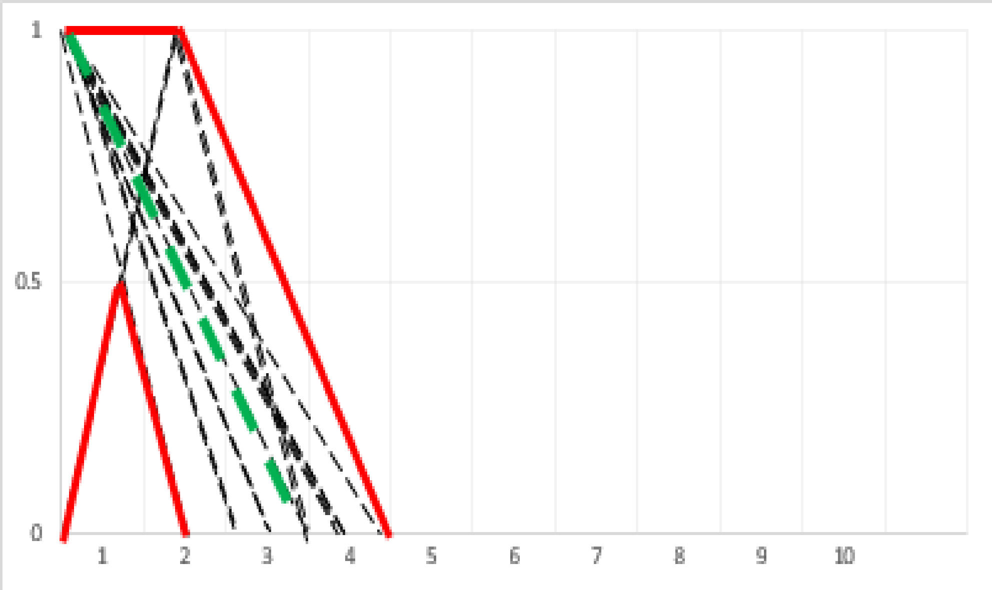

The generated "moderate" interval type-2 fuzzy sets of the knowledge level



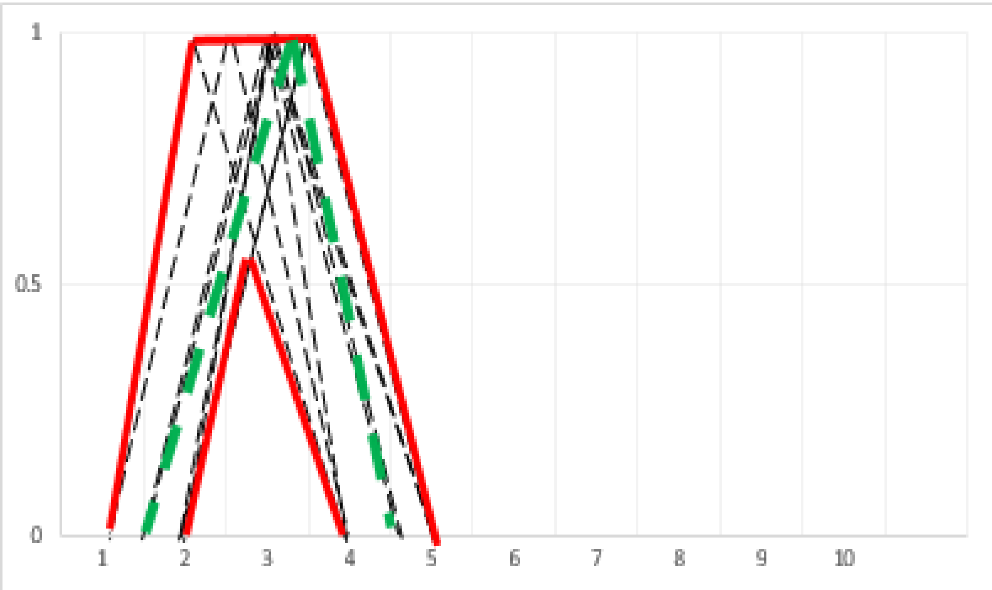

The generated "High" interval type-2 fuzzy sets of the knowledge level



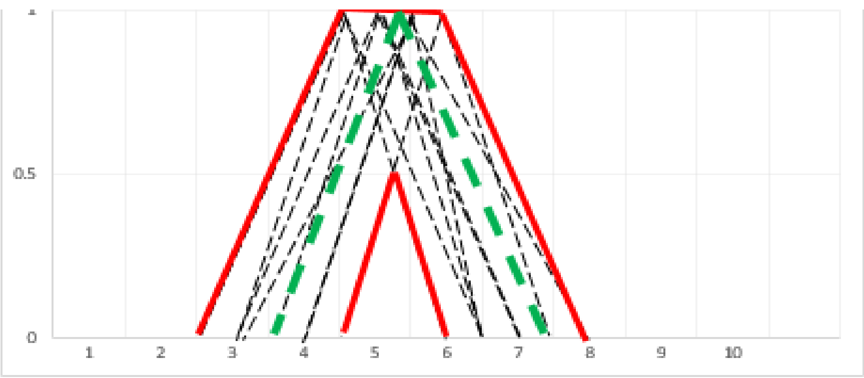

**The generated "very High" interval type-2 fuzzy sets of the knowledge level**



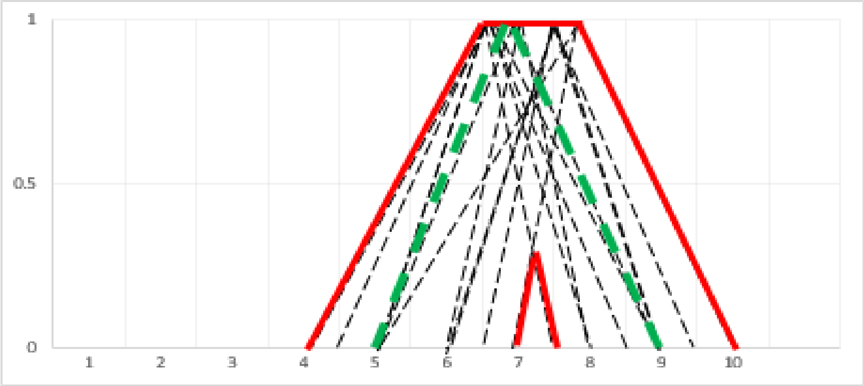

The generated "very easy" interval type-2 fuzzy sets of the difficulty level



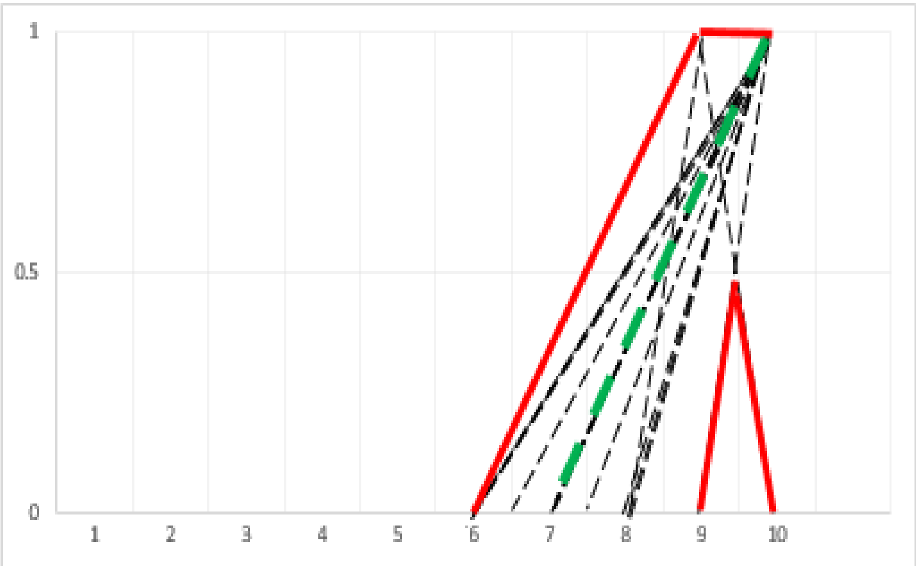

The generated "easy" interval type-2 fuzzy sets of the difficulty level



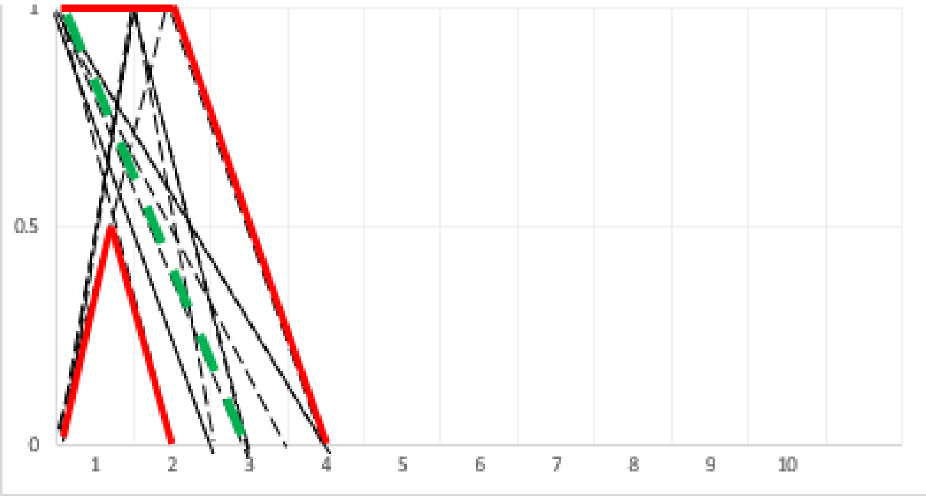

The generated "Moderate" interval type-2 fuzzy sets of the difficulty level



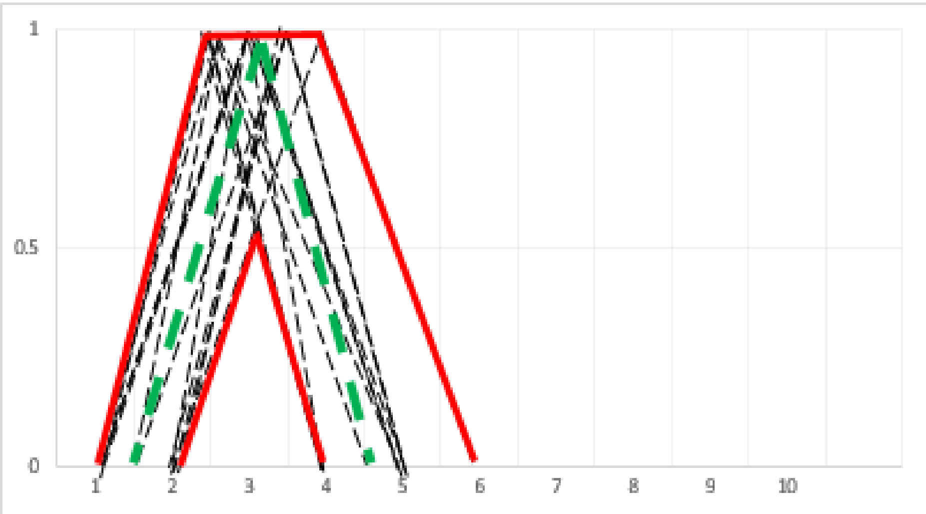

The generated "Difficult" interval type-2 fuzzy sets of the difficulty level



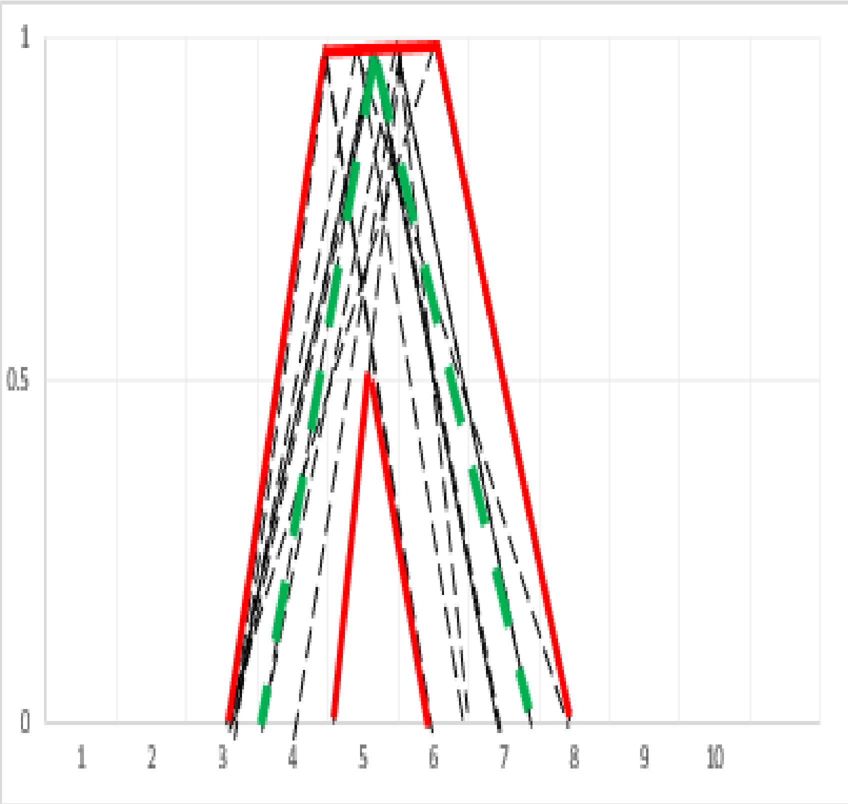

The generated "Very Difficult" interval type-2 fuzzy sets of the difficulty level



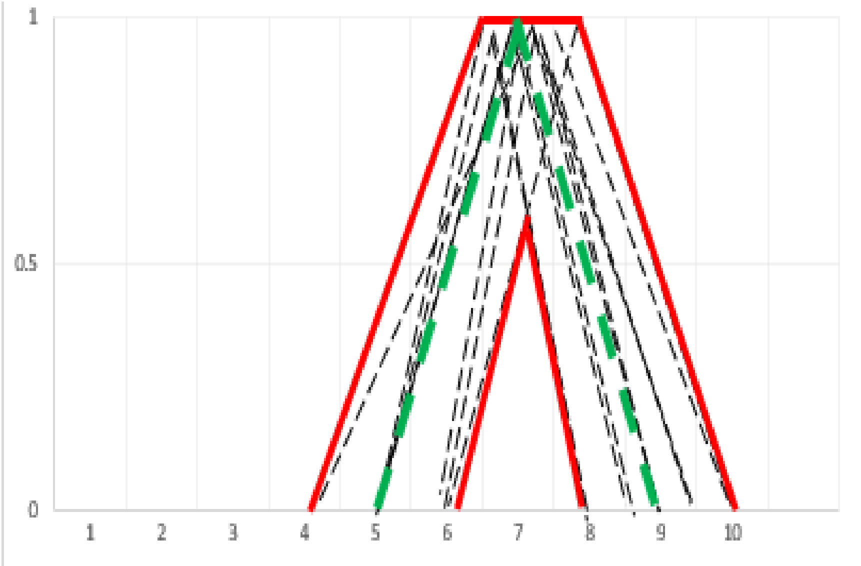

**The generated "Very Short" interval type-2 fuzzy sets of the Needed Time to study**



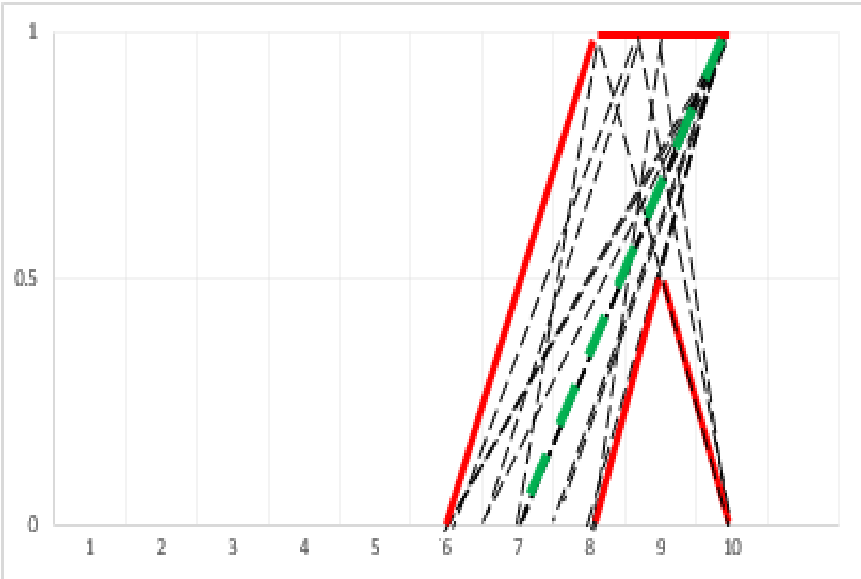

**The generated "Short" interval type-2 fuzzy sets of the Needed Time to study**



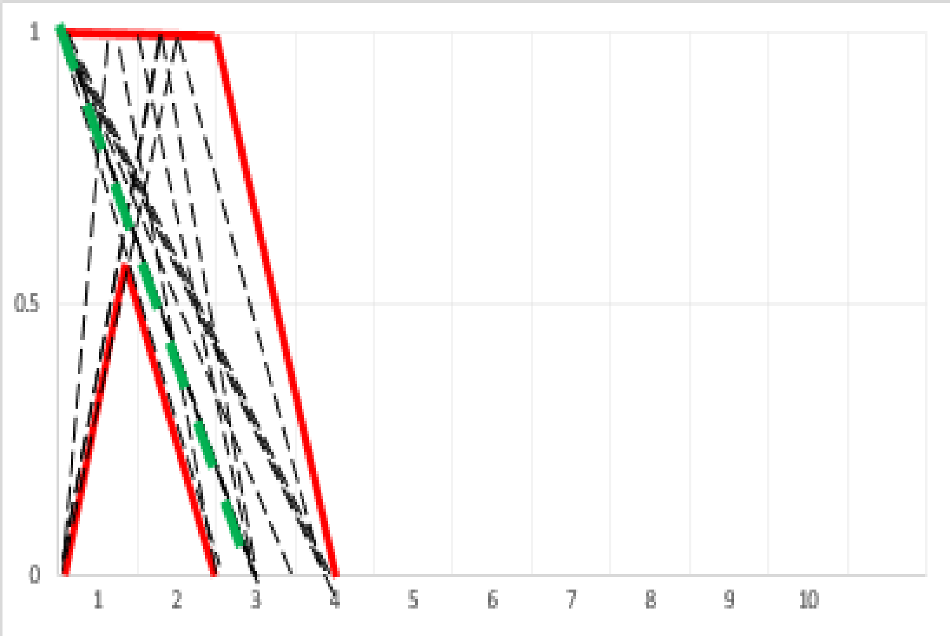

The generated "Moderate" interval type-2 fuzzy sets of the Needed Time to study



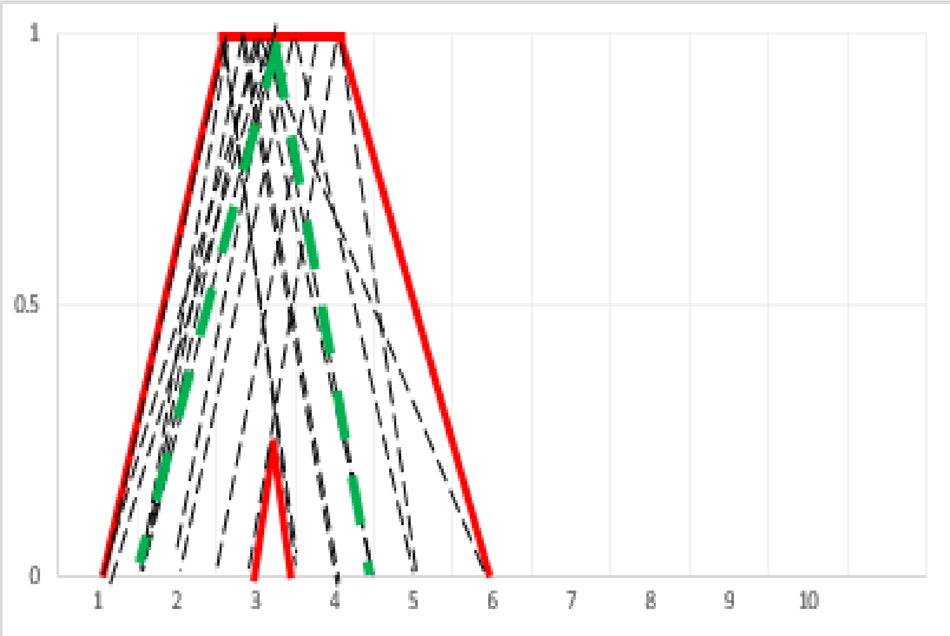

The generated "Long" interval type-2 fuzzy sets of the Needed Time to study



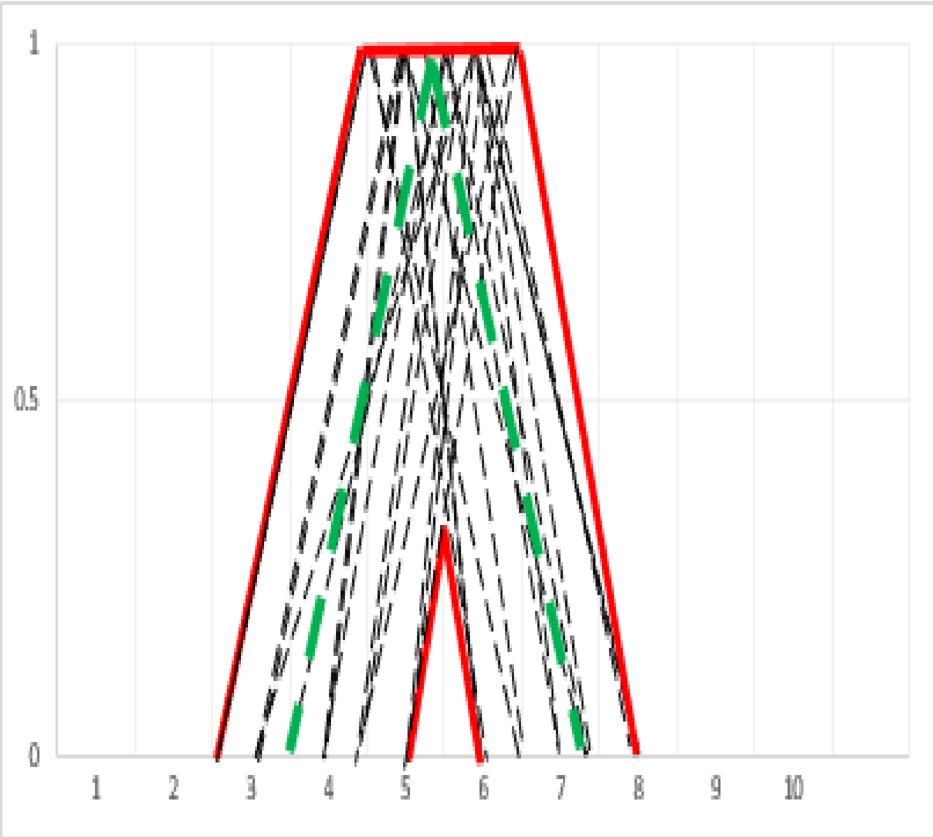

The generated "Very Long" interval type-2 fuzzy sets of the Needed Time to study



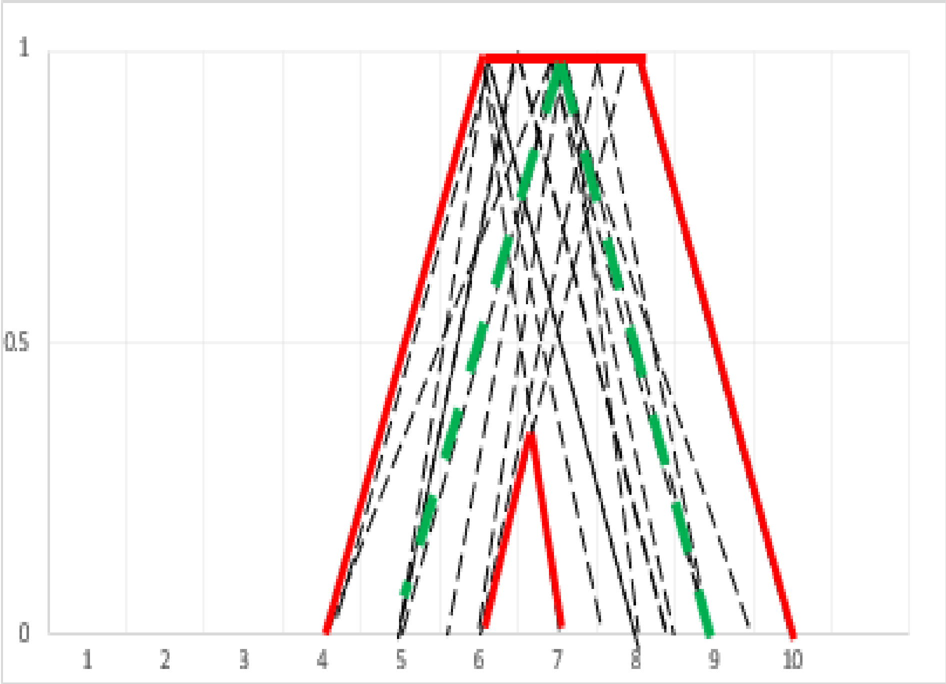

The generated "Very Weak" interval type-2 fuzzy sets of the preferred learning style category



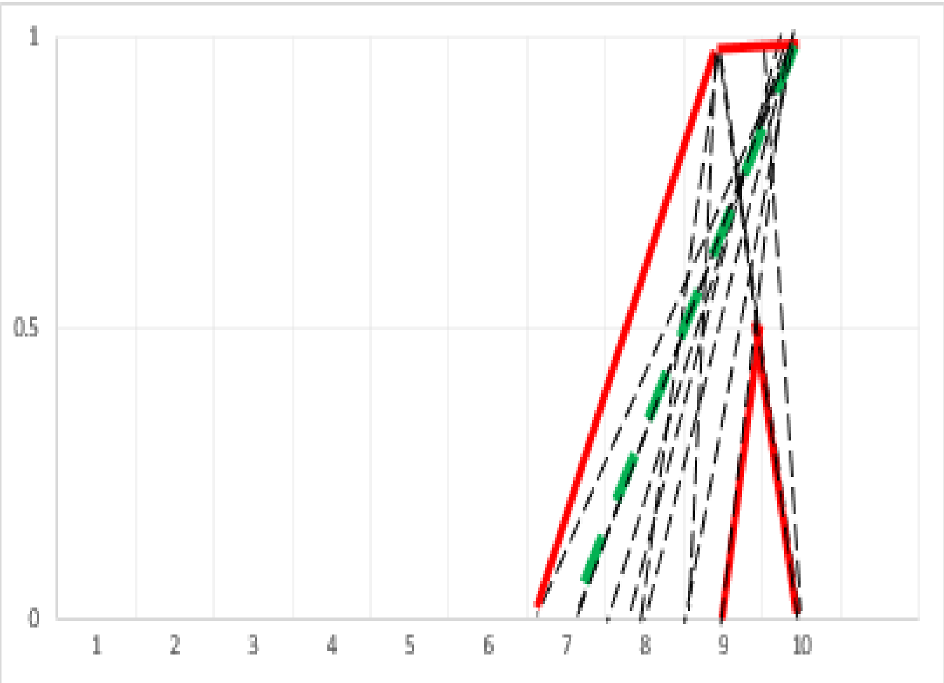

The generated "Weak" interval type-2 fuzzy sets of the preferred learning style category




The generated "Moderate" interval type-2 fuzzy sets of the preferred learning style category

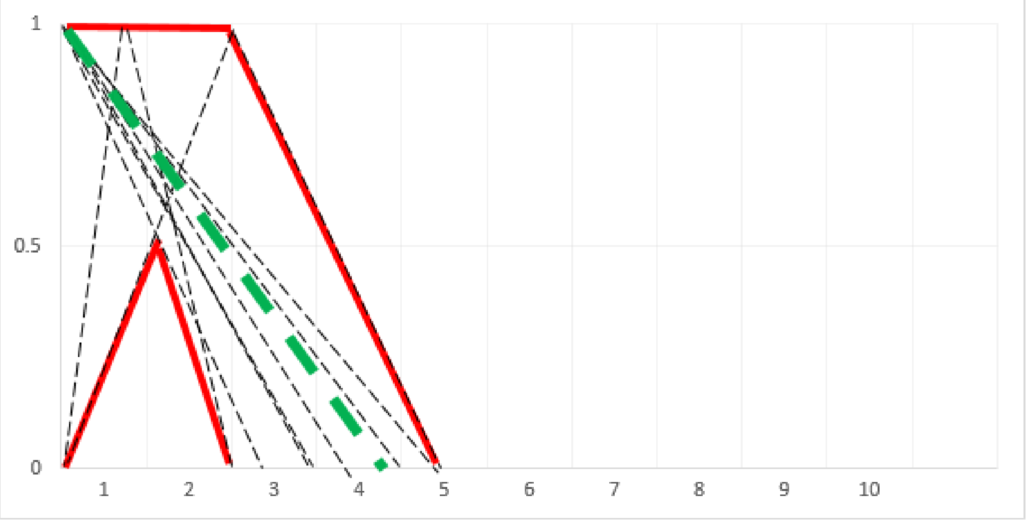



The generated "Strong" interval type-2 fuzzy sets of the preferred learning style category

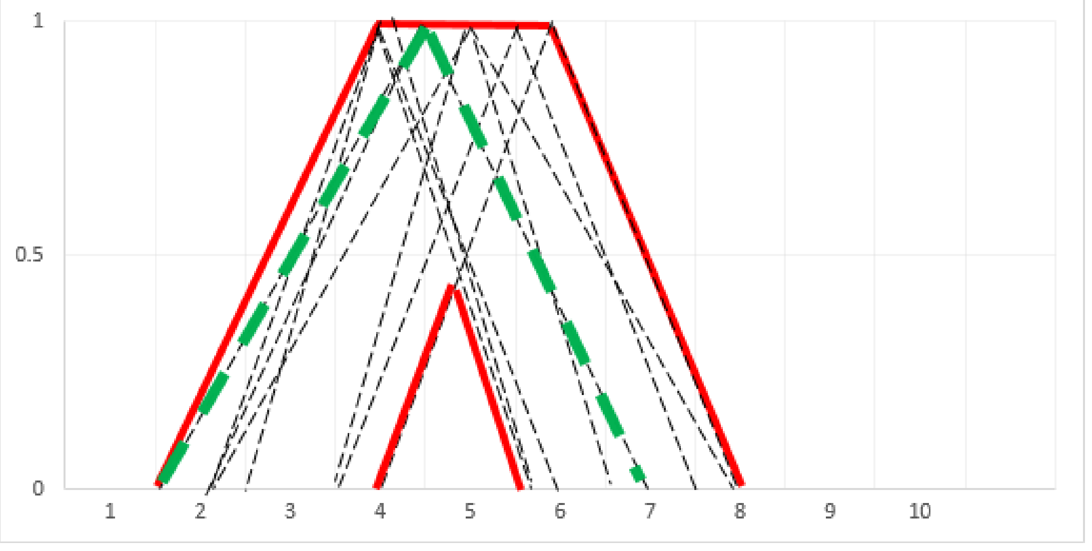



The generated "Very Strong" interval type-2 fuzzy sets of the preferred learning style category

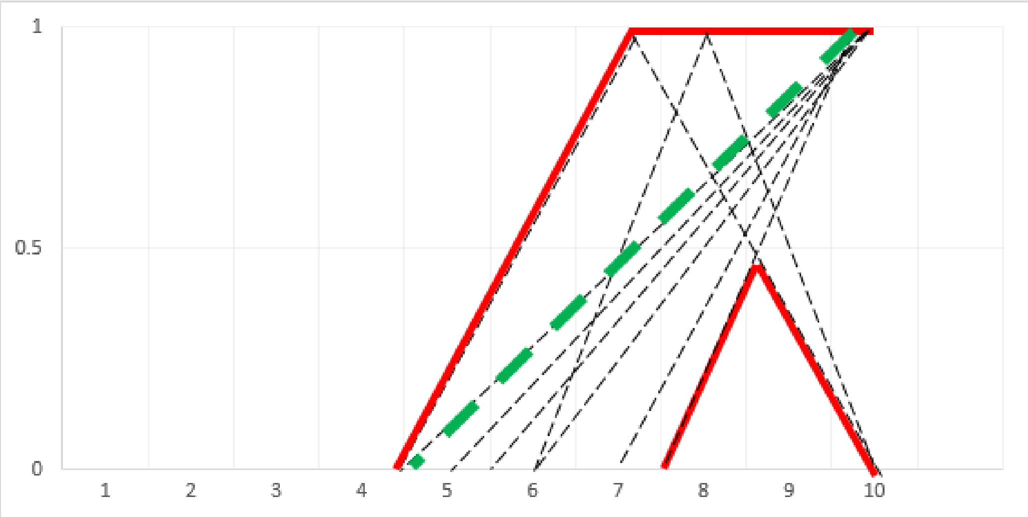
# Appendix B: Chapter 4: Sample from the extracted MFs




**The generated "Low" interval type-2 fuzzy sets of the recommendation to use the instructional approaches**




**The generated "Moderate" interval type-2 fuzzy sets of the recommendation to use the instructional approaches**




**The generated "High" interval type-2 fuzzy sets of the recommendation to use the instructional approaches**