EXPLORING ADJUSTABLE AUTONOMY IN ONLINE TUTORING SYSTEMS

Abdulkareem Alzahrani

School of Computer Science and Electronic Engineering

University of Essex

This thesis is submitted for the degree of

Doctor of Philosophy

March 2017

Abstract

Learning and teaching have been influenced greatly by the rapid development of technology. For instance, through the use of soft computing techniques, it would be possible to create an artificially intelligent autonomous tutor agent, which can ease the burden on teachers and enhance learning outcomes through its more personalised interaction with students. Providing students with automated guidance, such as directing students through the most appropriate content sequence is one aim of online tutoring systems. However, in most of the available tutoring systems, users neither have the ability to adjust the tutor agent's autonomy level nor fully control the rules applied by the tutor agent. Thus, this thesis has sought to overcome these shortcomings by proposing a system called the 'Adaptive Course Sequencing Approach' (ACSA) which enables students to adjust the autonomy level of the tutor agent and gives teachers the ability to directly communicate with the tutor agent to create the sequencing rules and alter them at any time during the learning experience. This is achieved with fuzzy logic, which has the capability of producing human-readable sequencing rules as well as managing the uncertainty of measuring some students' levels of knowledge. We hypothesise that by equipping intelligent educational environments with adjustable autonomy mechanisms, the students' learning outcomes will be enhanced. This research was divided into seven phases and involved a large number of participants (1725 in total) to assess the need for adjustable autonomy mechanisms in online tutoring systems and to explore the way of providing these mechanisms in ACSA, thereby demonstrating the hypothesis by two empirical experiments. The results showed that applying adjustable autonomy mechanisms

significantly improved the students' learning outcomes and that the students who adjusted the autonomy level more than once performed slightly better than those who adjusted it once only. In addition, applying the collaborative-driven agent method, which relies on machine learning to generate and optimise the sequencing rules, led to improving the students' learning outcomes and highly satisfying the teachers.

To my parents . . .

To my wife . . . To my sons . . .

With warm love and full respect . . .

Acknowledgements

First and foremost, thanks to the Almighty Allah for helping me during my PhD journey.

I would like to thank my parents for being a source of inspiration to me. The exceptional and extraordinary love and support provided by them makes the difference of my life. I am also deeply indebted to my sincere wife, my lovely sons, my wonderful brothers and sisters for their unlimited love and support.

My great appreciation and gratitude go to my supervisors, Dr. Michael Gardner and Prof. Victor Callaghan, for their guidance, support and feedback throughout my years of PhD study. From them I have learnt thinking skills, academic rigour, and how to research effectively. Thanks to their enthusiasm, inspiration, and the great efforts to make my PhD studies beneficial. Thanks also to my teachers who contributed in building up my skills and knowledge. My sincere thanks go to Dr. Ibrahim Assiri, Mr. Ahmed Alshahrani, Dr. Abdullah Martini and Mr. Abdullah Alqahtani.

This PhD programme would not have been possible without the financial support of "Albaha University" in the Kingdom of Saudi Arabia. Thanks to their unforgettable support. Thanks also to King Abdulaziz University for accepting to run the empirical experiments on its campus, and to the University of Essex for providing me with all the required resources to successfully carry out this research programme. Thanks to the reviewers, who reviewed my publications, and the board meeting members (Dr. Martin Colley and Prof. Klaus McDonald-Maier) for their constructive comments which have raised the standard of my publications and research skills.

I would like to thank my colleagues at the Immersive Education Lab and the Intelligent Environments research groups. Working in such a friendly and harmonious environment has contributed to this gratifying experience. Lastly, my best wishes go to my friends Dr. Khalid Almohammadi, Mr. Ans Alghamdi and Dr. Zakarya Absi for their help and sincere friendship.

Table of Contents

List of Figures **xiii**

List of Tables **xxi**

1 Introduction **1**

1.1 An Exemplary Scenario to Illustrate the Rationale 2

1.2 Hypotheses 4

1.3 Aims and Objectives 5

1.3.1 Educational Aims and Objectives 5

1.3.2 Technical Aims and Objectives 5

1.4 Methodology 6

1.5 Contributions 10

1.6 Thesis Structure 11

2 Background and Literature Review **13**

2.1 E-Learning 13

2.2 Intelligent Tutoring Systems (ITS) 14

2.2.1 ITS Components 16

2.2.2 ITS Architecture 19

2.2.3 ITS and E-Learning 24

2.2.4 ITS and Machine Learning (ML) 25

2.3 Adaptive Educational Systems (AES) 26
2.3.1 Adaptive Learning Path 26
2.4 Autonomy and Adjustable Autonomy 30
2.5 Fuzzy Logic 46
2.5.1 Fuzzy Logic Components 47
2.5.2 Hierarchical Fuzzy Systems 51
2.6 Recommender Systems 52
2.7 Pedagogical Background and Literature Review 54
2.7.1 Learning and Pedagogical Theories 54
2.7.2 Tutoring 55
2.7.3 Teacher-centred and Student-centred learning approaches 56
2.7.4 Learning Objects Model 57
2.8 Discussion 59

3 The need for adjustable autonomy in educational environments: A survey 61
3.1 Survey Design 61
3.2 Survey Results 66
3.2.1 Demographic results 66
3.2.2 Main results of the survey 70
3.3 Discussion 92

4 The Adaptive Course Sequencing Approach (ACSA) 95
4.1 ACSA Agents and their Roles 96
4.2 ACSA Conceptual Model 98
4.2.1 Learning objects metadata (LOM) 100
4.2.2 Student profile 100
4.2.3 Adaptation model 102

4.2.4 Human-agent Teamwork Panel 102
4.2.5 Context agent 103
4.2.6 iTutor agent 105
4.2.7 Analyser 106
4.2.8 User interface 109
4.3 Adjustable Autonomy Mechanisms 119
4.4 Learning Framework 123
4.5 Discussion 129

5 Exploring Pedagogical Benefits of Adjustable Autonomy 131
5.1 Experimental Philosophy 132
5.2 Experimental Infrastructure 136
5.2.1 Extracting Fuzzy membership function 136
5.2.2 Structuring the hierarchical levels 137
5.2.3 Creating the sequencing rules 139
5.2.4 Extracting the most appropriate rule 142
5.3 Experiments and Results 143
5.4 Discussion 151

6 Exploring Pedagogical Benefits of Machine Learning 153
6.1 Experimental Approach and Rationale 154
6.2 Experimental Infrastructure 156
6.2.1 Generating sequencing rules 156
6.2.2 How to find the best fitting lesson 161
6.3 Experiments and Results 164
6.4 Discussion 168

7 Exploring Teachers' Opinions about ACSA **171**

7.1 Survey Design 172

7.2 Survey Results 176

7.2.1 Demographic results 176

7.2.2 Survey's main results 180

7.3 Discussion 203

8 Conclusions and Future Work **207**

8.1 Reminder of the Thesis' Aims and Hypotheses 208

8.2 Contributions 209

8.3 Summary of Achievements 213

8.4 Future Work 216

References **219**

List of Figures

2.1 The system architecture for Andes Physics Tutor 21

2.2 The system architecture for Almohammadi et al. ITS 22

2.3 The system architecture for CRISTAL system 23

2.4 The system architecture for iRead system 24

2.5 The autonomy spectrum suggested by Barber and Martin 31

2.6 The distribution of the potential next-generation alarm clock along the IP Continuum 32

2.7 Degrees of autonomy corresponding to varying nested ranges of action available to an agent 41

2.8 The Adjustable Autonomy Intelligent Environment (AAIE) Architecture Model made by Matt et al. 44

2.9 Fuzzy logic system 47

2.10 Membership function in a triangular shape 49

2.11 Fuzzy processing example 51

2.12 Teacher-centred and student-centred learning continuum 57

3.1 The participants' genders 67

3.2 The participants' age groups 68

3.3 Previous education level 69

3.4 Had you heared about ITS before? 70

3.5 The participants' responses for the statement "During my learning life, I have re-studied some lessons or part of lessons in different modules" 71
3.6 The participants' responses to the statement "I lose my concentration when I am taught a lesson or part of a lesson that I have already learnt and I have still mastered". 72
3.7 The participants' responses to the statement "I feel bored when I am taught a lesson or part of a lesson that I have already learnt and I have still mastered" 73
3.8 The participants' responses to the statement "I lose my motivation towards a module when it covers subjects that I have already learnt and I have still mastered" 74
3.9 The participants' responses to the statement "If I could choose my own learning path (syllabus), I would not restudy the lessons that I have previously learnt and I have still mastered" 75
3.10 The participants' responses to the statement "Restudying a lesson can sometimes be a good learning strategy" 76
3.11 The participants' responses to the statement (When I learn something, I always prefer to choose what I am going to learn) 78
3.12 The participants' responses to the statement (I learn better if I can choose the modules' lessons and their sequencing) 79
3.13 The participants' responses to the statement (The most important thing that makes me decide whether to learn a lesson or not is the low knowledge I have about it) 80
3.14 The participants' responses to the statement (Usually, I feel that I do not have the skills that allow me to choose the most appropriate learning path for me (to plan what I am going to learn)) 81

3.15 The participants' responses to the statement (when I am learning a module, I would be interested in knowing the learning paths that other students have chosen, particularly those who have a level of knowledge similar to mine) . 82

3.16 The participants' responses to the statement (I value any recommendation from the teacher about the most appropriate learning paths for me) 83

3.17 The participants' responses to the statement (Usually, I want the teacher to guide me to the appropriate lessons and not allow me to choose by myself). 85

3.18 The participants' responses to the statement (Usually, I prefer if the teacher guides me to study a lesson which is appropriate to my knowledge level but gives me the freedom to follow or disregard his/her guidance). 86

3.19 The participants' responses to the statement (Usually, I prefer if I am given the full freedom to choose what I want to study without any intervention). . 87

3.20 The participants' preferences of the three guidance mode 88

3.21 The participants' responses to the statement (my preferred guidance mode differs from time to time (between the three guidance modes mentioned in the survey description)). 89

3.22 The participants' responses to the statement (the three modes of guidance mentioned in the survey description are enough to achieve my learning needs). 90

4.1 The ACSA elements' roles 97

4.2 ACSA Conceptual Model 99

4.3 IEEE PAPI specification for student profile 101

4.4 An example of the adaptation model management services 103

4.5 Reporting the students' interaction while doing the test 104

4.6 Reporting the students' interaction in XML format 105

4.7 The input membership function of knowledge level for every lesson 108

4.8 Example of JSON request on a particular student's marks at a particular time sent to the analyser . . . 109
4.9 The updated marks for every lesson as appeared in the student interface . . 110
4.10 The FAQ and help page containing questions with their answers, images and videos explaining how to use the system . . . 111
4.11 Five learning styles provided for every lesson to accommodate the learning needs for all students . . . 111
4.12 The user interface for the full autonomy level . . . 112
4.13 The user interface for the partial autonomy level . . . 113
4.14 The user interface for the no autonomy level . . . 114
4.15 The teacher can add the Group (s)he is teaching . . . 115
4.16 A list of the registered students' names, university numbers and university branch names as presented in the teacher interface . . . 116
4.17 The teacher can see a list of his/her students summarising the time of registering, logging-in and logging-out . . . 116
4.18 A table of students' updated marks details as presented in the teacher interface 117
4.19 The teacher can see the rules (s)he has already edited or approved . . . 117
4.20 A list of weak rules as presented in the teacher interface . . . 118
4.21 A table of all potential and active rules with details that help the teacher when he/she wants to edit, delete or approve a rule . . . 118
4.22 The teacher can edit the rule output . . . 119
4.23 ACSA teaches students the computer skills in a practical way. The question appearing in this figure asked the student to make a title for the chart (s)he had already done in the previous steps . . . 125
4.24 Example of the ACSA positive feedback for a correct answer . . . 126
4.25 Example of a scaffolding provided by ACSA when the answer is incorrect . 126

4.26 Example of a post-test 127
4.27 The learning framework life cycle 128

5.1 Illustration of how people want to seek guidance while learning (e.g. reading a book) 133
5.2 The controllability added to the learning process when utilising an adjustable autonomy 134
5.3 The membership function for the level of knowledge 137
5.4 The hierarchical classification for lessons 138
5.5 A screen-shot of the sequencing rules voting system 141
5.6 The rules in hierarchical level 1 141
5.7 Example of the rules in the hierarchical level 2 142
5.8 Plot of means for the groups' learning gain 149
5.9 The students' preferences for the three guidance modes during the experiment 150

6.1 The input membership function of knowledge level for every lesson 158
6.2 Example of the knowledge levels crisp sets when sent to the analyser 163

7.1 Participants' gender 177
7.2 Participants' age 178
7.3 The participants' responses to "Have you heard about ITS before?" 179
7.4 The participants' responses to "Have you used an ITS previously?" 179
7.5 The participants' responses to "Have you used a LMS previously?" 180
7.6 The participants' responses to "In general, how much are you satisfied with the rules that were generated by the system?" 182
7.7 The participants' responses to "the generated rules in the system are enough to teach students" 183

7.8 The participants' responses to "Did you alter (edit) some of the rules that were generated by the system?" 185

7.9 The participants' responses to "to what extent are you satisfied with the rules editing tools?" 187

7.10 The participants' responses to "to what extent are you satisfied with the policy responsible for activating the rules?" 188

7.11 The participants' responses to "it is important to differentiate the policies, which activate the rules, based on the guidance level" 189

7.12 The participants' responses to "creating sequencing rules which take into account the individual differences between students as well as the policy of activating these rules need time and effort from teachers" 190

7.13 The participants' responses to "What is your opinion about making the system generate the rules on your behalf (when you do NOT have the ability to change these rules)?" 191

7.14 The participants' responses to "What is your opinion about making the system generate the rules on your behalf (when you do have the ability to change these rules)?" 192

7.15 The participants' responses to "making the system responsible of generating the rules on my behalf relieved some of the burden on me" 193

7.16 The participants' responses to "giving me the ability to access the rules and alter them enhances their quality" 194

7.17 The participants' responses to "the three autonomy levels (full, partial and no autonomy) are enough to fulfil students' needs" 196

7.18 The participants' responses to "It is a good strategy to give the student the ability to choose the preferred level of autonomy" 197

7.19 The participants' responses to "sometimes, I want to enforce (oblige) some students to learn a lesson (without giving them the option to study another lesson)" 198
7.20 Participants' responses to "there are some students to whom I want to recommend a lesson to study and they are free to study it or study another one" 198
7.21 The participants' responses to "It is good to give some students the freedom to choose what they want to study in their preferred sequence" 199
7.22 The participants' responses to "in the future, I want my students to study in this intelligent system" 200
7.23 The participants' responses to "In general, to what extent are you satisfied with the system?" 200

List of Tables

2.1 Levels of automation of decision and action selection 34

2.2 The scale for the US Army Future Combat System (FCS) 35

2.3 Proud et al. level of autonomy assessment scale 37

3.1 Summarising the results of the first part of the questionnaire 76

3.2 Summarising the results of the second part of the questionnaire 80

3.3 Summarising the results of the third part of the questionnaire 84

3.4 Summarising the results of the fourth part of the questionnaire 90

4.1 Example of the test's report 106

4.2 Example of reporting the students' interactions towards the test's questions 107

4.3 The levels of adjustable autonomy in our approach 123

5.1 The calculation of rules required when adopting a fuzzy hierarchical rule-based approach 139

5.2 Statistical details of the first experiment's results 149

5.3 The significant differences between the groups calculated using Tukey's HSD post hoc test 150

6.1 Statistical description of the learning gain for the adjustable autonomy and full autonomy groups in the first and second experiments 166

7.1 Statements in the first group 173
7.2 Statements in the second group 173
7.3 Statements in the third group 174
7.4 Statements in the fourth group 175
7.5 Statements in the fifth group 175

Acronyms

Term	Description
ITS	Intelligent Tutoring System
AES	Adaptive Educational System
AEHS	Adaptive Educational Hypermedia System
ACSA	Adaptive Course Sequencing Approach
LOM	Learning Object Meta-data
LMS	Learning Management System
PAPI	Public and Private Information for Learners
MOOC	Massive Open Online Course
ML	Machine Learning
FIS	Fuzzy Inference System
TDM	Teacher-driven Method
CDM	Collaborative-driven Method

Terminology

Term	Description
Human-agent	teacher and student
Tutor-agent	known as ‘pedagogical agent’ and refers to a software component typically employed to fulfil a series of pedagogical aims in an educational system [1]
Multi-agent	tutor agent and human-agent
Autonomy level	the degree to which the student controls the level of the tutor agent’s autonomy. Note: in the whole thesis the term of autonomy level refers to the autonomy of the tutor agent rather than autonomy of the student.
Guidance mode	used interchangeably with ‘autonomy level’

List of Publication

Journal Publications

1. K. Almohammadi, H. Hagras, B. Yao, **A. Alzahrani**, D. Alghazzawi, and G. Aldabbagh, "A type-2 fuzzy logic recommendation system for adaptive teaching," Soft Computing, vol. 20, no. 181, pp. 1—15, Aug. 2015.

2. A. Alzahrani, **A. Alzahrani**, F. K. Al Arfaj, K. Almohammadi, and M. Alrashidi, "AutoScor: An Automated System for Essay Questions Scoring," Int. Journal of Humanities Social Sciences and Education (IJHSSE), vol. 2, no. 5, pp. 182—187, May 2015.

Conference Publications

1. K. Almohammadi, B. Yao, **A. Alzahrani**, H. Hagras, and D. Alghazzawi, "An interval type-2 fuzzy logic based system for improved instruction within intelligent e-learning platforms", in 2015 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Istanbul, 2015, pp. 1-–9.

2. **A. Alzahrani**,A. Alghamdi, F. Alarfaj and M. Gardner, "The Use of Sentiment Analysis in an Immersive Education Environment to Measure Student Satisfaction and

Engagement", in the Workshop, Short Paper and Poster Proceedings from the inaugural Immersive Learning Research Network Conference (iLRN), Prague, 2015, pp. 41–43.

3. A. Alzahrani, **A. Alzahrani**, F. Alarfaj, K. Almohammadi and M. Alrashidi, "An Automated Scoring Approach for Essay Questions," in International Conference on Education in Mathematics, Science and Technology (ICEMST), Konya, Turkey, May 2014, pp. 488—492.

4. **A. Alzahrani**, V. Callaghan, M. Gardner, and A. Alzahrani. "Towards Personalised and Adaptive Learning Paths in Immersive Educational Environments", King's College London, UK, November 2013, pp. 259.

5. **A. Alzahrani**, V. Callaghan, and M. Gardner,"Towards Adjustable Autonomy in Adaptive Course Sequencing", in Intelligent Environments (Workshops), Athens, Greece, 2013, vol. 17 of Ambient Intelligence and Smart Environments, pp. 466-–477.

Chapter 1

Introduction

The use of e-learning platforms has overcome the traditional place and time constraints and is now able to accommodate a large number of distance learners, opening up a wide range of learning resources to them. However, some existing platforms are not adaptive to accommodate individual differences amongst students. The deficiencies of these platforms have resulted in a "one size fits all" approach, in which all students follow the same sequence of lessons, regardless of their knowledge level and preferences. Hence, there has been a persistent need for educational systems that personalise and adapt lessons' sequence to fit individual students' learning needs.

Surveying prior work in this area resulted in finding lack of studies concerning the possible ways that make sequencing systems more adaptable, personalised and controllable by offering methods that allow students to adjust the amount of assistance received from the tutor agent and enable teachers to communicate directly with the tutor agent to govern the learning process. Thus, this thesis is motivated to address the noted shortcomings by augmenting online tutoring systems with adjustable autonomy and mixed initiative mechanisms, and by adopting fuzzy logic, which offers human-readable sequencing rules and is a means of handling uncertainties concerning some students' characteristics, such as their level of knowledge. As the name suggests, a fuzzy classifier is a classifier that utilises fuzzy classification rules in the form of a condition (if part) and a consequence (then part). Its popularity stems from the fact that fuzzy rules mimic the way people represent linguistic knowledge and handle uncertainty, resulting in a more natural process that is easy to deal with.

On the other hand, adjustable autonomy in education is inspired from the principle that teachers often adjust the amount of support they give to a student in order to encourage independent thinking or better guide the students' overall learning performance. In intelligent tutoring systems, the teacher is replaced by a tutor agent and it falls on the agent design as to how to mimic the variable help that teachers naturally provide. In tutor agent research, such an ability in a tutor agent is referred to as adjustable autonomy. In this study, I am applying adjustable autonomy to mimic the teachers' strategy for adapting the amount of help given, together with providing students with a mechanism to adjust their preferred level of autonomy in response to inevitable differences between the students. This application has to balance students' preferences and pedagogical constraints and standards without breaking them.

This chapter aims to introduce the main idea of the thesis. It starts by illustrating the rational using an exemplary scenario (Section 1.1). The thesis hypotheses are introduced in Section 1.2. The aims and objectives of the thesis are explained in Section 1.3. The methodology which the thesis was followed is explained in Section 1.4. The thesis contributions are highlighted in Section 1.5. Finally, the thesis structure is introduced in Section 1.6.

1.1 An Exemplary Scenario to Illustrate the Rationale

Tony is a professor in the Department of Computer Science in a British university. He has a long and rich experience in the development of his field and he has dealt with students from different backgrounds and various nationalities. He is currently supervising three PhD students, Joe, Hannah and Steve. Joe is 58 years old and he was a manager for 20 years before he started his PhD last year. He used to hold meetings with his staff on a weekly basis and plan monthly projects for the company he worked in. He has extensive experience and he is very independent and self-confident. Hannah is 26 years old and she is in her first year of PhD studies. She has not worked before and the whole PhD research area is new to her. Steve is 33 years old. He finished his MSc in Computer Science seven years ago and then he worked part-time in a software development company, where he led individual projects alone and was sometimes part of a work team. He is in his third year of his PhD and he is planning to submit his thesis within the minimum period.

To start with Joe, he has been managing the relationship with his supervisor to a great extent. He has so far designed his own plans of study and he rarely sets up a meeting schedule with his supervisor. Instead, he follows his own study plans and requests meetings with his supervisor after he submits a draft of a chapter or the results of an experiment. He does not discuss his study plans with his supervisor, and his supervisor is only a source of feedback for his work. Tony, the supervisor, is comfortable with the way Joe is managing his studies and is generally happy with the drafts he is submitting but he has requested Joe to arrange a schedule for meetings with him when Joe approaches the final year, just to ensure that Joe is on track to submit his thesis on the proposed deadline.

Hannah is the other extreme of Joe. She is still trying to find her feet in the first few months of her study and she has asked Tony to have a meeting with her every second week. She is not quite sure about her study plans and she is anxious about meeting the criteria of the confirmation board meeting at the end of the year, where the University agrees for the proposal of her study. Tony is aware of Hannah's worries and he is offering her as much support and guidance as he can. Hannah is working hard and she is trying to follow Tony's plans and advice to the letter. She is happy with the guidance she is receiving from Tony and she feels she is making good progress towards the confirmation board meeting.

Steve's relationship with Tony has varied throughout the PhD study period. When he started his PhD, he was more or less like Hannah, relying completely on Tony, until he passed the confirmation board meeting. In the second year of his study, he started to be more flexible in his relationship with his supervisor. He would often follow his own study plan, but Tony would request a meeting with him once every month to have an update on his progress and bring him back on track if necessary. Tony would sometimes also set up deadlines for him to submit draft chapters. Now that Steve is approaching the final submission deadline, Tony has set up a schedule for meetings with him and the deadlines are stricter. Steve is happy with his progress and is confident he can finish before the submission deadline.

The above story illustrates that learners may have different preferences about their learning and the amount of assistance they may need from their teachers, and these preferences may be affected by their experience and educational background and may change over time.

1.2 Hypotheses

This research aims to assess four hypotheses:

1. Students using online tutoring systems differ in their individual desired level of autonomy. Moreover, this level sometimes differs between students and over time for an individual student depending on factors such as the student's learning-needs and preferences as well as the current lesson and subject. Therefore, equipping online tutoring systems with adjustable autonomy mechanisms will allow the student to control the amount of assistance and choose the preferred level of autonomy, which will bring a better alignment of learning needs and lead to optimising the learning gain.

2. It is possible to devise a conceptual architectural model capable of adapting the sequence of learning content, allowing students to personalise the way of receiving the

sequence, making the tutor agent capable of producing sequencing rules and giving the teachers the ability to control the learning process.

3. Machine learning has the ability to produce sequencing rules which can be used to guide students to learn better and are similar to the rules generated by teachers.

4. Giving the teachers the ability to control the generated rules will enhance the rules and will satisfy the teachers.

1.3 Aims and Objectives

The research aims and objectives can be classified into educational and technical.

1.3.1 Educational Aims and Objectives

The educational aims and objectives the thesis aimed to fulfil are:

1. **Understanding the student's learning needs and preferences**. Regarding the flexibility of the guidance in an adaptive course sequencing approach, this research investigates what the student's preferences and learning needs are.

2. **Studying the need for adjustable autonomy in the adaptive course sequencing approach**. This research explores the need for adjustable autonomy mechanisms in the adaptive course sequencing approach to give the possible students the right to choose the preferred autonomy level.

1.3.2 Technical Aims and Objectives

The technical aims and objectives this thesis was motivated to achieve are:

1. **Identifying the conceptual architectural model for adjustable autonomy online tutoring systems.** This work identifies the individual agents' roles in the proposed

multi-agent system. In addition, it defines a conceptual architectural model with its components and functionalities for the adjustable autonomy online tutoring system.

2. **Implementing the architecture for an adaptive course sequencing approach** to make this type of systems more adaptive, agent-collaborative and controllable. This involves finding the suitable way to encode the learning experiences in fuzzy rules.

3. **Exploring adjustable autonomy in adaptive course sequencing systems.** This involves comparing between different students' learning outcomes at every level of autonomy as well as when allowing them to adjust the autonomy level. The comparison includes two different methods: the teacher-driven method, in which teachers are required to supplement the system with the sequencing rules, and the collaborative-driven method, where the agent observes the students' learning behaviours and generates these rules utilising machine learning. The teachers in this method can control and approve the rules at the run-time. In addition, this aim involves exploring the ways that enable teachers to control the learning process and investigating their opinions regarding the proposed system.

1.4 Methodology

This research is multi-disciplinary (computer science, education and psychology) and is based on a user-centred design methodology starting with a clear identification of pedagogical and learning needs obtained from students and informed by appropriate learning theories and frameworks. The technical work involved the iterative building and testing of a number of solutions. This was pedagogically evaluated in the context of a clear empirical research framework. In this multi-disciplinary research, there were two main complementary pedagogical and technical aspects. In technological terms, this research investigated the possibility of augmenting the adaptive course sequencing approach with an adjustable autonomy capability.

This involved the development of a conceptual architectural model, which was constructed as a way of delivering the required functionalities. These functionalities cover the adaptive pedagogical needs for individual students as well as the teachers' requirements. In addition, the model offers a collaborative environment for the multi-agent (i.e. teachers, students and the tutor agent) to enhance the learning process. Thus, a student, based on his/her profile, learning needs and preferences can set his/her preferred level of agent autonomy and the system will use this to guide him/her through his/her appropriate learning path. The students can share their learning experiences with the tutor agent, enabling the latter to automatically generate new rules or optimise the existing ones. Furthermore, teachers can be involved in controlling the learning process by creating/adjusting the sequencing rules and/or defining policies that will be used by the tutor agent to distinguish the active rules from the potential ones, which in turn will give teachers more control of the tutor agent. On the other hand, from an educational and pedagogical standpoint, the research studied the effectiveness of implementing adjustable autonomy mechanisms in the adaptive course sequencing approach. The research was divided into different phases.

- During the first phase, the author gained a better understanding of the related concepts and theoretical frameworks in education, online tutoring systems, and adjustable autonomy.

- In the second phase, the subject domain to be taught by the system was chosen. In addition, this phase involved choosing a number of lessons, constructing the related on-line lessons and constructing the assessments for those lessons.

- The third phase investigated the students' learning needs and preferences regarding the adaptive course sequencing approach in general and adjustable autonomy in particular. Therefore, a questionnaire was distributed to students and the results analysed, which contributed to achieving the following research objectives: 1) understanding the student's learning needs and preferences, 2) studying the need for adjustable autonomy in the adaptive course sequencing approach.

- In the fourth phase, the research addressed the conceptual architectural model for the adjustable autonomy intelligent tutoring system. In addition, this phase involved defining the model's components and functionalities, and explained how adjustable autonomy can be utilised in the model. By doing this phase, the aim of identifying the conceptual architecture model for the adjustable autonomy online tutoring systems was achieved.

- In the fifth phase, a web-based adaptive course sequencing approach was built based on the architectural model. This consisted of mapping the subject space, initialising each student's profile, developing the observation mechanisms to observe the student's learning and building the tutor agent. By doing this phase, the aim of implementing the architecture in the adaptive course sequencing approach was fulfilled.

- The first experiment was conducted in the sixth phase and its aims were: 1) to train the system to build an effective adaptation model for the next experiment; 2) to investigate and compare the average of the students' learning gain at every level of autonomy, as well as when giving the students the ability to adjust the autonomy level. At the beginning of this phase, there were no rules, i.e. it was a "cold-start issue". Hence, teachers were first required to create the sequencing rules to be used in the whole of this phase (i.e. a teacher-driven method was adopted). Students were divided into four groups for evaluation purposes:

  – Group (1) Adjustable autonomy group: students studied in the adjustable autonomy mode, where students choose the preferred level (full, partial or no autonomy) at any time.

  - Group (2) Full autonomy group: students studied using the full autonomy level, where the agent controls the sequence of lessons and the student cannot disregard the guidance of the agent.
  - Group (3) Partial autonomy group: students studied using the partial autonomy level, where the agent offers guidance but the student is free to follow this guidance or not.
  - Group (4) No autonomy group: students studied using the no autonomy level, where the agent does not provide any guidance for the student.

  The research questions related to this phase were answered using the students' learning results (i.e. taking a quantitative approach).

- In the seventh phase, the second experiment adopted the collaborative-driven method, where the human and machine agents collaborate in generating and enhancing the sequencing rules. The aims in this phase were: 1) to generate the sequencing rules from the collected dataset and solve the issue of conflicting rules; 2) to find a better way that allows the teachers to control the automatically generated rules; 3) to study how the students can enhance the existing rules; 4) to study how the agent can generate new rules (how to tackle the issue of the lack of rules at the start); 5) to compare between the collaborative-driven and teacher-driven methods in terms of the students' learning outcomes.

- Another area of evaluation was conducted by surveying the teachers' opinions about the ACSA and its functionalities. Thus, a questionnaire covering both qualitative and quantitative questions was distributed amongst the teachers.

1.5 Contributions

The major contributions of this research are as follows:

- Proposing a novel method of designing online tutoring systems based on employing adjustable autonomy mechanisms.
- Developing a theoretical model of adjustable autonomy for education.
- Translating the theoretical model into both a technical and pedagogical implementation.
- Establishing and testing a real adjustable autonomy online tutoring system with real learners and a real course of study.
- Conducting an extensive trial of adjustable autonomy in education, leading to a large sample of quantitative and qualitative data, which, upon analysis, unveiled valuable findings.

In addition, a number of secondary contributions can be outlined as follows:

- Understanding students' learning needs and concerns regarding the sequencing of lessons and the level of assistance they demand from their teachers on the one hand and investigating teachers' views about the ACSA system.
- Assigning more informative value to the sequencing rules in the system to enable the teacher and the tutor agent to define the active rules from the set of all the automatically generated rules.
- Allowing for multi-agent collaboration in creating and optimising the sequencing rules.
- Making online tutoring systems more adaptable and flexible by involving teachers in the design and operational phases.

- Making the tutor agent services accessible by other e-learning systems, which facilitates the construction of new online tutoring systems in the future through utilising the pedagogical decisions of other tutor agents.

1.6 Thesis Structure

The remaining chapters in this thesis are organised as outlined below:

Chapter two presents the background and related studies. The investigated issue is in a multidisciplinary area. Thus, various topics in the literature are reviewed in the related technical and pedagogical fields. This involves intelligent tutoring systems, autonomous agents and adjustable autonomy, fuzzy logic, and the related learning and pedagogical theories.

Chapter three surveys the students' learning needs following a quantitative research approach. This includes the students' preferences and requirements when sequencing learning content and the way of guiding students through these sequencing rules.

Chapter four explains the ACSA's agents and their roles. It then illustrates the ACSA's conceptual model with its components and functionalities. That is followed by a theoretical discussion of utilising adjustable autonomy in educational environments. That discussion is concluded by suggesting the suitable levels of autonomy to be offered in ACSA. The learning framework which is adopted in our ACSA is also described in this chapter.

Chapter five reports the first large scale trial of executing ACSA. The aim of that experiment is to explore the benefits of equipping the ACSA with adjustable autonomy mechanisms when the ACSA has the "cold-start" issue or when the learning institutions who apply the ACSA decide not to rely on the agent-driven method. Another aim of this experiment is to gather a dataset of the students' learning behaviours.

Chapter six explains how the dataset was analysed to generate sequencing rules. It reports the second trial to investigate how much adjustable autonomy and machine learning can enhance the students' learning gain. It also provides a discussion of the degree to which the introduction of these mechanisms optimise the learning outcomes in general and contribute to improving the collaborative team work in a multi-agent learning environment.

Chapter seven explores the teachers' views and opinions about their use of ACSA.

Chapter eight summarises the thesis's aims, hypotheses, achievements and contributions. It then highlights appropriate future work and finishes the thesis by drawing an image of the future of the field.

Chapter 2

Background and Literature Review

This chapter describes the background and related literature of the thesis. It starts by defining e-learning, identifying its shortcoming and highlighting the importance of intelligent tutoring systems (ITS). This is followed by describing the features of and architectures of ITS, highlighting the importance of merging ITS and e-learning systems, and explaining the use of Machine Learning in ITS. Then the chapter moves to describe adaptive educational systems (AES) in general and survey previous adaptive learning path systems. The following section explains in detail autonomy agents, levels of autonomy and the concept of adjustable autonomy, with an example of applying the latter in real life. This is followed by explaining fuzzy logic and recommender systems. Then a review of the utilised pedagogical theories, concepts and frameworks is summarised in the following section. Finally, the last section is discussed the raised issues based on the surveyed literatures and how it can be tackled.

2.1 E-Learning

E-learning (electronic learning) can be defined as *"instructional content or learning experience delivered or enabled by electronic technologies"*[2], [3]. This definition is a broad one; it involves any kind of electronic technology that is used for educational purposes, such as online learning and mobile learning. It also involves intelligent tutoring systems and adaptive learning systems. However, most of the literature uses the term e-learning to mean online learning. This in turn makes some researchers restrict e-learning to the delivery og content via the internet as in Jones' definition of e-learning [4]. Thus, in this thesis, the term "e-learning" is used to denote online learning.

The use of e-learning has increased due to its benefits. Some of these benefits include creating exciting opportunities for people to study regardless of the time and place. Another benefit is that this form of learning can save time and cost for learning institutions, teachers, instructors, content providers and students [5]. These benefits and others encourage the investment in this form of learning. For example, the learning management systems (LMS) market is expected to grow from $ 4.07 billion in 2015 to $ 11.34 billion in 2020 [6].

On the other hand, e-learning has some drawbacks. The most important drawback is the need for human intervention to create/alter learning activities and learning paths. As an example of e-learning is normally not intelligent enough to generate or adapt learning paths to fit students' learning needs. Thus, it becomes more persistent to utilise artificial intelligence techniques to bridge this gap.

2.2 Intelligent Tutoring Systems (ITS)

According to John Self, "*ITSs are computer-based learning systems which attempt to adapt to the needs of learners and are therefore the only such systems which attempt to "care" about learners in that sense. Also, ITS research is the only part of the general IT and education field which has as its scientific goal to make computationally precise and explicit forms of educational, psychological and social knowledge which are often left implicit*" [7].

The first part of Self's definition focuses primarily on the adaptive nature while the last part stresses the fact that researchers contribute to learning sciences. The term "caring" can be viewed as attentive, as well as sensitive to the cognition and emotions of the learner, which can also be regarded as good tutoring. From the definition, ITS can be defined as ”learning through adaptive interaction between the learner and the system“ [8].

Woolf [9] introduced some visions for ITS. The first vision is to have a “teacher for every student” or a “community of teachers for every student”. This necessitates supplementing various types of teaching techniques, obtaining multi-modal input among students, which includes the use of handwriting, facial expression, speech and body language, and socialising learning by offering social activities. Another vision is making ITS recognise students’ individual differences, such as their individual learning styles, prior knowledge, demographics, learning needs and preferences, and current emotions. Then, based on these, the ITS decide on the best fitting learning material(s) and teaching style(s). The way of deciding this is another vision in which ITS know how to teach. Apart from having data or figures representing facts about a topic, the systems also have models of the domains learned. The field contains objects and processes that show trends or relationships between the topics studied. The model logically explores the knowledge in the domain, then uses the student’s reasoning regarding that knowledge to engage in discussions, as well as providing answers to questions on different topics [9]. Several leaders including John Self [10], [11], [12], Jaime Carbonell [13], [14], and William Clancey [15] were responsible for the development of ITS. The first ITS to be implemented was introduced in 1970 by Jaime Carbonell in his PhD thesis. He developed a system called Scholar which allowed students to explore the geographical features of South America. The system was different from classical computer-based instruction because it could provide responses to students’ questions by analysing the semantic network of geographical knowledge. In 1979, William Clancey introduced the first ITS that relied on an expert system called GUIDON. The system was also the first recognised attempt in the field of teaching medical knowledge [15], [16]. In 1981, Clancey developed NEOMYCIN, which is a knowledge representation system, to be used in the second version of GUIDON [17]. In addition, GUIDON become as a standard for developing intelligent medical tutor systems [18]. In terms of academic activities related to the ITS field, the first conference named The International Conference on Intelligent Tutoring Systems (ITS) was organised in 1988 by Claude Frasson. This conference became a biannual conference since 1992 and the most recent one was held in June this year (2016) [19]. Another biannual conference in the area is Artificial Intelligence and Education (AIED), which began in 1989, and the most recent conference was in 2015 [20]. Moreover, the Society of AIED has an official peer-reviewed journal called The International Journal of Artificial Intelligence and Education (IJAIED).

2.2.1 ITS Components

Intelligent tutor systems emerged from the combination of many systems, including expert systems, data annotations and representation, "Big Data" and data analytics. These together provide the foundation on which modern intelligent tutors are built. The functions provided by each of these component enable intelligent tutors to analyse learners' characteristics, representing the important topics, and adjusting the learning approach to achieve a better performance. Like human tutors, intelligent tutors require a large amount of knowledge about students with different levels and types of abilities. This knowledge is important in order to teach different students in a way that at least compares favourably with good teachers. Furthermore, ITS require knowledge about the domain, student and teaching method as well as knowledge on how to best recognise the strengths of computer systems and how best to utilise such strengths to provide required personalised teaching functions.

The well-known components of ITS are the domain, the student, tutoring and communication models [9], [21]. It should be noted that two types of ITS can be classified based on their use of these four components: the systems either use 1) all of the four components, or 2) a combination of some of them. The systems that use all the four components may follow the teaching cycle which starts with searching the domain model to determine the topic that will be used to develop a customised program. This is followed by reasoning about the student's activities, stored in the student model. While using tutoring hints or knowledge, the system chooses a presentation style from options in the communication model [9]. The following sections describe these ITS components in more detail.

Domain model

This represents information about specific problems. It includes entities, definitions, processes, skills, and relations. In some situation it defines how an expert might perform in the domain, such as administering medications for a disease [22], generating algebraic equations [23], or multiplying numbers [24].

Student model

This represents the level of the student's conceptual understanding of the domain and describes how to reason about the student's knowledge of the domain. In its specific meaning, it contains information regarding the typical student's skill within the domain and information about current students. Examples of the later include possible misconceptions about a domain, time spent on particular problems, the hints requested during learning, and the preferred presentation and learning style [25], [26]. Two components are involved in student modelling, namely the student model and the diagnostic model. The student model provides some information related to the student such as his/her skills, goals, attitude, knowledge level and preferences. The diagnostic model is the inference process which updates the student model in the end [27], [28].

Tutoring model

This model comprises the series of decisions implemented to identify a representation and a descriptive assessment of the learning of knowledge, skills, and competencies [8].

This involves defining the way the tutor intervenes, adapts the feedback and motivates and encourages the student. This is influenced by the prior or expected knowledge level, emotions and learning styles of students [9]. Teaching methods, strategies and expertise are represented in the tutoring model by encoding and reasoning the teachers' teaching behaviours while teaching, and the students' learning behaviours while interacting with the system and by studying pedagogical theories to be knowledge tutoring resources [26], [29]. The interaction between the learner and the tutor in ITS takes different forms, such as scaffolding, hints [30] and guidance [31].

Teachers and Tutoring Model. Surveys conducted on the release of tutoring systems reveal that although these systems exist in large numbers, there are very few aimed at teachers. Additionally, even those released do not trigger enthusiasm from teachers to employ them. The reason for their lack of effectiveness is that they have a poor adaptation to the learning context. A study evaluating what motivates teachers to use an intelligent tutor found that teachers are more likely to use the system that makes them more creative [32]. Therefore, the tutor model needs to be adapted by opening it up to teachers, as suggested by Bourdeau and Grandbastien [8]. They stated that the tutoring model should be opened up to the tutors when there are preparations required for a learning sequence, that is when adding or replacing exercises. Additionally, the model can also be opened up to the tutors when the behaviour of the system during the learning sequence is being addressed. This involves the development of weighing strategies that correspond to personal preferences, as well as the exploitation of feedback offered after a session [8].

REDEEM is an authoring tool for tutoring strategies which allows the ITS's teachers, without requiring prior knowledge of using technology, to include aspects of their teaching experiences, for example in sequencing the learning content [33]. A number of papers tested the usability of REDEEM and they presented promising results [34], [35]. However, REDEEM, as other authoring tools, focuses on the preparation and development phases of an

ITS rather than the operational phase. Teachers sometimes need to access the tutoring model in run-time to track the automated agent's teaching progress and to intervene if necessary, but these tools are not sufficiently flexible to give the teachers this ability. Another limitation of REDEEM is that it lacks intelligence and adaptability as it does not personalise the content to meet the student's learning needs [9].

Bourdeau and Grandbastien highlighted the importance of providing ITS with more flexibility by opening the tutoring model up to teachers. However, offering students this capability is in need of more research [8].

Communication model

This model represents methods adopted for communicating between students and the computers. Examples of devices and processes used in the communication model are graphical I/O interfaces, animated agents (e.g. 3D avatar tutor), and other dialogue mechanisms. Typical communication includes graphical illustrations, managing communication, and discussing a student's reasoning [9].

2.2.2 ITS Architecture

Nwana [36] surveyed a variety of ITS architectures and found that there was a strong relationship between the tutoring philosophy used and its architecture in an ITS. This leads to an issue of defining an architecture in a way that can be applied in all ITS since they differ in their learning and teaching strategies. Nwana stated, "It is almost a rarity to find two ITS based on the same architecture, which results from the experimental nature of the work in the area" [36]. Furthermore, ITS may differ based on the required level of intelligence in the architecture's components. For instance, the ITS which have intelligence in the domain model may automatically generate answers to novel and complex problems; thus, students can always have new problems to work on. However, these systems may have simple methods for teaching those problems (i.e. less or no intelligence in the tutoring model) [37]. These reasons result in mostly having an individual architecture model for each ITS. For instance, the architecture of Andes physics tutor (shown in Figure 2.1) divided into two environments namely: authoring environment and student environment. The authoring environment is used for producing new problems. Hence, the instructor should create both problem definitions and their related rules. The “problem solver” utilises the inserted rules and definitions to automatically create the “solution graph” which is a model of the problem solution space. However, the student environment has its own components such as: 1) the Workbench which is a graphical user interface enable student to use the system, 2) Action Interpreter which tracks the student’s inputs to provide personalised prompt feedback and offering more detailed feedback through Andes Help System. 3) Student model which has information of each student’s progress, the features (s)he used and the help (s)he received. 4) The Assessor which provides probabilistic estimates the student mental state using Bayesian Network (BN) [38].

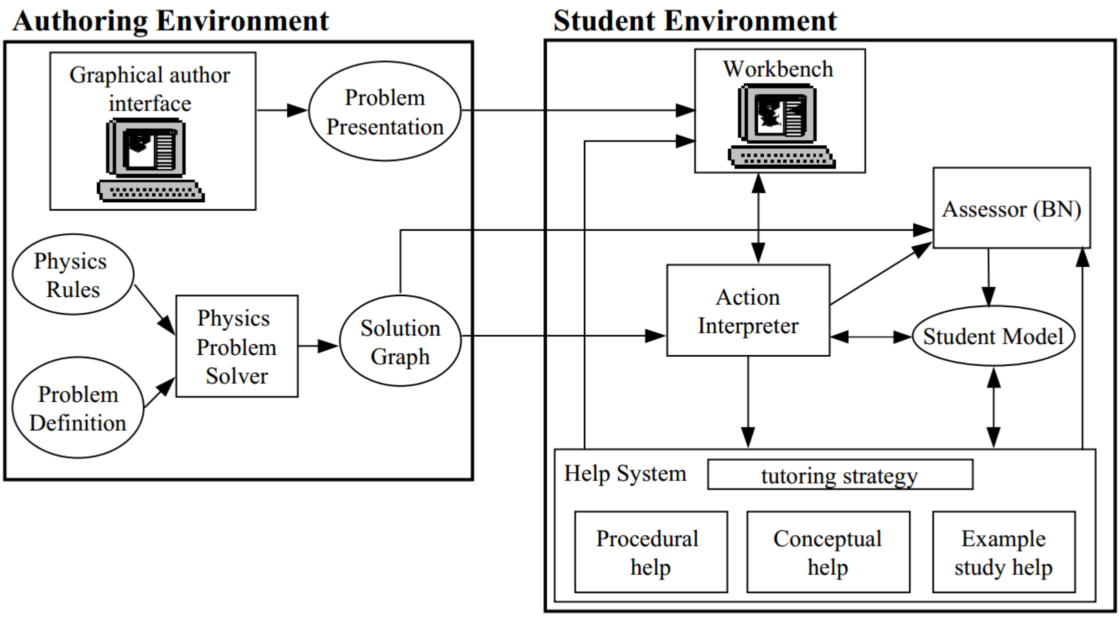


Fig. 2.1 The system architecture for Andes Physics Tutor [38]

Another different system architecture can be seen in Figure 2.2. It is for a type-2 fuzzy logic based recommendation system for adaptive teaching across interactive e-learning environments. The architecture is divided into four parts; e-learning environment, observer component, fuzzy logic component and IT2FLS & adaptation component. The e-learning environment has distance, and on-site students and their engagements are presented to the teacher's screen. In the training phase, the observer component is responsible for gathering students' engagements and the corresponded tutorial action taken by the teacher to learn new rules. Then, the observer component passes the data to the Fuzzy logic component to generate new fuzzy rules or extract the appropriate one. However, in the using phase, the observer component is responsible for monitoring the students' engagements and passes the data to IT2FLS & adaptation component to recommend the teacher about the appropriate tutorial action [39].

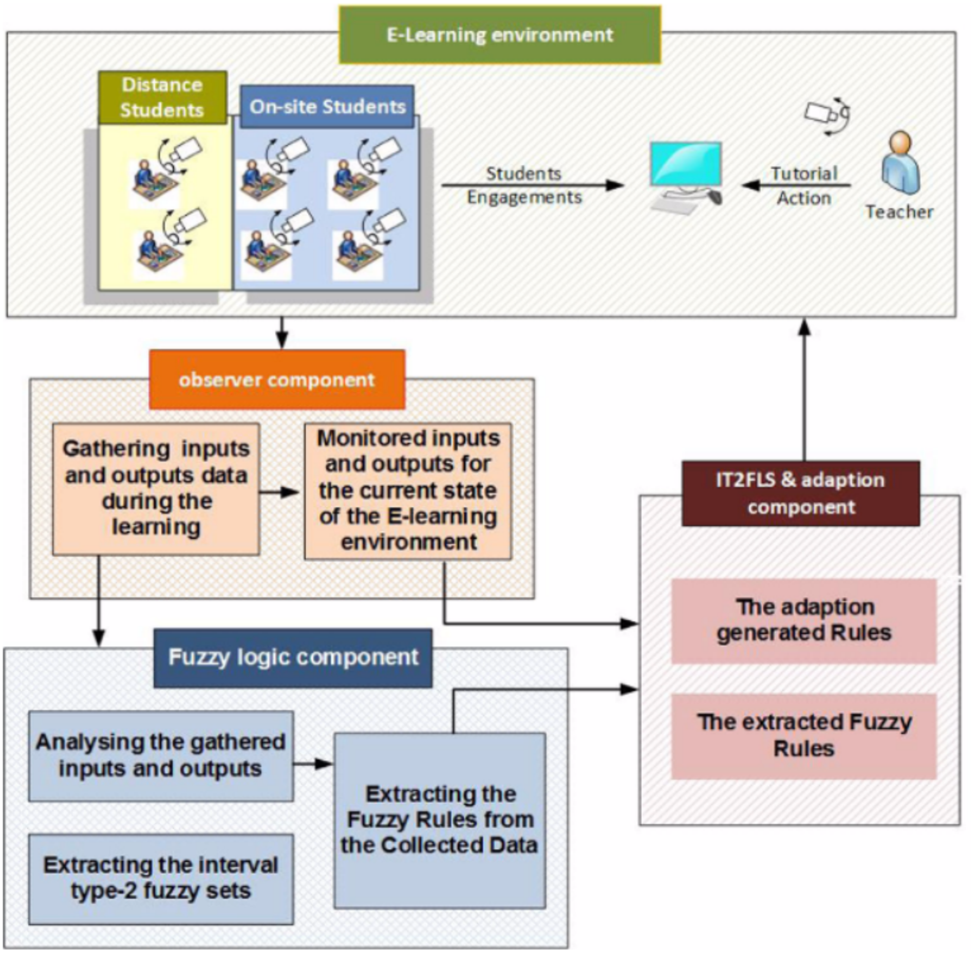


Fig. 2.2 The system architecture for Almohammadi et al. ITS [39]

The system architecture for CRISTAL systems (shown in Figure 2.3), spans across real world and simulated environment. Learner and consultant work in the real world environment; the learner sends a report to the consultant and the latter sends direct feedback back to the learner. In addition, all of the reports as well as the related corrections are stored in a database. Hence, the collected data is used to build a learner model. The training module utilises the learner model to adapt the learning tasks in the real world [40].

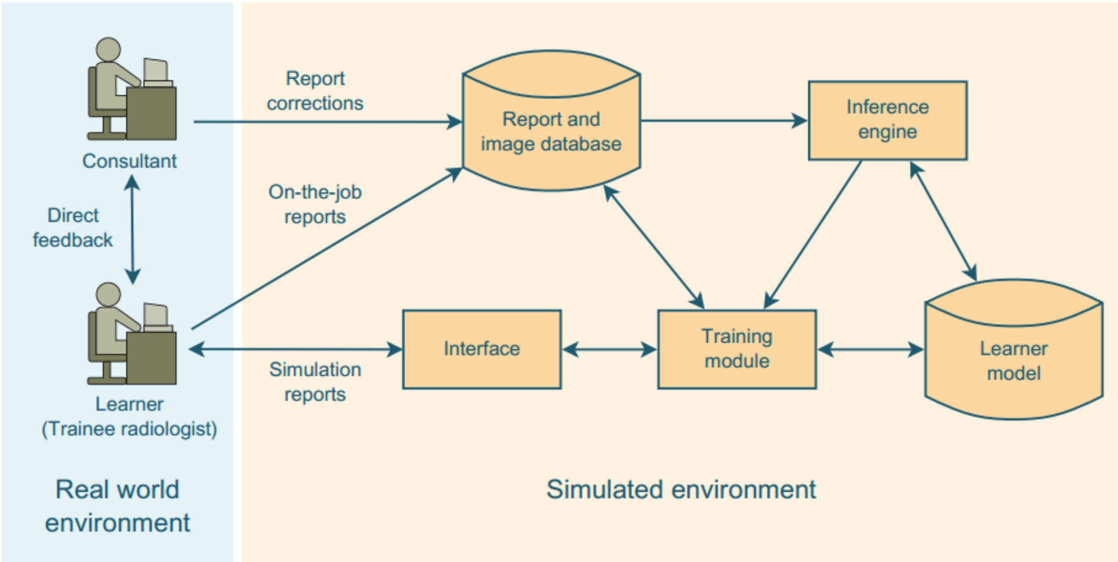


Fig. 2.3 The system architecture for CRISTAL system [40]

Figure 2.4 shows the system architecture for iRead system which is a collaborative reading environment. The system enables readers to read a text and analyses the annotations made by each reader to build a personality profile for each reader [41].

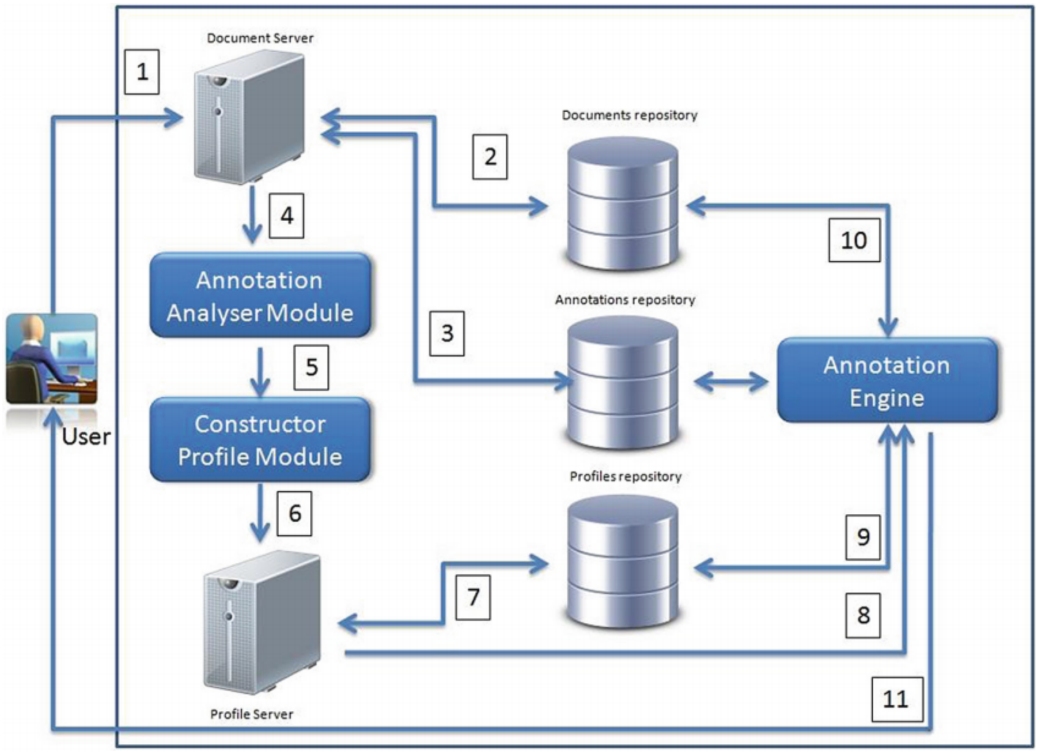


Fig. 2.4 The system architecture for iRead system [41]

2.2.3 ITS and E-Learning

The integration of ITS and e-learning on the web overcomes the limitations of both systems. This can be done by providing ITS with large scalability, accessibility, re-usability, allowing both local and distributed crowd users, standardisation, and updatable learning resources [42]. ITS can solve the limitations of e-learning such as the problems of a "one-size-fit-all" approach and any lack of learning and cognition by supplementing the students' observing and diagnosing techniques and learning from their behaviours to personalise their individual learning. Active Math and iHelp are examples of these integrated systems. They adapt the learning objects, which are compatible with SCORM[1], utilising ontology-based, semantic

[1] Sharable Content Object Reference Model (SCORM) is a collection of standards and specifications for e-learning

web and data mining methods [9], [42]. In addition, the benefits of the ITS have attracted some researchers to study the way of making their e-learning systems more intelligent as in [26].

2.2.4 ITS and Machine Learning (ML)

ML is a sub-domain of computer science which stemmed from the study of computational learning theory in artificial intelligence and pattern recognition. It refers to a system's ability to acquire new knowledge through large-scale observations rather than by being explicitly programmed with that knowledge [43]. ML techniques can be utilised in ITS to identify optimal teaching strategies [39], [44], acquire some new knowledge about students, infer some of their hidden characteristics and identify their skills [45], [46], [47], [48]. Moreover, they are utilised to enhance the computer's responses [49], [50] and detect unexpected behaviours [51]. These techniques can enhance teaching by observing students' learning behaviours and generating rules about the students or domain. In addition, these techniques benefit ITS by promoting their flexibility, minimising their cost, adapting to new students, learning about human learning, and reasoning under uncertainty. In a massively crowded educational environment, teachers are incapable of encompassing all the students'different learning needs and levels of knowledge, and there is no one-for-all teaching strategy that they can follow to ensure that their students make the awaited progress or achieve the desired outcomes. This uncertainty highlights how paramount it is to rely on machine learning, which can be governed by a constant self-evaluative and self-improving process based on the behaviour of massive crowds of learners [9]. Although the use of ML techniques in ITS looks promising, they have some limitations, such as the risk of failure (e.g. misleading students), which necessitates utilising them with a caution [52], and the ambiguity of why and how ML techniques work in terms of learning [9]. Another limitation is that modelling human learning is not an easy task. ML techniques try to recognise patterns in human learning, but these patterns do not necessarily have an obvious semantic component, do not easily translate into cognitive models of human capability, and are not easily validated in epistemological terms [9].

2.3 Adaptive Educational Systems (AES)

Many existing e-learning systems follow a "one size fits all" approach where the system ignores the differences between students in their levels of knowledge, previous experiences, preferences, abilities/disabilities, preferred learning style(s), affective variables and learning goals [53]. This may negatively influence the students' motivation and may result in them dropping out of their course [54], [55]. However, adaptive educational systems try to overcome this issue by personalising the students' learning experience, often utilising artificial intelligence algorithms and soft computing techniques [56] [57]. Hence, these systems can observe students' learning behaviours, collect data and deduce rules from these data to be used by a pedagogical tutor agent. Furthermore, these systems adapt the course to different variables, which include learner variables (e.g. cognitive abilities, metacognitive skills, learning style and affective states) and instructional variables (e.g. feedback given, sequencing of content, "scaffolding" approaches and different views of the material) [58]. These systems are similar to ITS in terms of benefiting from artificial intelligence. However, AES focus more on adapting navigation support, knowledge representation and learning style [59], [60].

2.3.1 Adaptive Learning Path

The adaptive learning path or the adaptive course sequencing aims to generate a personalised course for individual students by dynamically choosing the most suitable sequence of lessons

[61], [62], order of questions/problems (task sequencing) [63], [64], [65], [66], or sequencing teaching operations [67], [68].

To date, some research has been conducted to investigate the issues related to content sequencing. For example, Idris et al. [69] were motivated to avoid the use of rule-based adaptation since it needs much cost and effort. They did not identify the adaptation model as a repository containing rules for adaptation. Rather, they identified it as a model employing soft computing techniques to sequence and select the learning object[2]. They clustered the learning objects based on related concept(s). To achieve this, they trained the system with 129 learning objects. At the beginning, domain experts were asked to value the relevance of each learning object to each concept; 1 if the concept is closely related, 0.5 if the concept is slightly related and 0 if it is not relevant. Then they utilised a self-organising map (SOM)[70], which is an unsupervised neural network technique, to cluster the subsequent learning objects into groups based on the similarity of the concepts in the learning objects. They then addressed the issue of choosing the most appropriate set of learning objects related to the student's knowledge level as a classification issue. Thus, they utilised Artificial Neural Networks (ANN) to classify the learning objects that best suited the student based on his/her mastery knowledge level of each concept. The limitations of this research were that they did not concentrate more on the issue from the point of view of the student model/profile as there was uncertainty in some of the students' characteristics, such as the level of knowledge. In addition, their work can be seen as suggesting a set of learning objects rather than sequencing them.

Brusilovsky and Vassukeva [56] discussed how the traditional sequencing technology of an ITS can be applied in large-scale web-based education. They introduced three approaches for answering this question. The first approach was to use sequencing mechanisms for testing if the "next step" predefined by the instructor was a good choice or not. This approach can help in exploring whether the assessment undertaken by a student requires knowledge

[2] It seems to the author that they mixed the concept of the agent and the model.

that has not been studied yet. The drawback of this approach is that it does not provide a personalised and adaptive sequencing of the materials for the students. The second approach was adaptive generation of courseware, which aimed to adaptively generate the whole course in “one shot” before the students started learning. The limitation of this approach is that the generated courses are not really very adaptive, since they are never re-sequenced (if needed) at run-time. Their last approach was called dynamic courseware generation, and it aimed to generate a personalised and adaptive sequencing of a course. The advantage of this approach is that it dynamically “re-plans” the course if the student does not perform as expected. However, the shortcoming in Brusilovsky’s and Vassukeva’s work is that it did not study the ways of guiding students through the learning path. In addition, their work relied on predefined sequence choices. This method overloads teachers and instructors, although the machine learning technique can help in releasing some of the load by observing students and hence generating sequencing rules. Another limitation is that whilst they explained that the first approach could be used for reporting the appropriateness of the next step in the sequence, they did not however explain how the teachers could access the sequencing rules to solve the reported issues.

Karampiperis and Sampson [71] aimed to imitate the procedures done by instructors to construct the learning path utilising a statistical approach. Their method required the instructors firstly to rate the importance of each piece of learning content to the student. The adopted algorithm then, presented the potential learning paths and chose the appropriate one for the student’s preferences and cognitive characteristics. This proposed approach is not effective with systems that have a very large number of items of learning content.

Semet et al. [72] utilised ant colony optimisation for producing the optimal learning path for a student. The learning contents were presented as nodes in a navigation graph. The nodes were linked to each other, with arcs representing as hypertext links. The proposed approach automatically and gradually modified the learning path based on the evaporation of the "virtual pheromones", which reflected the success/failure of learners modelled roaming around the graph [72].

Vassileva [73] proposed a prototype system called ADOPTA which aims to adaptively deliver the learning content based on the individual student's performance and learning style. In addition, ADOPTA has tools that facilitates the process of creating the learning content. ADOPTA considers supporting the adaptability to the student's preferred learning style(s) and his/her learning objectives which were missing in the most of the prior works. In terms of evaluating the effectiveness of ADOPTA, a number of 49 students used ADOPTA to study XML course. Their results were compared with a number of 42 students who studied the course without using ADOPTA. The results indicated that the average result for Students who used ADOPTA was 77.9%. Whereas, the students who studied in non-adaptive method got 67.1%. This indicated how much is ADOPTA effective. However, I believe that students could gain more knowledge if they could choose the preferred way of guidance through the suggested sequencing. Moreover, instructors overloaded with extra work when they were asked to create the needed adaptive rules. Nevertheless, machine learning techniques can produce adaptive rules which in turns will release burden on instructors.

Although various technologies have been used to tackle the issues surrounding different possible course sequences, there is still a need for conducting research in this area [74]. One of the issues that needs more investigation is the way of delivering the suggested sequence of materials and guiding students through it. The previous studies did not discuss this issue although it is very important. Some research questions as what the students' learning needs and preferences towards the guidance modes are, how to meet the variable learning needs and preferences of individual students and whether students' learning gain improves when allowing them to control the amount of assistance received. Another gap in the previous studies is the lack of investigating the issue from the teachers' point of view. This requires making the ITS more controllable, flexible and adaptable for the teachers, so, they can access the adaptation model, which stores the sequencing rules, and make changes at the run-time without disrupting the learners. Moreover, there is a shortage of studies of the best way of relying on the tutor agent to produce the sequencing rules by learning from learning behaviours of the crowd of students. This involves exploring the way of managing the teachers' and the tutor agent's roles. Thus, this thesis was motivated to overcome these gaps by utilising adjustable autonomy, which will be explained in the next section.

2.4 Autonomy and Adjustable Autonomy

The agents allow us to utilise technology that, in addition to acting on our behalf, has a meaningful aim and can learn new actions or reject certain actions by reasoning about its own actions. This in turn has contributed to the advancement from automatic systems to autonomous-agent ones which are capable of not only doing the actions themselves but also adapting these actions based on the contextual circumstances [75], [76]. According to Hexmoor et. al., agents are known to have a certain level of autonomy [77]. Wooldridge and Jennings defined autonomy as when*"agents operate without the direct intervention of humans or others, and have some kind of control over their actions and internal state"* [78]. Maes defined autonomous agents as *"computational systems that inhabit some complex dynamic environment, sense and act autonomously in this environment, and by doing so realise a set of goals or tasks for which they are designed"* [79]. Brustoloni defined them as *"systems capable of autonomous, purposeful action in the real world"* [80].

Hexmoor et al. considered two types of interaction for the study of autonomy. The first one is the human and machine interaction, where the agent acquires the actions and adapts them to suit the human preferences. In this case, the human is usually the reference point for the agent. In this sense, a device is said to be autonomous if it faithfully implements the actions required by the human and has access to all the human choices. The second type is the interaction between a group of agents [77], which is out of the scope of this thesis.

Autonomy is often viewed as the degree of separation of an agent to the human user with respect to the user-centric systems. Beale and Wood described the autonomous agents as being *"able to work on behalf of their user without the need for any interaction or input from the user. They act without your presence, tirelessly performing tasks"* [81].

The obvious question concerns the amount of autonomy which is aimed to be achieved in a computer system. The answer depends on the kind of task at hand, the application domain specifics, and the abilities of the agent. According to Barber and Martin (Figure 2.5), an agent can operate over the spectrum from 0 to 1 in three discreet autonomy levels which are:

1. Command-driven (Zero on the spectrum): In this level there are no decisions made by the agent in pursuit of its goal and it needs to obey orders given by other agents.

2. True consensus: The agent along with other decision making agents work as a team with an equal decision making control.

3. Locally autonomous/master (one on the spectrum): The agent makes decisions on its own and has the option to give or not give orders to other agents [82].

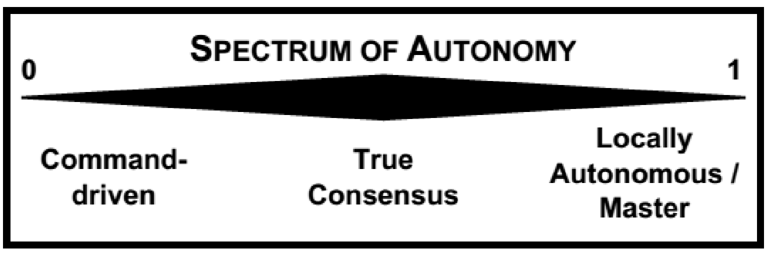


Fig. 2.5 The autonomy spectrum suggested by Barber and Martin [82]

The Interface Proactivity (IP) continuum was defined by Isbell and Pierce while studying adaptable user interfaces and is shown in Figure 2.6. The IP continuum shows the potential balances of proactivity between the system and the user. The term "proactivity" is used by

Isbell and Pierce for describing the relationship between the system and the user in terms of their responsibility for the actions required to be undertaken for achieving a certain goal. It should be noted, however, that their work does not focus directly on the levels of autonomy but their interface proactivity could rather be viewed as a continuum of agent autonomy. On the left side of the continuum is the Do It Yourself where the user is solely responsible for the performance of all the actions and completion of the tasks. On the right side of the continuum the system has more responsibilities in the performance and achievement of actions and tasks to the degree to which it can actively come to decisions and possess the responsibility to perform and complete the entire task. With respect to the continuum, the system has the maximum autonomy at this point. There are differences in the intermediate level with respect to the amount of assistance received by the user in the form of information, suggestions and directions [83].

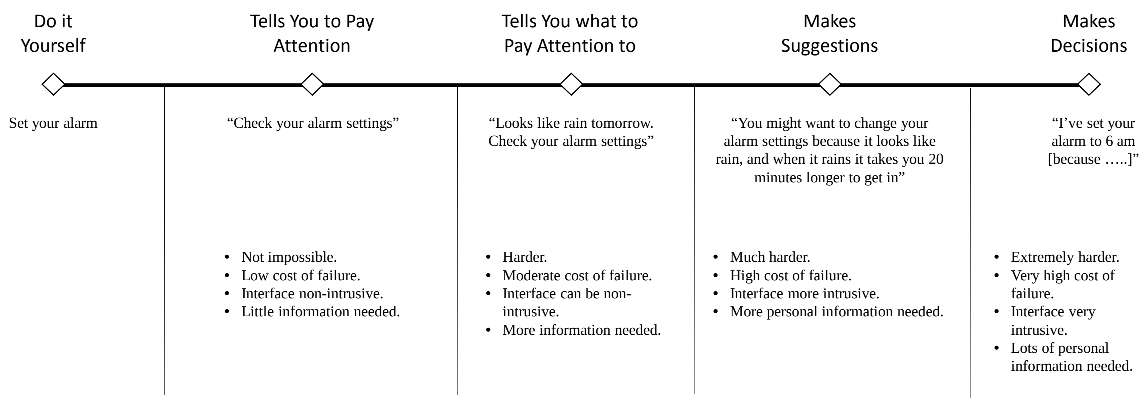


Fig. 2.6 The distribution of the potential next-generation alarm clock along the IP Continuum

Isbell and Pierce give an example of how the IP Continuum can be used to describe different levels of proactivity of an alarm clock system. The research by Isbell and Pierce is basically focused on the adaptive user interfaces. Their level of description of the degrees of proactivity along with the IP continuum has a more user centric view in relation to the autonomy spectrum by Barber and Martin. Autonomy is viewed with respect to the IP continuum to an agent or system that provides assistance to the user other than taking a supervisory role. It has the capacity to provide substantial insights to the distinct levels of autonomy at the user interface level.

Decades ago, Sheridan and Verplank [84] developed the levels of Human-Automation Interaction with consideration to semi and full automation. The work was advanced by Parasuraman et al. [85] with ten-point scales of automation (Table 2.1) catering for both decision making and action selection criteria. The scale provides a conceptual framework for considering what types and levels of automation ought to be implemented in a given system. In the scale, the higher the point up on scale the higher the automation in the systems and vice-versa. The premise of Parasuraman et al. [85] is the distinction on how automation is applied at various functional levels of the computer system. In this scheme, various functional levels such as information acquisition, information analysis, decision selection, and action implementation are automated at different levels on the scale. This is practically understood in the aspect of governance, which involves learning new actions, evaluating performance as a result of some action, and adopting the decision to re-learn based on the evaluation. This aspect of the system therefore requires a highly autonomous mechanism in intelligent environment in order to enable dynamic adaptation to changing conditions [76].

Table 2.1 Levels of automation of decision and action selection [85]

High	10	The computer decides everything, acts autonomously, ignoring the human
	9	Informs the human only if it, the computer, decides to
	8	Informs the human only if asked
	7	Executes automatically then necessarily informs the human
	6	Allows the human a restricted time to veto before action execution
	5	Executes a given suggestion if the human approves
	4	Suggests one alternative
	3	Narrows the selection down to a few
	2	The computer offers a complete set of decision/action alternatives
Low	1	The computer offers no assistance, human must take all the decisions and actions

Another scale for levels of autonomy was introduced by the US Army Future Combat System (FCS) (see Table 2.2).

Table 2.2 The scale for the US Army Future Combat System (FCS)[86]

Level 1 (Manual Operation) • The human operator directs and controls all mission functions. • The vehicle still manoeuvres autonomously.
Level 2 (Management by Consent) • The system automatically recommends actions for selected functions. • The system prompts the operator at key points for information or decisions.
Level 3 (Management by Exception) • The system automatically executes mission-related functions when response times are too short for operator intervention. • The operator is alerted to function progress. • The operator may override or alter parameters and cancel or redirect actions within defined time lines. • Exceptions are brought to the operator's attention for decisions.
Level 4 (Fully Autonomous) • The system automatically executes mission-related functions when response times are too short for operator intervention. • The operator is alerted to function progress.

There was production of a similar form of autonomy by Proud et al. that divided the system into four functional stages. Their research was based on the human space flight vehicles for the next generation [87]. Their system was divided into Observe, Orient, and Decide or Act (OODA) loop approach. They were utilised in the description of high level abstraction of the system's operation despite being designed for military combat operations process [88]. Gathering, monitoring and filtering of data was referred to as the observe functionality. On the other side, delivering a list of options with the help of trend prediction, analysis, integration and interpretation was referred to as the orient category. Decision making with respect to ranking of the available options was the decide functionality. Authority or execution of an act on the available option was referred to as the Act category. A set of eight distinct levels of autonomy were defined by Proud et al. with respect to each functional stage of the OODA loop [87] as indicated in Table 2.3. There was relative consistency in the different levels across the distinct phases. According to Proud et al., the levels were subdivided into three distinct sections. The user usually had higher authority than the authority in levels 1 and 2; the computer operated with respect to the interactions of the user in levels 3 to 5. The computer was completely independent in levels 6 to 8 while the user had a limited access to the override capability and information. In general, the levels description was the same as the 10-point scale of Parasuraman et al. However, they had further details on individual functional stages of the system instead of a single generalised scale.

Table 2.3 Proud et al. level of autonomy assessment scale [87]

L	Observe	Orient	Decide	Act
8	The computer gathers, filters, and prioritises data without displaying any information to the human.	The computer predicts, interprets, and integrates data into a result which is not displayed to the human.	The computer performs ranking tasks. The computer performs final ranking, but does not display results to the human.	The computer executes automatically and does not allow any human interaction.
7	The computer gathers, filters, and prioritises data without displaying any information to the human, though a "program function" in flag is displayed.	The computer analyses, predicts, interprets, and integrates data into a result which is only displayed to the human if the result fits the programmed context (context dependant summaries).	The computer performs ranking tasks. The computer performs final ranking and displays a reduced set of ranked options without displaying "why" decisions were made to the human.	The computer executes automatically and only informs the human if required by context. It allows for override ability after execution. The human shadows for contingencies.

L	Observe	Orient	Decide	Act
6	The computer gathers, filters, and prioritises information displayed to the human.	The computer overlays predictions with analysis and interprets the data. The human is shown all results.	The computer performs ranking tasks and displays a reduced set of ranked options while displaying "why" decisions were made to the human.	The computer executes automatically, informs the human, and allows for override ability after execution. The human shadows for contingencies.
5	The computer is responsible for gathering the information for the human, but it only displays non-prioritised, filtered information.	The computer overlays predictions with analysis and interprets the data. The human shadows the interpretation for contingencies.	The computer performs ranking tasks. All results, including "why" decisions were made, are displayed to the human.	The computer allows the human a context-dependant restricted time to veto before execution. The human shadows for contingencies.

L	Observe	Orient	Decide	Act
4	The computer is responsible for gathering the information for the human and for displaying all information, but it highlights the non-prioritised, relevant information for the user.	The computer analyses the data and makes predictions, though the human is responsible for interpretation of the data.	Both the human and the computer perform ranking tasks, and the results from the computer are considered prime.	The computer allows the human a pre-programmed restricted time to veto before execution. The human shadows for contingencies.
3	The computer is responsible for gathering and displaying unfiltered, unprioritised information for the human. The human is still the prime monitor for all information.	The computer is the prime source of analysis and predictions, with the human shadowing for contingencies. The human is responsible for interpretation of the data.	Both the human and the computer perform ranking tasks, and the results from the human are considered prime.	The computer executes decisions after human approval. The human shadows for contingencies.

L	Observe	Orient	Decide	Act
2	The human is the prime source for gathering and monitoring all data, with the computer shadowing for emergencies.	The human is the prime source of analysis and predictions, with the computer shadowing for contingencies. The human is responsible for interpretation of the data.	The human performs all ranking tasks, but the computer can be used as a tool for assistance.	The human is the prime source of execution, with the computer shadow for contingencies.
1	The human is the only source for gathering and monitoring (defined as filtering, prioritising and understanding) all data.	The human is responsible for analysing all data, making predictions, interpreting the data.	The computer does not assist in or perform ranking tasks. The human must do it all.	The human alone can execute decisions.

Adjustable autonomy emerges from the underlying concept of autonomy which is centred on building a set of actions, the relationship between the actions, respective scopes of each action, and the associated logical constraints governing the actions [89].

In Figure 2.7, the degree of autonomy is shown by the number of nested relationships between various actions; the nesting of regions defines the degree of autonomy and also enforces the logical constraints that govern the relationship between allowable actions. This way, actions are only obligated to perform actions that they are permitted to do. Another important aspect described in Figure 2.7 is the theoretically possible actions that could be taken by a maximally autonomous agent. Most of the actions defined are performed by agents in concert with other actions. For each agent, the range of the obligatory constraint controls how free the agent is. Agents with smaller sets of obligations and larger ranges of permitted actions are expected to act more freely and vice-versa [89]. Each of the concepts described above are modified to achieve a different autonomy of an agent – hence the concept of adjustable autonomy.

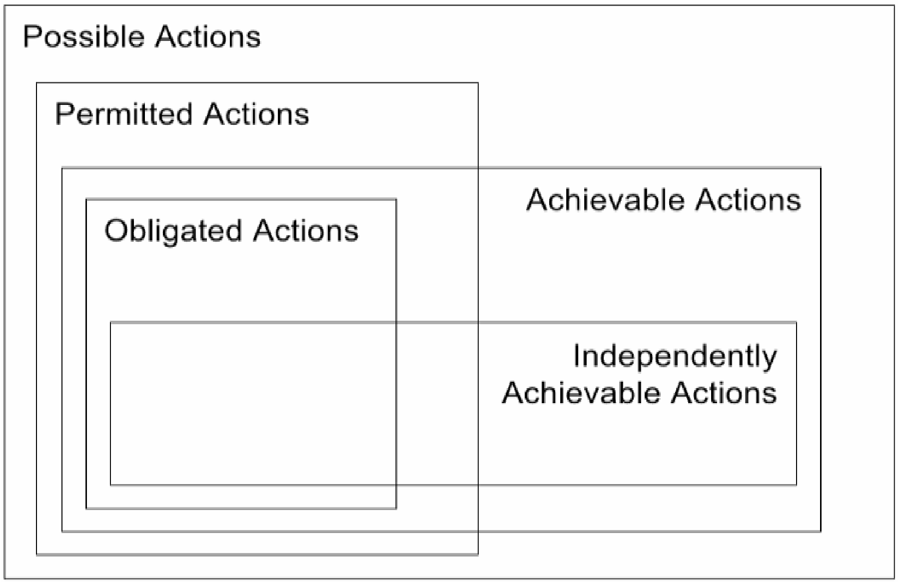


Fig. 2.7 Degrees of autonomy corresponding to varying nested ranges of action available to an agent [90]

The desired adjustment to the level of an agent's autonomy can be undertaken by a human, an agent, or by some third party. There are various aspects of this adjustment and one of them is the type or complexity of tasks or functions that an agent is permitted to execute [89]. Another aspect is the decisions about the specific function or task which are allowed to be controlled autonomously. The circumstance under which an agent will override manual control is another aspect of this adjustment. Furthermore, adjustment is also defined by the duration of the autonomous operation and the circumstances under which manual guidance is required [91]. Bradshaw et al. also formulated a general method for adjusting the autonomy of an agent that works by adjusting permissions, changing obligations through assigning new tasks and withholding already existing tasks assigned to and from the agent, restricting possible actions, and finally adjusting the functional capabilities of the agent [92].

Generally all the methods have the capacity to offer an approach for either forcing an agent to perform or prompting the agent to stop the performance of specific tasks, hence allowing alterations from the user based on its ability and performance. As specified in the previous definitions, autonomy relates at least to two actors. This means that the adjustment of an agent by the four dynamics requires another actor or agent to perform the tasks that have been stopped from the original agent, hence limiting its autonomy. In order to increase its autonomy, the agent requires performing certain actions on behalf of another actor. The effectiveness of the system depends on the balance of autonomy in the entire system, where this balance requires a certain level of autonomy which can be enhanced by allowing third parties to focus on the balance of autonomy or agents to work on it or handing the task to the user. There is a need for a specific mechanism that enables the delegation of tasks by the users and agents in addition to the capacity to partake in shared tasks and joint activities.

As identified by Bradshaw et al., a major challenge in adjustable autonomy is the requirement that the degree of autonomy is continuously and transparently consistent with declared policies ideally imposed and removed appropriately when desired. Bradshaw et al. also introduced the concept of “sweet spot”. According to this concept, an autonomous system is governed in a way that promotes the convenience to delegate work and the assurance of delegating such work to a trusted system with a minimum risk of failure [89].

Various researchers in the robotics and artificial intelligence field have studied the idea of adjustable autonomy while attempting to find out the mechanisms applicable in the computer systems and agents to enable the adjustment of their autonomy during running. Previous research consists of a variety of instances of successful adjustable autonomy systems in the robotics and artificial intelligence field. There was development of an adjustable autonomy system by Brookshire et al. for a coordinated robotics team that would allow for human intervention in tasks [93]. Three robots were utilised in their system with the attempt to place a suspended beam on two separate supports. Their system was designed in such a way that human beings have the capacity to take control of certain tasks with respect to the following instances: for pre-specified tasks, which are perceived as complex for the robot; if the robot does not complete the task but requests for help from the user; when the user wishes to intervene maybe for time management or fear of the robot making a serious mistake [94].

Dias et al. pay attention to adjustable autonomy for systems based on team work, where users, robots and agents share a peer to peer relationship based on a common goal [95]. Team members in their systems are picked up on the fly with respect to their knowledge and abilities in a task. The adjustment of autonomy deals with a mechanism of task sharing and task delegation with the aim of developing the most effective team through assigning the task to the most preferred team member. A "treasure hunt" scenario was utilised in Dias et al. for testing their adjustable autonomy system. The primary tasks included here were searching, mapping and localisation of treasure in addition to retrieval of treasure to a native location. Since a single member of the team could not complete the task on their own, there needed to be delegation to different members. If a team never completed a certain task due to various reasons, they were allowed to request for help from another team member for completion on their behalf. Delegating tasks is viewed as a very palpable approach of adjusting autonomy. Delegating a task to an agent translates it to possessing full autonomy based on that specific task in addition to having a certain level of autonomy based on the entire goal which needs a number of tasks for completion. Recently, a study [76], [96], [97], [98], [99], [100], [101] at the University of Essex designed and built a smart home autonomous system which collaborates with users to manage tasks common in homes. They formulated an Adjustable Autonomous Intelligent Environment (AAIE) model to enable adjustable environment in governance (see Figure 2.8). The Context Agent (CA) observes the user's action using the sensor readings. When there is a change in the environment's status, (CA) passes the required data to the Adjustable-autonomy Behaviour-Based Agent (ABBA) which uses this data for generating new rules or deciding which actions should be performed. Then the Coordinator of ABBA instructs the Action Agent (AA) how to drive the devices and actuators in the physical environment. The Interface Agent (IA) has GUI interface that allows the user to communicate and control the physical environment. ABBA has these components: two sets of behaviour rules and the behaviour arbiter, the coordinator, the learning component. Furthermore, the behaviour arbiter is responsible for classifying the rules into potential rule or active rule based on the rule confidence level.

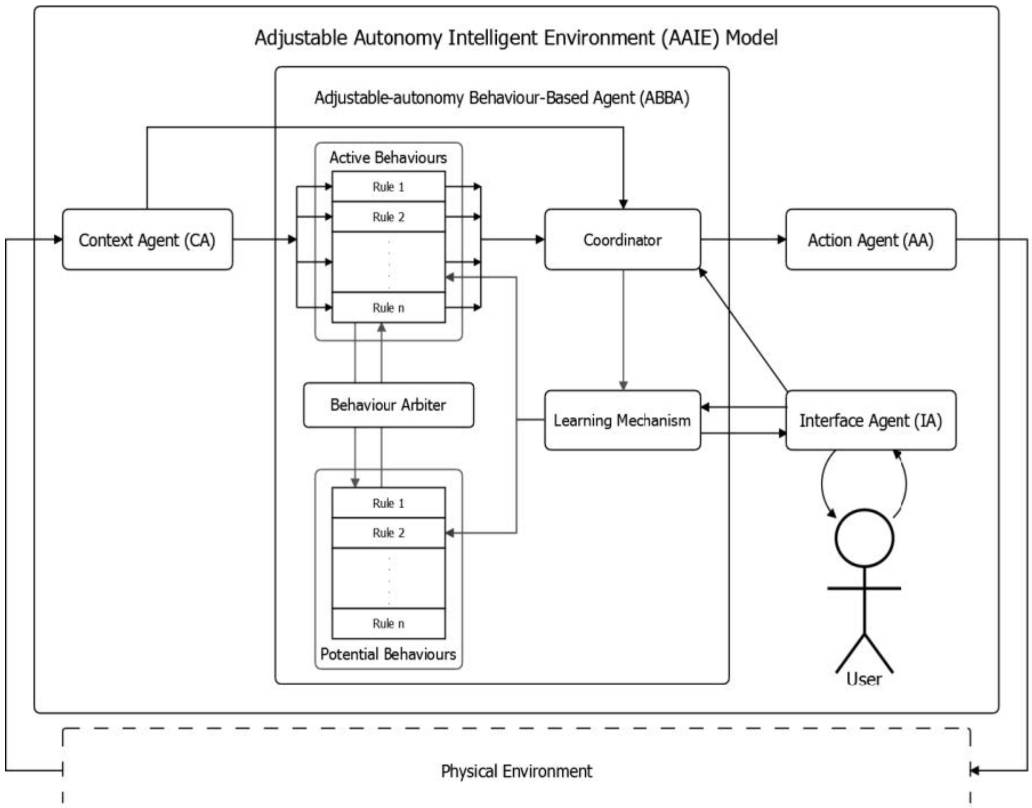


Fig. 2.8 The Adjustable Autonomy Intelligent Environment (AAIE) Architecture Model made by Matt et al. [101]

They categorised four levels of adjustability as full, high, low, and no autonomy. The agent manages the home in full autonomy, allows a user to manage the home completely, or in a semi-autonomy using mixed-initiative interaction. In details, in full autonomy, agents learn from user behaviour as a result of interaction, automatically create rules from the learnt observation, and adapt the rules overtime to achieve the desired objective. High or Semi-autonomous with high autonomy differs slightly from full autonomy in that it requires the confirmation of dynamically generated rules by the user. This way, users can accept, reject, or edit the rules generated by the agent. In low or semi-autonomous with low autonomy, the user is assisted by the agent with a suggestion to aid in generating the rules using an interface such as GUI. The end user driven or no autonomy is similar to low autonomy with the added difference that the user generates the rules without any assistance from an agent. As evident above, by enabling adjustable autonomy in an intelligent environment, users are equipped with the capability to change the control available for them and for autonomous agents. The choice of control is generally shaped by attitudes, devices, and agents of the systems. Other factors that shape the choices are the concerns of users, and the next paragraphs explore this in detail.

Various survey results indicate the usefulness of adjustable autonomy management systems for an intelligent environment. Differences in styles, user preference, trust, and dynamic control of autonomy level constitute the major findings as reported by many results [98]. A typical example in the survey is that people prefer a higher level of control over personal systems such as entertainment and a lower level of control over systems such as heating and lighting, which are not associated with a particular user experience and perception.

The results of the quest for a trade-off between autonomous agents, direct control, and assurance indicate that people differ in the level of autonomy in different contexts and for different sub systems of intelligent environment. However, it is worth mentioning that these views may drastically change overtime [101]. In understanding the attitude and preference of users toward an intelligent environment, the study identified many factors which include the issues of user control, privacy, cognitive workload, realistic reliability of the agent, and the cost of failure. These issues reaffirm the need to employ adjustable autonomy mechanisms in intelligent environments. Such mechanisms should, among other things, allow users to ascertain the trade-off between achieving convenience with higher autonomy and control over the lower autonomy in a way that realises their desired objective [100].

On the other hand, mixed-initiative systems aim to offer agents the capability to dynamically and flexibly assume different roles, given the task to perform and the current situation [102], [103], [104]. This goal is conceptually supported in adjustable autonomy by developing the understanding required for an agent to operate optimally at the boundary between the agent and the human operator for any given context. To the users of adjustable autonomous systems, the boundary is maintained through reaching an acceptable trade-off between minimum interaction and the assurance that the system will not fail [89]. This concept of automaticity and assurance is furthered by other researchers to the investigation of a more dynamic approach to agent autonomy through the creation of the desired adjustable-autonomous system, which guarantees the personal objective of allowing agents to govern the system and the significance of maintaining a direct control. It is widely acknowledged that assuming absolute reliability on any system is not realistic, and computers, intelligent agents, and machines are expected to fail at some point [101].

2.5 Fuzzy Logic

Fuzzy logic is a common technique for user modelling with the capacity to imitate human reasoning with the help of natural language where words could translate to ambiguous meanings [105]. Professor L. A. Zadeh of the University of California came up with the idea of fuzzy logic at Berkeley in 1965, which led to publishing a landmark paper referred to as Fuzzy Sets [106].

Fuzzy Logic has attracted attention owing to its ability to handle uncertainty, such as defining the relationship between concepts in the domain model and attributes in the student model [107], [108]. In addition, Fuzzy logic has the ability to generate human-readable rules. This can help systems' users to understand and alter the rules easily [109], [110], [107]. For these reasons, Fuzzy logic became the appropriate choice to be adopted in this thesis.

2.5.1 Fuzzy Logic Components

Figure 2.9 represents a typical fuzzy logic system which is made of three major components: fuzzifier, fuzzy inference engine and defuzzifier. Crisp inputs are converted by the fuzzification module into fuzzified inputs. The fuzzified inputs are also called fuzzy sets. They then go through the inference engine for application of linguistic rules (in the form of If-Then). A collection of fuzzy conclusions makes up the output of the inference engine. These fuzzy conclusions are converted into crisp output by the defuzzication module [111].

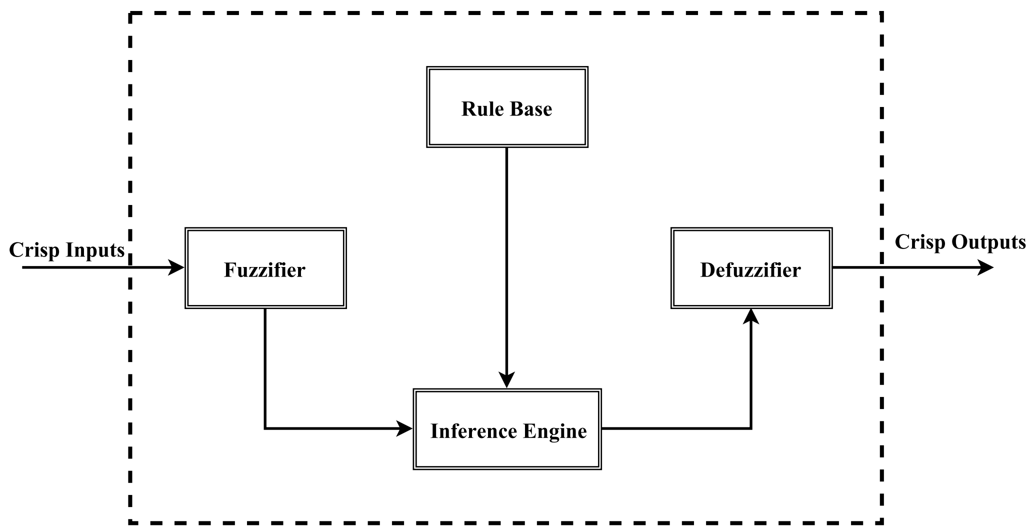


Fig. 2.9 Fuzzy logic system

Fuzzifier

The initial step in the application of a fuzzy inference system is fuzzification. Two processes are generally involved in fuzzification: the membership of the input and output variables is derived and then they are represented with linguistic labels. This process is similar to mapping or converting classical sets to fuzzy sets in distinct degrees. There is conversion of the fuzzy sets into an equal shape of the membership function. The level to which a certain input parameter belongs to the output fuzzy sets is represented by the curve values of the membership function [112],[113].

The membership function adapts various forms: bell curves, trapezoids, triangles or any other shape provided it is a representation of the distribution of information. For instance, three values could be used to characterize the triangular shape of the fuzzy sets: left boundary (L), centre (C) and right boundary (R). The formula (2.1) is used to calculate the membership value of x on A the triangular fuzzy subject for a crisp input value x [111].

$$\mu_A(x) = \begin{cases} (x-a)/(b-a) & a \leq x \leq b \\ (c-x)/(c-b) & b \leq x \leq c \\ 0 & otherwise \end{cases} \tag{2.1}$$

Figure 2.10 shows a fuzzy set with five membership functions in a triangular shape. The element whose level of membership in the given set is equivalent to 1 represents the core of a fuzzy set. The boundary of a fuzzy set shows the extent to which all elements with their level of membership in the particular set are between 0 and 1 (in exception of 0 and 1) [112]. The fuzzy control rule is defined after the definition of the membership functions for both input and output.

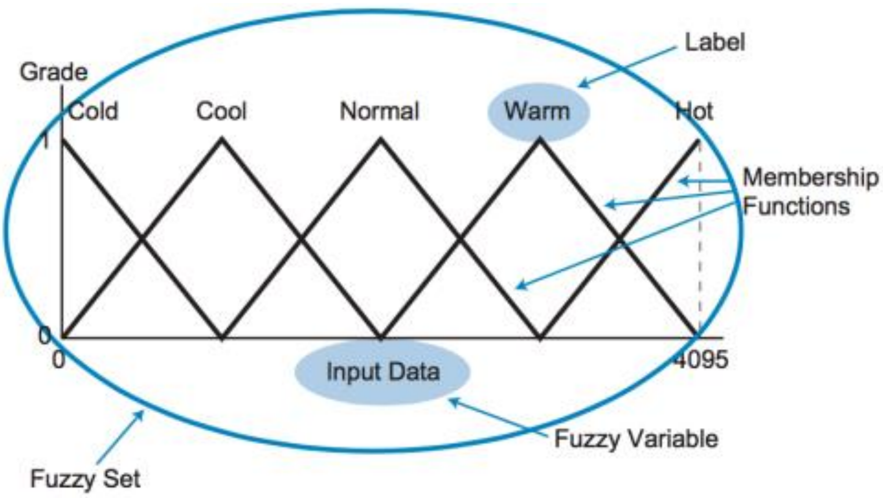


Fig. 2.10 Membership function in a triangular shape [114]

Fuzzy Inference Engine

Knowledge is represented in distinct forms with respect to artificial intelligence. Human knowledge can be expressed with utilisation of the natural language expressions such as:
IF premise (antecedent), THEN conclusion (consequent)
Fuzzy logic utilises the inferencing or reasoning process, which is made of IF-THEN rules each giving an outcome or response. A fuzzy rule represents a simple IF-THEN rule with a condition and a conclusion [111]. There is a collection of IF-THEN rules in a fuzzy inference engine that are learnt with the help of automated approaches like learning from examples (LFE) or obtained from experts. This thesis utilises both techniques, which are to be discussed later. The inputs provided by the fuzzifier (the membership values) are applied to antecedents of the fuzzy rules (i.e., the output). Fuzzy set operations like OR (union) and AND (intersection) are used to evaluate the fuzzy rules and the combination of the outcomes of individual rules. Basically, there is activation of a rule if an input condition is sufficient to the IF part of the rule statement. The outcome is a control output based on the THEN

part of the rule statement. There is activation of more than one rule simultaneously in the FIS controller process. The controller in this case evaluates all the triggered rules so as to derive a single outcome value before proceeding to the defuzzification process. Figure 2.11 (a) indicates one fuzzy output Y_1 and two fuzzy inputs X_1 and X_2. Figure 2.11 (b) indicates a representation of the nine possible rules that cover the two inputs. The four in the figure fully represent the four activation points for the two input readings X_1 and X_2. With respect to the input values in Figure 2.11 (a), rule 1 will be triggered by the inputs since $X_1 = ZR$ AND $X_2 = NL$. Two outputs will hence be generated for $Y_1 = NL$ where one will be at a grade of 0.6 (with respect to the input value of X_1) the other will be at a grade of 0.75 (based on the value of X_2). Considering a fuzzy logic situation where two outcome values are produced by an AND relationship and a two-input rule, the controller selects the outcomes showing the lowest grade which is 0.6NL in this case as indicated in 2.11 (c) [114].

Defuzzifier

This component is responsible for converting the fuzzy output to crisp output in order to make it available to real applications. In some cases, there is no need for mapping the fuzzy output to crisp output which makes this component optional (as in fuzzy reasoning systems) [115].

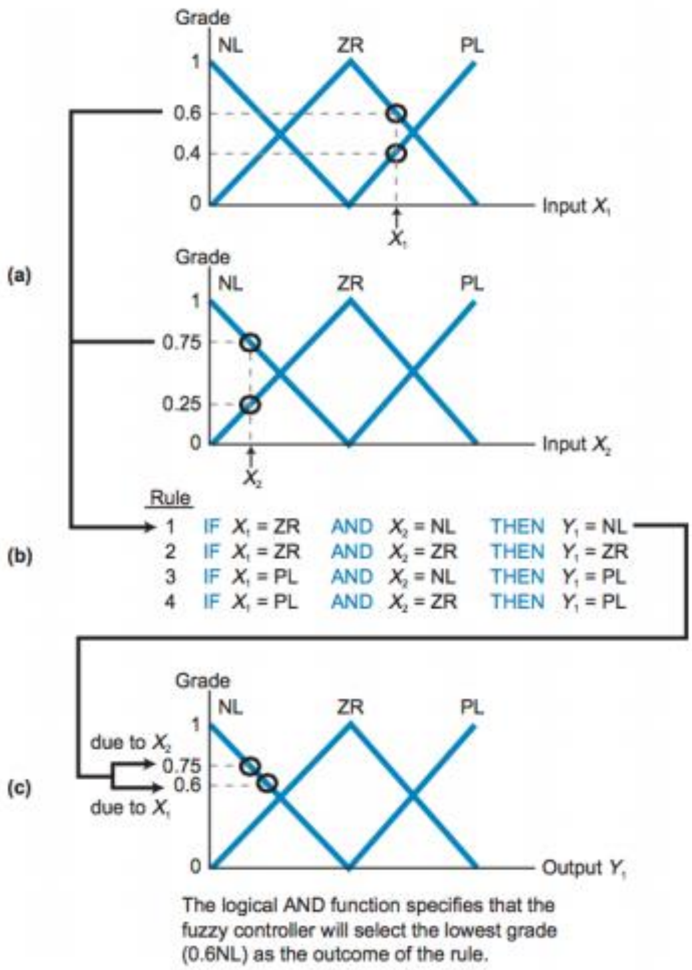


Fig. 2.11 Fuzzy processing example [114]

2.5.2 Hierarchical Fuzzy Systems

The hierarchical fuzzy systems have influenced some researches in various topics, such as robotics [116], [117], fuzzy-neural modelling [118], control [119], [120], [121] pattern classification [122], [123], function approximation [124], [125], and linguistic modelling [126]. In terms of the effectiveness of hierarchical fuzzy systems, Torra compared these systems with standard fuzzy systems, and the results indicated that hierarchical fuzzy systems can enhance the interoperation and transparency and are effective in reducing the number of needed rules [127]. Brown and Harris suggest in [128] to use a hierarchical structure of fuzzy rule bases to cause the number of rules to grow linearly. The literatures show that research on the hierarchical fuzzy logic has promising results, as in [129], [130], [131], [132], [133], [134].

2.6 Recommender Systems

Online tutoring systems provide guidance or recommendation to their users, which emphasises the importance to surveying the concepts of the recommender systems to help in finding some solutions while developing the thesis' proposed system.

The Recommender Systems (RSs) can be defined as *"software tools and techniques providing suggestions for items to be of use to a user"* [135] [136], [137]. Different decision-making processes are linked to the suggestions, such as what movie to see, what items to buy or what book to read [138].

The research area of the recommender systems could be considered as a multi-disciplinary field emerging from approximation theory [139], forecasting theories [140], information retrieval [141], and cognitive science [142], and was related to consumer modelling [143] and management science [144]. The recommendation systems rely on the user(s) profile(s) and the item(s) characteristics to give the recommendation. Based on the way of producing the recommendations, the recommendation systems can be categorised into three categories: Content-based recommendations, collaborative methods and hybrid methods [145]. In the content-based recommendation, the recommendation of an item to a user is based on his/her own similar preferred items. In the collaborative method, the recommendation of an item to a user is based on the other similar users' preferences. Two steps are usually involved in this method: 1) the system searches for individuals who share similarities with the current user, and then 2) it makes use of their data and calculates the ratings of use in order to recommend an item or items to the current user. There are a few techniques to implement this type of recommender system, the most famous of which is perhaps the Nearest Neighbour Algorithm, which is used for classification and regression in order to recognise the pattern of use. Another technique is the Latent Factor Model, where the system infers the pattern of use based on measurable and observed data. The hybrid method is a combination between the two aforementioned methods (i.e. the content-based and the collaborative methods). Each of the three recommender system types has its own limitations. For instance, in the collaborative and content-based methods, the problem of cold start is very common, where the system does not have enough information about the item or the user.

2.7 Pedagogical Background and Literature Review

This section presents a brief background about the related theories, concepts and frameworks in the pedagogical and educational field.

2.7.1 Learning and Pedagogical Theories

Jonassen and Land state that there has never been such an agreement on the psychological fundamentals of educational theories [146]. However, Greeno, Collins and Resnick outline three major educational perspectives based on different assumptions: the associationist, cognitive and situative perspective [147]. These three perspectives have also been followed by Mayes and de Freitas [148]. The associationist perspective (learning as activity) emphasises task analysis and involves a sequence of elements to composite skills. What results is a highly focused set of objectives which are perceived as learning competencies. The cognitive perspective (learning as achieving understanding) emphasises conceptual development which focuses on the need to achieve an understanding of the variety of unifying principles relating to a domain. With respect to this view it is possible to design the outcomes of learning on meta-cognitive terms. The educational objective is the attainment of learning and promoting autonomy in learners. The situative perspective (learning as social practice) attempts to describe the objectives of learning with respect to the establishment of disciplinary practices of representation and discourse. This is in addition to paying attention to learning results that rely on setting up the collaborative learning outcomes and relationships based on learning with regards to the peers. It also allows for the formulation of learning outcomes based on the legit practices of designing and solving actual issues [148].

2.7.2 Tutoring

Tutoring is a type of education and a means of offering instructions. Studies show that it has two properties. The first property includes the tutor/student ratio (1/3 but in most cases 1/1). In this sense, tutoring is a personalised instruction because a tutor attends to one student. The second property is guidance, also called tutor control, which may be done collaboratively with the learner using discovery or cognitive apprenticeship [149]. Tutoring can be understood well after the clarification of two aspects of education. Firstly, provision of instruction is the role of the tutor while the learning process is the part of the learner. The learning process may occur whether formal or informal instructions are provided. Secondly, the tutoring process focuses on personalising the learning process through different interactions. On the other hand, tutoring can also be considered as a locus of control whereby there is involvement of one or mixed initiatives. In this view, the dialogue between the tutor and the learner involves the tutor focusing on asking questions until the student gains knowledge and becomes aware of the process. When viewed as an adaptation, tutoring has a different role compared to that of teaching. In teaching, the teacher focuses on the learner to adapts to the class while in tutoring the tutor focuses on adapting to the student. Although tutoring and teaching are two different things, they usually overlap during normal settings but may even be played by one person [8].

Extensive research has revealed that tutoring in ITS is comprised of both guidance and interaction between the tutor and the learner [150]. The interactions can be a single or mixed initiative. The extent of learning differentiates tutoring from teaching or lecturing. Teaching and lecturing can happen without the interaction between the tutor and the student and, therefore, results in little learning, while in tutoring there must be interaction. The most important feature that differentiates tutoring from teaching and lecturing is the interaction process. As a result, the main problem experienced by the developer of ITS is to create a system that allows interaction, as well as precise adaptation, and at the same time shape the tutoring behaviour through reasoning from data collected from interactions between the learner and the system using machine learning techniques [8]. Research on student and agent models has continued to develop in ITS research design. However, the tutoring function of the system has received most of the attention [150], [151], [152], [153].

2.7.3 Teacher-centred and Student-centred learning approaches

The teacher-centred learning approach, also known as teacher-oriented teaching [154], is the traditional approach where *"students put all of their focus on the teacher. The teacher talks, while the students exclusively listen. During activities, students work alone, and collaboration is discouraged"* [155]. In this approach a number of advantages are recognised. For example, this approach ensures that the students will not miss any important topic, the classroom will be a quiet place and teachers can control students easily. However, it misses the benefit of collaboration and the students cannot improve their communication skills. In addition, it may become boring for some students since they are passive in this type of learning. A study by [156] showed that some students did not welcome this approach and preferred the teacher-centred learning approach.

On the other hand, student-centred learning approach, also known as experiential learning [157], flexible learning [158] and self-directed learning [159] can be defined as shifting the focus of instruction from the teachers to the learners, which means an *"increased sense of autonomy in the learner"*, and an *"interdependence between teacher and learner"* [160]. Burnard explained the students' role in this approach by stating that *"students might not only choose what to study, but how and why that topic might be an interesting one to study"* [157]. On the other hand, the teachers roles differ in this approach in that they become facilitators and coaches rather than primary evaluators and information-givers [161]. This means they should engage students in their study and assist them to achieve the learning gaols [162]. The literature shows how much effective this approach is [160]. For instance, a comparison between the two approaches was made by Lonka and Ahola in Helsinki for a duration of six years and the results showed that the study skills in the teacher-centred approach group were developed better but slower [163]. Another study found that this approach increased the students' motivation, participation and grades in an information technology module [164]. In [160], students also found that this approach was more respectful to them and exciting and it increased their confidence [160].

While the two approaches are often presented in a dichotomy, O'Neill and McMahon view this dualism as a continuum in reality. They look at teacher-centred learning and student-centred learning as two ends of a continuum, where learning moves from one approach to another depending on three criteria illustrated in Figure 2.12: the level of student choice, student activity and direction of power [159]. Based on this continuum, it is plausible to argue that having an online tutoring system that gives the learner the opportunity to change his/her position on the continuum is likely to appeal to many learners and may lead to positive results in learning.

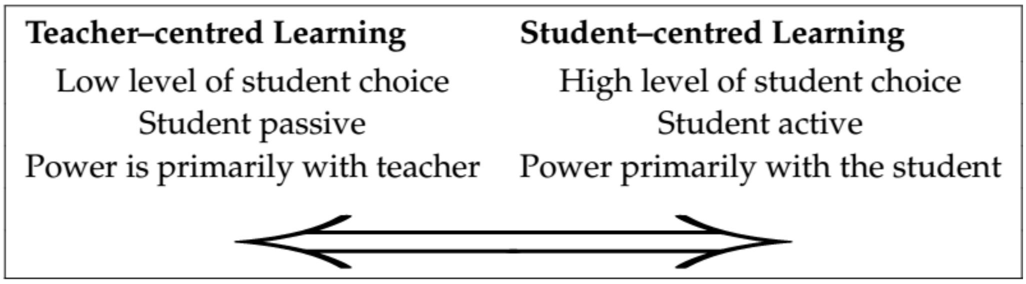


Fig. 2.12 Teacher-centred and student-centred learning continuum [159]

"It is time for us to start addressing the more complex and interesting task of joining together teacher-centred and learner-centred instruction" [165].

2.7.4 Learning Objects Model

This model of learning leans towards viewing the learning object as digital resources that are reusable to encourage learning [166]. People have different perceptions regarding learning objects [167]. The model has evolved from being based on reusing learning materials to the development of standards for technology in learning. The model can be viewed as more of technological and instructional model [148]. The model is also reliant on the learning standards and specifications developed by the Learning Technology Standards Committee of the Institute of Electrical and Electronic Engineers in 1996. Their definition of learning objects is an entity which is capable of being re-used during technology supported learning [168].

Using the term “object” instead of “resources” or “material” raises controversy. While owing it to the computer science paradigm of object orientation, it is not favourable for the constructivist and epistemological means of educationalists. The main concept behind object orientation is the miniature learning materials that are reusable through different ways and over a number of times. The learning design approach deals with the control over sequences of learning materials and is favourable to the instructivist approaches where learning is comprehended through practice and time [148]. Using learning objects also exposes individuals to a broadened access with respect to the limitless locations where they can be reached. Recording the sequence of use of the objects enhances extra functionality, which is dependent on the place and context of use. In addition, the strength of the learning object model is Interoperability [168]. The objects are mostly preferred due to their reusability and their broadened access. However, some weaknesses have been recorded, ranging from change in standards, which are a barrier to development, to neutrality of the objects, which enables the tutors to develop their unique pedagogic way to the material, to no specification of the context [148]. The lack of context specificity means that issues may arise in the learning environment as to the embedment of the object. It is also assumed that there is the capacity to independently develop learning objects from tutors, which is problematic. The debate on learning objects has cleared the differences between the constructivist approaches and instructional design where the producer of the learning materials is the learner. The major concern is whether the debate will structure the issue of reusability and design of learning objects [148].

2.8 Discussion

This chapter introduced some background of e-learning and intelligent tutoring systems (ITS), including their components and architecture, the possible benefits of integrating the e-learning and ITS as well as the benefits of utilising machine learning techniques in ITS. In addition, It surveyed the literature on the prior adaptive learning path systems. It showed that the issues related to the contents sequencing have been explored using different techniques, yet these studies have focused on how to sequence the materials but have not paid much attention to how to guide students through these sequences. This issue is important and worth more investigation, as students have different preferences, and when the online tutoring systems meet these variable preferences, the students can find a better alignment to their individual learning needs, which leads to promoting their knowledge. Another issue is that there is lack of studies discussing how to make these systems more controllable and adaptable for teachers' requirements as the teachers need to control the learning process while students are interacting with the online tutoring systems. On the other hand, shifting some teachers' tasks to the tutor agent (e.g. sequencing learning contents) can ease the burden on the teachers. However, there is still a need to study how to make this shift happen under teachers' control. To overcome these limitations, this thesis aims to explore the use of adjustable autonomy in online tutoring systems. Thus, this chapter introduced the idea of adjustable autonomy mechanisms and their use in intelligent environments where the users are capable of adjusting the agent's autonomy level on a scale starting from a user-driven end to an agent-driven end. These studies introduced promising results which influenced this thesis. On the other hand, when the tutor agent observes students' behaviours to generate sequencing rules, there is a need to present these rules in a human-readable form in order to allow teachers to read and modify them. Thus, it was decided to utilise fuzzy logic in this study, and, hence, this chapter also included a description of the concept of fuzzy logic. Moreover, the chapter introduced some of the relevant pedagogical and educational background. The next chapter surveys the students' learning needs related to the course sequencing and adjustable autonomy.

Chapter 3

The need for adjustable autonomy in educational environments: A survey

After surveying the literature to identify the lack of use of utilising adjustable autonomy in online tutoring systems and the need for adapting the sequence of lessons for the students' needs, a further step was to gain an insight into the students' point of view about their learning needs, which are related to both issues. Thus, this chapter aims to clarify these needs before describing the conceptual model for our approach.

This chapter has three sections: an explanation of the survey design is presented in Section 3.1, the results are introduced in Section 3.2. Finally, the last section is discussed the chapter outcomes.

3.1 Survey Design

The targeted students were those who had been studying an online course in Saudi Arabia, where the experiment following this survey would take place.

Before initiating the survey, a crucial step which had to be considered was the determination of the survey goals. This was followed by forming the questions based on the goals as well as defining how these questions would be answered and how the results would be measured [169].

The main goal of this survey was to contribute to achieving the pedagogical aims of the research, which were set out in Chapter 1. More specifically these were:

1. understanding students' learning needs and preferences in sequence of lessons for the students' needs in intelligent tutoring systems.

2. studying the need for adjustable autonomy in the adaptive course sequencing approach to give the students the capability to choose their preferred autonomy level in the guidance agent.

The next step after defining the survey's goal was to form the appropriate questions. It should be noted here that exploring all the students' learning needs and preferences in sequencing lessons is a very difficult task as they are subject to individual definitions; thus there is uncertainty in defining some of the students' learning needs, and, when trying to investigate many of them, the survey may become too long and complicated and this in turn may lead to receiving unreliable answers [170]. For this reason, it was decided to concentrate more on exploring the learning needs that contribute to testing the research hypotheses.

The survey was divided into two sections. The aim of the first section was to gather demographic information about the participants (i.e. gender, age group, educational level and whether they had heard about ITS before). It is worth noting that all the questions in this section gave the students the option of "prefer not to say" as some of these questions were personal ones. The second section had four main objectives which were to:

1. understand some aspects of the students' feelings and attitude (e.g. feeling bored, losing concentration, losing motivation) when they undertake a lesson that they had already mastered.

2. clarify the need for offering a way to adapt the sequence of lessons on each topic to fit the students' learning needs.

3. determine how much the students want to rely on the experiences of other students and teachers when choosing the best sequence for them.

4. identify the students' needs for adjusting the guidance level, to determine how many levels of autonomy should be offered and what their descriptions are.

While the first three objectives contribute to realising the first pedagogical aim of this research, the fourth objective is to help achieve the second pedagogical aim.

In addition, the questions in the second section were closed questions designed using a five point Likert Scale due to its popularity and wide acceptance. The scale's labels were from "strongly agree" to "strongly disagree". Following that, the introduction of the survey was formulated and 17 statements were carefully created in a way that was considered not to influence the participants' opinions. These 17 statements were classified into four groups, each of which was planned to contribute to achieving one of the four objectives mentioned above. It should be noted here that the survey was written in Arabic as it is the participants' first language.

The literature highlights to what extent the negative feelings are affected by the learning experience, which is in turn a major reason behind failure in colleges according to [171], [172]. Thus, the first group of questions was aimed to achieve the first objective (i.e. understand some of the students' feelings such as feeling board, losing concentration, losing motivation, when they undertake a lesson that they have already mastered.) and contained six statements:

1. During my learning life, I have re-studied some lessons or parts of these lessons in different modules.

2. I lose my concentration when I am taught a lesson or part of a lesson that I have already learnt and I have still mastered.

3. I feel bored when I am taught a lesson or a part of a lesson that I have already learnt and I have still mastered.

4. I lose my motivation towards a module when it covers subjects that I have already learnt and I have still mastered.

5. If I could choose my own learning path (syllabus), I would not restudy the lessons that I have previously learnt and I have still mastered.

6. Restudying a lesson can sometimes be a good learning strategy.

The second group of statements were formulated to fulfil the second objective (i.e. clarifying the need for offering a way to adapt the sequence of lessons on a topic to fit the students' learning needs):

1. When I learn something, I always prefer to choose what I am going to learn.

2. I learn better if I can choose the modules' lessons and their sequencing (if I could choose my own learning path).

3. The most important thing that makes me decide whether to learn a lesson or not is the knowledge level I have about it.

The third group of statements was intended to help with meeting the third objective (i.e. knowing how much the students tend to rely on other students' and teachers' experiences when choosing the best sequence for them):

1. Usually, I feel that I do not have the skills that allow me to choose the most appropriate learning path for me (to plan what I am going to learn).

2. When I am learning a module, I would be interested in knowing the learning paths that other students have chosen, particularly those who have a level of knowledge similar to mine.

3. I value any recommendation from the teacher about the most appropriate learning paths for me.

The fourth group of statements aimed to contribute to achieving the fourth objective (i.e. identifying the students' learning needs for adjusting the guidance level to determine how many levels of autonomy should be offered and what their descriptions are). Hence, it was assumed that there were three important modes/levels of guidance that students may need in their learning life, namely:

1. Full guidance (FG): here the teacher chooses what the student should learn; the latter does not have the ability to choose his/her learning path.

2. Partial guidance (PG): the teacher recommends the learning path for the student and the student is given the flexibility to follow the recommendation or not.

3. No guidance (NG): the student has full responsibility to find his/her own learning path.

Thus, the survey statements for this group were:

1. Usually, I want the teacher to guide me to the appropriate lessons and not allow me to choose by myself.

2. Usually, I prefer if the teacher guides me to study a lesson which is appropriate to my knowledge level but gives me the freedom to follow or disregard his/her guidance.

3. Usually, I prefer if I am given the full freedom to choose what I want to study without any intervention.

4. My preferred guidance mode varies from time to time (between the three guidance modes mentioned in the survey description).

5. The three modes of guidance mentioned in the survey description are sufficient to fulfil my learning needs.

As for administering the survey, it was decided to put the survey online in the hope of receiving a large and varied number of responses in a relatively short time. An online survey is an effective method in terms of shortening the time needed to insert the received responses into the computer for analysis purposes. Therefore, the statements were created with Google Forms and then they were piloted on a small sample who varied in terms of age, gender and levels of previous study to ensure that the whole survey was easily understandable before distributing it. Subsequently, after ensuring that all the statements were clear to the piloting sample of students, the survey was distributed to the participants via email and social media (i.e. Twitter, Facebook, etc.). The targeted participants were those who studied or intended to study an online course.

3.2 Survey Results

A total number of 234 responses were received over a period of four months starting from September 2013. The survey's results were classified into two main parts that are described in the next two sections: Section 7.2.1 illustrates the demographic information of the participants and Section 7.2.2 illustrates the results from the main statements.

3.2.1 Demographic results

The survey was concerned with identifying four demographic characteristics of the participants, namely gender, age, highest previous educational level of attainment and previous knowledge of intelligent tutoring systems. In the sample, 41.03% of the participants were females while 55.13% were males, and 3.85% preferred not declare their gender (see Figure 3.1).

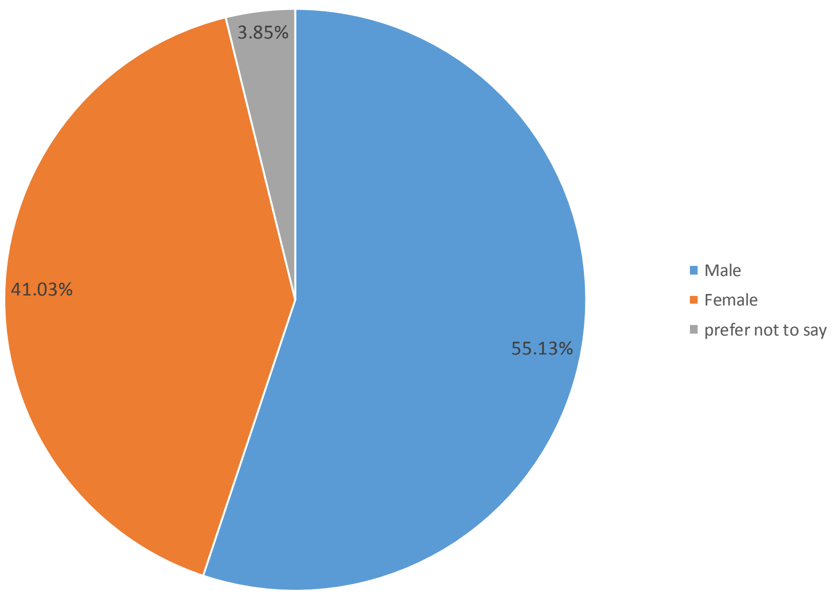


Fig. 3.1 The participants' genders

In terms of the participants' age groups, the results reveal that the participants had a wide range of ages; approximately a third of the participants were between 18 and 30 while a quarter of the participants were between 31 and 35 years old. Moreover, nearly two fifths of the participants were 36 years old or above, but a small minority of them were below 18 year old (2.14%) (see Figure 3.2).

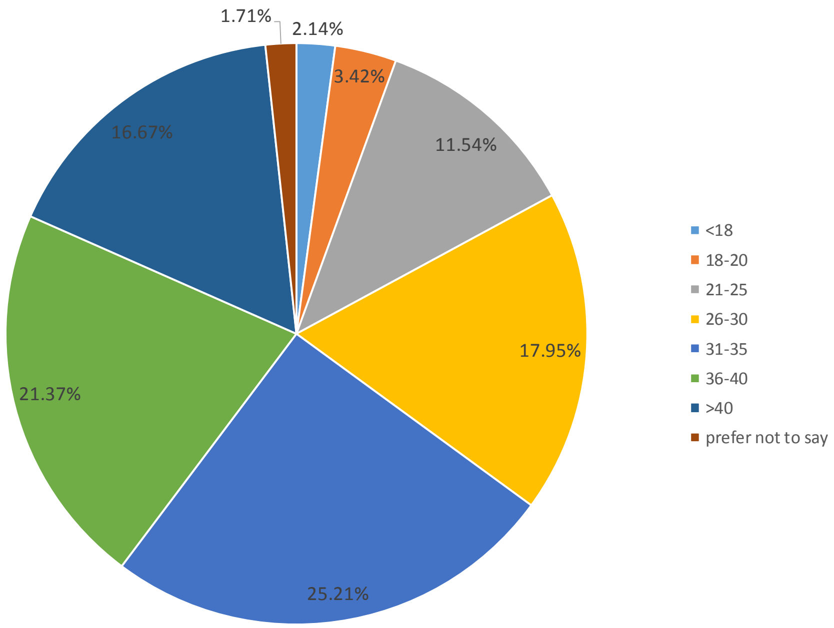


Fig. 3.2 The participants' age groups

In terms of the highest level of educational achievement, half of the participants already had a diploma and/or bachelor degree, while nearly 36% had a postgraduate degree. 11.97% had the senior secondary school or A-Level qualifications whereas 0.85% only had the intermediate school or GCSE qualifications. 0.85% of the participants had other educational qualifications, whereas 0.43% of them preferred not to say (see Figure 3.3).

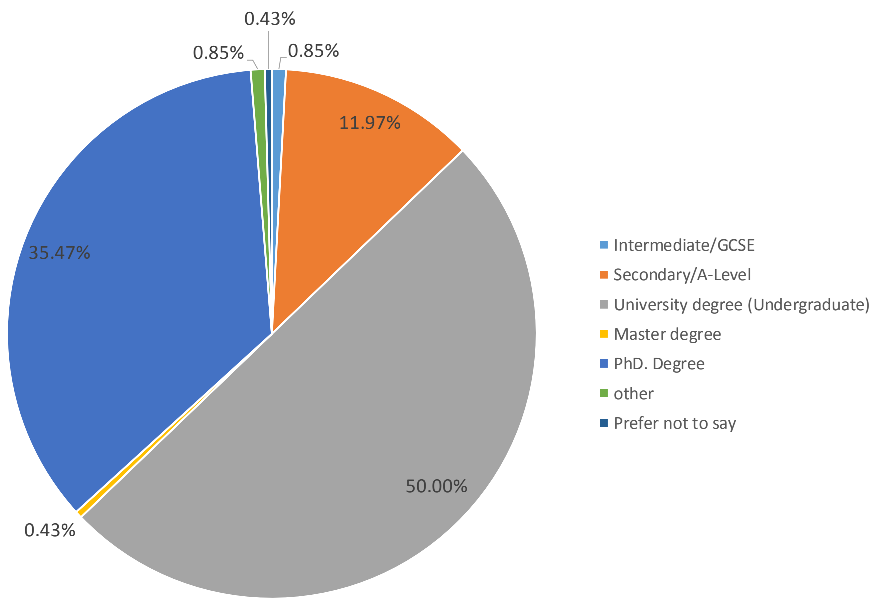


Fig. 3.3 Previous education level

With regard to the question of whether the participants had heard about intelligent tutoring systems, 49.57% said they had heard about them, 26.50% said they had not and 23.08% preferred not to say. Two missing answers were received and reported the question as not applicable to them (0.85%) (see Figure 3.4).

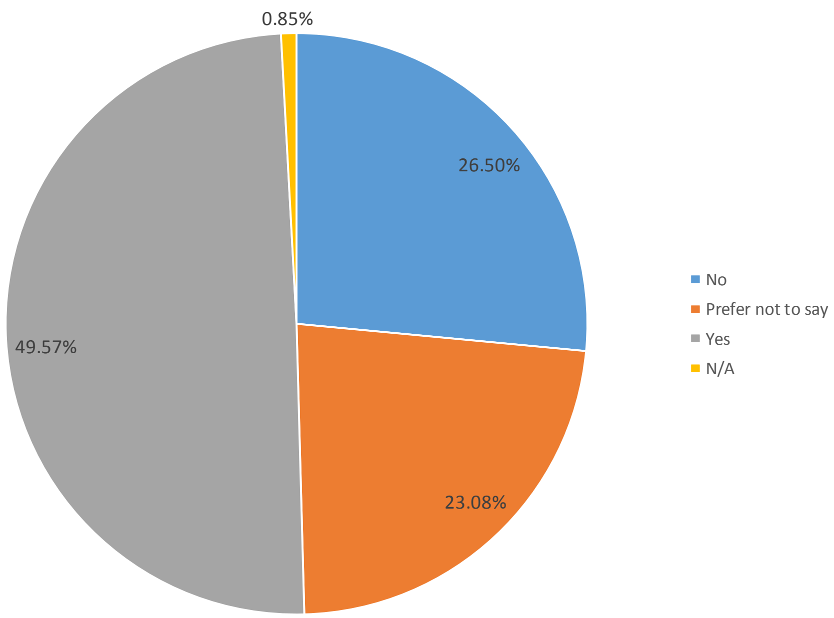


Fig. 3.4 Had you heared about ITS before?

3.2.2 Main results of the survey

The analysis of the obtained answers started by measuring the reliability of participants' responses by utilising Cronbach's Alpha (α). Thus, the Cronbach alpha(α) score was calculated, following equation 3.1.

$$\alpha = \frac{N \cdot \bar{c}}{\bar{v} + (N-1) \cdot \bar{c}} \tag{3.1}$$

Where N is the number of items, $\bar{c}$ is the average inter-item covariance among the items and $\bar{v}$ equals the average variance. According to the Statistical Consulting Group (UCLA), a value of the reliability coefficient α of 0.70 or more is considered to be acceptable in the majority of social-science researches [173]. Hence, the result of Cronbach Alpha (α) obtained (0.832) which revealed that the reliability of the responses could be considered to be good.

In the next subsections, the results from the 17 statements are reported based on their classification according to the objectives they fulfil.

Identifying the students' experiences regarding re-studying a lessons they master

The answers received for the first statement "During my learning life, I have re-studied some lessons or parts of lessons in different modules" show that the vast majority of students (93.16%) agreed that they had re-studied lessons on various topics. 5.56% were neutral and only 1.28% disagreed (see Figure 3.5). This shows that the participants in general can recognise the repetition of some topics with the overall syllabus of their course.

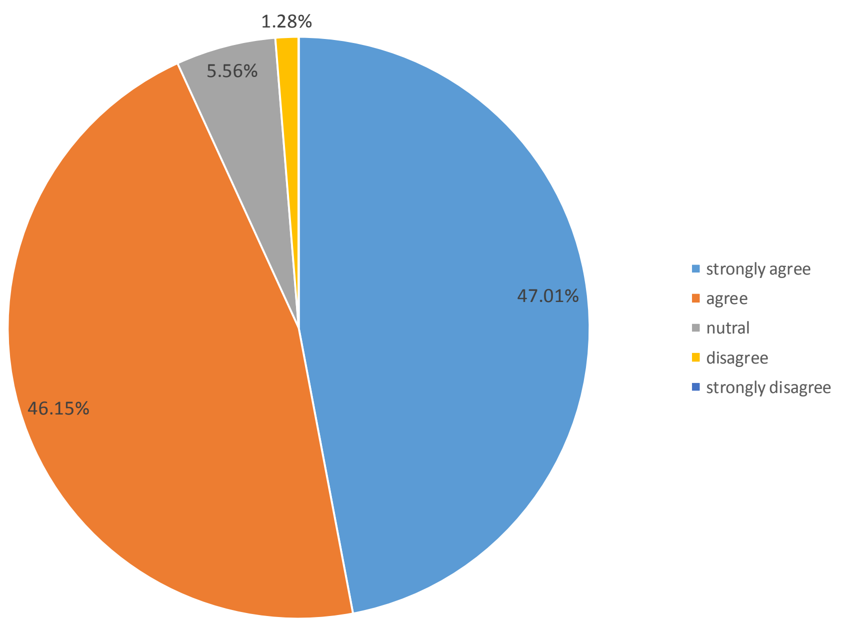


Fig. 3.5 The participants' responses for the statement "During my learning life, I have re-studied some lessons or part of lessons in different modules"

With regard to the students' feelings, the first negative feeling to explore was the loss of concentration while re-studying a lesson. More than a half of participants (58.97%) showed a degree of agreement when they were asked if they lost their concentration when re-studying a lesson, whereas nearly a third of them were neutral, 8.97% disagreed and 2.99% strongly disagreed with this statement (see Figure 3.6.)

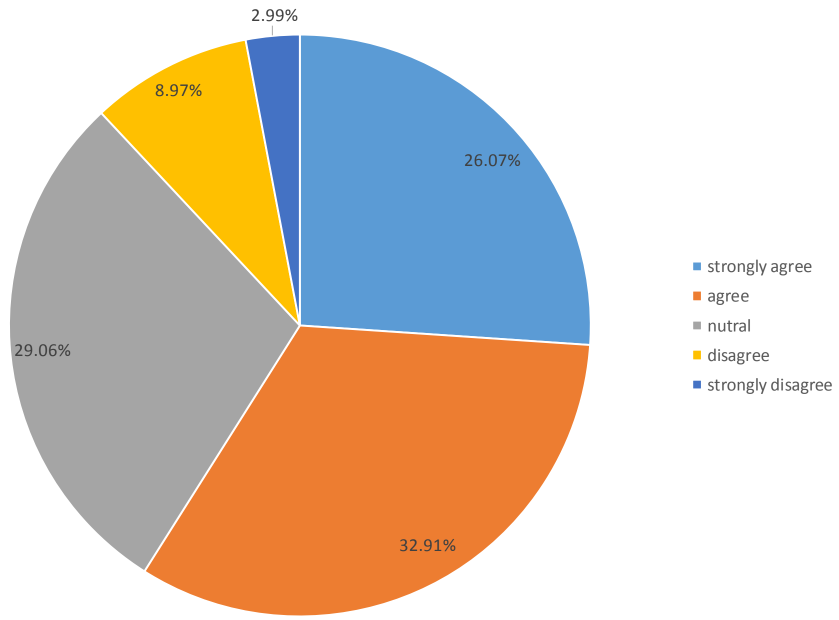


Fig. 3.6 The participants' responses to the statement "I lose my concentration when I am taught a lesson or part of a lesson that I have already learnt and I have still mastered".

The second negative feeling was boredom when re-studying a lesson. Nearly three quarters of the students indicated a level of agreement (38.89% strongly agreed and 35.47% agreed), while 19.23% were neutral, 4.70% disagreed and 1.71% strongly disagreed (see Figure 3.7). This result supports previous findings which indicate that there is a link between restudying already mastered information and feeling bored (e.g. [174],[175]).

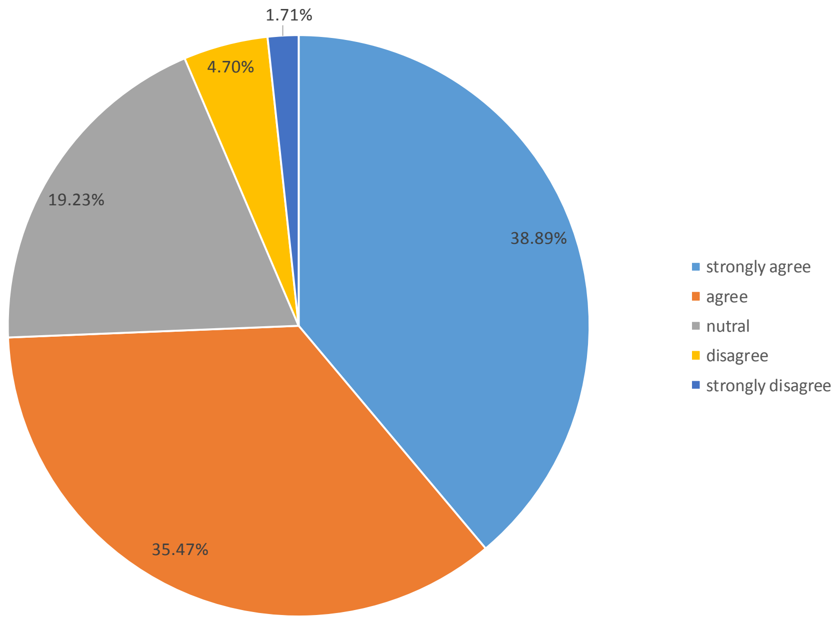


Fig. 3.7 The participants' responses to the statement "I feel bored when I am taught a lesson or part of a lesson that I have already learnt and I have still mastered"

The third important feeling believed to negatively affect students' learning performance was the loss of motivation towards the module due to the repetition of lessons. The results show that the majority of the participants revealed a level of agreement (42.31% strongly agreed and 38.03% agreed), while 13.25% of the answers were neutral, 4.7% disagreed and 1.71% strongly disagreed (see Figure 3.8).

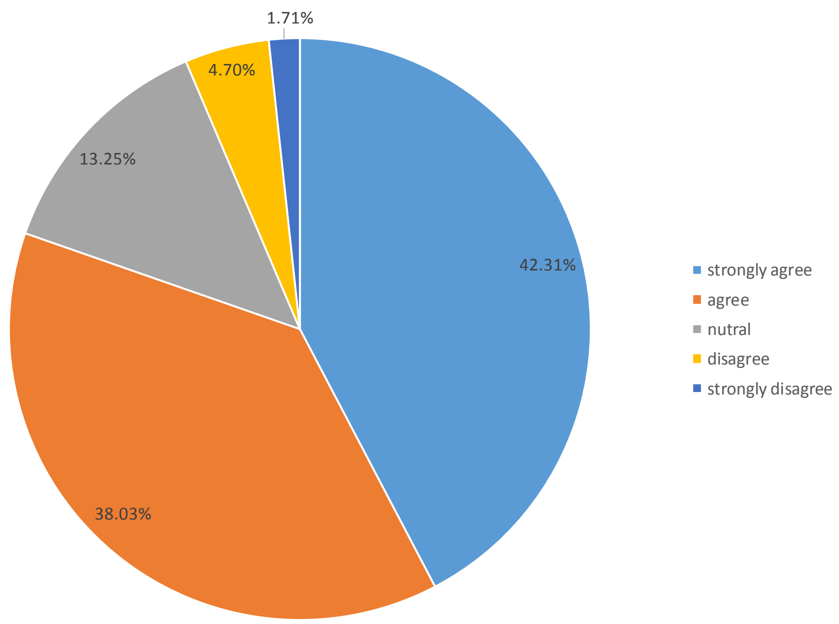


Fig. 3.8 The participants' responses to the statement "I lose my motivation towards a module when it covers subjects that I have already learnt and I have still mastered"

The survey took a further step to ask the participants about whether they would restudy the lessons they had already mastered, or not, when they could control their learning path. The results for this statement indicate that the majority of them (82.05%) agreed or strongly agreed, whereas 13.68% expressed neutrality and 4.27% disagreed (see Figure 3.9).

This finding reveals how much students feel they need to skip various lessons that are still being taught in different modules and this can also indicate that when students have a way of controlling their learning process, they are most likely to concentrate on the lessons they do not yet know rather than re-study the lessons or concepts they already know well.

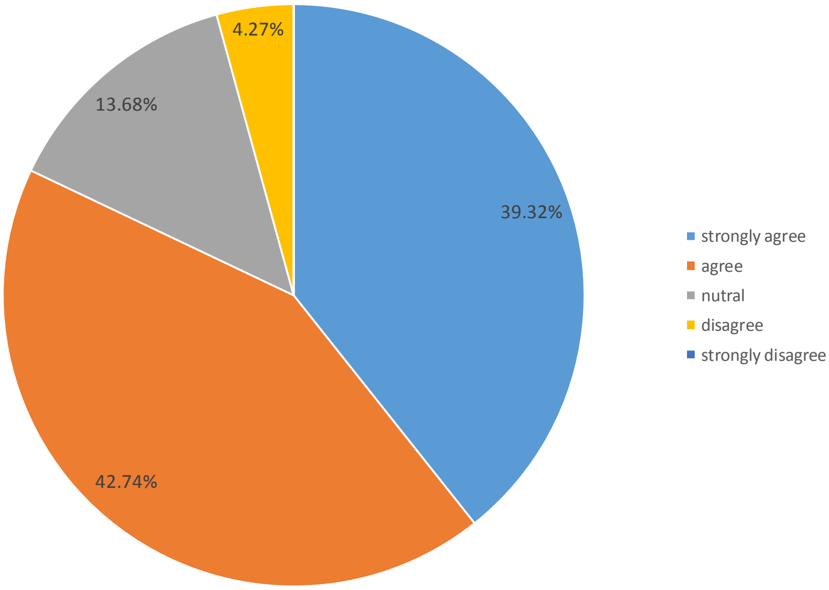


Fig. 3.9 The participants' responses to the statement "If I could choose my own learning path (syllabus), I would not restudy the lessons that I have previously learnt and I have still mastered"

As for the question of whether restudying a lesson can sometimes be a good learning strategy, the results show that 20.94% strongly agreed and 51.28% agreed, while 22.22% were neutral, 4.7% disagreed and 0.85% strongly disagreed (see Figure 3.10). This means that although the majority of the participants had a negative feeling towards re-studying a lesson, they believed that restudying a lesson can sometimes be a good learning strategy. This may indicate that there is a need for offering a way which allows students to adjust the guidance level; for example, in a situation if a student prefers to be fully guided by a tutor and the automated tutor (based on the previous students' experience) guides the student to skip a lesson the latter has good knowledge about, the student should be able to adjust the autonomy level of the tutor to study that lesson if (s)he believes (s)he needs to re-study it.

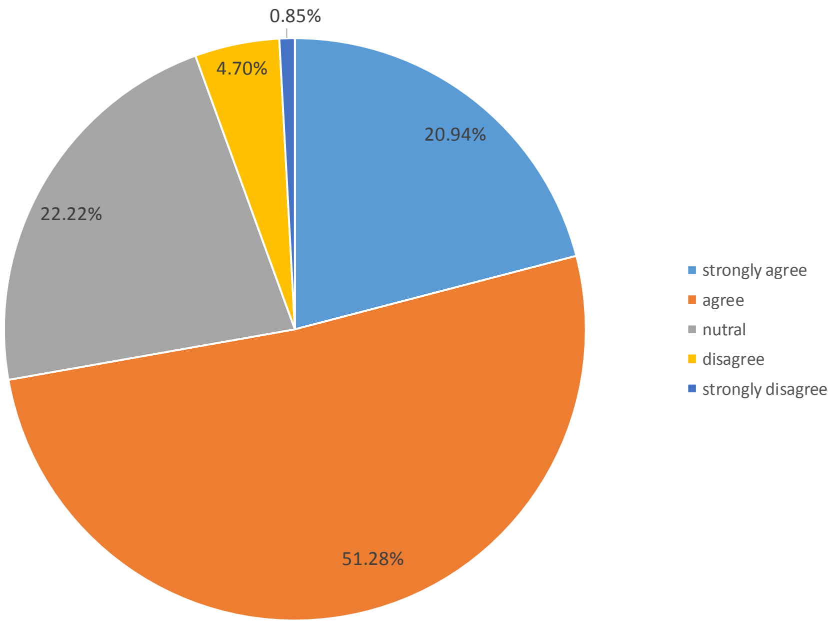


Fig. 3.10 The participants' responses to the statement "Restudying a lesson can sometimes be a good learning strategy"

Table 3.1 Summarising the results of the first part of the questionnaire

Question	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
During my learning life, I have re-studied some lessons or parts of these lessons in different modules.	47.01%	46.15%	5.56%	1.28%	0%
I lose my concentration when I am taught a lesson or part of a lesson that I have already learnt and I have still mastered.	26.07%	32.91%	29.06%	8.97%	2.99%

Question	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
I feel bored when I am taught a lesson or a part of a lesson that I have already learnt and I have still mastered.	38.89%	35.47%	19.23%	4.7%	1.71%
I lose my motivation towards a module when it covers subjects that I have already learnt and I have still mastered.	42.31%	38.03%	13.25%	4.7%	1.71%
If I could choose my own learning path (syllabus), I would not restudy the lessons that I have previously learnt and I have still mastered.	39.32%	42.74%	13.68%	4.27%	0%
Restudying a lesson can sometimes be a good learning strategy.	20.94%	51.28%	22.22%	4.7%	0.85%

Clarifying the need for adapting the lessons' sequence to fit the students' learning needs

The answers received for the first statement in this group "when I learn something, I always prefer to choose what I am going to learn" indicate that more than half of the participants strongly agreed (54.27%) and more than a third of them agreed (37.61%) while 8.12% of them were neutral and no one showed any level of disagreement (see Figure 3.11).

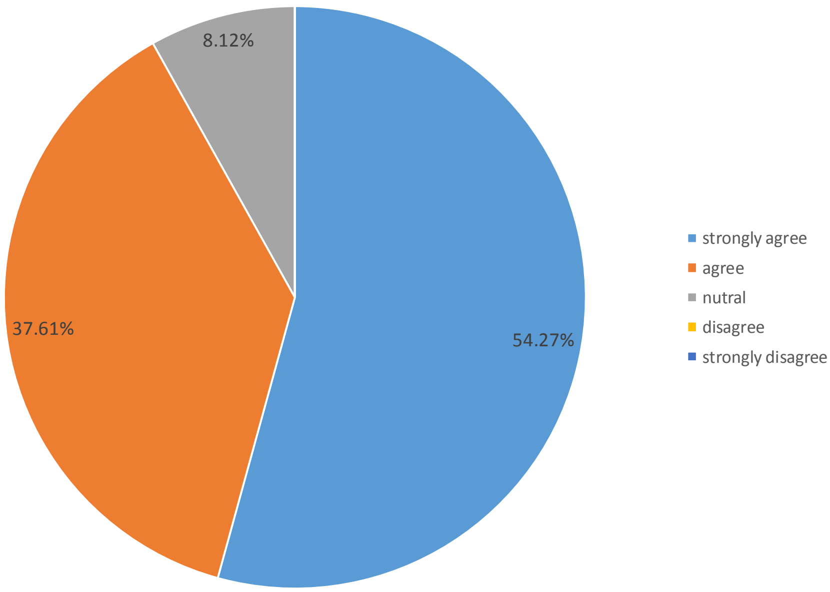


Fig. 3.11 The participants' responses to the statement (When I learn something, I always prefer to choose what I am going to learn)

The next statement in this group was concerned with the effect of the participants' preferences of choosing what they want to learn towards their learning outcomes. Hence, they were asked to what extent they agreed with this phrase: "I learn better if I can choose the modules' lessons and their sequencing (if I could choose my own learning path)". Their responses showed that nearly 90% of them agreed (59.83% strongly agreed and 29.06% agreed) while 8.97% were neutral and around 2% disagreed (1.71% disagreed and 0.43% strongly disagreed) (see Figure 3.12).

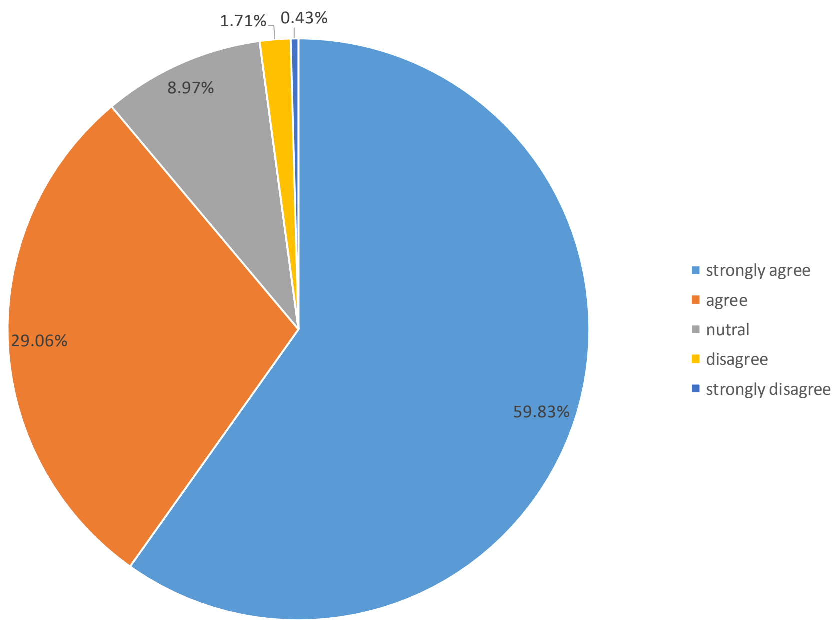


Fig. 3.12 The participants' responses to the statement (I learn better if I can choose the modules' lessons and their sequencing)

The responses to the statement "The most important thing that makes me decide to learn a lesson or not is the knowledge level I have about it" show that the majority of the participants agreed to that (50.43% strongly agreed and 35.90% agreed) while 10.68% were neutral and a small minority disagreed (2.99%) ()see Figure 3.13).

As this factor was so important and the results supported this claim, we decided to take it as a rule input when designing our system (ACSA).

Table 3.2 Summarising the results of the second part of the questionnaire

Question	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
When I learn something, I always prefer to choose what I am going to learn.	54.27%	37.61%	8.12%	0%	0%
I learn better if I can choose the modules' lessons and their sequencing (if I could choose my own learning path).	59.83%	29.06%	8.97%	1.71%	0.43%
The most important thing that makes me decide whether to learn a lesson or not is the knowledge level I have about it.	50.43%	35.9%	10.68%	2.99%	0%

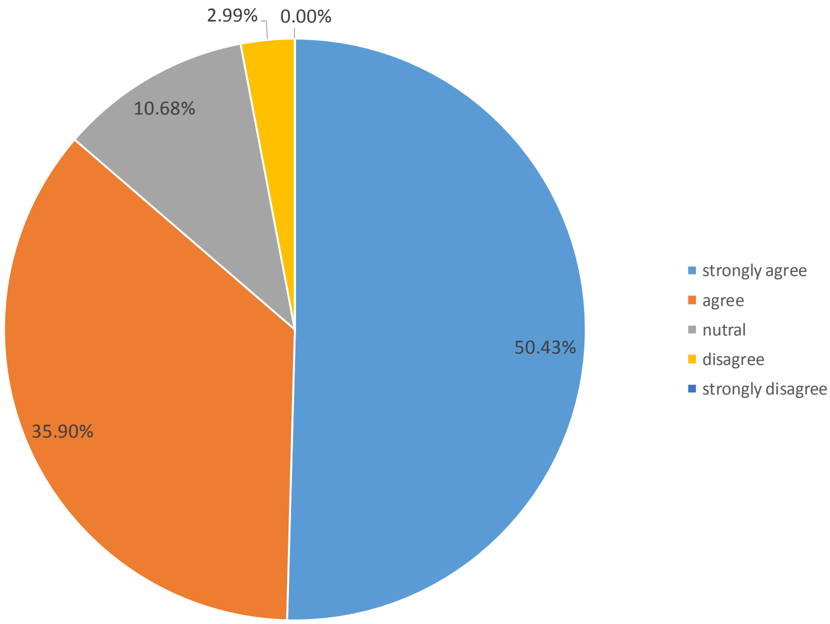


Fig. 3.13 The participants' responses to the statement (The most important thing that makes me decide whether to learn a lesson or not is the low knowledge I have about it)

The need for collaborative filtering to make a decision on the best sequencing

When thinking about some of the reasons behind urging students to seek help in a learning situation, the first reason that may occur to anyone is the weakness of their skills or knowledge in that situation, which affects his/her progress. Thus, the participants were asked about their agreement with this phrase: "Usually, I feel that I do not have the skills that allow me to choose the most appropriate learning path for me (to plan what I am going to learn)". The results for this statement showed that nearly half of the participants agreed to that statement (17.09% strongly agreed and 32.05% agreed), whereas 31.20% were neutral, 13.68% disagreed and 5.98% strongly disagreed (see Figure 3.14).

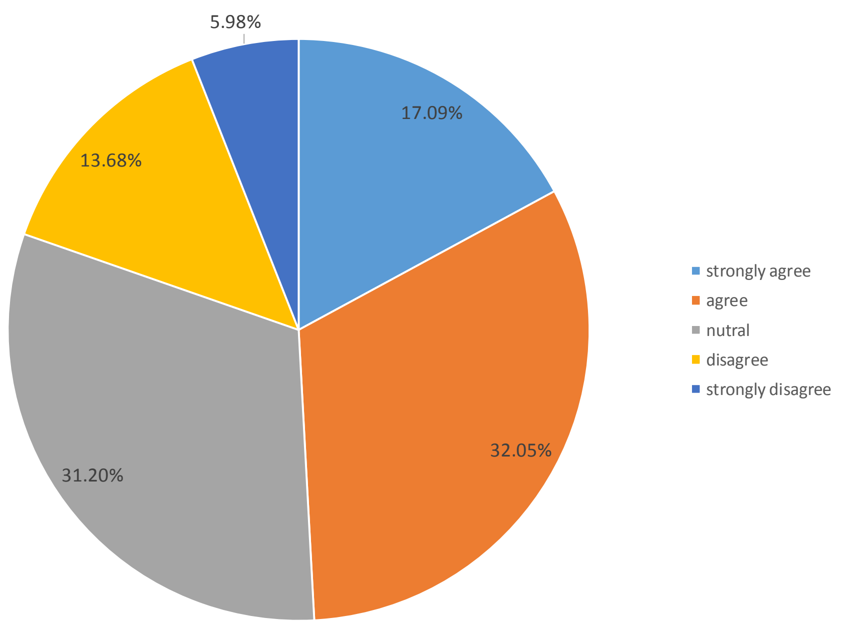


Fig. 3.14 The participants' responses to the statement (Usually, I feel that I do not have the skills that allow me to choose the most appropriate learning path for me (to plan what I am going to learn))

In addition to the previous statement, the statement "when I am learning a module, I would be interested in knowing the learning paths that other students have chosen, particularly those who have a level of knowledge similar to mine" was aimed to know how much the students want the help from other similar students. The results indicated that more than three quarters of the participants agreed (34.19% strongly agreed, 42.74% agreed) while 18.80% were neutral, 3.85% disagreed and 0.43% strongly disagreed (see Figure 3.15).

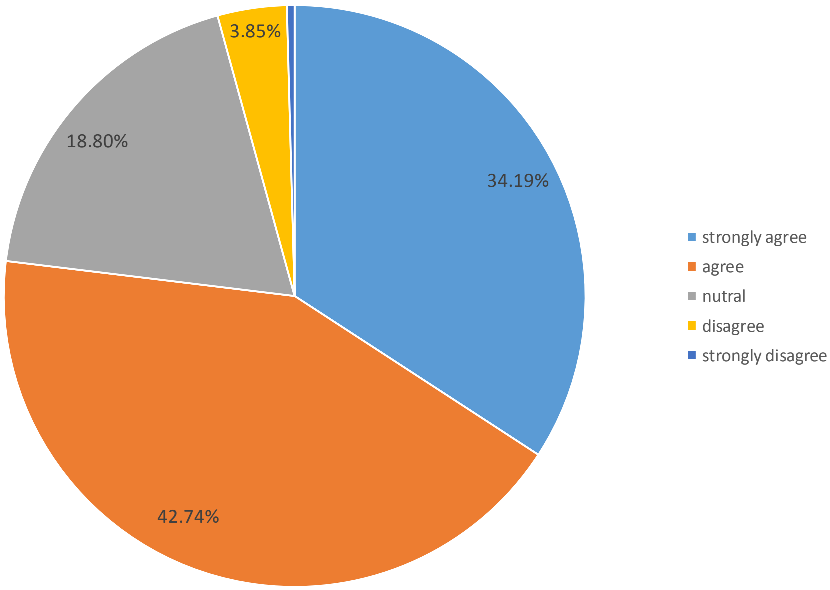


Fig. 3.15 The participants' responses to the statement (when I am learning a module, I would be interested in knowing the learning paths that other students have chosen, particularly those who have a level of knowledge similar to mine)

This proves how much students want to learn from other similar students' experiences. Thus, it is so important to offer a method to the intelligent tutoring systems to learn from students' learning behaviours in order to take pedagogical decisions which can be applied to teach students based on other similar students' behaviours. In that case, the tutor model or the adaptation model in intelligent tutoring systems should not be monopolised only by the experts. There should be some degree of flexibility which allows students to contribute to guiding other similar students. Hence, the intelligent agent will learn from students when they decide the sequence of the lessons and fill the tutor/adaptation model with the needed rules, which describes the characteristics of the students who did the sequence and the resulting sequence.

Another resource for seeking help when wanting to decide the lessons' sequence is the teachers. In the survey, the participants were asked to rate their agreement with the statement "I value any recommendation from the teacher about the most appropriate learning paths for me". The results revealed that more than half of the participants strongly agreed (53.42%), more than the third agreed (38.03%) and the other minor percentages were neutral, disagreed and strongly disagreed (7.69%, 0.43% disagreed and strongly disagreed, respectively) (see Figure 3.16).

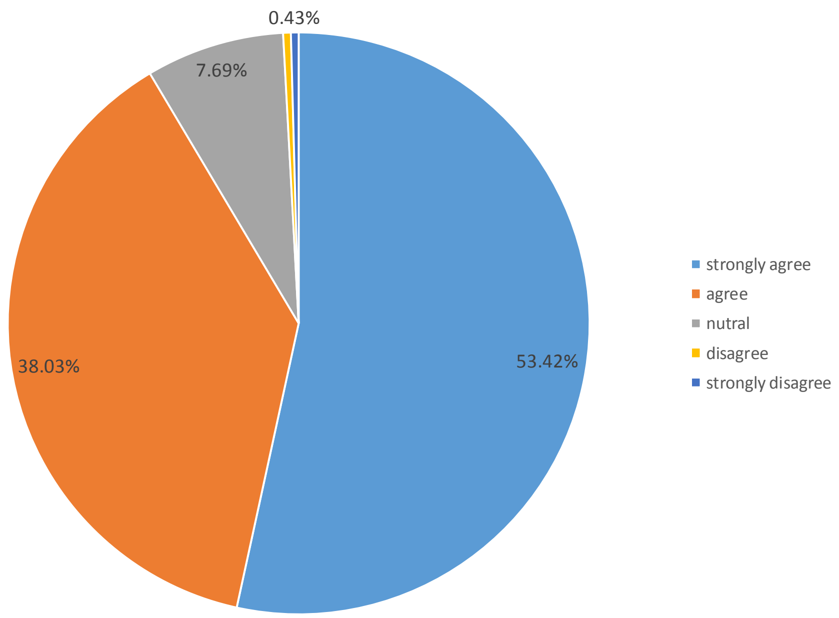


Fig. 3.16 The participants' responses to the statement (I value any recommendation from the teacher about the most appropriate learning paths for me)

This ascertains the importance of teachers' role even though many of the participants said they wanted to have the freedom and flexibility of choosing what they wanted to learn, as has been previously discussed.

The results for this group's three statements highlighted the importance of offering a way that allows the multi-agents in the intelligent tutoring system to collaborate to control the learning process. This highlights the need to apply the adjustable autonomy mechanisms and the mixed-initiative interaction as they allow the user to create and/or control the applied rules.

Table 3.3 Summarising the results of the third part of the questionnaire

Question	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
Usually, I feel that I do not have the skills that allow me to choose the most appropriate learning path for me (to plan what I am going to learn).	17.09%	32.05%	31.2%	13.68%	5.98%
When I am learning a module, I would be interested in knowing the learning paths that other students have chosen, particularly those who have a level of knowledge similar to mine.	34.19%	42.74%	18.8%	3.85%	0.43%
I value any recommendation from the teacher about the most appropriate learning paths for me.	53.42%	38.03%	7.69%	0.43%	0.43%

Identifying the students' learning needs for adjusting the guidance level

In the first three statements of this group, the participants were not asked to rank the three levels of guidance as the ranking would indicate that the students may not need to change the level of guidance according to their learning needs. It was also thought that the ranking would not allow the research to obtain detailed information about the students' preference for each of the three levels. Alternatively, the students were asked about the degree of preferring the level in general.

The responses received for the first statement "Usually, I want the teacher to guide me to the appropriate lessons and not allow me to choose by myself" were as follows: 23.08% strongly agreed, 35.90% agreed, 27.78% were neutral, 9.83% disagreed and 3.42% strongly disagreed. (see Figure 3.17)

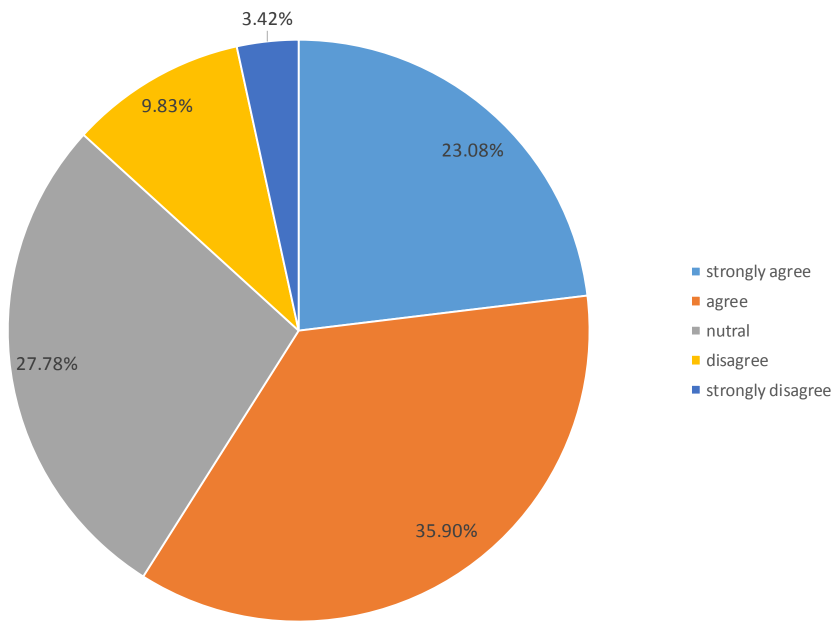


Fig. 3.17 The participants' responses to the statement (Usually, I want the teacher to guide me to the appropriate lessons and not allow me to choose by myself).

The responses received for the second statement "Usually, I prefer if the teacher guides me to study a lesson which is appropriate to my knowledge level but gives me the freedom to follow or disregard his/her guidance" were as follows: 40.17% strongly agreed, 40.60% agreed, 14.53% were neutral, 3.42% disagreed and 1.28% strongly disagreed. (see Figure 3.18)

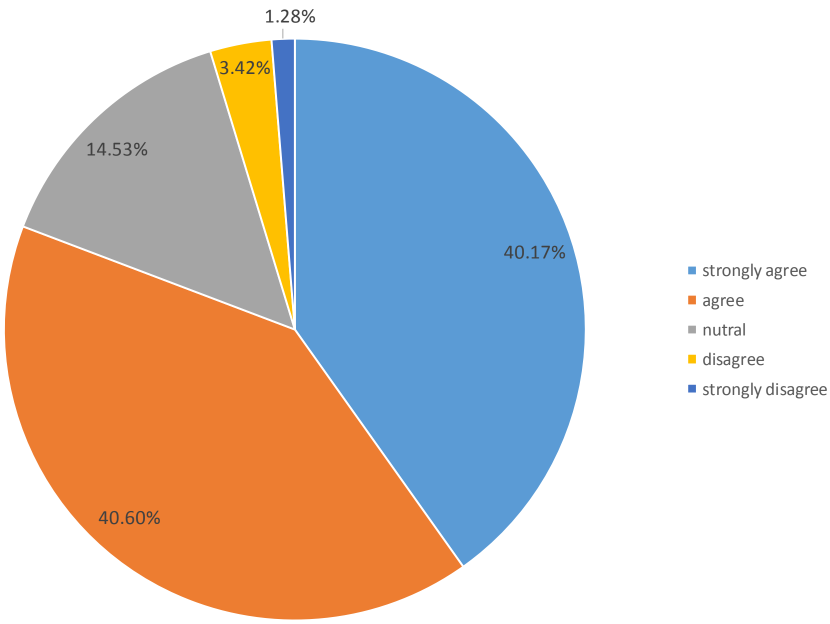


Fig. 3.18 The participants' responses to the statement (Usually, I prefer if the teacher guides me to study a lesson which is appropriate to my knowledge level but gives me the freedom to follow or disregard his/her guidance).

For the third statement "Usually, I prefer if I am given the full freedom to choose what I want to study without any intervention", 24.79% of the participants strongly agreed, 29.06% agreed, 29.49% were neutral, 12.82% disagreed and 3.85% strongly disagreed (see Figure 3.19).

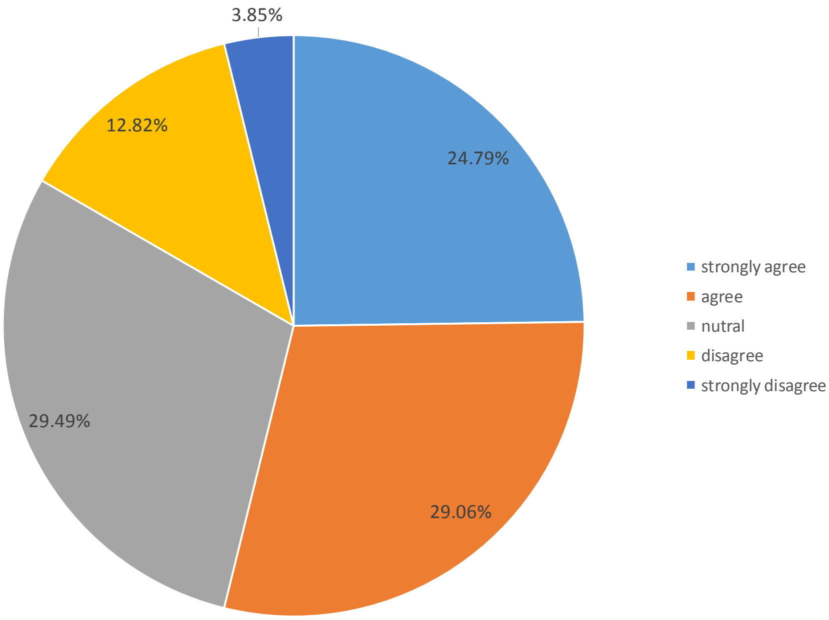


Fig. 3.19 The participants' responses to the statement (Usually, I prefer if I am given the full freedom to choose what I want to study without any intervention).

The previous three statements asked students about their preferences regarding the three levels of guidance: full guidance (FG), partial guidance (PG) and no guidance (NG) and their responses varied; while most of the students stated that they preferred to have access to the three levels of guidance together (33.7%), 5.9% of them said they did not prefer any of the three levels or gave neutral responses. As for those who preferred two types of guidance, 20.5% reported that they preferred to have access to both PG and FG, 10.2% said they would like to have PG and NG, but only 1% chose NG and FG as their preference. In terms of individual guidance levels, 16.2% reported that they preferred PG, 8.5% preferred to choose NG and only 3.4% stated that they would rather choose FG (see Figure 3.20).

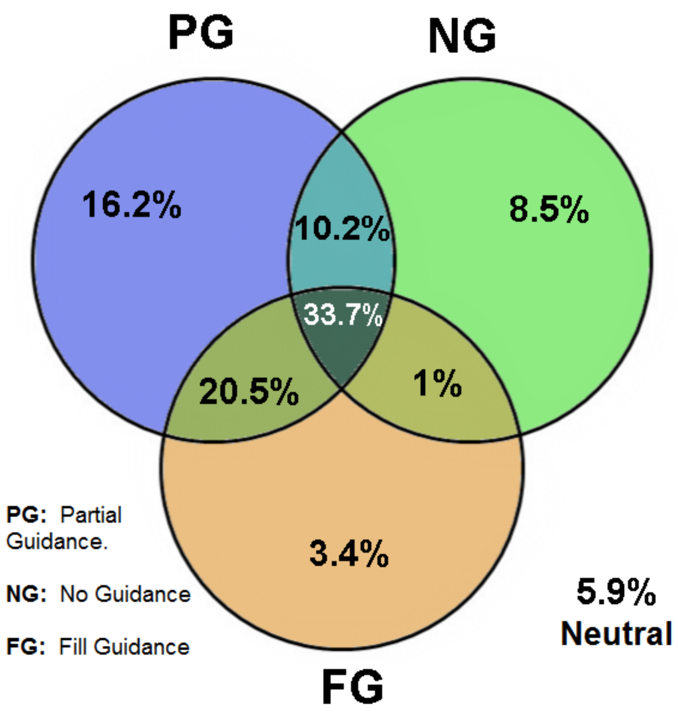


Fig. 3.20 The participants' preferences of the three guidance mode

Now, to see if the students' learning needs regarding the best suitable level of guidance is changeable over the time, the lessons or the modules, the participants were asked to rate their agreement with the statement "my preferred guidance mode differs from time to time (between the three guidance modes mentioned in the survey description)." The results revealed that the majority of participants agreed (42.74% strongly agreed and 37.61% agreed) while 14.10% were neutral, 4.70% disagreed and 0.85% strongly disagreed (see Figure 3.21).

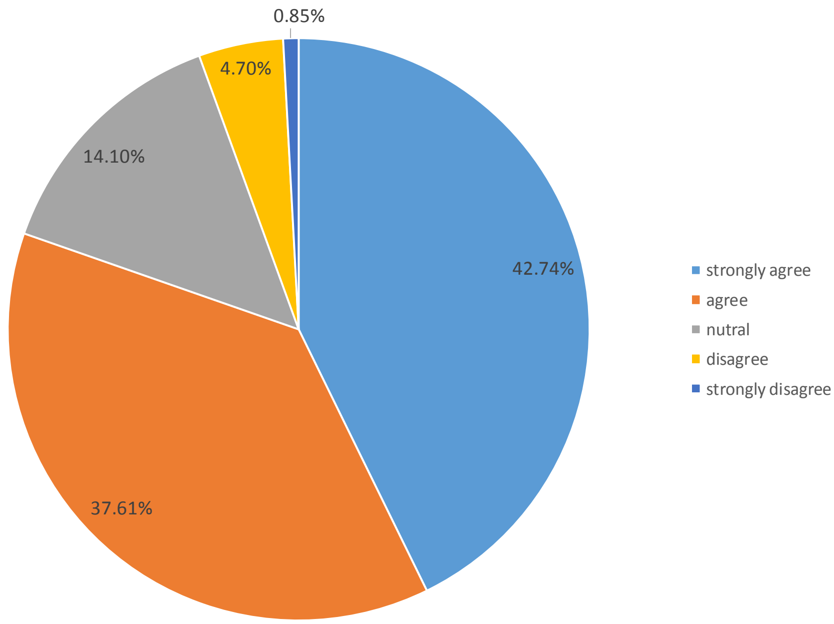


Fig. 3.21 The participants' responses to the statement (my preferred guidance mode differs from time to time (between the three guidance modes mentioned in the survey description)).

This highlights once again that there should be a way to equip the system with the adjustable autonomy mechanisms to allow the students to adjust the autonomy level to the preferred level and the system should promptly respond to that.

The last point to be investigated in this group was whether or not the suggested three levels were enough to fit the students' learning needs. The statement was, "the three modes of guidance mentioned in the survey description are enough to achieve my learning needs". More than three quarters of the participants expressed their agreement to that statement (38.89% strongly agreed and 37.61% agreed), whereas 14.10% were neutral, 8.55% disagreed and 0.85% strongly disagreed (see Figure 3.22).

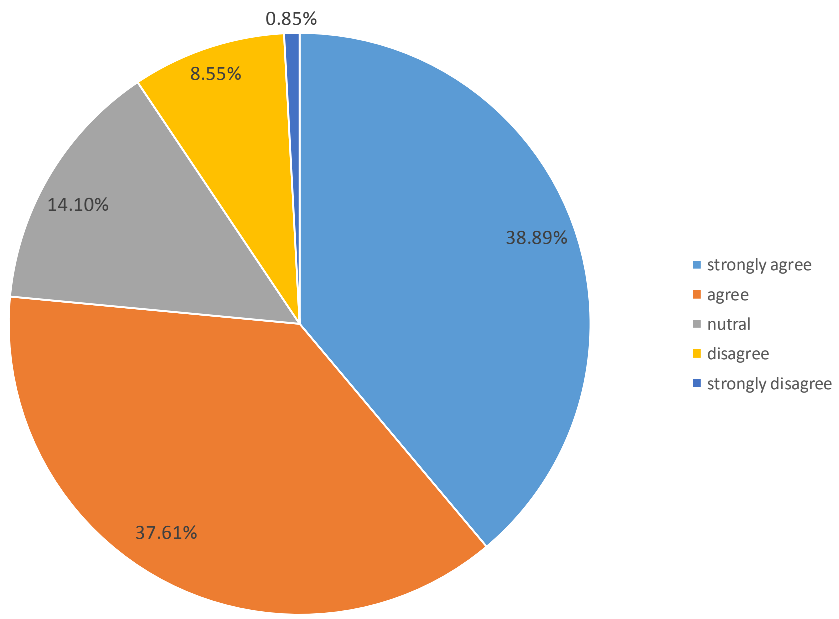


Fig. 3.22 The participants' responses to the statement (the three modes of guidance mentioned in the survey description are enough to achieve my learning needs).

Table 3.4 Summarising the results of the fourth part of the questionnaire

Question	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
Usually, I want the teacher to guide me to the appropriate lessons and not allow me to choose by myself.	23.08%	35.9%	27.78%	9.83%	3.42%

Question	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
Usually, I prefer if the teacher guides me to study a lesson which is appropriate to my knowledge level but gives me the freedom to follow or disregard his/her guidance	40.17%	40.6%	14.53%	3.42%	1.28%
Usually, I prefer if I am given the full freedom to choose what I want to study without any intervention	24.79%	29.06%	29.49%	12.82%	3.85%
My preferred guidance mode varies from time to time (between the three guidance modes mentioned in the survey description	42.74%	37.61%	14.1%	4.7%	0.85%
The three modes of guidance mentioned in the survey description are sufficient to fulfil my learning needs	38.89%	37.61%	14.1%	8.55%	0.85%

3.3 Discussion

The chapter's core aim was to clarify some related learning needs and preferences from students' point of view. This aim was decomposed into four objectives: 1) understanding some aspects of students' feelings and attitude when they undertake a lesson that they already master; 2) clarifying the need for adapting the lessons' sequence to fit the students' learning needs; 3) determining how much students want to rely on other students' and teachers' experiences when choosing the best sequence; and 4) identifying students' learning needs for adjusting the guidance level. A quantitative research method was followed to reach these objectives by distributing an online survey. A total of 234 responses were analysed and the results indicated that many students wanted to be involved in controlling the learning process and have the ability to decide what to learn (i.e. sequencing the lessons). The results also showed that many students experienced some repetition of lessons while following different modules. In addition, many students expressed negative feelings when repetition occurred, although they admitted that this could be an effective technique for learning. One of the interesting findings is that, for many students, the most important factor which played a role in deciding whether to learn a lesson or not was the level of knowledge of that lesson. Despite the fact that some students had concerns about having the skills that would allow them to decide the sequence of lessons, most of them agreed that the three autonomy levels were sufficient for them to achieve their learning objectives and that their preferences for any of the three levels might vary according to the context. In general, the students appreciated the teachers helping them to choose the appropriate learning path and they also valued sharing experiences with other students, particularly those with similar knowledge levels.

The reviewed literature (reported in Chapter2) showed that there is a gap in involving online tutoring systems' users (i.e. students and teachers) in the design and operational phase of the system. From the survey's findings, we infer that involving students and teachers is worthwhile as it may contribute to improving the process of fulfilling students' learning needs. In addition, allowing students to adjust the guidance level is a persistent need as it makes the system more adaptable to suit their variable learning needs. Moreover, by offering students a way that allows them to control what they learn, the issue related to the negative feelings while re-studying a lesson can be tackled [58], [175]. The next chapter provides an explanation of how these learning needs can be fulfilled in an on-line tutoring system.

Chapter 4

The Adaptive Course Sequencing Approach (ACSA)

The previous chapters highlighted a gap in offering students and teachers a way to control the learning process in online tutoring systems. They also indicated that students need to have control over what to learn as, according to them, this makes them learn better. However, students have variable preferences regarding how much they want to control the learning process. A suggested solution to overcome this issue is by utilising adjustable autonomy mechanisms. Therefore, I devised a novel approach called Adaptive Course Sequencing Approach (ACSA) to fill this gap and meet students' and teachers' learning/teaching needs.

This chapter aims to achieve one of the research objectives, which is "identifying the conceptual architectural model for adjustable autonomy online tutoring systems" and to test one of the research hypothesis which states that "it is possible to devise a conceptual architectural model able to adapt the sequence of learning contents, allowing students to personalise the way of receiving the sequencing, making the tutor agent capable of producing sequencing rules and giving the teachers the ability to control the learning process". The chapter presents the theoretical and practical basis of the ACSA conceptual model and the way of enabling the adjustable autonomy and mixed-initiative mechanisms. It also describes the learning framework that was used in ACSA.

4.1 ACSA Agents and their Roles

The Adaptive Course Sequencing Approach (ACSA) is a web-based asynchronous learning approach which is capable of profiling students and suggesting appropriate learning paths through a set of lessons based on their profiles. It uses a fuzzy logic classification approach to predict the most appropriate lesson sequence for each student, based on his/her profile. The ACSA is equipped with adjustable autonomy and mixed-initiative mechanisms which allow both the tutor agent and human agents to collaborate in generating and enhancing the sequence rules, while also allowing students to adjust the tutor agent's autonomy level. In addition, it gives the teachers the ability to control the learning process by defining the policies in which the agent differentiates the active rules from the potential ones.

The ACSA functions as an eco-system comprising students, teachers, intelligent artificial tutors, knowledge repositories (books, web resources, etc.), and university management (setting up courses from both business and academic decisions); on the higher level, this also involves companies' needs and government policies. All of these contribute in some way to defining the learning objectives.

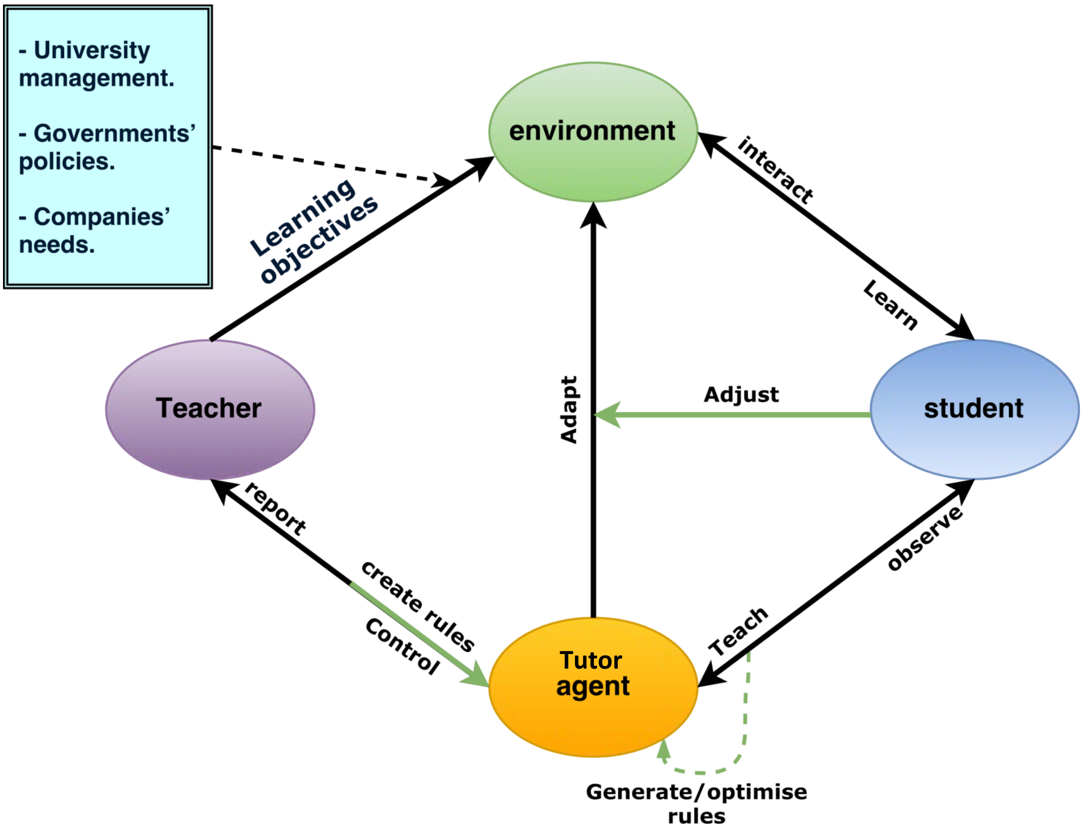


Fig. 4.1 The ACSA elements' roles

The survey's findings, reported in Chapter 3, show that there should be a way that allows both teachers and students to control the learning process and contribute in making decisions. In this way, teachers, students and the tutor agent contribute to enriching the learning process which, in turn, leads to enhancing the learning outcomes. Based on that, the roles of teachers, students and the tutor agent are going to be different from those in other intelligent tutoring systems which do not rely on the collaboration between the eco-system elements in forming the pedagogical decisions. The new roles can be described as shown in Figure 4.1.

- Teacher: 1) controlling the sequencing rules and the ability to contribute to creating them, 2) controlling the various policies, which differ based on the guidance mode and which are responsible for differentiating the active rules from the potential ones and 3) contributing to outlining the learning objectives; in this respect, teachers can benefit from students' use of the system, which is reported to teachers by the tutor agent.

- Student: 1) interacting with the environment to learn, 2) teaching the tutor agent how to sequence the lessons for the next similar students and 3) adjusting the way of introducing the sequencing (i.e. adjusting the guidance mode) to fit his/her learning preferences and needs.
- Tutor agent: 1) observing students' behaviours 2) generating new rules or optimising the existence rules based on the observation, 3) reporting individual students' interactions and 4) adapting the lessons' sequence in the environment based on the chosen level of autonomy and active rules.

4.2 ACSA Conceptual Model

The ACSA model was constructed as a way of delivering the required functionalities that cover the adaptive pedagogical needs for every student and answer the research questions. That was done based on the system requirements mentioned in Chapter1 and the survey results presented in Chapter3.

From the students' perspective, this model is able to give the student the freedom to choose a path through learning objects as well as offer a degree of guidance to the most appropriate learning path. From the teachers' perspective, this model offers a way of communication with the tutor agent to enhance the guidance rules, summarise the students' progress in the taught course in general or in every lesson, report the progress of individual students and access the educational resources to add, edit or delete any learning object. From the tutor agent perspective, this model allows the tutor agent to learn from the students' learning behaviours to build an effective and updated adaptation model which holds the guidance rules responsible for sequencing the course's lessons.

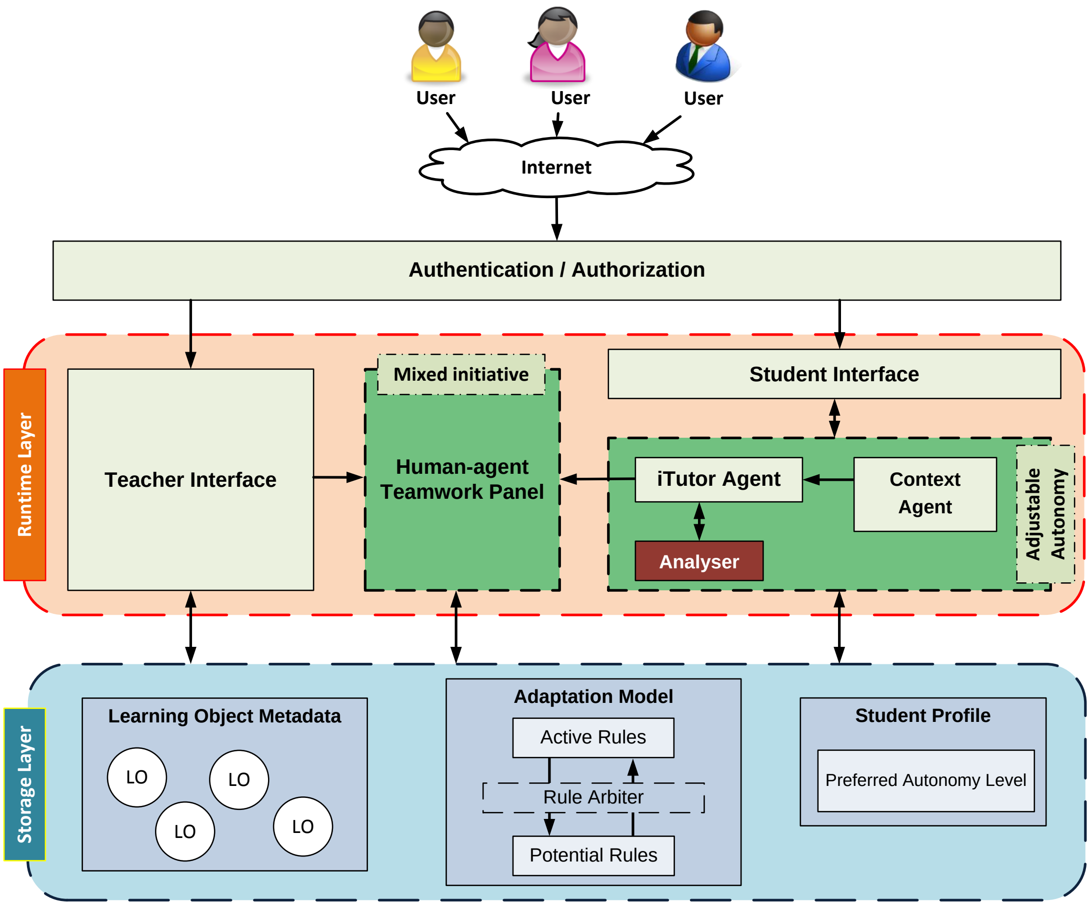


Fig. 4.2 ACSA Conceptual Model

The conceptual model is divided into two main layers: the runtime layer and storage layer. The runtime layer is responsible for performing adaptive and pedagogical functions. This layer has these components: user interface for both teachers and students, iTutor agent, context agent and analyser. Hence, the impact of the adjustable autonomy mechanisms appears more in the iTutor agent, the context agent and the analyser. Therefore, some functionalities in these components are performed in a different way for each autonomy level. The second layer is the storage layer. It has these components: learning object meta-data, student profile and adaptation model. The ACSA components are described in more details below.

4.2.1 Learning objects metadata (LOM)

This component is responsible for storing learning objects following IEEE (LOM) 1484.12.1 standard for the purpose of reusability and discoverability [176]. In addition, it is easily accessible by teachers for adding, updating or deleting any content.

4.2.2 Student profile

The student profile stores a wide range of data which can be inferred and reasoned using a soft computing technique to build a student model. All the interactions between the student and the system are stored in the student's profile with their time, the offered guidance by the iTutor agent, the student's behaviour towards the guidance and the preferred autonomy level for the student. This component follows, partially, the enhancement of IEEE-PAPI specification that was made by Wei and Yan as shown in Figure 4.3 [177]. Thus, this component has the following categories:

1. personal information: (name, address, reference and e-mail).
2. portfolio information: (degree, transcription, qualifications, certificates).
3. security information: (user name and password).
4. preference information: (language, preferred difficulty level, content preference and preferred time on each study).
5. performance information: (student ID, content ID, recoding-date-time (time begin and time end), pre-knowledge level, current knowledge level).
6. session information: (time of registration, time of logging in and out and client ip).

7. learning institution information: (learning institution name, learning institution branch name, student registration number and group number).

8. guidance information (applied rule, student behaviour towards it and time).

9. autonomy level: (level of autonomy).

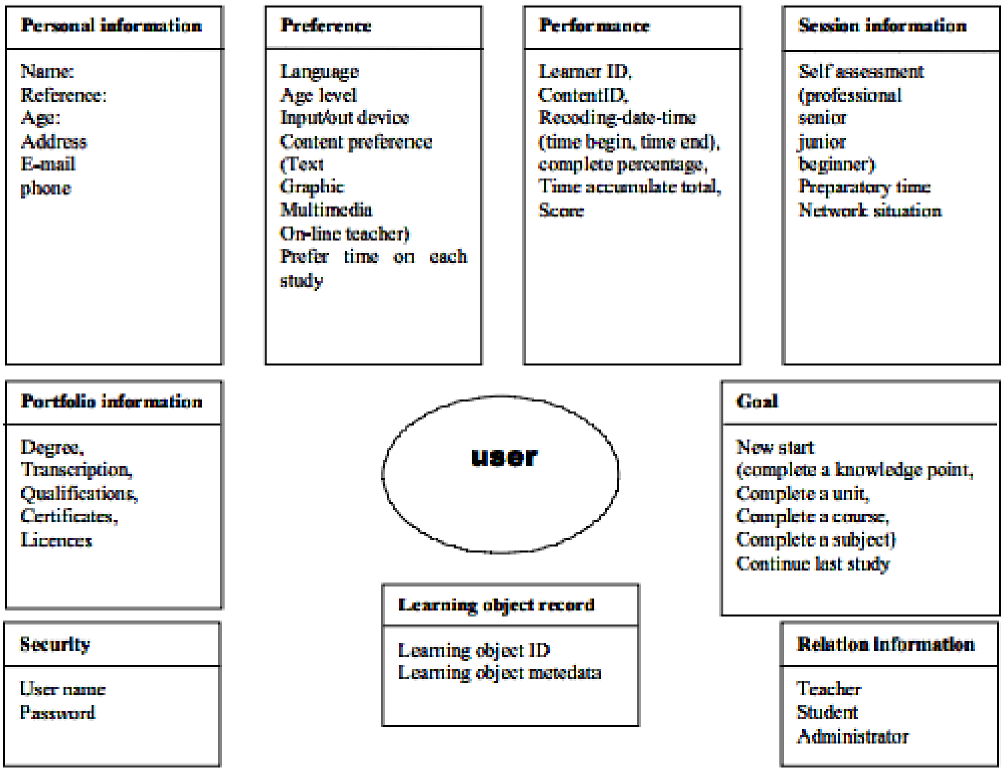


Fig. 4.3 IEEE PAPI specification for student profile [177]

The last three categories (learning institution information, guidance information and autonomy level) are not included in the enhancement of IEEE-PAPI specification and they are added here owing to their importance. The current study contributes to adjusting the specification by adding these three categories, which in turn opens doors for the specification to be used in the adjustable autonomy intelligent tutoring systems which may be applied in universities.

4.2.3 Adaptation model

The adaptation model contains guidance rules that are used by the iTutor agent. Two types of rules may comprise this model which are active rules and/or potential rules. The active rules are those that are created or edited by the teachers or pass the criteria which are set by the teachers and rely on the rule's number of followers and non-followers. On the other hand, the potential rules are those that are autonomously generated by the analyser and have not been created, approved or edited by the teachers or have not passed the criteria. The adaptation model can be provided with machine learned rules generated by the analyser or with fixed rules created by teachers. Each rule contains some important information, for instance who added or edited it, when it was added or edited, how many students followed or discounted the rule and how much the rule weighed. Some of these details are important for the analyser to mine the most appropriate rule for the current learning scenario (i.e. rule weight) or to distinguish the rule status, i.e. if it is an active or a potential rule. Other details may influence the teachers' decisions when they approve, edit or delete a rule (e.g. the number of followers or non-followers).

4.2.4 Human-agent Teamwork Panel

This component provides a way of communication between the iTutor agent and the teachers since the rules are readable (thanks to Fuzzy logic). Hence, the teachers can adjust and control the criteria/policies which are located in "the rule arbiter" which is in the adaptation model and is responsible for distinguishing the approved rules. Hence, the criteria may differ in each level of autonomy.

The iTutor agent in turn provides the teachers with a list of weak rules and equips each teacher with a list of the rules that are added or edited by that teacher. Moreover, the iTutor agent can notify the teacher if one of his/her edited or added rules has had more followers than non-followers. In addition, this component provides teachers with interactive tools that help them to search and sort the rules and explore the related details which make their decision of adding, updating the rules' consequences or deleting any rule more precise.

This component also logs the interaction between the teacher and the adaptation model in a separate repository, which will give useful information to future researchers about the teachers' behaviours towards the rules, particularly if this information was reasoned using a soft computing technique.

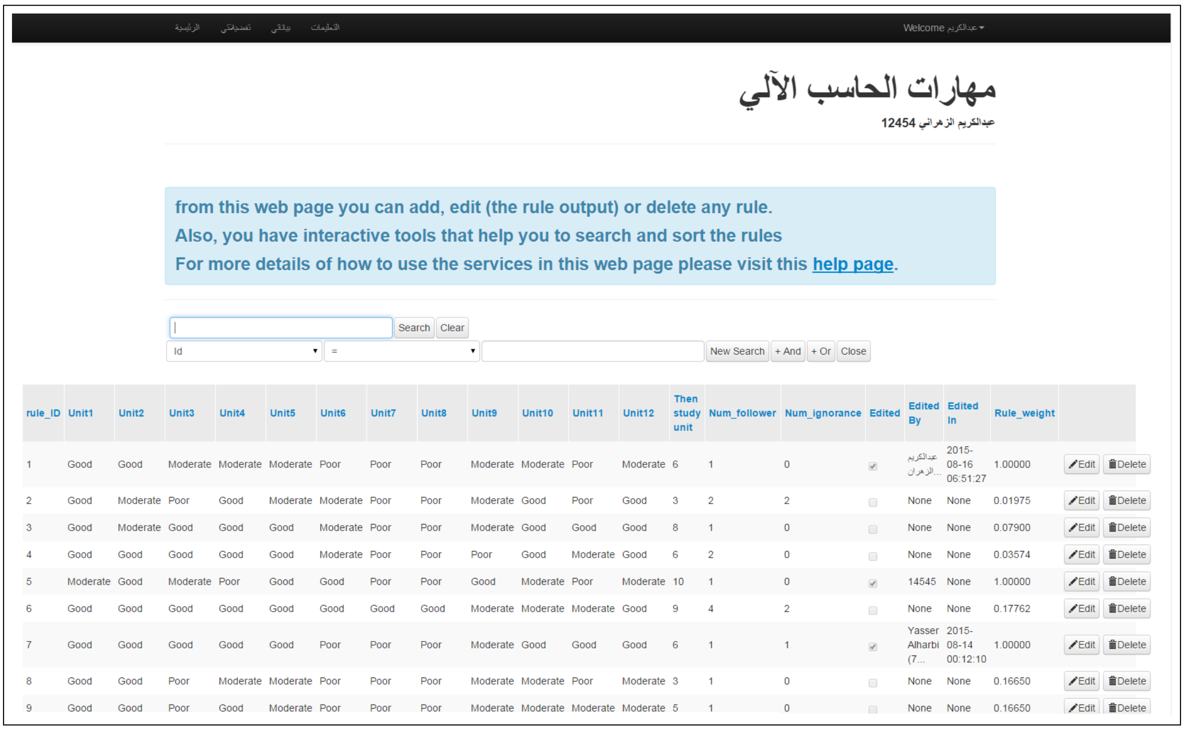


Fig. 4.4 An example of the adaptation model management services

4.2.5 Context agent

For achieving adaptivity, there should be a mechanism for capturing certain characteristics of individual learners and utilise the captured data for adapting the content's sequence [178]. Thus, the main functionalities of this agent are to track students' learning behaviours, pass the information to the student profile and infer the iTutor agent if there is any change in the student's knowledge level or current learning scenario.

The full details of the students' interactions while doing a pre- or post-test will be reported as soon as the student finishes the test. An example of this report can be seen in Figure 4.5 where the student in this example has got 62.5% score by answering six (out of eight) questions correctly. This report is saved as an XML file (for interoperability purposes) (see Figure 4.6), parsed and then stored in the student profile (see Table 4.1 and Table 4.2).

The context agent is affected by the chosen level of autonomy. For students in the partial autonomy level, this agent tracks the student's behaviour towards the tutor agent guidance; whether the student follows the offered guidance or ignores it. Then, it updates the number of followers or non-followers in the executed guidance rule in the adaptation model. However, this function is not applied for students in the full autonomy level because students in this level do not have the choice to disregard the rules. Furthermore, the context agent is responsible for collecting the needed data in the training phase and passing it to be stored in the sequencing dataset which will be used by the analyser to generate rules.

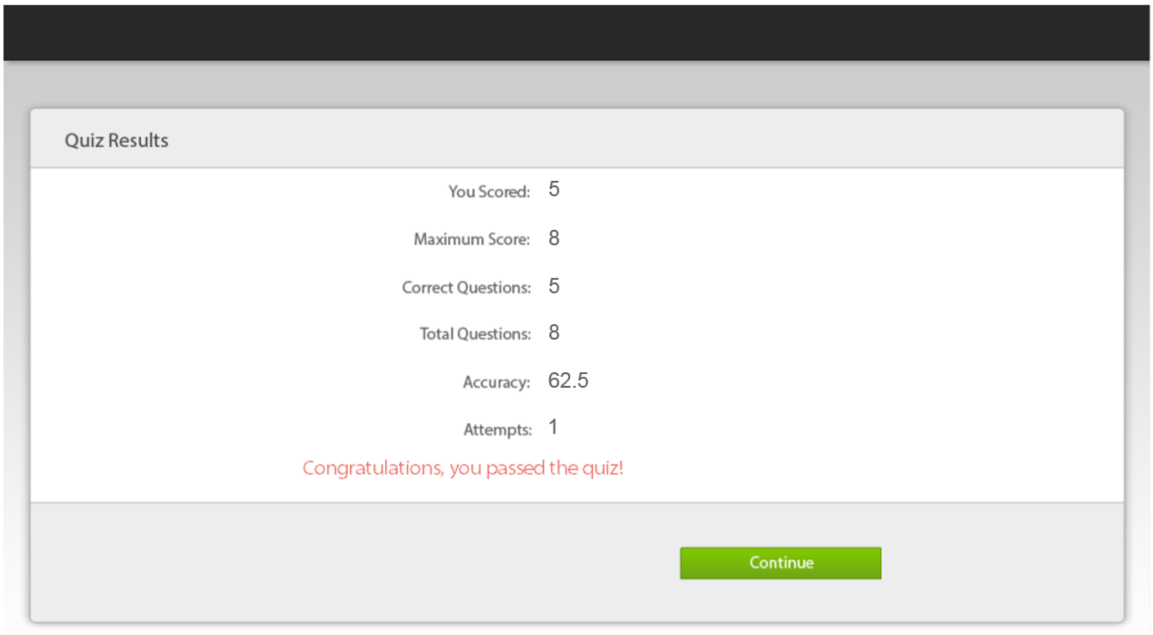


Fig. 4.5 Reporting the students' interaction while doing the test

```xml
<Course>
  <CompanyName value="Essex"/>
  <DepartmentName value="cs"/>
  <CourseName value="009"/>
  <LearnerName value="abdulkareem Alzahrani"/>
  <LearnerID value="aaalza@essex.ac"/>
  <LessonName value="save_assessment"/>
  <QuizAttempts value="1"/>
  <TotalQuestions value="4"/>
  <Variables>
    <cpQuizInfoStudentID value=""/>
    <cpQuizInfoStudentName value=""/>
    <Text_Entry_Box_1 value="mark"/>
  </Variables>
  <Result>
    <CoreData>
      <Status value="incomplete"/>
      <Location value="7"/>
      <Score value="25"/>
      <SessionTime value="00:00:46"/>
    </CoreData>
    <InteractionData>
      <Interactions>
        <Date value="03/05/2014"/>
        <InteractionTime value="22:57:28"/>
        <InteractionID value="save_icon"/>
        <ObjectiveID value="008_save"/>
        <InteractionType value="choice"/>
        <CorrectResponse value="1"/>
        <StudentResponse value="0"/>
        <Result value="W"/>
        <Weight value="1"/>
        <Latency value="00:00:00"/>
        <Attempt value="1"/>
      </Interactions>
      <Interactions>
        <Date value="03/05/2014"/>
        <InteractionTime value="22:57:54"/>
        <InteractionID value="save_fileName"/>
        <ObjectiveID value="008_save"/>
        <InteractionType value="fill-in"/>
        <CorrectResponse value="A.mark"/>
        <StudentResponse value="A.mark"/>
        <Result value="C"/>
        <Weight value="1"/>
        <Latency value="00:00:16"/>
        <Attempt value="1"/>
      </Interactions>
      <Interactions>
        <Date value="03/05/2014"/>
        <InteractionTime value="22:58:01"/>
```


Fig. 4.6 Reporting the students' interaction in XML format

4.2.6 iTutor agent

This agent is the process manager or the pedagogical action agent. It manages learning activities, guides the student based on his/her knowledge level in every lesson, autonomy level and the active guidance rules in the adaptation model.

When the student registers in the system, the iTutor agent will ask the student to complete a series of pre-tests which will measure the student's previous knowledge level in the relevant lesson. The student cannot start studying using the system unless (s)he finishes all the

Table 4.1 Example of the test's report

id	student id	learning unit	total questions	mark	latency
55529	7389	4	5	62.5	00:04:46
56207	7389	1	8	100	00:02:11
56208	7389	3	5	100	00:06:04
56209	7389	4	5	100	00:02:26
56210	7389	8	7	100	00:02:58
56211	7389	5	8	100	00:01:41
56212	7389	6	9	92.31	00:03:54
56213	7389	7	6	50	00:03:40
56214	7389	11	7	100	00:01:36
56215	7389	10	8	100	00:03:30
56216	7389	9	11	100	00:04:31
56217	7389	7	6	50	00:08:45

pre-tests. Thus, his/her pre-knowledge level will be known to the iTutor, which in turn makes the iTutor guidance more practical and effective. Students are asked to complete the pre-tests based on their own knowledge not by relying on external resources. If a student is in the full autonomy or partial autonomy level, the iTutor agent will send a request (in a JSON format) to the analyser web-service to extract the most appropriate rule amongst the active ones (see Figure 4.8). The iTutor agent will then apply the extracted rule based on the student's autonomy level chosen. In addition, the iTutor agent will extract the relevant learning objects from the learning object repository and ask the student to start studying the recommended lesson and then undertake the lesson's post-test. After that the test's report will be issued and passed to the iTutor agent. Furthermore, when the iTutor agent recognises that the student needs to be guided, the iTutor agent will communicate with the analyser again to find the most appropriate rule for the current learning scenario.

4.2.7 Analyser

The membership functions for the input data were extracted based on teachers' opinions. They were asked to represent each fuzzy set, for example poor, moderate and good, on a scale

Table 4.2 Example of reporting the students' interactions towards the test's questions

id	Res. id	date & time	description	result	weight	latency
753809	55529	02/12/2015 08:49:38	click view tab	C	2	00:00:50
753810	55529	02/12/2015 08:49:44	click view full screen	C	2	00:01:02
753811	55529	02/12/2015 08:51:49	click page layout tab	W	2	00:01:46
753812	55529	02/12/2015 08:52:58	click direction	W	1	00:01:03
753813	55529	02/12/2015 08:53:07	choose horizontal	C	1	00:00:05
758040	56207	15/12/2015 20:38:08	click start Windows button	C	2	00:00:56
758041	56207	15/12/2015 20:38:25	click all programs	C	2	00:00:13
758042	56207	15/12/2015 20:38:42	click Microsoft office	C	2	00:00:13
758043	56207	15/12/2015 20:38:47	choose Excel	C	2	00:00:02
758044	56207	15/12/2015 20:39:18	click Office choice	C	2	00:00:17
758045	56207	15/12/2015 20:39:27	click close workbook	C	2	00:00:05
758046	56207	15/12/2015 20:39:59	click formula bar	C	2	00:00:22
758047	56207	15/12/2015 20:40:05	click active cell	C	2	00:00:03

from 0 to 100 as a triangle. Then the average for each point in the triangle (a, b and c) was calculated to be a final applied membership function (see Figure4.7). The analyser utilises the fuzzy rule based classification approach. The extracted fuzzy rules and the membership functions enable the analyser to generate fuzzy logic rules or extract the most appropriate lesson (the rule consequence or class) when the iTutor agent passes the needed input data. When the input data is passed, this component starts the functionality by fuzzifying the crisp inputs to produce fuzzy sets (the singleton fuzzifier was utilised due to its simplicity and popularity). The inference engine will then be used to map the inputs' fuzzy sets to the appropriate class (lesson). All the fired rules with their associated rule weight (using product implication) and class will be aggregated in the defuzzification, where the class (lesson) for the highest rule weight will be extracted.

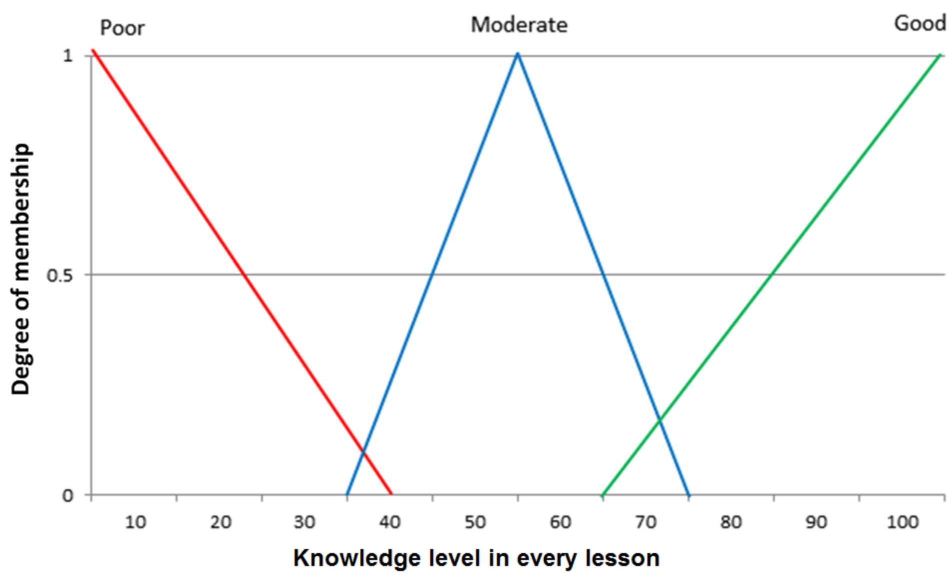


Fig. 4.7 The input membership function of knowledge level for every lesson

One of the system's distinguishing features was building the analyser as a web-service, which allows any authorised system connected to the internet to send the student's knowledge levels in JSON format in response to a HTTP request using the POST method, thereby helping the analyser to respond with a rule that matches the student's needs. Hence, making the tutor agent a web-service enables any online tutoring system to benefit from the agent's pedagogical decisions. This inevitably facilitates the construction of new online tutoring systems in the future through utilising the pedagogical decisions of other tutor agent web-services, which can save the time, effort and financial resources required for establishing a new online system from scratch. This can be achieved when the pedagogical decisions and recommendations are shared publicly among educational institutions


```
"studentMarks": {
"lesson01": 100,
"lesson02": 100,
"lesson03": 87.5,
"lesson04": 82.35,
"lesson05": 83.33,
"lesson06": 93.55,
"lesson07": 100,
"lesson08": 0,
"lesson09": 85,
"lesson10": 100,
"lesson11": 100,
"lesson12": 0
}
```


Fig. 4.8 Example of JSON request on a particular student's marks at a particular time sent to the analyser

4.2.8 User interface

For Students the student's user interface has many features that reach his/her needs. The list below summarises the features that are included in the interface:

درجاتك ببرنامج الإكسل

الدرجة	عنوان الوحدة
100.0	فتح واستكشاف إكسل
54.55	التعامل مع ملف إكسل
50.0	إدخال البيانات
100.0	الضبط
100.0	التحرير
46.15	التنسيق
66.67	صيغ ودوال
50.0	التعامل مع الجداول
100.0	الطباعة
100.0	الرسوم البيانية
66.67	التعامل مع ورقة العمل
100.0	رسائل الخطأ

Fig. 4.9 The updated marks for every lesson as appeared in the student interface

1. The student can adjust the autonomy level at any time and ACSA will respond to that promptly.
2. The student can see his/her updated marks for every lesson in a motivated layout that differentiates the pass or failure lessons (see Figure 4.9).
3. The student can access and edit his/her profile.
4. The student can access the FAQ and help the web-page (see Figure 4.10).
5. The student can learn the lesson which is explained in different teaching methods (see Figure 4.11).
6. The student can pause, rewind or forward the streaming and control the sound volume.

Fig. 4.10 The FAQ and help page containing questions with their answers, images and videos explaining how to use the system

Fig. 4.11 Five learning styles provided for every lesson to accommodate the learning needs for all students

However, the presentation of the lessons list differs based on the chosen autonomous level:

1. A student in the full autonomy level can see only one lesson and the related learning activities. An encouraging hint will be presented to him/her to motivate him/her to study the presented lesson and have a high score to move to the next lesson (see Figure 4.12).

2. A student in the partial autonomy level can see all the offered lessons and the iTutor agent will highlight the lesson recommended to be presented to him/her to motivate him/her to study the presented lesson and have a high score to move to the next lesson. The student can study the recommended lesson or study another one (see Figure 4.13).

3. A student in the no autonomy level can see all the offered lessons and can study whatever (s)he prefers from the list (see Figure 4.14).

Fig. 4.12 The user interface for the full autonomy level

Fig. 4.13 The user interface for the partial autonomy level

Fig. 4.14 The user interface for the no autonomy level

For Teachers The teacher's interface offers a variety of features that cover the teacher's needs:

1. The teacher can add the group (s)he is teaching during the term (see Figure 4.15).
2. The teacher can then see a list of names of the registered students for every group (see Figure 4.16).
3. The teacher can see a summary list of the student interaction (i.e. the registration time, the login time and the logout time) (see Figure 4.17).

4. The teacher can see a table containing the updated marks for every student in every lesson. The table is presented in a way that allows the teacher to easily distinguish the pass or fail marks and the lessons that have not been studied yet (see Figure 4.18).

5. The teacher can log into the lessons' list to discover the course content.

6. The teacher can add/edit or delete any learning object.

7. The teacher can access the adaptation model manager services. to:

   - adjust the criteria of the active rules for the full and partial autonomy level.
   - see a list of the rules (s)he has edited or approved (see Figure 4.19).
   - see a list of the weak rules (see Figure 4.20).
   - explore the active and potential rules with their related information (the number of followers, the number of non-followers, who edited or approved the rule and when if it was edited or approved) (see Figure 4.21).
   - edit or delete any rule (see Figure 4.22).

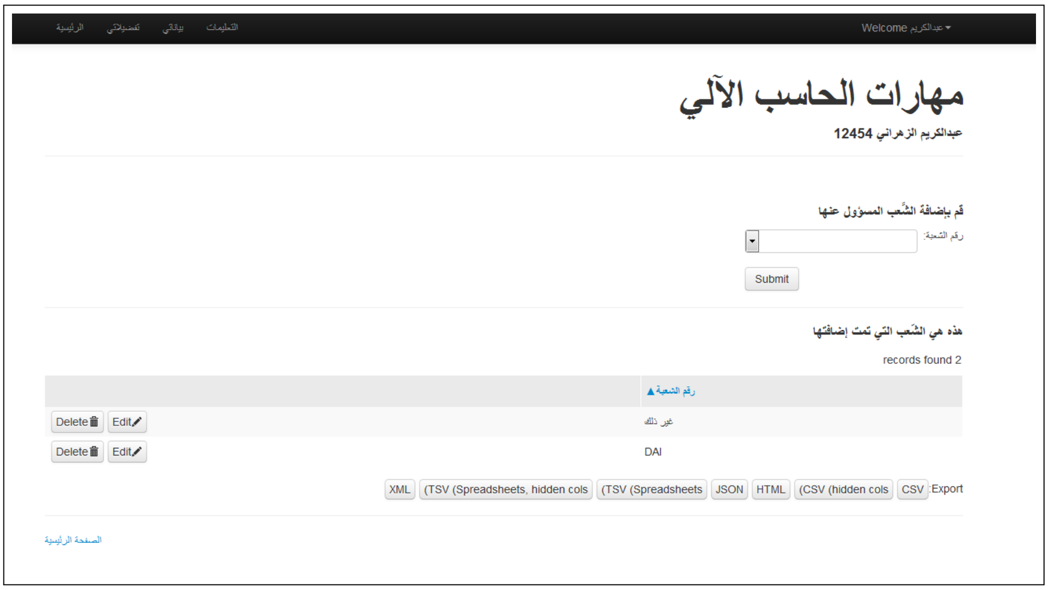
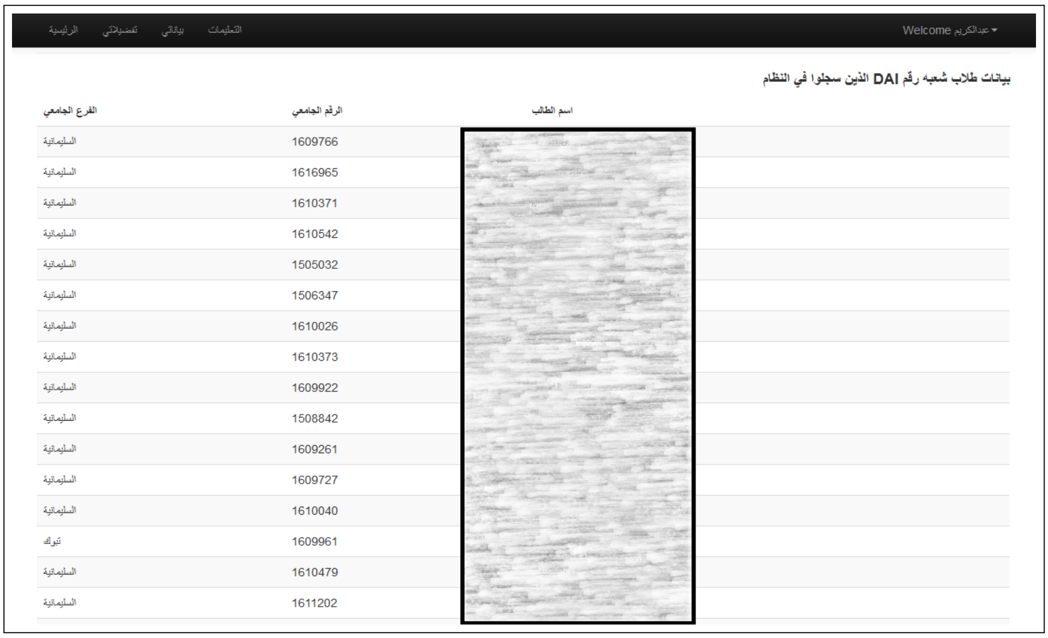
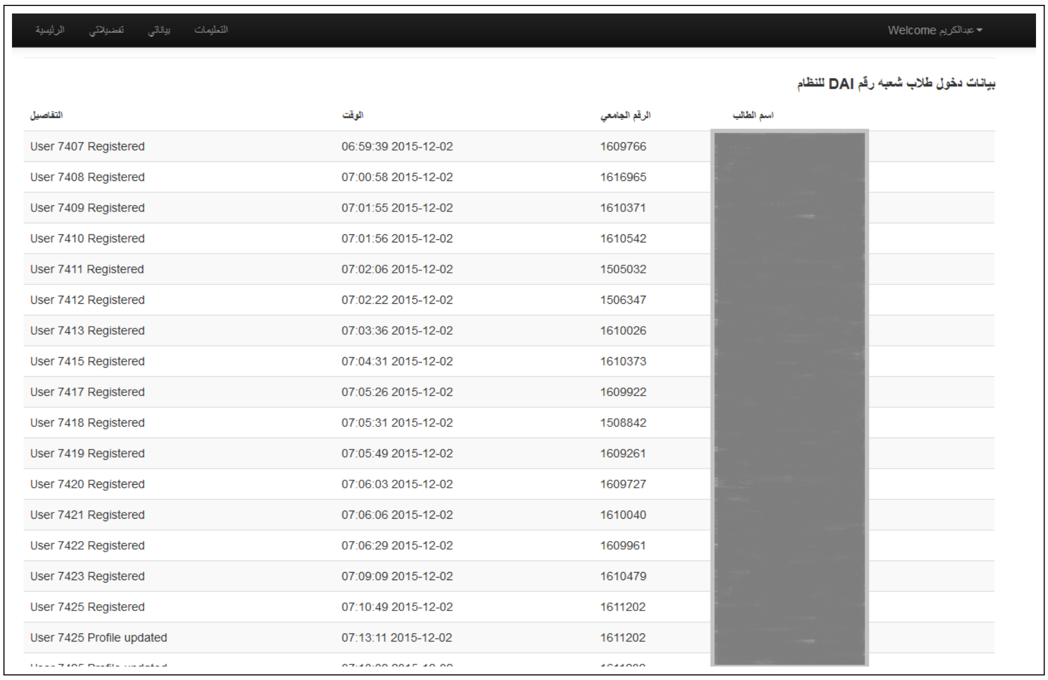


Fig. 4.15 The teacher can add the Group (s)he is teaching



الفرع الجامعي	الرقم الجامعي	اسم الطالب
السليمانية	1609766	[redacted]
السليمانية	1616965	
السليمانية	1610371	
السليمانية	1610542	
السليمانية	1505032	
السليمانية	1506347	
السليمانية	1610026	
السليمانية	1610373	
السليمانية	1609922	
السليمانية	1508842	
السليمانية	1609261	
السليمانية	1609727	
السليمانية	1610040	
تبوك	1609961	
السليمانية	1610479	
السليمانية	1611202	

Fig. 4.16 A list of the registered students' names, university numbers and university branch names as presented in the teacher interface



التفاصيل	الوقت	الرقم الجامعي	اسم الطالب
User 7407 Registered	06:59:39 2015-12-02	1609766	[redacted]
User 7408 Registered	07:00:58 2015-12-02	1616965	
User 7409 Registered	07:01:55 2015-12-02	1610371	
User 7410 Registered	07:01:56 2015-12-02	1610542	
User 7411 Registered	07:02:06 2015-12-02	1505032	
User 7412 Registered	07:02:22 2015-12-02	1506347	
User 7413 Registered	07:03:36 2015-12-02	1610026	
User 7415 Registered	07:04:31 2015-12-02	1610373	
User 7417 Registered	07:05:26 2015-12-02	1609922	
User 7418 Registered	07:05:31 2015-12-02	1508842	
User 7419 Registered	07:05:49 2015-12-02	1609261	
User 7420 Registered	07:06:03 2015-12-02	1609727	
User 7421 Registered	07:06:06 2015-12-02	1610040	
User 7422 Registered	07:06:29 2015-12-02	1609961	
User 7423 Registered	07:09:09 2015-12-02	1610479	
User 7425 Registered	07:10:49 2015-12-02	1611202	
User 7425 Profile updated	07:13:11 2015-12-02	1611202	

Fig. 4.17 The teacher can see a list of his/her students summarising the time of registering, logging-in and logging-out

Fig. 4.18 A table of students' updated marks details as presented in the teacher interface

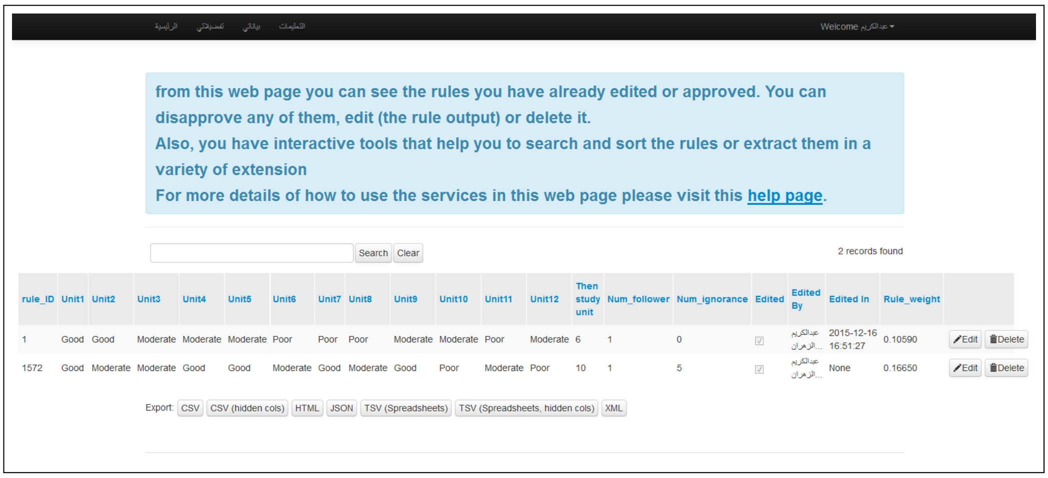
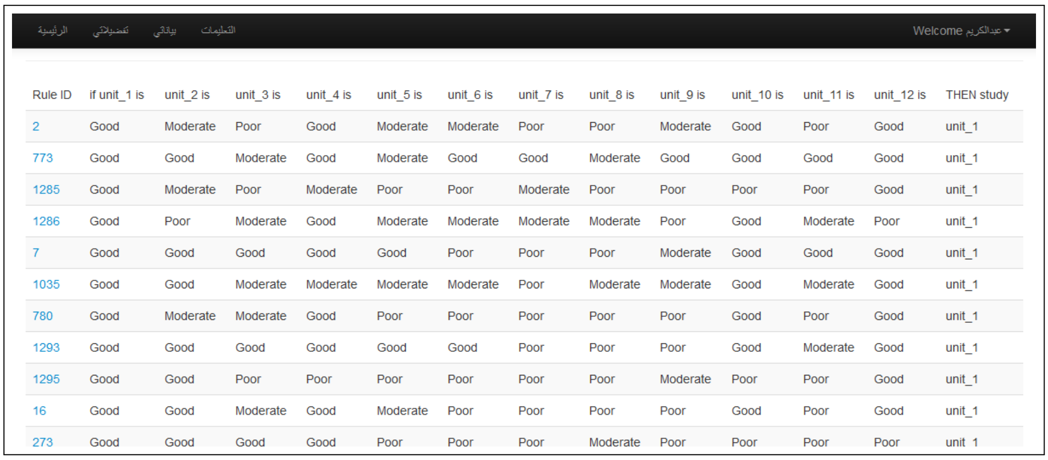
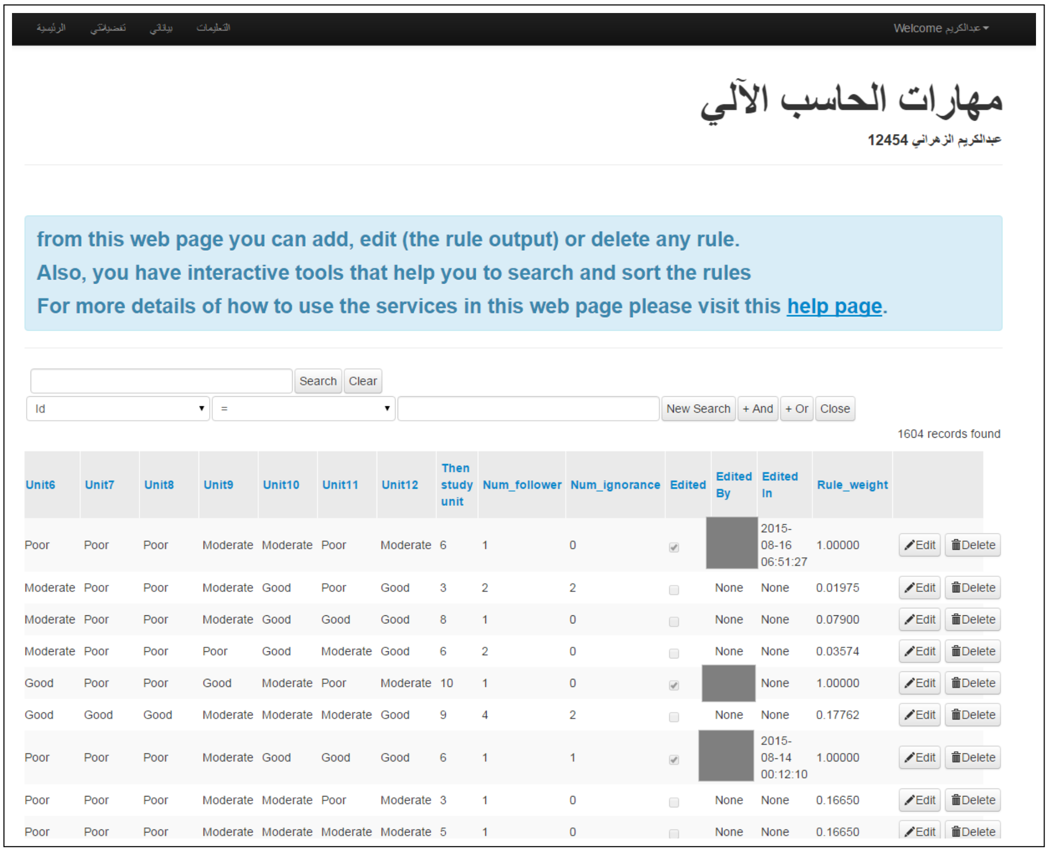


Fig. 4.19 The teacher can see the rules (s)he has already edited or approved



Rule ID	if unit_1 is	unit_2 is	unit_3 is	unit_4 is	unit_5 is	unit_6 is	unit_7 is	unit_8 is	unit_9 is	unit_10 is	unit_11 is	unit_12 is	THEN study
2	Good	Moderate	Poor	Good	Moderate	Moderate	Poor	Poor	Moderate	Good	Poor	Good	unit_1
773	Good	Good	Moderate	Good	Moderate	Good	Good	Moderate	Good	Good	Good	Good	unit_1
1285	Good	Moderate	Poor	Moderate	Poor	Poor	Moderate	Poor	Poor	Poor	Poor	Good	unit_1
1286	Good	Poor	Moderate	Good	Moderate	Moderate	Moderate	Moderate	Poor	Good	Moderate	Poor	unit_1
7	Good	Good	Good	Good	Good	Poor	Poor	Poor	Moderate	Good	Good	Good	unit_1
1035	Good	Good	Moderate	Moderate	Moderate	Moderate	Poor	Moderate	Moderate	Good	Moderate	Good	unit_1
780	Good	Moderate	Moderate	Good	Poor	Poor	Poor	Poor	Poor	Good	Poor	Good	unit_1
1293	Good	Good	Good	Good	Good	Good	Poor	Poor	Poor	Good	Moderate	Good	unit_1
1295	Good	Good	Poor	Poor	Poor	Poor	Poor	Poor	Moderate	Poor	Poor	Good	unit_1
16	Good	Good	Moderate	Good	Moderate	Poor	Poor	Poor	Poor	Good	Poor	Good	unit_1
273	Good	Good	Good	Good	Poor	Poor	Poor	Moderate	Poor	Poor	Poor	Poor	unit_1

Fig. 4.20 A list of weak rules as presented in the teacher interface



Unit6	Unit7	Unit8	Unit9	Unit10	Unit11	Unit12	Then study unit	Num_follower	Num_ignorance	Edited	Edited By	Edited In	Rule_weight		
Poor	Poor	Poor	Moderate	Moderate	Poor	Moderate	6	1	0	☑	[redacted]	2015-08-16 06:51:27	1.00000	Edit	Delete
Moderate	Poor	Poor	Moderate	Good	Poor	Good	3	2	2	☐	None	None	0.01975	Edit	Delete
Moderate	Poor	Poor	Moderate	Good	Good	Good	8	1	0	☐	None	None	0.07900	Edit	Delete
Moderate	Poor	Poor	Poor	Good	Moderate	Good	6	2	0	☐	None	None	0.03574	Edit	Delete
Good	Poor	Poor	Good	Moderate	Poor	Moderate	10	1	0	☑	[redacted]	None	1.00000	Edit	Delete
Good	Good	Good	Moderate	Moderate	Moderate	Good	9	4	2	☐	None	None	0.17762	Edit	Delete
Poor	Poor	Poor	Moderate	Good	Good	Good	6	1	1	☑	[redacted]	2015-08-14 00:12:10	1.00000	Edit	Delete
Poor	Poor	Poor	Moderate	Moderate	Poor	Moderate	3	1	0	☐	None	None	0.16650	Edit	Delete
Poor	Poor	Poor	Moderate	Moderate	Moderate	Moderate	5	1	0	☐	None	None	0.16650	Edit	Delete

Fig. 4.21 A table of all potential and active rules with details that help the teacher when he/she wants to edit, delete or approve a rule

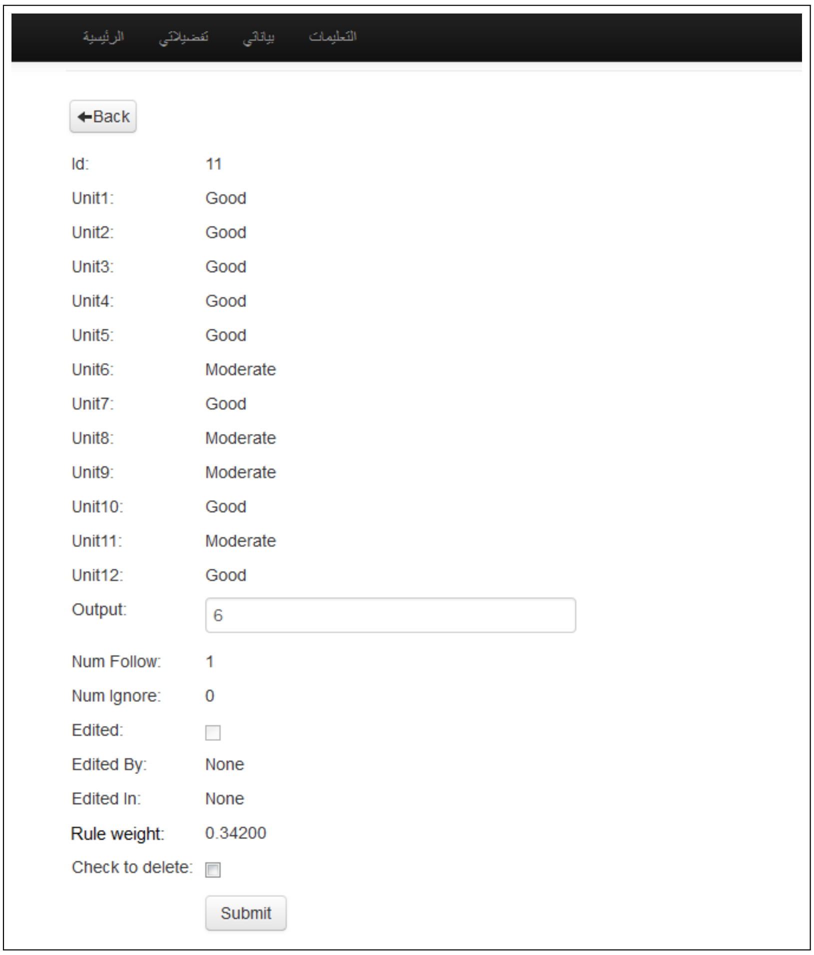


Fig. 4.22 The teacher can edit the rule output

4.3 Adjustable Autonomy Mechanisms

There is considerable debate about whether the autonomous agent should be employed in the intelligent environment. Some researchers are convinced of the value of an autonomous agent [179], [180], [181] while others show conservative opinions towards it [182], [183]. However, when discussing employing an autonomous agent in the intelligent educational environment, the distance between these two opposite views becomes wider [74], [184], [185], [186], [187]. That is related to many reasons. One of these reasons is that in the intelligent educational environment different users are using the environment (students and teachers at least) and each one of them has different roles. Another reason is the great and difficult constraints and policies which border the users' (e.g. teachers and students) roles. In addition, the users' roles differ based on the adopted pedagogical theories. For example, some may follow the teacher-directed teaching method, which gives the teacher full responsibilities for guiding students, while others may follow the student-centred learning method, which shifts some of these responsibilities from teachers to students. In other words, the intelligent educational environments are distinguished by the number of users with their overlapping roles and the variety of policies and constraints which control the learning process.

On the other hand, surveying the current intelligent educational environments, there seems to be a gap in utilising autonomous agents owing to the high concerns of who controls the learning process, trust, reliability and the high cost of failure. Therefore, many of the current systems employ teacher-driven agents, where the teachers take the full responsibility for driving the system by creating the pedagogical rules. This in turn increases the burden on the teachers, particularly when they are taking into their account fulfilling the different students' learning needs and preferences which may change over time or topic for the individual student. This issue becomes more complicated when dealing with a massively crowded educational environment or when teaching students who cannot introduce or show their learning preferences (e.g. children or students with special learning needs). Furthermore, another recognised gap in these environments is that students do not have the ability to contribute to making pedagogical decisions nor control the learning process. This means that these environments are autonomously driven from the students' point of view and there is no employment for the student-driven agent. In pedagogical terms, "students-directed teaching" is not employed as it should be in these environments. This leads to making the students adapt their learning needs and preferences to suit the introduced pedagogical materials while these environments should be adaptable to fulfil the students' various and changeable preferences.

Although employing an autonomous agent in the educational field has some obstacles and shortcomings as has been reported in the examples above, it can overcome the teacher-driven approach's limitations. This can be achieved by utilising machine learning techniques to learn from the students' learning behaviours and generate the rules used by the system to create automated guidance in an appropriate way, as has been applied in the intelligent environment in [100] and [188]. Applying teacher-driven or agent-driven systems in educational environments for optimising the learning process has its benefits and drawbacks. Thus, it becomes more persistent to find a way of blending these approaches together so that the limitations can be overcome and advantages can be augmented. Hence, the intelligent educational environment will become more flexible, convenient, supportive, collaborative and governable when both approaches are utilised together.

This utilisation of the two approaches can be achieved by equipping the intelligent educational system with adjustable autonomy mechanisms and mixed-initiatives interactions. By applying such mechanisms, many benefits may be gained for both the tutor agent and human agents (e.g. teachers and students). For example, applying these mechanisms may enhance the guidance rules by offering a way of collaboration between human agents and the tutor agent. Additionally, this helps in avoiding the confusion that may occur if the tutor agent and the human agents control the environment autonomously. Another possible advantage here is that the mechanisms reduce the burden on the teacher by changing his/her role from only creating the pedagogical guidance rules to controlling the criteria and policies of the active rules as well as approving, adding or altering any of them. Furthermore, there are other valuable advantages such as increasing the users' convenience when using the system and motivating students when they are given a degree of responsibility to collaboratively control the learning process, contribute in making pedagogical decisions and learn about other students' preferences, which helps them benefit from one another's learning experiences, as concluded in Chapter 3. Applying the aforementioned mechanisms may also benefit the teachers by offering this creative environment which may motivate them to adopt these intelligent solutions that optimise the learning performance and outcomes. This optimisation will in turn advantage the eco-system ACSA's elements. For example, it can reveal some hidden pedagogical and learning requirements which help university managements when taking their decisions.

On the other hand, deciding the offered levels of autonomy in ACSA is another research objective. Hence, these levels should meet the students' preferences and should not cause inconvenience to students while learning. For example, in Ball and Callaghan's work, two participants revealed their negative feelings regarding the semi-autonomous levels (i.e the high autonomy and the low autonomy level); the first one declared that the high level would be avoided as it contentiously presented a suggestion rule to be confirmed when (s)he did some actions and that bothered her/him. Similarly, the second participant said that (s)he would be wary of using the semi-autonomous (low autonomy and high autonomy) settings because from her/his past experience, it was found that the system might give suggestions which could be very annoying. (S)he supported her/his opinion with the example of the "search term correction functionality" of on-line search engines, which appears when searching for something and the search system supposes that there is a spelling mistake and then asks:"Did you mean: ...?" (S)he added that this was annoying him/her as (s)he made sure that what (s)he meant when (s)he performed the search initially was correct [100]. Thus, in ACSA, the chosen levels concern the balance between the learning needs and preferences, and the avoidance of causing negative attitudes. In addition, based on the survey results conducted and concluded in Chapter 3, it was decided, at this stage, to offer only the three levels described in Table 4.3.

Table 4.3 The levels of adjustable autonomy in our approach

Autonomy Level	Description
Full autonomy	The tutor agent takes the guidance responsibility and guides the student from one lesson to another. In this level, students cannot ignore the guidance.
Partial autonomy	The tutor agent offers guidance concerning the most appropriate lesson to study. In this level, students can follow or ignore the guidance.
No autonomy	The tutor agent does not provide any guidance.

Students who will be guided are those in the full autonomy level and partial autonomy level. In the full autonomy level, the iTutor agent presents only the learning activities and learning objects related to the most appropriate lesson. Hence, the student will be fully guided and (s)he cannot ignore the guidance. In the partial autonomy level, the iTutor agent presents a list of available lessons and the related learning activities and offers guidance to the most suitable lesson. Hence, the student can follow or ignore the guidance in this level. However, in the no autonomy level, the iTutor agent presents a list of available lessons without offering any guidance.

4.4 Learning Framework

The decision regarding the topic for the lessons used in the experiments was based on the author's concerns about the ease of finding a varied sample of voluntary participants with enough and various pre-knowledge. This point was so important to ensure that the system in the training phase would have a variety of rules in a short time as the students differed in their pre-knowledge.

Owing to that, it was decided to adopt teaching Microsoft Excel as the focus of the experimental lessons. It is part of a general computer skills module taught in King Abdulaziz University for Bachelor students in the foundation year and it is often a job requirement to master the use of this computer application. This course is delivered using Blackboard (a learning management system LMS). However, there is still a need for the university to provide personalised help and guidance for individual students as the gap in the students' pre-knowledge is recognised in this course and the number of registered students is high. Thus, it was hoped that a good number of motivated students would take part in the experiments and that some of them might be familiar with some of the module's lessons. Another point is that students differ in the pre-knowledge they have when they start undertaking the course. The author experienced this when he taught this course; some students had studied some lessons of the course in their secondary schools and they varied in how much they remembered from these lessons while others did not have this opportunity. The chosen test bed (King Abdulaziz University) was based on an established research relationship the author had with that University. All of the lessons were created based on the King Abdulaziz University's existing teaching resources so that the research could be part of real teaching needs. In addition, this gave the author a good opportunity to rely on approved and qualified learning resources. It should be noted that the university is considered strict in approving its modules; it follows the National Commission for Academic Accreditation and Assessment Standards (ACAAA) for quality assurance and accreditation of higher education programs.

The system in the current study taught practical lessons and examined students in practical ways. Thus, for example, when a student studied drawing a chart, (s)he was tested in an interface similar to the M.S Excal interface and (s)he had to follow the practical steps to fulfil the correct answers. The aim of doing this was to shift the learning activities of the computer science skills from theory to practice, which would meet the students' learning needs and make them more involved in the learning process (see Figure 4.23).

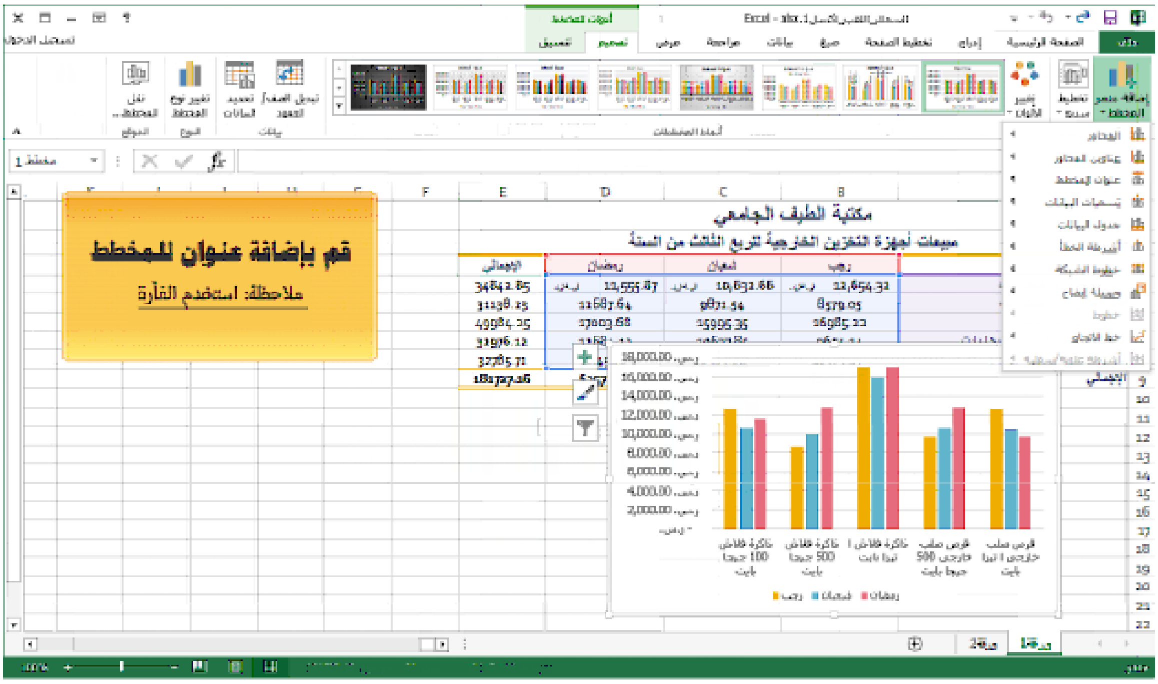


Fig. 4.23 ACSA teaches students the computer skills in a practical way. The question appearing in this figure asked the student to make a title for the chart (s)he had already done in the previous steps

The topic was divided into twelve lessons and every lesson was explained in different teaching methods to fulfil student preferences and learning needs. The teaching methods that were chosen to be applied in the system were lectures (recorded in video), Powerpoint slides, learning by example (demonstration), practical and simulation training and quizzes. The learning activities in the practical training were built in a way that allowed students to discover the correct steps to achieve the learning objectives. Thus, students would receive a positive feedback when answering correctly (see Figure 4.24) or a prompt message for helping in finding the correct answer (see Figure 4.25).

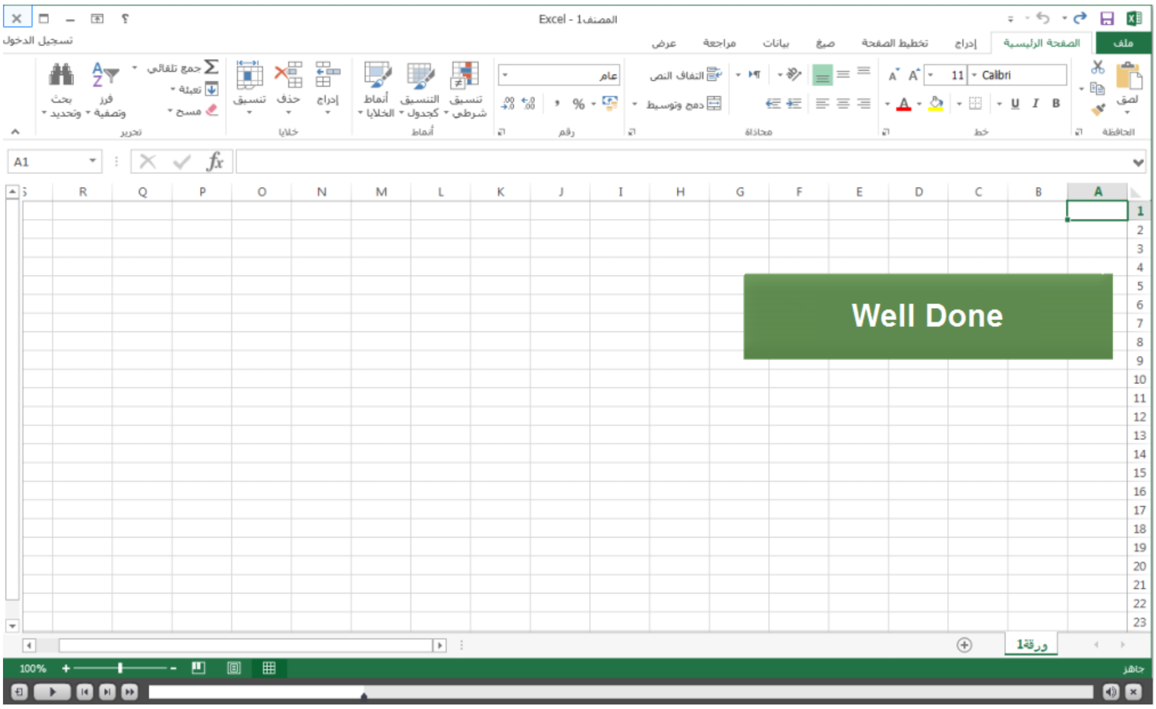


Fig. 4.24 Example of the ACSA positive feedback for a correct answer

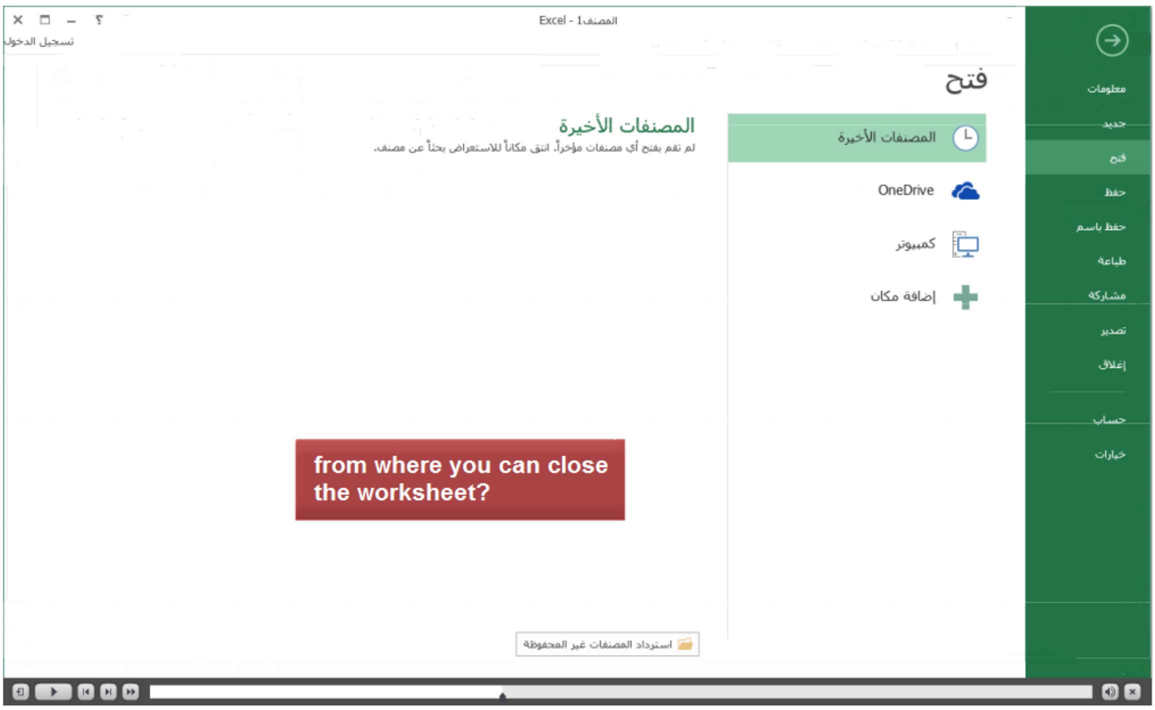


Fig. 4.25 Example of a scaffolding provided by ACSA when the answer is incorrect

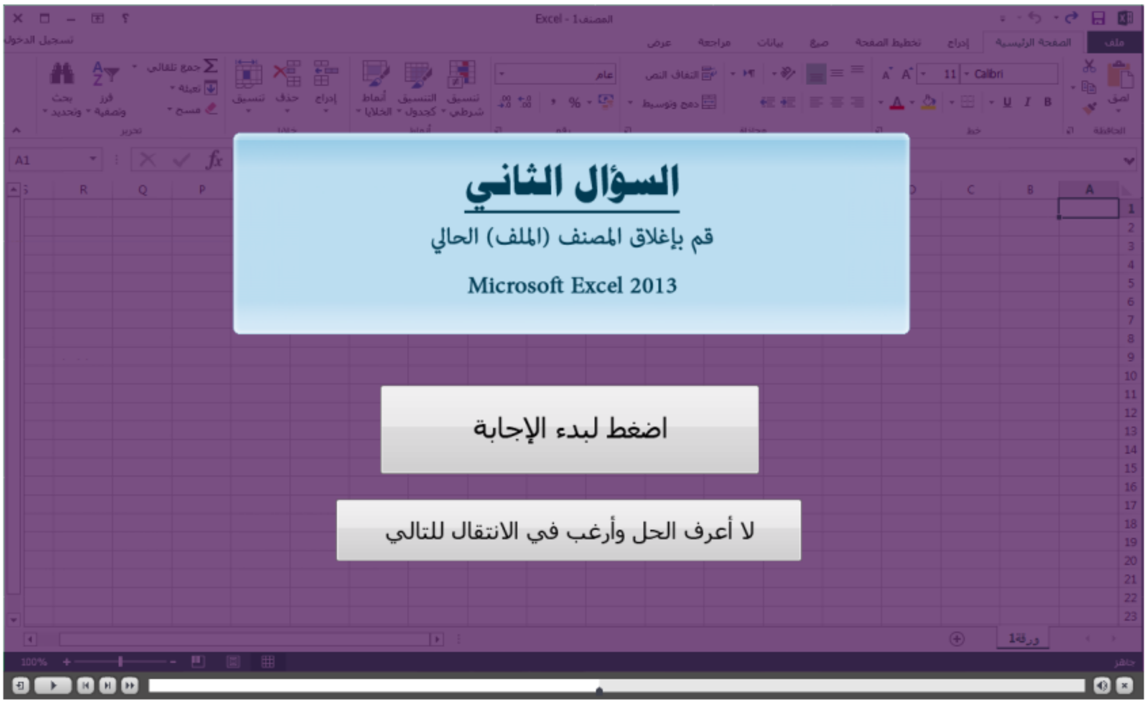


Fig. 4.26 Example of a post-test

Determining students' pre-knowledge in every lesson is an important task for students, teachers, the tutor agent and for evaluation purposes. When students take a pre-test, the teacher/tutor agent is informed about how much knowledge they already have. This results in tailoring the learning contents and providing an appropriate learning path to fit the students' learning needs. This also helps in avoiding the redundancy of lessons, which causes a negative feeling for students, as reported in Chapter 3. Thus, in this thesis the ACSA's students had to take a series of 12 pre-tests and each pre-test measured the student's pre-knowledge (from 0 to 100 scale) in one of the 12 lessons. It is also worth noting that, in both experiments, the students had similar pre- and post-tests in order to ensure the fairness of the comparison.

The adopted learning framework scenario was as follows:

1. to ask the student to complete a series of pre-tests which reflect his/her pre-knowledge in all lessons. Hence, the student will not move to the next steps unless (s)he finishes

all the pre-tests. Moreover, the student is asked to do the pre-tests based on his/her own knowledge not by relying on external resources.

2. the student should study a lesson (based on his/her choice or the sequencing rules). This is effected by the chosen level of autonomy.

3. the student should do a relevant post-test to measure the level of understanding in the lesson.

4. after the student's level of knowledge is updated, the student should do step (2) and step (3) for the remaining lesson(s).

Note that this cycle differs if the student adjusts the level of guidance autonomy to the no autonomy level.

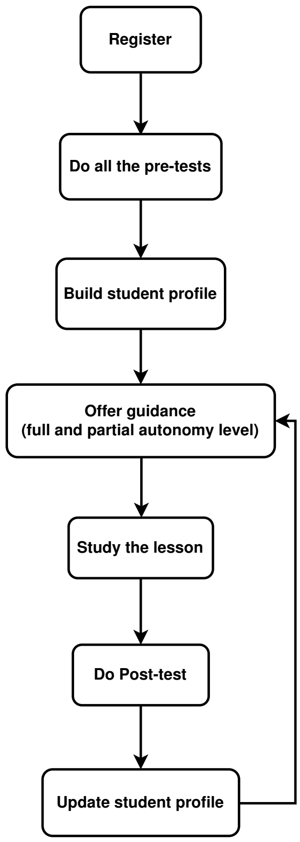


Fig. 4.27 The learning framework life cycle

4.5 Discussion

The ACSA allows students, teachers and the intelligent artificial tutor agent to collaborate in enhancing and controlling the learning process. That was achieved by equipping ACSA with the adjustable autonomy mechanisms where the teachers can create and/or control the pedagogical rules at any time during the learning sessions without causing any disruption to the learning process. The students can adjust the level of the received guidance to fit their learning needs. They can also contribute in teaching the agent how to sequence the lessons for the next similar students. The agent can generate new rules or optimising the existing rules by observing them and guiding them based on these rules. After defining the ACSA's agents and their roles, the conceptual model was illustrated as a way of delivering the required functionalities which cover the adaptive pedagogical needs for the individual students. The model consists of two main layers which are the storage layer and the runtime layer. The storage layer has the components that are responsible for storing the individual students' data (i.e. the student profile), the learning contents' data (i.e. LOM) and the pedagogical guidance's data (i.e. adaptation model). The runtime layer has these components: teacher interface, student interface, human-agent teamwork panel, iTutor agent, context agent and the analyser. ACSA offers three levels of autonomy for students which are the full autonomy, partial autonomy and no autonomy levels. In the full autonomy, the agent has the full responsibility to guide the student and the latter cannot discount any offered guidance. In the partial autonomy, the agent offers guidance and the student can follow or disregard that guidance. In the no autonomy, the agent does not offer any guidance. Hence, the student takes this responsibility. ACSA can be adjusted to follow one of two methods for generating the sequencing rules. The first method was called the teacher-driven method, in which teachers are required to create sequencing rules, whereas the second method was called the collaborative-driven method in which the students explicitly collaborate in generating and optimising the sequencing rules and teachers are able to control the generated rules. On the other hand, ACSA follows four steps in its learning framework. The first step starts after the student is registered and his/her profile is created. In this step the student should do all the pre-tests; thus ACSA can distinguish his/her prior knowledge levels. The second step is affected by the chosen level of autonomy; in this step the student should study a lesson based on his/her choice (if (s)he is in the no autonomy level or in the partial autonomy level) or based on the offered guidance (if (s)he is in the full autonomy level). The third step is to ask the student to do the post-test for the current lesson where ACSA can measure his/her level of understanding. The fourth step is to update the student's profile and iterate between the second and third steps until fulfilling the learning objectives. The next chapter reports the first live-in experiment using ACSA which was run to explore the pedagogical benefits of the adjustable autonomy.

Chapter 5

Exploring Pedagogical Benefits of Adjustable Autonomy

In the previous chapter, the author presented the ACSA conceptual model, which aimed to meet the pedagogical needs of both students and teachers. To investigate the possible pedagogical benefits of adjustable autonomy in ACSA, the first live trial was successfully run with 1320 students. The ACSA in this trial adopted the teacher-driven method, in which the teachers were required to create the needed sequencing rules. The aim of this chapter is to explore the use of adjustable autonomy in an adaptive course sequencing approach and to test the hypothesis that equipping the online tutoring system with adjustable autonomy mechanisms will allow the student to control the amount of assistance and choose the preferred level of autonomy, which will bring a better alignment of the students' learning needs to course resources and lead to optimising the learning gain.

This chapter is structured into four sections. Section 5.1 outlines the experimental philosophy. Section 5.2 defines the system infrastructure where the teacher-driven method is adopted. Section 5.3 introduces the conducted experiment and its results. Section 5.4 discusses the chapter outcomes.

5.1 Experimental Philosophy

Students differ in their preferred way of seeking guidance, as shown in Chapter 3, and the scenario below illustrates this point.

Zack is a man who had moved to a bungalow house with a large garden. He intended to start learning gardening to take care of the garden and enjoy his time. He bought a gardening book “From A to Z: A Guide to Gardening” to start his self-learning. After reading some pages, he found that he wanted to focus more on some topics which were not clear for him. Therefore, he used the internet to ask for help in the Gardening Forum “My experience in Gardening” advertised in the back cover of his book and limited to readers of that book. After a short time, he received a reply from Jolya, who had a similar experience before. She guided Zack to read section 2.6 then 5.3 of the book. That guidance was so helpful for Zack as he saved his time and found exactly what he wanted to learn. Zack enjoyed his self-reading and gained more knowledge without seeking help from others. However, after some days, Zack faced an issue with the cherry tree in his garden and he used the book to find a solution. Zack found some solutions but he wanted more details. Thus, he again sought help from others in the Forum. He was advised by five members, three of whom advised him to read section 7.6 then 7.9 while the other two advised him to read section 8.2 then section 9.5. Zack decided to follow the recommendation he received from the three members as their recommendation looked more reliable to him. Thus, he started reading section 7.6 and then he needed to read some important information that was discussed in section 7.8. Hence, he read that section and found that there was no need to read the recommended section 7.9 so he did not read that part. Zack enjoyed the newly discovered hobby of gardening and now he sometimes searches and learns new tips and tricks without any help from others. One day, Zack intended to buy some pets and take care of them in his garden. He was worried as he had no experience at all in this matter. He tried to learn through books as he did with gardening, but he found himself unable to concentrate on what he wanted to learn. Thus, he asked an expert to visit his house and he followed exactly what the expert advised him.

This short story illustrates possible learning behaviours regarding how people seek guidance when learning new skills. It indicates that they differ in the guidance level they need from time to time, as was shown previously by the survey's results in Chapter 3. It can be seen

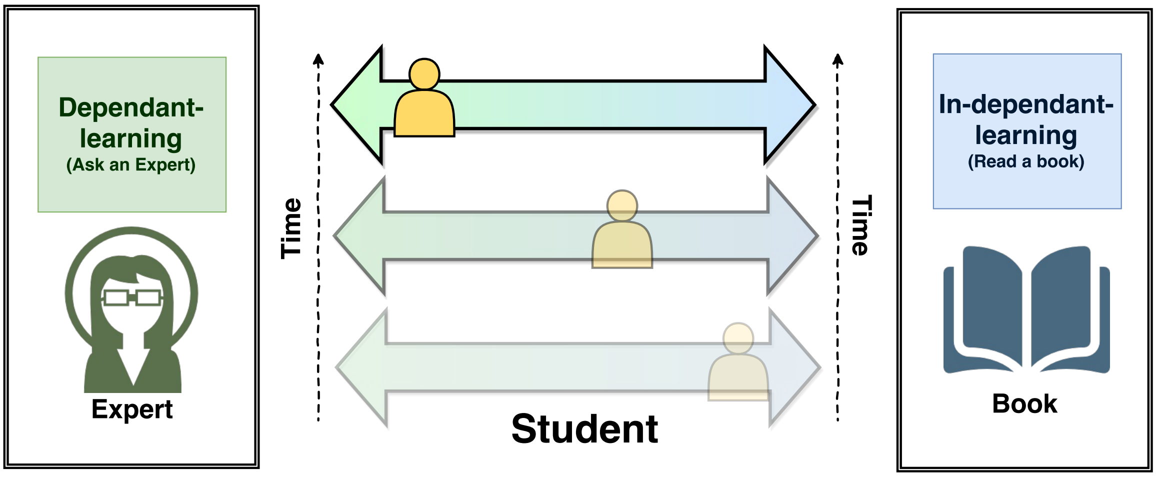


Fig. 5.1 Illustration of how people want to seek guidance while learning (e.g. reading a book)

Figure 5.1 shows that there are two opposite ends of scale of student's self-dependency while learning. These sides are dependent-learning, where the student depends on others expertise, and independent-learning, where the student depend on his/her own learning (e.g. reading a book). Hence, student can decide how much self-dependency (s)he want while learning. Based on the Zack's story, it can be seen how Zack's preferred level of guidance differed while he was learning; he started learning without any guidance as he wanted to discover the area himself without being disturbed, then he sought a recommendation and he fully obeyed that guidance. Then he returned to the lowest level of guidance as when he started his reading (i.e. with no guidance). After a while, when he found an issue, he sought a recommendation but received two different recommendations and chose to follow one of them. He adjusted the recommendation to fit his learning needs by only following a part of that recommendation. Later, in new situation, Zack preferred to be fully guided by an expert when he found himself hesitant and wanted to seek direct guidance to the targeted knowledge.

Zack had the ability to control what to learn and how to learn. However, when taking a further step and thinking about the learning process at universities, students may not have full control. One can recognise that many elements play different roles in the learning process at universities. Some of these elements are students, teachers, university management (setting up courses from both business and academic decisions); on a higher level, this involves the companies' needs and the governments' policies. When thinking of offering an online tutoring system, other elements should be added, such as an intelligent tutor agent, and knowledge repositories (book, web resources,. . . ,etc.).

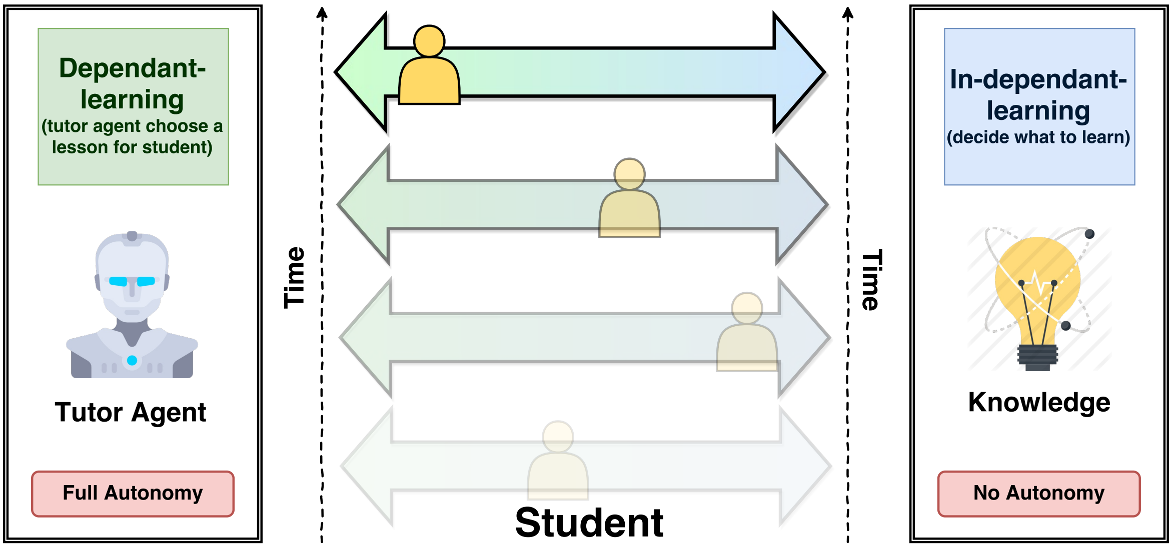


Fig. 5.2 The controllability added to the learning process when utilising an adjustable autonomy

In such interactive and elements-rich eco-systems, students need to be involved more and feel they have control over the system. Thus, each student can adjust the learning dependency level (s)he prefer at any time as shown in Figure 5.2.

Note, that the dependency level shown in Figure 5.2 is from the student's prospective. However, in tutor agent prospective this can be seen as the autonomy level. Thus, when a student prefer the dependent-learning that means the tutor agent should be fully autonomous.

In addition, there is often a gap in bringing teachers closer to the systems by shifting their roles from being users with very limited control over the system to involving them more in the design phase [8] and even in the operation phase. Hence, involving teachers more in the system has many possible benefits such as speeding-up the design time, adjusting the system to meet the teachers' or the learning institutions' learning objectives, which differ between institutions and over time, controlling and governing the system and avoiding the risk of failure.

One possible method to bridge that gap and to meet students' changeable learning needs is by adopting the adjustable autonomy mechanisms which were applied in different intelligent environments, such as in [101] and [189], and in robotics [95], [190], [191], [192], [193], [194], [195]. This study explores equipping online tutoring systems (ACSA as an example) with adjustable autonomy mechanisms as an attempt to make these systems more flexible, creative, governable and adaptable. It also helps in minimising the risk of failure resulting from misleading or misguiding students.

On initialising the system, there were no rules in the adaptation model (i.e I made a "cold-start"). Therefore, the challenge was in how this issue could be tackled when wanting to involve the teachers in the design loop. In technical terms, the challenge is in how teachers can communicate with the tutor agent in an understandable way without having to create an interpreter or middle layer. This is the same issue that may occur when designing the online tutoring system and the learning institutions decide to adopt the "teacher-driven method". These issues can be tackled by utilising Fuzzy Logic and adjustable autonomy. Fuzzy Logic has the capability of producing, or allowing teachers to produce, human-readable sequencing rules; thus, the teachers and the tutor agent can communicate with each other. Furthermore, adjustable autonomy offers teachers the ability to control the system totally by creating the rules. In the current experiment, the teachers were required to provide ACSA with sufficient rules to cover all the sequencing possibilities. In the next section, I will explain the difficulties encountered when my ACSA system was provided with these rules and describe how these difficulties were resolved.

5.2 Experimental Infrastructure

Before starting the experiment, my ACSA system had no sequencing rules (i.e it had a "cold-start"). In this case, the aim was to find a possible method to fill the adaptation model in ACSA with sufficient and appropriate rules. This situation is similar to when a learning institution (e.g. the university) wants to adopt a teachers-driven method (i.e. it does not want to rely on the tutor agent nor on the crowd of students to model the students' learning behaviours). To overcome this issue, ACSA offers a way for the teachers to create the sequencing rules and govern them at any time within the learning without causing any disruption to the learning process. Thus, the teachers in this experiment were required to provide ACSA with sufficient rules at the start to cover all the sequencing possibilities.

5.2.1 Extracting Fuzzy membership function

Defining fuzzy sets is an important step to begin with. Thus, a number of twelve teachers were asked to define the required linguistic labels (i.e. poor, moderate and good) on a scale from 0 to 100 as a triangle. Then I calculated the average of each point in the triangle (a, b and c). This calculation was used as a final applied membership function (see Figure5.3).

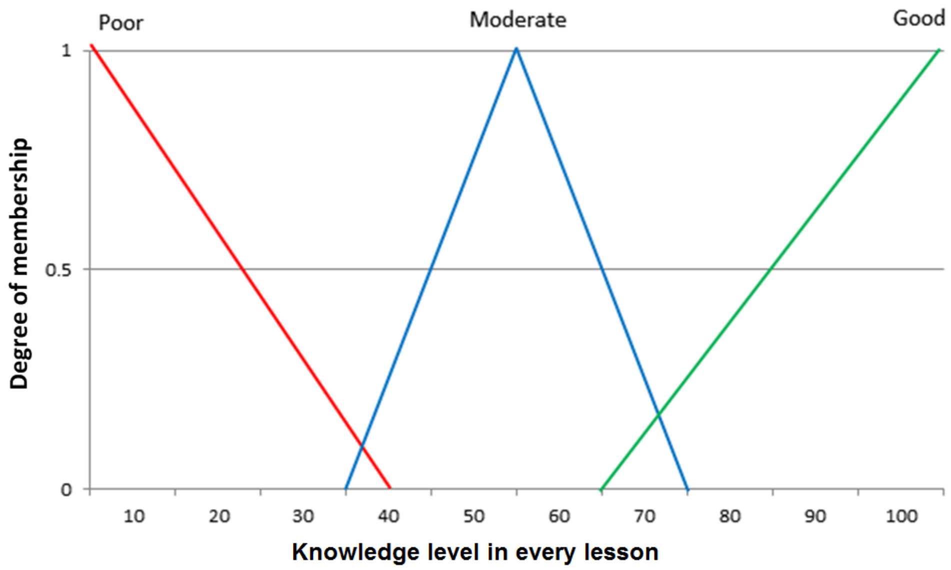


Fig. 5.3 The membership function for the level of knowledge

5.2.2 Structuring the hierarchical levels

The number of rules R was calculated using the following formula (5.1) [122], [196],

$$|R| = O(V^N) \tag{5.1}$$

where V was the number of fuzzy sets, N was the number of input variables and R is the set of rules.

Our system used variables with 12 inputs to describe the lesson options together with three fuzzy linguistic labels (i.e. poor, moderate and good). This led to an exponential increase in the number of rules [120], [197], [198], leading to some $3^{12} = 531441$ rules being required to cover every sequencing possibility. As it was impossible to create and manage such a large number of rules, not to mention the fact that processing them would have had a negative impact on the system performance [134], [199], a fuzzy hierarchical rule-based approach was adopted, where the required number of rules was dramatically decreased [119], [120], [199].

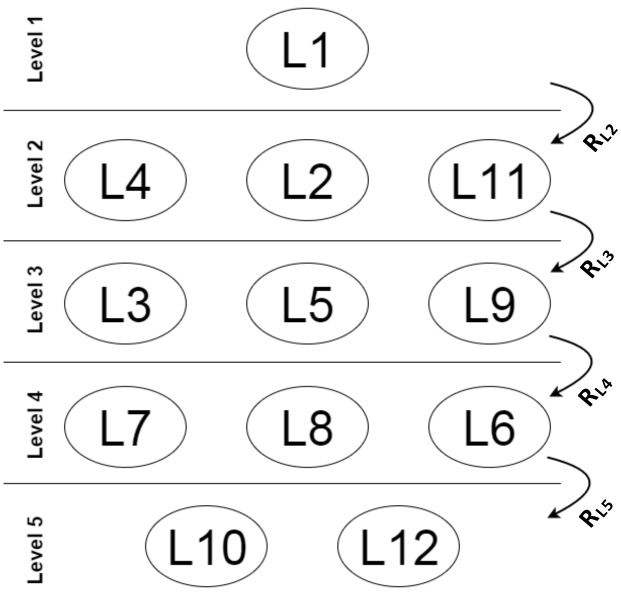


Fig. 5.4 The hierarchical classification for lessons[1]

To follow this approach, the twelve teachers were asked to classify the lessons into hierarchical levels based on the lessons' dependence on one another. The teachers views resulted in having a number of five hierarchical levels and in each level there is a number of one, two or three lesson(s) (see Figure 5.4). By classifying the lessons into hierarchical levels many possible benefits will be obtained. For instance, classifying the lessons into hierarchical level benefited the system as it reduced the load of iterating through all the rules to find the appropriate rule to apply. It also benefited the teachers by requiring fewer rules to be created and managed. In pedagogical terms, a student could not study a lesson unless (s)he had studied the previous lesson(s) in the hierarchy, which helped pedagogically by ensuring that students followed the lesson dependency policies. However, one possible drawback here was that when a teacher found that there was a need to "upgrade" a lesson to, or "downgrade" a lesson from a hierarchical level, there was a need for a change to be made over the rules.

[1]Note: the lessons' numbers (L) indicate the lessons' IDs, not the sequence of them.

Based on the classification of the lessons into these hierarchical levels, the rules in every level were unique and the function of these rules was to sequence the lessons at each level or inform the analyser to move to the next level. This meant that the number of rules increased linearly with the number of inputs variables [120]. Thus, the number of needed rules in our system was calculated using the following equation (5.2):

$$| R |= O(\sum_{s=1}^{Z} V^{i^{(s)}}) \tag{5.2}$$

where Z is the number of hierarchical levels and $i^{(s)}$ is the number of input variables in the s^{th} hierarchical level, $i^{(s)} \in N$. From this calculation, it can be seen that the total number of needed rules decreased dramatically to be 93 (see Table 5.1).

Table 5.1 The calculation of rules required when adopting a fuzzy hierarchical rule-based approach

level	number of rules
1	3
2	27
3	27
4	27
5	9
total	93

5.2.3 Creating the sequencing rules

In this experiment, the system adopted a multiple-input-single-output hierarchical fuzzy logic classification where each rule has a number of i inputs, representing the characteristics of knowledge levels, and single output denoting the appropriate lesson for the s^{th} hierarchical level. In addition, the rules were created by the twelve teachers and, therefore, there was no need to assign a weight for each rule. There have been numerous research studies concerning the use of fuzzy rules that do not have rule weights, such as [124] [200] [201] [202].

The number of hierarchical levels was defined by the following lines. In the s^{th} hierarchical level where $s = 1, \ldots, Z$, the l^{th} rule has i inputs $x_p^{(s)} = \{x_1^{(s)}, \ldots, x_i^{(s)}\}$ and $x_p^{(s)} \in x_n$, $n = 1, \ldots, N$, where N is the number of inputs over all the hierarchical levels. It also has a single output $y^{(sl)}$ which denotes the class (lesson) $C^p = 1, \ldots, k$ and $C^p \in C^h$, $h = 1, \ldots, W$, where W is the number of classes over all hierarchical levels.

$$\text{if } x_1^{sl} \text{ is } A_1^{q^*} \ \ldots \ \text{and } x_i^{sl} \text{ is } A_i^{q^*} \text{ then } y^{sl} \text{ is } C^p \tag{5.3}$$

There are M number of rules in s and l is the rule index, $l = 1, \ldots, M$, and for each input of x_p^s, there are V fuzzy sets $A_p^{q^*}, q = 1, \ldots, V$. Hence, each hierarchical level s has its unique inputs x_p^s and classes C^p.

After specifying the number of hierarchical levels, classifying the lessons into these levels and defining the structure of the rules for each level, the twelve teachers were asked to contribute in creating the rules. They could do that by voting for the most appropriate lesson (i.e. rule's output) for each rule in each hierarchical level. I developed a sequencing rules voting system to ease this process (see Figure 5.5). The chosen rules were those had taken the highest vote from the teachers.

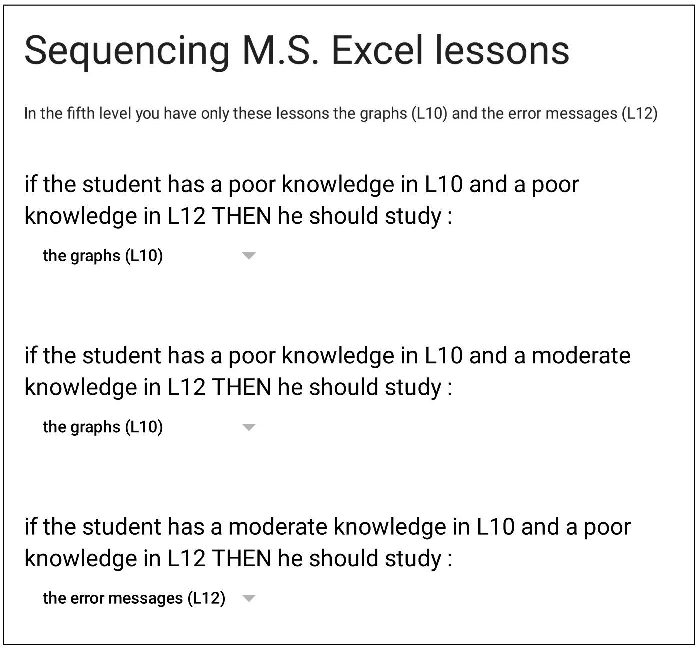


Fig. 5.5 A screen-shot of the sequencing rules voting system

The result was a set of 93 rules that covered all the sequencing possibilities. For example, in the first hierarchical level, there was only one input variable (lesson), requiring three rules, as shown in Figure 5.6; in the second hierarchical level, however, there were three input variables (lessons), requiring 27 rules, as can be seen in Figure 5.7.

```
Level 1:
R1:    IF L1 is poor THEN study L1
R2:    IF L1 is moderate THEN study L1
R3:    IF L1 is good THEN move to Level_2
```

Fig. 5.6 The rules in hierarchical level 1

```
Level 2:
R1:     IF L4 is poor AND L2 is poor AND L11 is poor THEN study L2
R2:     IF L4 is poor AND L2 is poor AND L11 is moderate THEN study L2
.                                                               .
.                                                               .
.                                                               .

R27:    IF L4 is good AND L2 is good AND L11 is good THEN move to Level 3
```

Fig. 5.7 Example of the rules in the hierarchical level 2

It should be noted that the last rule in every hierarchical level was the one which informed the analyser to move to the next level.

5.2.4 Extracting the most appropriate rule

At this stage, there was a sufficient number of sequencing rules that had been created by the teachers in five hierarchical levels, together with their associated membership functions. This helped in defining the students' knowledge levels in order to adjust the learning path based on the sequencing rules. Note that the system agent would pass the student's knowledge levels to the analyser if, 1) the student was operating in a full or partial autonomy mode and 2) one of his/her knowledge levels were changed or (s)he started a learning session. Thus, when the analyser was requested to extract the most appropriate rule, it would iterate through the two steps below until finding the rule.

Step1: define the current level and its inputs

When the series of input variables (i.e. the student's knowledge levels) was passed to the analyser, the latter started from the first hierarchical level, using only the knowledge level(s) of this level's input(s). For instance, the first iteration started in the first level with a single input (i.e. lesson 1). Thus, the analyser excluded all the input variables except input 1.

Step2: calculate the firing strengths for each rule at that level

The firing strength of each rule in the hierarchical level s was calculated using the product implication shown in the following equation 5.4, [203]:

$$f^{(sl)} = \mu_{A_1^q}(x_1^{(sl)}) \times \cdots \times \mu_{A_i^q}(x_i^{(sl)}) \tag{5.4}$$

where s is the current hierarchical level, l is the rule index, and i is the number of input variable(s) in the l^{th} rule.

After calculating all the rules' firing strength within the hierarchical level s, the one with largest firing strength indicated the executed rule for that s^{th} level. The executed rule might guide the student to study a particular lesson or might ask the analyser to move to the next hierarchical level $(s+1)$. In this case, the steps 5.2.4 and 5.2.4 were repeated until finding the appropriate rule, which in turn informed the tutor agent to guide the student to study a particular lesson.

5.3 Experiments and Results

The experiment was undertaken between November 2014 and March 2015 in King Abdulaziz University at Saudi Arabia, involving a total of 1320 students divided randomly and equally into four groups.

1. Group (1): Adjustable autonomy group: they studied in the adjustable autonomy mode, where students can choose the preferred level (full, partial or no autonomy) at any time.
2. Group (2): Full autonomy group: they studied in the full autonomy level, where the agent controls the sequence of lessons and the student cannot disregard the guidance.

3. Group (3): Partial autonomy group: they studied in the partial autonomy level, where the agent offers guidance but the student is free to follow this guidance or not. Note that adjustable autonomy allows the student to switch autonomy levels completely at well, whereas partial autonomy means the student has to choose whether to follow the guidance or not at every step.

4. Group (4): No autonomy group: they studied in the no autonomy level, where the agent does not provide any guidance for the student.

The system was available for use 24/7 as there was an expectation of students registering or studying different lessons or doing learning activities at any time.

After finishing the experiment, the results of the pre-tests, post-tests and learning gain for the students in each group were analysed.

In terms of the violation of the normality assumption, this violation should not leads to major issues as long as there is a large sample size (>30) [204]. This means that using a parametric test with a large sample is acceptable even though the data is not normally distributed [205]. This also means that we can assume that the data is normally distributed when the sample size is large enough [206] ,[207]. In this experiment, the sample size is 1320, so, I assumed that the data is normally distributed.

The results of the pre-tests revealed that while the students had some pre-knowledge about the module (the groups' means (M) on the pre-test were each more than 45% as shown in Table 5.2), there was no statistically significant difference, as shown by the ANOVA test, between the groups $(F = 1.007, p = 0.389)(p \gg 0.05)$ in the pre-tests' results, indicating that the groups had similar starting points; in other words, the selected M.S. Excel learning module and the groups chosen were appropriate for the experiment, which meant that there was no significant advantage amongst the students' pre-knowledge that might have made comparisons later unfair.

Next, the average of learning gain was calculated for students in each group following the equation (5.5).

$$lg_l = \frac{1}{N}\sum_{i=1}^{N}(post_i - pre_i) \tag{5.5}$$

where (lg_l) is the average learning gain for students in group l, N is the number of students in group l, $(post_i)$ is the average of student i's post-tests and (pre_i) is the average of student i's pre-tests. The average gain for each group is presented in Table 5.2.

The ANOVA test was run to compare between the groups at a significance level of 0.05. The results showed that there was a statistically very highly significant difference between the groups $(F = 18.876, p = 0.001)(p \ll 0.05)$ in the learning gain results. ANOVA test cannot reveal which pair of groups caused the difference. Hence, post hoc tests such as Tukey's HSD help in getting this result. For this purpose we used Tukey's HSD (honest significant difference) test due its popularity in the ITS and AES fields (e.g. of researches used Tukey's HSD: [208], [39] and [209]). The calculation of Tukey's HSD was done following this formula 5.6.

$$HSD = \frac{M_i - M_j}{\sqrt{\frac{MS_w}{n_h}}} \tag{5.6}$$

Where $M_i - M_j$ is the difference between the pair of means. MS_w is the Mean Square within variance and n is the number in the sample size in the h^{th} group [210].

The result of Tukey's HSD illustrated in Table 5.3. Based on this result, it was observed that the adjustable autonomy group (lg=31.57) and the no autonomy group (lg=17.32) were the most significantly different groups compared to other pairings, as shown in Figure 5.8 and Table 5.2. Furthermore, the adjustable autonomy group differed significantly from the full autonomy group (lg=23.17) and the partial autonomy group (lg=24.06). However, the full autonomy group and the partial autonomy group did not differ significantly from each other (less than 1 percentage point improvement in the partial autonomy group, compared with the full autonomy group).

When comparing between the students who had the ability to adjust the autonomy level and those who did not have this ability, it was evident that applying adjustable autonomy mechanisms can help students to obtain approximately 8.4 more percentage points on average than their peers in the full autonomy group and 7.5 more percentage points than their peers in the partial autonomy group. Interestingly, the students' learning gain in the adjustable autonomy group is likely to increase to 14.2 more percentage points in comparison with the no autonomy group (see Table 5.2). The better learning gain for the adjustable autonomy group might have happened due to the fact that the students in this group had the ability to transfer to other guidance modes and, consequently, benefit from the advantages of these but avoid their limitations (both the advantages and limitations of every mode for any student may differ between individuals). An example of the benefits of adjustable autonomy is that if a student has no time or energy for learning a particular lesson that the agent fully guided him/her to study and which needs plenty of time, then the student in that case can adjust the tutor agent's autonomy level to the no autonomy level, where (s)he does not receive any guidance and can focus more by studying a short lesson. One may also argue that in MOOC systems, where there is a huge number of students from different cultures interacting with tutor agents, for the latter to give pedagogical decisions based on students' behaviours (i.e. making generalisations), some of these decisions may not be compatible with some cultures and backgrounds, and the preferred way of introducing these decisions may not be either. Hence, adjustable autonomy can help the students from other cultures or unusual backgrounds through more personalised decisions and preferences. One can also argue that the students in the adjustable autonomy group learned better because of the feeling of responsibility the students had by taking some control themselves, which may have motivated them. Another possible explanation is that the students in the adjustable autonomy group had more flexibility to make personalised decisions over the system by tweaking the received amount of guidance to suit their learning needs. This does not mean that the teachers did not fulfil the students' learning needs when they were teaching; in a massively crowded online learning system, when the one-to-one learning approach is adopted and the number of students who are interacting with the system is very large, the human teachers may not know all the individual learning needs for each of the students. Alternatively, the teachers may try to fulfil the general learning needs and here the adjustable autonomy can help students who may not be happy with the generalisation used by the MOOC system to choose what suits them best.

To gain deeper insight, further analysis was conducted for the adjustable autonomy group and the students were classified into two sub-groups:

1. Sub-group (AA1): students who had changed the guidance mode during the learning.
2. Sub-group (AA2): students who chose the preferred guidance mode and maintained it.

This classification helped in exploring whether changing the guidance mode allowed students to learn better than keeping to one mode. Thus, the data from the students' logs were analysed to obtain some helpful information and it was found that:

- Seven out of the best ten students' learning gain in the adjustable autonomy group changed the guidance mode more than once. (i.e. 70% of the best ten learning gain were for students from sub-group (AA1)).
- Only one out of the ten students with the lowest learning gain changed the guidance mode more than once. (i.e. 90% of the ten students with the lowest learning gain were from sub-group (AA2)).
- The average of learning gain for students in sub-group (AA1) was 33 percentage points.
- The average of learning gain for students in sub-group (AA2) was 30 percentage points.

- No one guidance mode was chosen by the majority of the students in their learning, as can be shown in Figure 5.9.

These facts highlight how important it is to equip online tutoring systems with adjustable autonomy, due to the fact that the preferred guidance mode does vary between students, and even for a single student and that the adjustable autonomy helps students to find the most appropriate guidance at any time. Although the students in subgroup (AA2) were in one of the other modes for the whole time, it might be argued that this was an effect of being able to choose they believed was the optimum mode and then feeling in control over the learning environment that was making this difference. On the other hand, one explanation for the fact that the (AA1) subgroup has better learning gain than the (AA2) subgroup is that the students in (AA1) were keen to find the most suited guidance mode and adjust it based on their changing needs, whereas the students in (AA2) were passive and they themselves became adapted to the mode they chose at the beginning.

When the adjustable autonomy group is excluded from the comparison, a research question can be asked here, namely, if high-quality sequencing rules were provided, would the students who were fully guided learn better than those who were only partially guided? An independent sample t-test was run to measure the difference between the partial autonomy group and the full autonomy group at a significance level of 0.05. The results indicated that there was no statistical significant difference between the full and partial autonomy groups $(p = 0.647)(p \gg 0.05)$. However, the calculation of lg still shows that students in the partial autonomy group improved slightly more than those in the full autonomy group. This may have happened due to the flexibility given to the students in the partial autonomy group, in which they were able to choose what to learn in order to meet their learning needs. This finding supports the results obtained from the survey regarding giving the students the freedom to choose their learning path (see Chapter 3).

Table 5.2 Statistical details of the first experiment's results

Group	Pre-test (%)	Post-test (%)	Learning gain (lg)
Adjustable autonomy	46.4182	77.9842	31.566
Full autonomy	48.5039	71.6718	23.1678
Partial autonomy	45.6248	69.6803	24.0555
No autonomy	48.183	65.5063	17.3233

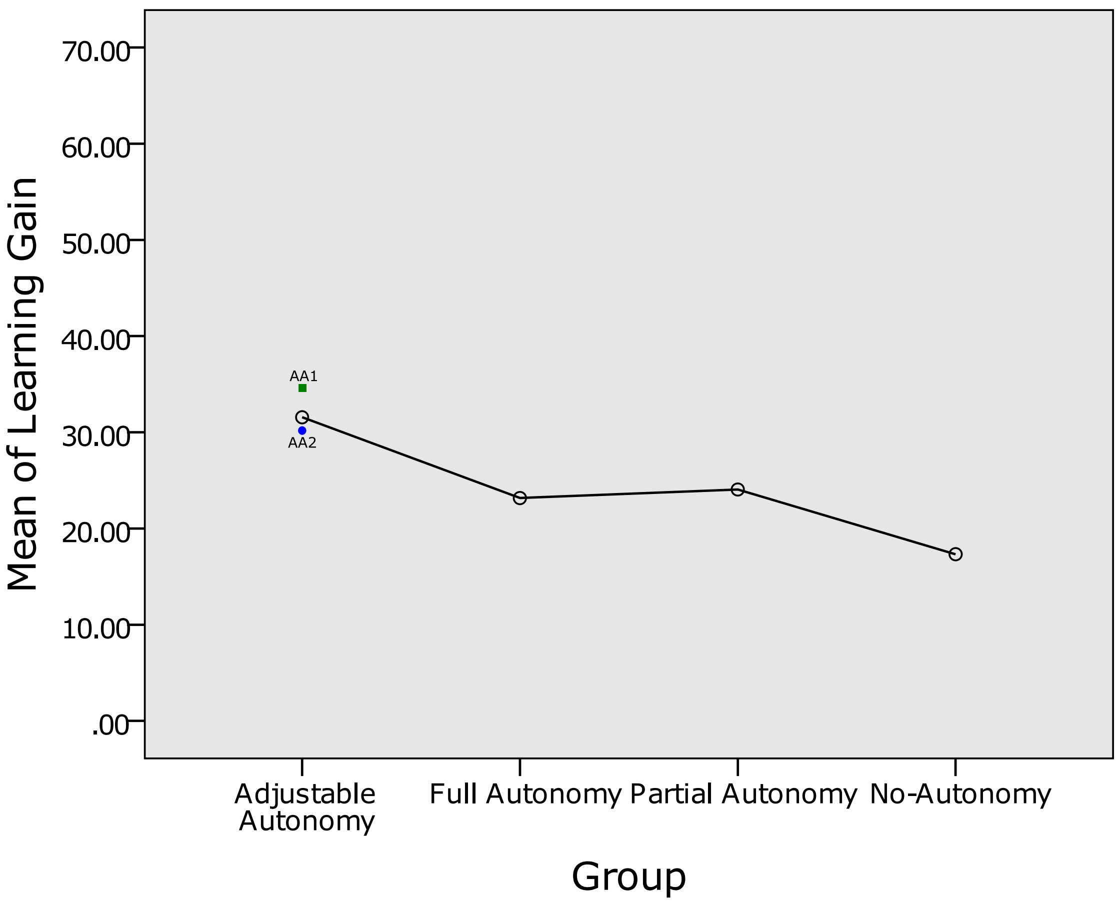


Fig. 5.8 Plot of means for the groups' learning gain

Table 5.3 The significant differences between the groups calculated using Tukey's HSD post hoc test

(I) group	(J) group	Sig.
Adjustable autonomy	Full autonomy	0.001 ***
	Partial autonomy	0.001 ***
	No autonomy	0.001 ***
Full autonomy	Adjustable autonomy	0.001 ***
	Partial autonomy	0.966
	No autonomy	0.012 *
Partial autonomy	Adjustable autonomy	0.001 ***
	Full autonomy	0.966
	No autonomy	0.002 **
No autonomy	Adjustable autonomy	0.001 ***
	Full autonomy	0.012 *
	Partial autonomy	0.002 **

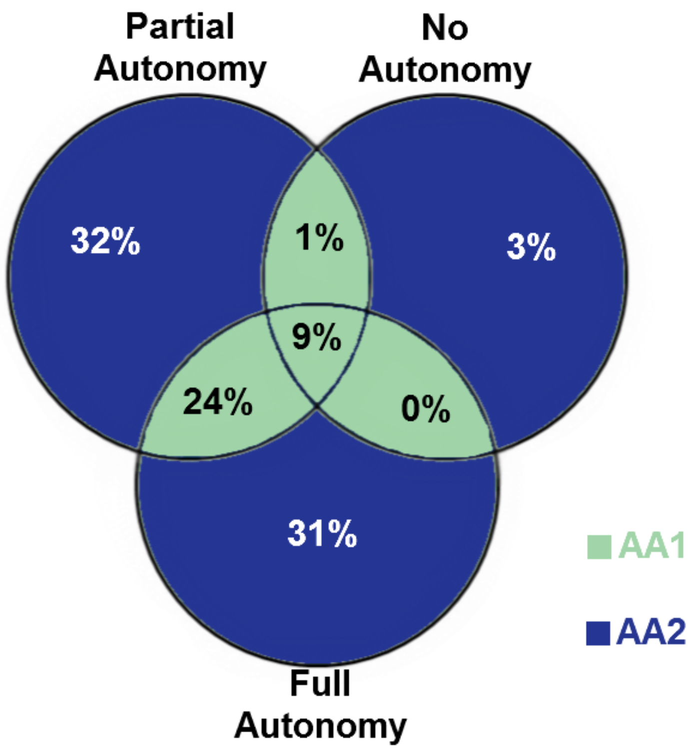


Fig. 5.9 The students' preferences for the three guidance modes during the experiment

Surveying some previous works such as:[56], [69], [71], [72], [73] resulted in finding that there is a persistent need to accommodate the changeable needs for individual students in terms of the way of guiding them through the appropriate learning path (see Chapter 2). In addition, in ITS and e-learning systems there are three ways of guiding students; 1) full guidance, 2) partial guidance and 3) no guidance as was explained previously in this chapter and the results in this chapter witness that applying adjustable autonomy mechanisms in ITS enhances the students' learning outcomes more than adopting only one guidance mode (i.e. full guidance, partial guidance or no guidance).

5.4 Discussion

This chapter explored the pedagogical benefits of utilising adjustable autonomy. It focused on the situation where the rules were created by teachers, which would be the case when the intelligent system was first started (i.e a "cold-start" situation) and would also occur when an authority (e.g. learning institutions, such as a University, etc.) adopts a "teacher-driven method". The chapter also highlighted the fact that it is impossible for teachers to create and manage all the necessary rules, if these are not organised hierarchically. Thus, it suggested that the fuzzy hierarchical rule-based approach should be adopted, where in this case the lessons are classified into five levels based on their dependencies. Following that, the conducted large scale live trial was successfully run and it indicated that the group using adjustable autonomy significantly outperformed other groups in terms of their improvement in performance. It was shown that students were able to achieve better when they had the ability to adjust the amount of received guidance to fit their learning needs and preferences. In addition, no single guidance mode was preferred over the others by the majority of the students, and it was revealed that when students changed their guidance mode based on their changing needs, their outcomes improved.

The chapter also provided evidence for Hypothesis 1, which states that students using online tutoring systems differ in their individual desired level of autonomy of the system, that this desired level sometimes differs between students and for individual students over time due to the change in learning needs, subject and lesson, and that equipping the tutoring system with adjustable autonomy allows students to control the amount of assistance they received and choose their preferred level of autonomy, eventually leading to optimising their learning gain. Additionally, this study helped in demonstrating a part of Hypothesis 2, which states that it is possible to devise a conceptual architectural model that is able to adapt the sequence of learning content, allowing students to personalise the way they received the sequence. Although the chapter showed promising results, it did not use all the functionality in the ACSA's conceptual architectural model (e.g. autonomously generating sequencing rules by the tutor agent). Thus, the next chapter is motivated to investigate this issue further.

Chapter 6

Exploring Pedagogical Benefits of Machine Learning

In the previous chapter, the agent only utilised the sequencing rules provided by teachers since there was a "cold-start" issue; although the concept of autonomous agent enables the agent to learn and act based on what has been learnt, this concept was not applied in the study described in Chapter 5. Thus, this chapter discusses the benefits of utilising such machine learning algorithms as well as adjustable autonomy mechanisms, which were suggested to overcome the limitations of agent-driven learning/teaching processes to optimise the students' learning outcomes for a given topic. It also answers the following question: to what extent do these mechanisms and algorithms enhance the students' learning gain? In addition, the chapter provides a discussion of the degree to which the introduction of these mechanisms optimises the learning experience in general and contributes to improving the collaborative teamwork in a multi-agent learning environment.

The chapter is structured into four sections. Section 6.1 discusses the experimental approach. Section 6.2 explains the infrastructure of the system that was added to allow these mechanisms and algorithms to be utilised. Section 6.3 introduces the conducted experiment and its results. The last section discuses the chapter's findings.

6.1 Experimental Approach and Rationale

Chapter 5 discussed the benefits of utilising adjustable autonomy mechanisms in ACSA when the latter was "started from cold" or when making ACSA a teachers-driven agent. In that case, the teachers were fully responsible for creating the sequencing rules and could alter them at any time. The drawback of that approach is that some of the intelligent functionalities of the ACSA were disabled. For instance, the tutor agent could not contribute to making a decision on what was the most suitable learning path for any student nor generate new rules. In addition, students in the partial autonomy level could not contribute to enhancing the sequencing rules by voting for their appropriateness when following or ignoring the guidance. Another drawback is that as long as teachers are fully responsible for driving the system, they will become more heavily loaded with work. In pedagogical terms, this may take some of their precious time to mange and test the sequencing rules rather than focus on some of their important teaching tasks. Although that approach may have some aspects that satisfy some teachers, as the system is completely under their control, its aforementioned drawbacks merit more investigation in order to find a way of overriding them without breaking the pedagogical constraints.

This chapter explores the advantages of applying the collaborative-driven method to model students' learning behaviours, to inform and enhance pedagogical decisions in terms of sequencing the learning content. Hence, the tutor agent can learn from the students' learning behaviours to generate sequencing rules. In addition, mixed initiative mechanisms are utilised to allow teachers to communicate with the tutor agent in order to define the policies which will be used to distinguish the active rules and provide the teachers with the opportunity to intervene, create, activate and alter sequencing rules without disrupting the learning process. It is worth noting, though, that in order to ensure the quality of the sequencing decisions, the learnt rules will not be activated and applied unless they are matched with the teachers' policy or approved personally by them.

As in the previous experiment, students in the current experiment had the ability to adjust the level of autonomous guidance to the individual desired level: full autonomy, partial autonomy and no autonomy. However, the difference between this experiment and the previous one (Chapter 5) from students' prospective is that students here collaboratively and implicitly taught the tutor agent how to optimise sequencing rules, which determined the order of lessons.

It is worth mentioning that adopting the hierarchical fuzzy logic helped in overcoming the issue of the massive number of required rules through dramatically reducing these required rules, as reported in Chapter 5. However, in this chapter, producing the rules was the agent's responsibility and the agent was able to generate a massive number of rules. Thus, it was decided not to adopt the hierarchical fuzzy logic in the second experiment (only fuzzy logic).

There is lack of studies in ITS and AES fields that examine the effectiveness of fuzzy logic in learning from the students' behaviours to produce pedagogical rules [211], [212]. Therefore, Almohammadi et.al. were motivated to investigate how much fuzzy logic is effective in learning from the students' learning behaviours. They evaluated different fuzzy logic approaches (i.e. type-1-fuzzy-logic-based counterpart system [211], interval type-2 fuzzy logic system [44], [213], and zSlices-based general type-2 fuzzy system [212]) and their extensive studies found that the use of fuzzy logic in learning from students' learning behaviours resulted in improving the learning outcomes. However, there is still a need in examining fuzzy logic in generating rules for sequencing the learning content. Furthermore, this examination should involve allowing the teachers to access the rules to add, delete or alter any of them in the run-time.

Adopting fuzzy logic in ACSA to learn from students' behaviours and produce sequencing rules has many possible benefits. For example, the generated rules are those common rules which are used by a large number of students. It can be argued that although ACSA requires a massive number of rules to cover all the possibilities, some of these possibilities are very unlikely to occur. Another point is that the hierarchical fuzzy logic makes some constraints for students. For example, if the agent recognises that students prefer to study a lesson in level 1 in the hierarchy then move to a lesson in level 4, the agent/teacher cannot generate a rule that breaks the constraint and recommend the next students to follow that learning path. In other words, the hierarchical fuzzy logic makes unbreakable constraints which may not give the system the desired flexibility.

6.2 Experimental Infrastructure

To build an effective online tutoring system that relies on machine learning, there must be procedures to ensure that the component responsible for holding the descriptive pedagogical model (i.e. adaptation model) has realistic and effective rules. These procedures start by identifying what type of data should be collected, when and how to collect them, and how to give these data a meaning (i.e. how to convert them from raw data to rules). In addition, in our contribution, the procedures involved offering a manageable method of giving the multi-agents the ability to collaborate in generating and optimising the pedagogical model. This method defined the multi-agents' roles and responsibilities and offered a pedagogical environment that allowed the agents to learn from each other without breaking the strict pedagogical policies and constraints.

6.2.1 Generating sequencing rules

Four steps were followed to build the adaptation model: gathering the student's knowledge characteristics and the chosen learning path, "fuzzyfying" the knowledge levels, extracting raw rules and avoiding conflicts between rules.

Step1: gathering the student's knowledge characteristics and the chosen learning path

This experiment utilised the data gathered in the first experiment, by assessing the students' knowledge level (scored from 0 to 100) for every lesson and observing their learning behaviours in choosing their learning path through the lessons offered in ACSA. This was then followed by reading and storing the targeted (chosen) lesson as well as the knowledge level for every lesson. This procedure was done for every student when (s)he decided to learn a different lesson, or when his/her knowledge levels were updated.

Hence, ACSA constructed a pedagogical descriptive model[1] of the possible students' learning paths based on their knowledge characteristics; this was achieved by gathering the required data, generating a set of multi-inputs (knowledge levels) and single output class (lesson) pairs of data. This relation is formulated in this equation (6.1) [214].

$$(x^{(t)};C^{(t)}), \quad (t = 1,2,\ldots,N), \tag{6.1}$$

where N is the number of data instances, $x^{(t)} \in R^n$, and $C^{(t)} \in R^k$. The ACSA analyser extracted rules that illustrated the influence of the k^{th} output lesson variable $C^{(t)} \in R^k$ by the input variables $x = (x_1,\ldots,x_n)^{(t)}$.

Step2: fuzzifying the knowledge level

After gathering the pairs (each consisting of twelve inputs variables and one output variable) in the N number of the data instances, the fuzzification phase was started by linguistically labelling the x_n^t inputs variables (knowledge levels) using the membership functions shown in Figure 6.1.

Firstly, the analyser calculated the membership values $\mu_{A_s^q}(x_s^{(t)})$ for each membership function following the equation 6.2

[1] i.e. the adaptation model, see section 4.2.3 on page 102.

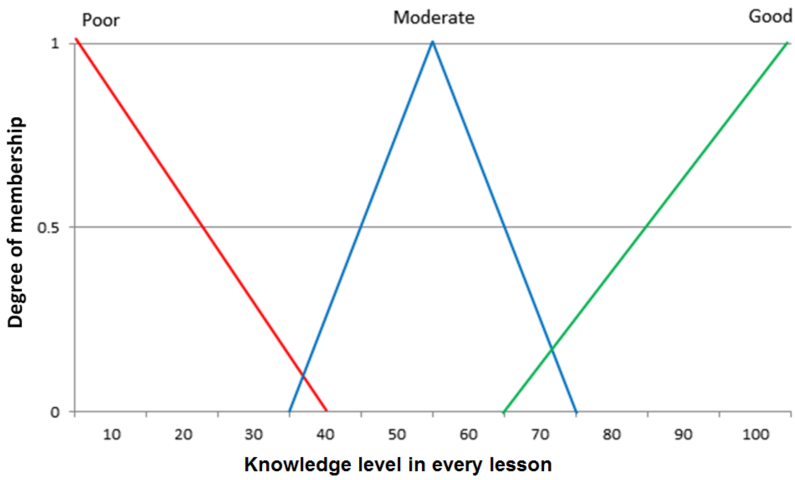


Fig. 6.1 The input membership function of knowledge level for every lesson

$$\mu_{A_s^{q^*}} x_s^{(t)} \geq \mu_{A_s^q} x_s^{(t)} \tag{6.2}$$

where $\mu_{A_s^q}$ are the membership values for the x_s input variable $s = (s_1, \ldots, s_n)$ and the q^* is the fuzzy sets $q^* \in \{1, \ldots, V\}$ [215],[203]. It should be noted that the calculation involved all the fuzzy sets $q = 1, \ldots, V$ and the maximum $\mu_{A_s^q}$ determined the linguistic label A_s^q, which represented each input variable x_s. The above calculation was limited to the inputs as the outputs were classes not crisp sets. Thus, our system adopted the fuzzy classifier approach where the outputs were not categorised using the relevant fuzzy membership functions. Alternatively, the outputs were class variables which denoted the targeted lessons for the characteristics of the knowledge, which were fuzzified in the inputs.

Step3: extracting raw rules

In this step, an if-then rule was generated for each data instance taking this form (6.3):

$$\text{if } x_1^{(l)} \text{ is } A_1^{q^*} \ \ldots \text{ and } x_n^{(l)} \text{ is } A_n^{q^*} \text{ then } y^{(l)} \text{ is } C^h \tag{6.3}$$

where l is the rule index, $l = 1,\ldots,M$, where M is the number of rules. There are W class variables C_1^h $h = 1,\ldots,W$ defined for output y_1^l, and for each input x_s, there are V fuzzy sets $A_s^{q^*}, q = 1,\ldots,V$.

In addition, the analyser calculated the firing strength $f^{(l)}$ of every rule following this equation 6.4 [203], [214], [215].

$$f^{(l)} = \mu_{A_q}(x_s) = \prod_{s=1}^{n} \mu_{A_s^q}(x_s^{(l)}) \tag{6.4}$$

When fulfilling this stage, the analyser ended up with rules as well as their firing strength $f^{(l)}$ (i.e. weights)[2] and the M number of these rules was equal to the N number of the data instances gathered in step 1.

Step4: avoiding rules conflict

Actually, when achieving this stage there were some conflicts between the rules; conflict here refers to the fact that some of the rules had similar antecedents A_q. In this case, conflicting rules were categorised (i.e. a group for each set of rules with similar antecedents) ($G_{A_q}^m$), where m is the number of rules in the group. Then, in each group, the rules were classified into sub-groups based on their consequences C_q. This ended up with n number of rules in every sub-group. Thus, the analyser iterated through the groups one by one, firstly calculating the confidence $c(A_q \implies C_q)$ for each rule (see equation 6.5)

$$c(A_q \implies C_q) = \frac{\sum_{x_s \in \text{Class } C_q} \mu_{A_q}(x_s)}{\sum_{s=1}^{m} \mu_{A_q}(x_s)} \tag{6.5}$$

The confidence can be seen as a numerical approximation of the conditional probability. Moreover, it can be viewed as measuring the validity of $A_q \implies C_q$ [216]. The confidence

[2] note: this is not the final rule weight for the conflicting rules

calculated the total of the firing strengths of the rules that had similar class C_q in the G_{A_q} divided by the total of the rules' firing strengths of all rules in G_{A_q}.

The support can be seen as the coverage grade of training patterns by $A_q \implies C_q$ [217], [218], [219]. The m is the number of rules in the current group G_{A_q}. The analyser calculated rule support $s(A_q \implies C_q)$ based on this equation (6.6).

$$s(A_q \implies C_q) = \frac{\sum_{x_s \in \text{Class } C_q} \mu_{A_q}(x_s)}{m} \tag{6.6}$$

Then the final rule weight was calculated following the equation (6.7) [217].

$$CF_q = s(A_q \implies C_q) \cdot c(A_q \implies C_q) \tag{6.7}$$

When identifying learning needs related to the current study, it was found that when dealing with the rules, teachers wanted other details which indicated how many students followed this learning path and how many disregarded it. This information was added to every rule by calculating the number of followers FL and non-followers NFL of the rule based on these equations (6.8), (6.9).

$$FL_{(G_{A_q})} = n \tag{6.8}$$

where n is the number of rules in the sub-group to which the current group belongs. In other words, FL indicates the number of rules that are similar to the current rule in terms of the antecedents and class.

$$NFL_{(G_{A_q})} = m - n \tag{6.9}$$

where m is the number of rules in the group to which the current group belongs. In other words, NFL indicates the number of rules that have similar antecedents but their classes are not similar to the current rule's class.

It is worth noting that the calculations, in equations (6.5), (6.6) and (6.7), were performed for the conflicting rules. However, for the non-conflicting (i.e. unique) rules the $CF^l = f^l$, $NFL = 0$ and $FL = 1$ by default as these rules were uniquely generated once (by one student on one occasion).

The analyser repeated these calculations in Step 4 for every rule in the group G_{A_q}. Then, the rule that had the highest weight CF_q would be selected from the rules in the group. In addition, this process of solving the conflict was repeated for all the groups [217], [218], [219]. Upon reaching this stage, the result was unique rules that had this form:

$$\text{if } x_1^{(l)} \text{ is } A_1^{q^*} \ \dots \text{ and } x_n^{(l)} \text{ is } A_n^{q^*} \text{ then } y^{(l)} \text{ is } C^h \text{ with } CF^{(l)}\ FL^{(l)}\ NFL^{(l)} \tag{6.10}$$

6.2.2 How to find the best fitting lesson

Step1: identifying the active rules

ACSA offers a collaborative way of controlling the rules extraction process. Teachers define the active rules borders by identifying the policy that distinguishes this type of rules for every guidance level. This involves defining the minimum number of followers and the maximum number of non-followers for the rule to be activated. It is noteworthy that this definition may differ according to the applied guidance level, as the risk of failure when guiding students in the full autonomy level is higher than in the partial autonomy level. Thus the policy should perhaps be strict for the full autonomy level but rather flexible for the partial autonomy guidance level, as students can contribute in voting for the validity of rules before applying them for the full autonomy level. Therefore, one of the contributions of this research is to offer a way that gives the teachers the possibility to differentiate the active rules policy depending on the guidance level. Furthermore, ACSA allows teachers to intervene to activate any rule even during the learning sessions without causing interruption. As a consequence, the practical and good rules which do not match the active rules policy can be manually activated. This, in turn, gives the activation process more flexibility without breaking the pedagogical constraints.

The activation process also involves the contribution from the ACSA agent when learning from the students' behaviours in the no autonomy level and asking the analyser to reason these behaviours then update the number of followers or non-followers of the highest weighted rule or create a new rule if no rule has been found.

I believe this way of collaboration in identifying the active rules based on the level of guidance will enhance the quality of the active rules.

Step2: Extracting the most appropriate rule

When a student in full or partial autonomy level starts the learning session or when his/her knowledge level is updated, the iTutor agent will send a request (in a JSON format as shown in Figure 6.2) to the analyser web-service containing the updated marks $x_p(x_{p1},\ldots,x_{pn})$ to extract the most appropriate rule R_w amongst the active rules $R \in S$.

```
"studentMarks": {
"lesson01": 100,
"lesson02": 100,
"lesson03": 87.5,
"lesson04": 82.35,
"lesson05": 83.33,
"lesson06": 93.55,
"lesson07": 100,
"lesson08": 0,
"lesson09": 85,
"lesson10": 100,
"lesson11": 100,
"lesson12": 0
}
```


Fig. 6.2 Example of the knowledge levels crisp sets when sent to the analyser

Assuming that there is S set of fuzzy rules formed as in (6.10), when the student's knowledge levels x_p is passed to the analyser, x_p will be classified following the single winner method in the equation (6.11) that was explained in [217], [220], [221], [222] and used in educational system by [223].

$$\mu_{A_w}(x_p) \cdot CF_w = \max\{\mu_{A_q}(x_p) \cdot CF_q | R_q \in S\} \tag{6.11}$$

Now, the winner rule R_w will denote the best lesson (rule winner consequence C_w) that should be studied for the x_p knowledge levels. If more than a consequence were found, then the analyser would reject the rules and notify teachers of these winner rules R_w to approve one of them. Meanwhile, the system would not wait for the teachers' response to guide this student. Thus, to ensure that the student is not left without any guidance, the system would suggest a new rule.

Thus, in the case of $R_w \neq 1$ a new rule will be generated following these steps:

1. identify the lesson(s) the student proved to be poor in.
   1.1. if the number of lessons $= 1$, then guide the student to study this lesson.
   1.2. if the number of lessons > 1, then:
      1.2.1. identify the lessons' dependency levels from the learning object metadata (LOM) and guide the student to the lesson which is in the highest dependency level (i.e. the lesson on which other poor lessons depend).
      1.2.2. if there are more than one lesson in the highest dependency level, then guide the student to the most important lesson depending on the lesson's degree of importance from (LOM).
   1.3. if the number of lessons $= 0$, then move to the next step.
2. identify the lesson(s) the student proved to be moderate in and do similar steps to the ones mentioned above.

If the student is in partial autonomy, the system will track his/her learning behaviour and record the selected lesson, as a consequence of the new rule. The system will later be able to track other similar behaviours by other students, which may end up in activating this new rule if the latter meets the teachers' policy.

6.3 Experiments and Results

The experiment was run between September/2015 and January/2016 with a total number of 157 students. The students were divided randomly in two groups as below:

1. Group (1): Adjustable autonomy group (experimental group): students in this group could adjust the autonomy level at any time (78 students).

2. Group (2): Full autonomy group: students in this group were studied only in the full autonomy level (79 students).

The purpose of forming only the two groups above is that this chapter does not compare between each of the autonomy levels and the adjustable autonomy mode as this was achieved in the previous chapter. It rather compares between two different methods (i.e. teacher-driven method and collaborative-driven method). The need for the first group was due to the fact that the adoption of adjustable autonomy is the novelty in ACSA, whereas the need to form the second group (i.e. full autonomy) stemmed from the fact that students in the full autonomy group were fully guided by the agent, which isolated the impact of controllability and gave us more accurate results.

The system was set up to be used 24/7 as there was an expectation that students might register and study different lessons or perform learning activities at any time.

Following the teacher-driven method in ACSA means that the teachers are required to create all the needed rules while the agent and the students cannot contribute to generating nor enhancing the rules. However, the collaborative-driven method allows the ACSA human and machine agents to collaborate in generating and enhancing the rules. The violation of the normality assumption should not leads to major issues as long as there is a large sample size (>30) [204]. This means that using a parametric test with a large sample is acceptable even though the data is not normally distributed [205]. This also means that we can assume that the data is normally distributed when the sample size is large enough [206] ,[207]. In this experiment, the sample size is 157; so, I assumed that the data is normally distributed.

In the beginning, the pre-test results were analysed to ensure there was no statistically significant difference between the groups and the comparison between the groups was fair.

ANOVA was used and the results show that there was no significant statistical difference between the groups $(F = 0.837, p = 0.474)(p > 0.05)$ in their performance on the pre-tests.

The average of learning gain for students was calculated in every group, following the equation (6.12),

$$lg_l = \frac{1}{N}\sum_{i=1}^{N} post - pre \tag{6.12}$$

where (lg_l) is the average of learning gain for students in group l, N is the number of students in group l, (post) is the average of a student's post-tests and (pre) is the average of a student's pre-tests.

The results of both groups, as well as the similar groups from the previous chapter, are reported in Table 6.1.

Table 6.1 Statistical description of the learning gain for the adjustable autonomy and full autonomy groups in the first and second experiments

Group	collaborative-driven method		teacher-driven method ⋆	
	N	learning gain (lg)	N	learning gain (lg)
Adjustable Autonomy	78	36.2926	330	31.566
Full Autonomy	79	28.9271	330	23.1678

⋆The presented results in this column are copied from the first experiment for the purpose of comparison

The t-test was run to compare between each pair of groups at the significant level (0.05). The result indicates that there was no statistically significant difference between the two groups' means $(p = 0.150)(p \gg 0.05)$. The improvement of the learning gain was estimated to be 4.7 points (standard error (SE)=3.3) but the evidence of that improvement was not enough, based on the p-value $(p = 0.150)$.

Some may argue that adjustable autonomy could not clarify the difference between the two methods since there might be some students who did not benefit from the tutor guidance in both methods and that the comparison between the two methods using the full autonomy results would clarify the difference. Using t-test, I compared between the two full autonomy groups and the result was $(p = 0.081)$. Although there was no significant difference between the two methods, the mean values suggest that the full autonomous tutor agent can guide students to learn on average 5.7 points better when replacing the teacher-driven method with the collaborative-driven one. However, there is not enough evidence to claim that since the p-value $(p = 0.081)$ is not significant at the 0.05 level.

This result affirms how reliable the collaborative method was in the sense that it was compared with a method that was led by teachers only. The result supports the results reported in Almohammadi et. al. papers [44], [48], [211], [212], [213]. However, in Almohammadi et. al. works, the students were fully guided by the intelligent system and as it was demonstrated here that if the students are given the ability to choose how to be guided, their learning outcomes will be improved more than being fully guided by the system with no choice. However, a limitation of ACSA in this thesis was that it adopted type-1 fuzzy logic rather than type-2 fuzzy logic which can handle the uncertainties encountered through interval type-2 fuzzy sets, which are characterized by a Footprint of Uncertainty that provides an extra degree of freedom in handling high uncertainty levels [39]. Thus, one aim I want to achieve in the future is to apply type-2 fuzzy logic thus each teacher or may be a student can define his/her own fuzzy sets which will give more controllability to the users and will enhance their learning outcomes as were demonstrated in these publications [48], [212]

The better results for the collaborative method does not mean that the teachers did not guide their students through their individual appropriate learning paths as the difference between the full guidance mode and the no-guidance mode in the first experiment shows that the teachers' guidance contributed to better learning outcomes, as reported in Chapter 5.

It can be argued that although the difference between the two methods is not significant, the collaborative method is worth to be adopted since it may reduce the burden on the teachers, encourage the teachers' and students' creativity and feeling of responsibility, speeding up the time needed to create an online tutoring system and meet the learning needs. These benefits and others were reported when experimenting the adjustable autonomy in the intelligent environment field [101].

6.4 Discussion

This chapter experimented the full functionalities of the ACSA conceptual architectural model by allowing the multi-agent to collaborate in enhancing the learning process. Firstly, the chapter discussed how the agent can generate sequencing rules from the gathered dataset in a form that helps the teachers to control these rules. By doing so, the teachers can read and understand the rules (human readable rules, thanks to Fuzzy Logic). They can gain more information about every rule, such as the number of followers and non-followers of the rule and if it was edited/approved by a teacher before. They can set up the policies that define to the agent the active rules from the potential rules based on the number of students who follow and/or do not follow the rule. In this experiment, the students can also adjust the level of guidance they want and, implicitly, it also means that they adjust the level of contribution they want to supplement (in order to generate and enhance the learning process).

On the other hand, a second live-in experiment was conducted to answer the question "how much improvement in the students" learning outcomes could be achieved when making ACSA follow a collaborative-driven method rather than the teacher-driven method?'. The results of the t-test showed that there was no significant difference between the two methods for the adjustable autonomy group. This, in turn, proves two of the research hypotheses: 1)"it is possible to devise a conceptual architectural model that is able to adapt the sequence of learning contents, allowing students to personalise the way of receiving the sequencing, making the tutor agent capable of producing sequencing rules and giving the teachers the ability to control the learning process"; 2)"Machine learning has the ability to produce sequencing rules which can be used to guide students to learn better, similar to the rules generated by teachers". The reliability of the collaborative-driven method is an important finding. This chapter proved it in terms of the students' learning outcomes. However, other benefits of this method from the teachers' prospective will be discussed in the next chapter.

Chapter 7

Exploring Teachers' Opinions about ACSA

This chapter aims to outline some of the teachers' experiences and opinions when using ACSA. Investigating teachers' opinions about ACSA is important as it measures the validity of the multi-agent learning process and explores teachers' opinions about the agent-generated rules, their views about being allowed to access the rules and alter them, their views about the collaborative method which allows the students and the tutor agent to collaborate in generating and optimising the rules, their opinions about the different guidance modes and the effectiveness of allowing the students to adjust the guidance level, and their general satisfaction with the ACSA and outlining its advantages and limitations.

The chapter is divided into the following sections: Section 7.1 describes the design of the survey. Section 7.2 introduces the results. Section 7.3 discusses the work done in this chapter.

7.1 Survey Design

The general goal of the survey was to explore the teachers' opinions about ACSA in order to contribute to achieving the research aim *"Exploring adjustable autonomy in adaptive course sequencing systems"* and to measure to what extent the ACSA model was able to deliver the required functionalities that cover the teachers' pedagogical needs.

The survey had two different sections. The first section aimed to obtain demographic information, such as gender, age, and prior knowledge about ITS and learning management systems (LMS). Answering the questions in this section was optional since it aimed to gain some personal information which might sometimes appear sensitive to some participants. The second part had the main questions, which can be classified into five groups based on the objectives they were designed to fulfil:

- identifying the teachers' opinions towards the generated rules;
- investigating their views about being allowed them to control the learning process;
- exploring their opinions about enabling the teachers to collaborate with the agent in generating and optimising the sequencing rules;
- exploring their views regarding giving the students the ability to adjust the guidance level in general, and specifically their opinions about each level of guidance;
- exploring their general views of ACSA and its pros and cons.

Two types of questions were included in these groups, these were open-ended and closed questions. The closed questions usually generate a higher response rate and are easier for analysis [224]. They also provide reliable data if the list of options given to the participants is comprehensive and exhaustive for all the possibilities. [169]. Open-ended questions, on the other hand, allow us to gain more and deeper knowledge (e.g. reasoning about the choices in a closed-ended question). By utilising both types of questions in a survey, the received responses should give a wide range of opinions and help in achieving the aims and objectives of the research. Thus, with consideration to not influence the participants' views, a total number of 18 closed questions plus some related open-ended questions were carefully created in each of the five groups. The tables (7.1 to 7.5) show the closed questions in every group. It should be noted that many of the closed questions were followed by some open-ended questions to obtain more information.

Table 7.1 Statements in the first group

statement	**choices**
In general, how much are you satisfied with the rules that were generated by the system?	five-point Likert scale from "very satisfied" to "very dissatisfied"
The generated rules in the system are enough to teach students.	five-point Likert scale from "strongly agree" to "strongly disagree"

Table 7.2 Statements in the second group

statement	**choices**
Did you alter (edit) some of the rules that were generated by the system?	three choices 'yes', 'no' and 'not sure'
To what extent are you satisfied with the rules editing tools?	five-point Likert scale from 'very satisfied' to 'very dissatisfied'
To what extent are you satisfied with the policy responsible for activating the rules?	five-point Likert scale from "very satisfied" to "very dissatisfied"
It is important to differentiate between the policies which activate the rules, based on the guidance level?	five-point Likert scale from "strongly agree" to "strongly disagree"

Table 7.3 Statements in the third group

statement	**choices**
Dictating sequencing rules which take into account the individual differences between students as well as the policy of activating these rules need time and effort from teachers.	five-point Likert scale from "strongly agree" to "strongly disagree"
What is your opinion about making the system generate the rules on your behalf (when you do NOT have the ability to change these rules)?	five-point Likert scale from "strongly agree" to "strongly disagree"
What is your opinion about making the system generate the rules on your behalf (when you do have the ability to change these rules)?	five-point Likert scale from "strongly agree" to "strongly disagree"
Making the system responsible for generating the rules on my behalf will relieve some of my burden as a teacher.	five-point Likert scale from "strongly agree" to "strongly disagree"
Giving me the ability to access the rules and alter them will enhance their quality.	five-point Likert scale from "strongly agree" to "strongly disagree"

Table 7.4 Statements in the fourth group

statement	**choices**
The three offered guidance levels (full, partial and no autonomy) are enough to fulfil students' needs.	five-point Likert scale from "strongly agree" to "strongly disagree"
It is a good strategy to give the students the ability to choose the level of guidance that suits them.	five-point Likert scale from "strongly agree" to "strongly disagree"
Sometimes, I want to enforce (oblige) some students to learn a lesson (without giving them the option to study another lesson).	five-point Likert scale from "strongly agree" to "strongly disagree"
It is good to give some students the freedom to choose what they want to study in their preferred sequence.	five-point Likert scale from "strongly agree" to "strongly disagree"
There are some students to whom I want to recommend a lesson to study but they are free to study it or study another one.	five-point Likert scale from "strongly agree' to "strongly disagree"

Table 7.5 Statements in the fifth group

statement	**choices**
In the future, I want my students to study in this intelligent system.	five-point Likert scale from "strongly agree" to "strongly disagree"
In general, to what extent are you satisfied with the system?	five-point Likert scale from "very satisfied" to "very dissatisfied"

The survey was designed using Google Form and the link of the survey was emailed to the teachers who dealt with the ACSA. All the teachers were invited to ask the researcher about any questions they may have about the survey and the researcher was available to respond to their questions either in person, via email or via video conferencing. The researcher was very keen not to give the participants any information that might affect their responses or make their views biased towards any particular preference.

7.2 Survey Results

Fourteen teachers responded and completed the survey. In the next subsections, the demographic information of the participants will be presented (Section 7.2.1) and then their responses to the main questions and statements will be introduced and discussed (Section 7.2.2).

7.2.1 Demographic results

As mentioned earlier, the survey identified five demographic elements about the participants, which were their gender, age, prior knowledge of ITS and experience of ITS and LMS.

In terms of gender, 42.86% of the participants were male while 35.71% were female and 21.43% of them preferred not to declare their gender (see Figure 7.1)

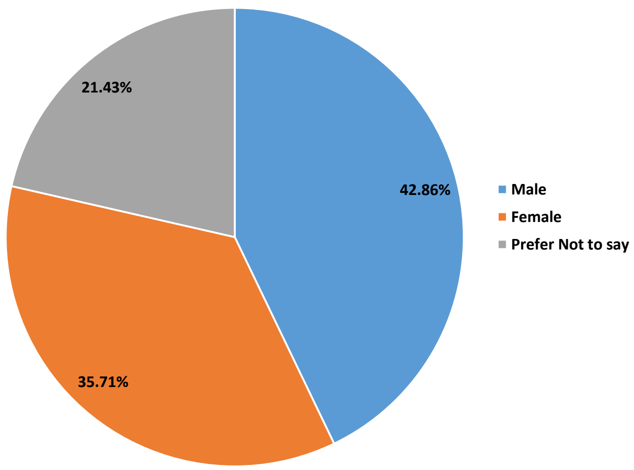


Fig. 7.1 Participants' gender

As for the participants' age, the results show that there were a variety of ages; more than a half of the participants were in the range between 31 and 40 (28.57% in the age group of 31-35 and 28.57% in the age group of 36-40). However, 14.29% of the participants were between the age of 26 and 30, 21.43% were in the age group of 41-45 and the remaining were between 46 and 50 years old (see Figure 7.2).

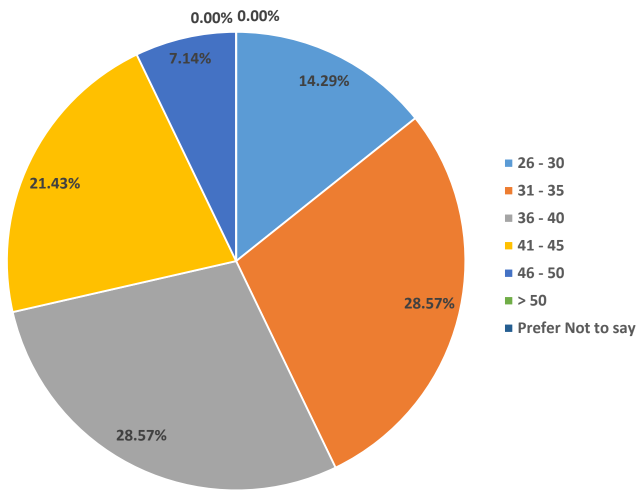


Fig. 7.2 Participants' age

The participants' responses to the questions relating to their prior knowledge of the ITS and LMS show that 57.14% had heard about ITS before while 35.71% had not, and 7.14 were not sure about that (see Figure 7.3). In addition, most of the participants (64.29%) had not used an ITS before while 28.57% had done so and 7.14% were not sure (see Figure 7.4). The use of LMS was more common amongst the participants; the results show that the majority of them (71.43%) had used a LMS before while 14.29% had not and 14.29% were not sure (see Figure 7.5).

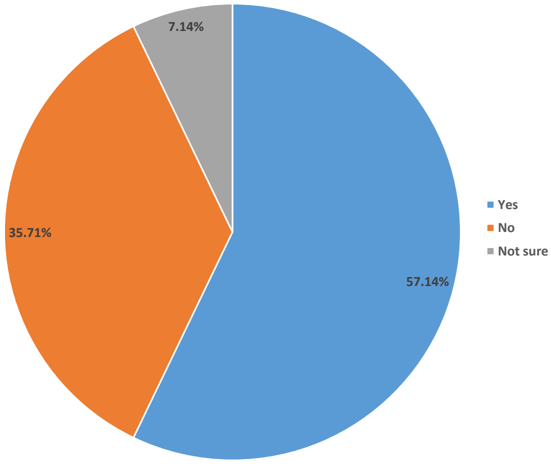


Fig. 7.3 The participants' responses to "Have you heard about ITS before?"

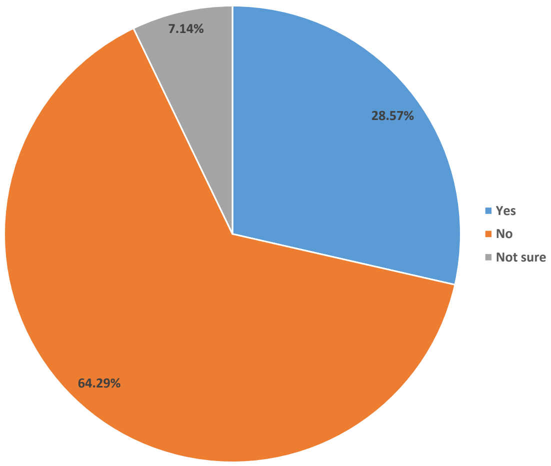


Fig. 7.4 The participants' responses to "Have you used an ITS previously?"

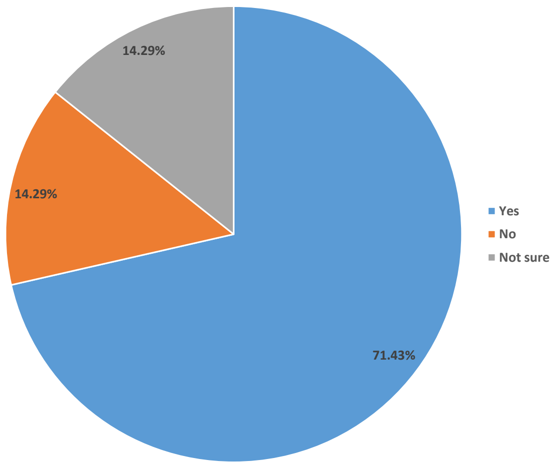


Fig. 7.5 The participants' responses to "Have you used a LMS previously?"

7.2.2 Survey's main results

First, before presenting and discussing the results in this section, the Cronbach alpha(α) score was calculated, following equation 7.1, to measure the reliability of the responses received for the close-ended questions [173].

$$\alpha = \frac{N \cdot \bar{c}}{\bar{\upsilon} + (N-1) \cdot \bar{c}} \tag{7.1}$$

Where N is the number of items, $\bar{c}$ is the average inter-item covariance among the items and $\bar{\upsilon}$ equals the average variance.

The result of Cronbach alpha (α) indicates that the reliability of the responses was strong (0.922).

In the next subsections, the results of the survey's main questions and statements will be reported in their groups.

Identifying the teachers' opinions towards the generated rules

Firstly, the teachers' satisfaction with the generated rules is an important point to be investigated. It can measure, to some extent, the validity and the accuracy of the agent functionalities which are responsible for generating the rules by learning from the students' learning behaviours. Thus, the responses received for the question "In general, how much are you satisfied with the rules that were generated by the system" show that more than two thirds of the participants were generally satisfied with the generated rules (35.71% very satisfied and a similar percentage somewhat satisfied) while 14.29% were dissatisfied (7.14% somewhat dissatisfied and a similar parentage very dissatisfied) and 14.29% of the participants were neutral (see Figure 7.6).

The above question was followed by an open-ended question to have insight into the reasons behind the participants' choices. Some teachers indicated that the generated rules were practical, very clear, perfectly generated and beneficial since they were produced by tracking students' behaviour; one teacher commented that these rules *"possibly match students' learning needs"*. Other teachers were also happy with being given control over the rules and being able to add to them or change them. One teacher was satisfied due to the fact that the rules were updated and modified automatically overtime; she added that *"they get all students to meet the requirements of the studies by guiding them to learn in the most common way they themselves use"*. Moreover, some of them stated that the generated rules cover many sequence possibilities and *"fulfil various and different choices"*. On the other hand, teachers who expressed their dissatisfaction with the generated rules gave different reasons for their opinions. One of the reasons they highlighted was that the rules needed a higher number of students. Another reason was related to the rules themselves in that these rules were seen as an extra load for the teachers who need to change, manually activate or delete some of these rules. One dissatisfied teacher opposed the whole idea by saying *"I don't believe that technology is good to take my roles"*. Another dissatisfied teacher emphasised that guiding students through the learning path is the teacher's responsibility and it cannot be done by relying on students.

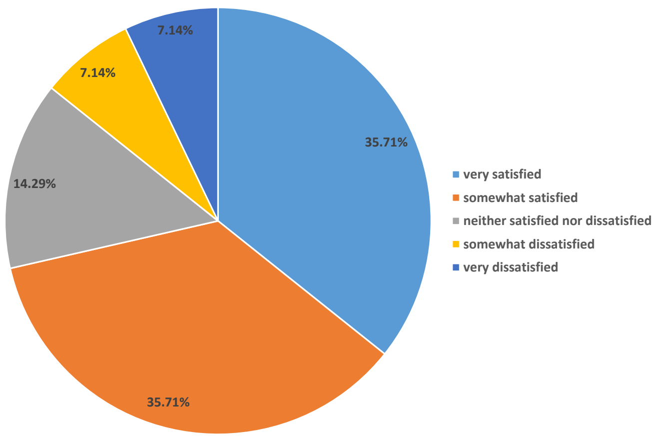


Fig. 7.6 The participants' responses to "In general, how much are you satisfied with the rules that were generated by the system?"

In response to the statement "the generated rules in the system are enough to teach students", 64.29% of the participants agreed (21.43% strongly agreed and 42.86% agreed) while 14.29% disagreed (7.14% disagreed and a similar percentage strongly disagreed) and 21.43% were neutral.

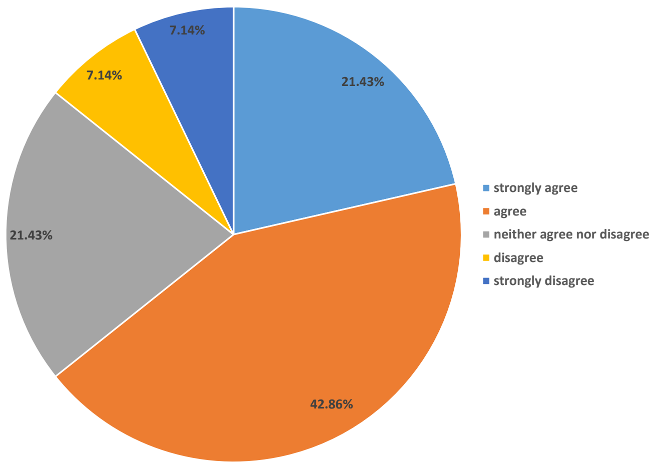


Fig. 7.7 The participants' responses to "the generated rules in the system are enough to teach students"

Investigating the teachers' views about allowing them to control the learning process

After identifying the teachers' opinions about the auto-generated rules, I moved to investigate their views about the offered functionalities in which they had the ability to control the learning process. Firstly, teachers were asked if they altered some of the auto-generated rules and nearly two thirds of them answered "yes" (64.29%) while 14.29% answered "no" and 21.43% were not sure (see Figure 7.8). The previous question was followed by an open-ended question "when could you tell that the rule was bad and needed to be altered?" A variety of answers were received and these can be categorised into the following:

- The rule output directs the student to study a lesson (s)he has become good at. One teacher stated that *"the rule is regarded as "poor" when a student obtains a very high score for unit x, but the rule recommends that the student should re-study unit x"*. Similarly, another teacher commented that the rule is bad *"when it instructs the student to learn a model that has already been covered with a high score"*. With a specific reference to the full autonomy level, where the student has to follow the guidance without being able to disregard it, one teacher considered the rule as bad *"when a* *student is getting a good score in a unit but the rule forces him to study it again"*. In that case, if a bad rule was applied that means the student might not progress very well. However, ACSA gives the teacher the ability to make a strict policy to the agent when mining in the rules for guiding a student who has chosen a full autonomy level. Thus, it can be ensured as much as possible that the agent will search for good rules only.

- The rule does not guide the student to study a lesson on which (s)he has got a "poor" mark before other lessons on which (s)he has had moderate or high marks. One teacher stated that *"if she has got a moderate mark in a lesson and a poor mark in another lesson then she should study the lesson with the poor mark first"*.

- The students' outcomes, when following the rule, can judge its validity. Hence, the bad rules are those that students obtained low marks when they followed them.

- The lessons' dependency plays a role in defining the good and bad rules; for instance, the bad rules are those that guide the student to study a lesson while the pre-requisite lesson(s) have not been covered yet. One teacher stated that *"if the student has got a high score on an advanced unit and a low score on an easy unit, and the advanced unit is dependent on the easy one, the system should not return the student to the easy unit as the student already achieved a high score on the advanced unit related to it"*.

- The rule has a high number of non-followers.

- The rule has a low number of followers.

- A careless or curious student creates the rule.

- Students give negative feedback about the rule *"if many learners did not consider the rule to be practical"*, as one teacher wrote.

- One teacher, who was not sure if (s)he had altered a rule before or not, defined the bad rules as those which are not generated or approved by an expert teacher. Another teacher, who did not alter any rule, stated that *"novice teachers do not have the ability to take educational decisions in advance, so how can we rely on technology in that case?"*.

The above description of the bad or weak rules' characteristics may influence other researches in the future.

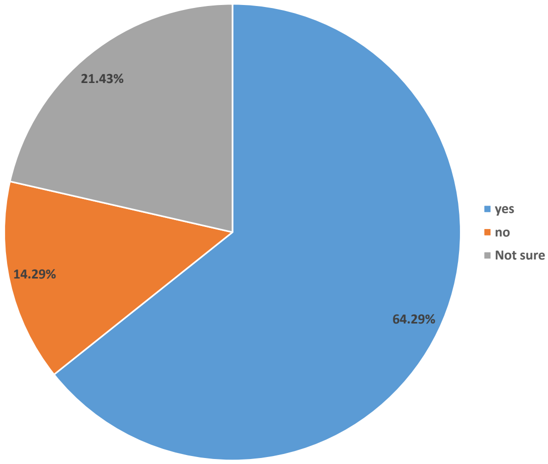


Fig. 7.8 The participants' responses to "Did you alter (edit) some of the rules that were generated by the system?"

ACSA offers two methods that allow teachers to control the rules:

1. The first method offers tools that help teachers to explore, activate, alter, add and delete any rule.

2. The second method allows teachers to control the policies that identify the active rules from the potential ones to the agent. In addition, it gives teachers more flexibility by allowing them to make different identifications for the full autonomy and partial autonomy levels. In other words, teachers can decide that the definition of active rules for the full autonomy level should be more restricted than for the partial autonomy level; thus, they can, for instance, make a unique definition of the full autonomy

level, such as this: "the active rules for the **full autonomy level** are those that guide students to follow a learning path which was **followed by at least 6 students** and **not disregarded by more than 4 students**". Similarly, teachers can make another definition for the partial autonomy level and they can be flexible in this definition as the students' learning behaviours in this mode help in optimising the rule.

Firstly, the teachers were asked about their satisfaction with the first method (browsing and altering tools). While 42.86% of them were very satisfied and 28.57% were satisfied, 14.29% were neutral and 14.29% were dissatisfied (see Figure 7.9). The teachers gave various reasons for their choices. One of the reasons is the usability of the offered tools, which was the most received comment. For instance one teacher wrote that *"editing and sorting items was very easy and could be done by any teacher even though he is not expert with computers"* and another teacher added that *"the system is flexible and able to amend or change the rule without any constraint"*. Another reason for teachers' satisfaction is the fact that this method gives teachers the sense of controlling the learning process. Additionally, it provides teachers with rich and beneficial details for every rule where they can see who altered/activated or added the rule and when, and the number of students who followed and did not follow it. Moreover, one teacher indicated that (s)he was happy with the way that the system notified him/her when the status of the rule which (s)he had edited was changed. One last reason for the teachers' satisfaction with the tool is that by presenting the bad and weak rules the tool saved some of their time. On the other hand, one teacher who was dissatisfied with the tool expressed the fact that the rules were huge for him/her and could be time-consuming; another teacher indicated that the tool needed some effort from teachers.

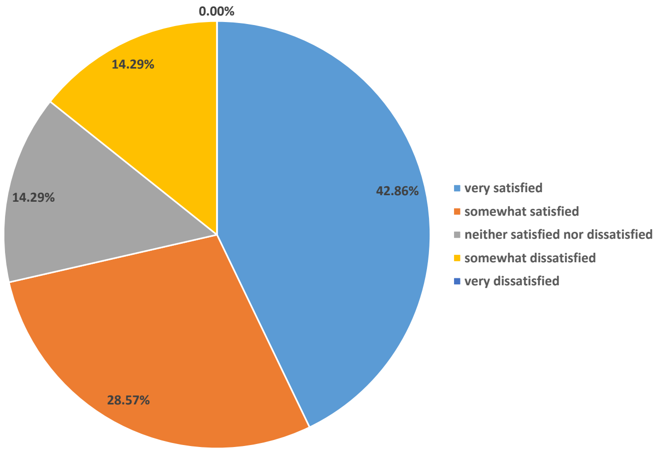


Fig. 7.9 The participants' responses to "to what extent are you satisfied with the rules editing tools?"

The teachers were also asked about their satisfaction with the second method. First, they were asked a general question about the extent to which they were satisfied with the policy responsible for activating the rules. The results show that more than three quarters of the participants were satisfied (50% were very satisfied and 28.57% were satisfied) while 14.29% were neutral and 7.14% were dissatisfied (see Figure 7.10).

The teachers reported different reasons behind their satisfaction with the second method. For example, one teacher was satisfied because (s)he found that this method eases the burden on teachers. (S)he wrote *"if it was not there, I must read all the rules and approve them manually"*. Another reason indicated by another teacher is that this method enhances the rules' quality when it allows for cooperation between teachers and the system (agent). The ability to have the control over the system is another reason; one teacher noted, *"this method shows the ability of the teacher to have control over the rules used and I have not encountered this facility in other systems"*; another teacher added, *"the tutor is artificial and I could not guarantee if it will teach correctly all the time so these methods allow me to have control"*. Moreover, one of the teachers indicated that this method can ensure to some extent that the bad rules will not be applied. One teacher also attributed her satisfaction to the fact that *"the criteria are reasonable and effective for the teaching and pedagogical process"*. However, a dissatisfied teacher raised his concern about this method's impact on teachers as it may make them lazy in scanning all the rules to find the bad ones and delete them.

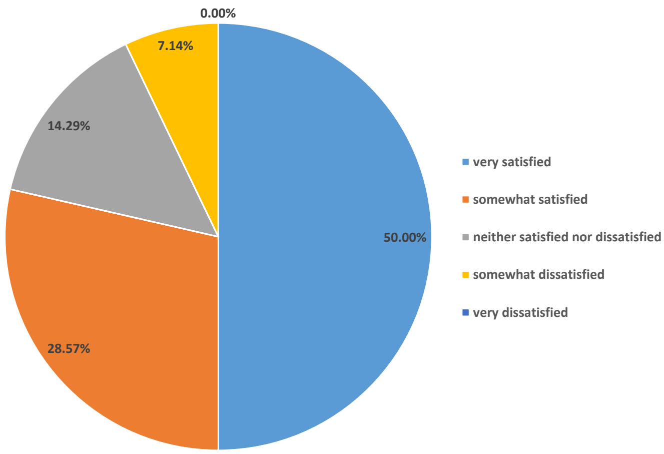


Fig. 7.10 The participants' responses to "to what extent are you satisfied with the policy responsible for activating the rules?"

Following the above question, the teachers were asked a more specific question about whether they agreed that it is important to differentiate the policies, which activate the rules, based on the guidance level. The majority of the participants agreed (42.86% strongly agreed and 35.71% agreed) while 14.29% were neutral and 7.14% were somewhat dissatisfied (see Figure 7.11).

The teachers' reasons behind their agreement with the importance of differentiating the policies show that, *"since these rules were extracted by learners"*, as indicated by one of the teachers, this can help in ensuring the quality of the rules (by defining a strict policy), particularly for the full guidance mode, as the guidance there is unavoidable. Teachers generally stressed the importance of differentiating the policies for the full autonomy level. One teacher stated, *"with bad rules, there might be a misguidance as students might be* *guided to an unsuitable unit and their choice will be restricted. So, in this type of guidance, it is important to be careful with rules before the deployment stage"*; another teacher wrote, *"if I am teaching a student and she is depending on me totally like in primary school, I must be extra careful"*; moreover, a third teacher wrote, *"I could see that learners who could not choose the lesson concentrated more, but if the tutor does the job wrongly, they will be misled"*. On the other hand, students in the partial guidance mode can help in enhancing the rules. One teacher noted, *"testing a number of the generated rules on a sample of students will help in validating those rules. The quality of the system increases"*. Other teachers were persistent and argued for the importance of these policies. One teacher wrote, *"In some way I can see that the fully guided students cannot decide not to study a unit. but the rules should be restricted for all students"*. Another teacher indicated that there is no need for these policies as the teachers should approve all of the rules without the agent's help.

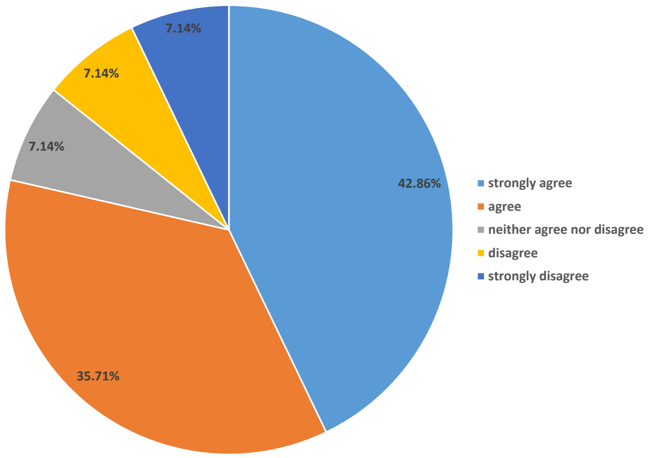


Fig. 7.11 The participants' responses to "it is important to differentiate the policies, which activate the rules, based on the guidance level"

It should be mentioned that the expressed reasons behind some teachers' dissatisfaction may reveal that some teachers may need more training in the future to deal with such intelligent systems so that they can manage the new tasks brought with this new technology.

For example, it is not necessary for a teacher to read all the generated rules and manually activate the practical ones; the agent will not use any rule unless it passes the criteria or the policy that was defined by teachers. Moreover, students can enhance the quality of the rules; thus the bad rules may not be followed by other students, which leads to de-activating these rules in the future.

Exploring their opinions about enabling them to collaborate with the agent in generating and optimising the sequence rules

ACSA offers a collaborative environment between the agents. This section reports some of the teachers' views about this notion of collaboration.

Firstly, teachers were asked about their agreement with the statement "creating sequencing rules which take into account the individual differences between students as well as the policy of activating these rules need time and effort from teachers" and the results revealed that the majority of the teachers agreed with that statement (57.14% strongly agreed and 28.57% agreed) while 14.29% were neutral (see Figure 7.12).

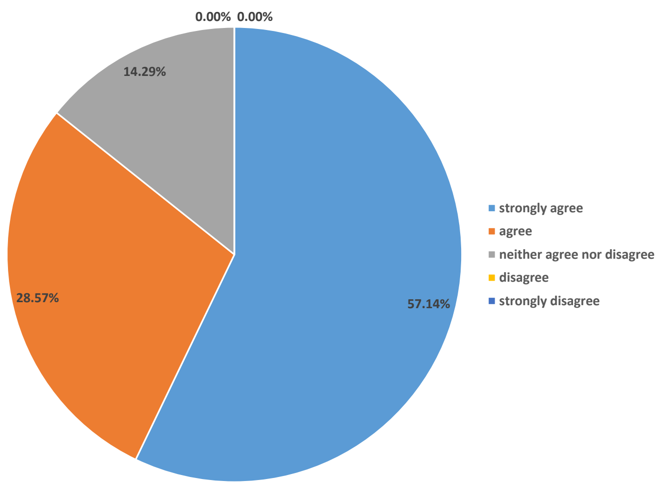


Fig. 7.12 The participants' responses to "creating sequencing rules which take into account the individual differences between students as well as the policy of activating these rules need time and effort from teachers"

Then, the teachers were asked about their opinions about making the process (auto-generating and applying the rules) performed autonomously by the agent without the teachers' interventions. The results show that a minority of the teachers strongly agreed (7.14%) and 14.29% agreed, whereas 14.29% were neutral, 14.29% disagreed and half of the teachers strongly disagreed (see Figure 7.13). This result indicates how much persistent the teachers are on not being involved in controlling the intelligent tutoring system.

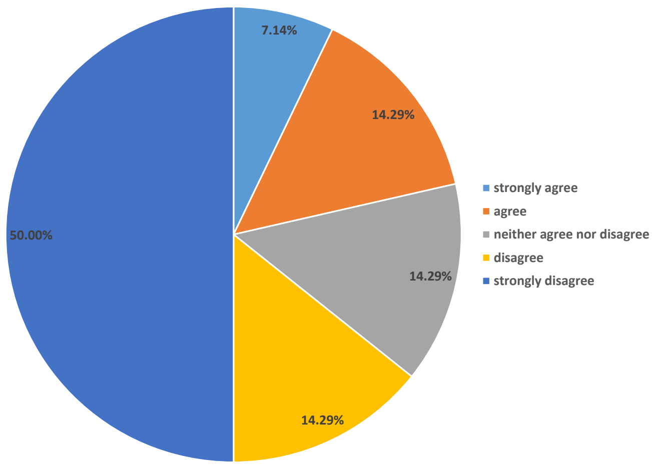


Fig. 7.13 The participants' responses to "What is your opinion about making the system generate the rules on your behalf (when you do NOT have the ability to change these rules)?"

After that, teachers were asked about their agreement with relying on the autonomy agent under their control. The results show that nearly three quarters of the teachers agreed (57.14% strongly agreed and 14.29% agreed) while 14.29% were neutral and a similar percentage disagreed (see Figure 7.14).

Teachers reported different views on which of the two methods (i.e. relying on the agent without their control, and relying on the agent with their control) was effective. One of these views is that *"no matter how intelligent the system is, it should be controlled by the teachers"* because *"some rules that are generated by the system may have poor quality"*. One teacher argued in favour of the benefit of allowing them to see the rules: *"the auto-generated* *rules might give the teacher an insight to define new fruitful rules. This is due to the fact that these rules are based on the system's observations of the students"*. Another teacher expressed his/her agreement with both methods and wrote, *"the system allowed me to define the conditions that the artificial tutor will use; it is somehow enough but when I can cooperate with the tutor to check the rules it will be more beneficial"*. Another view was in favour of the agent doing everything on their behalf since the rules need efforts; one teacher commented, *"the system does not need our editing since we put the criteria and the system will work on them. The system will still be effective for the instructional approach and it will ease the burden on us more and save our time more"*. Another teacher said she trusted the agent to generate the rules and sequence the tasks on her behalf since the rules were generated by observing the students. The last view was against using either of the two methods; two teachers believed that creating the rules was one of their tasks and they should not rely on any agent to achieve this.

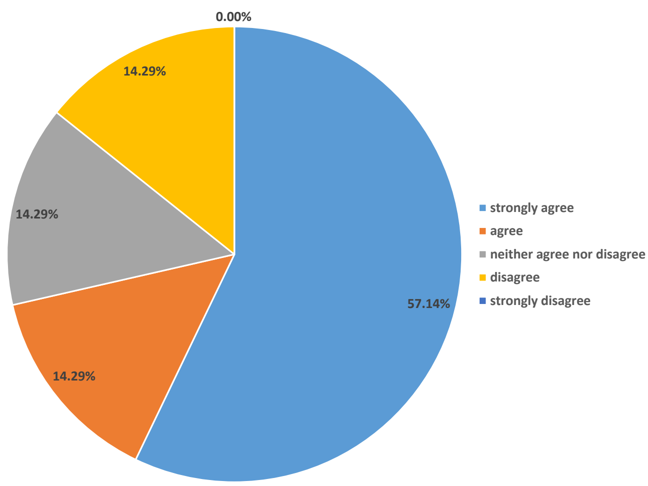


Fig. 7.14 The participants' responses to "What is your opinion about making the system generate the rules on your behalf (when you do have the ability to change these rules)?"

One possible benefit of utilising the autonomous agent is to minimise the burden imposed on the teachers. Thus, the teachers were asked to rate their agreement with this benefit in the context of allowing the agent to generate the rules on behalf of the teachers. The participants' responses show that more than half of the teachers agreed (35.71% strongly agreed and 21.43% agreed) while 21.43% were neutral, 14.29% disagreed and 7.14% strongly disagreed (see Figure 7.15).

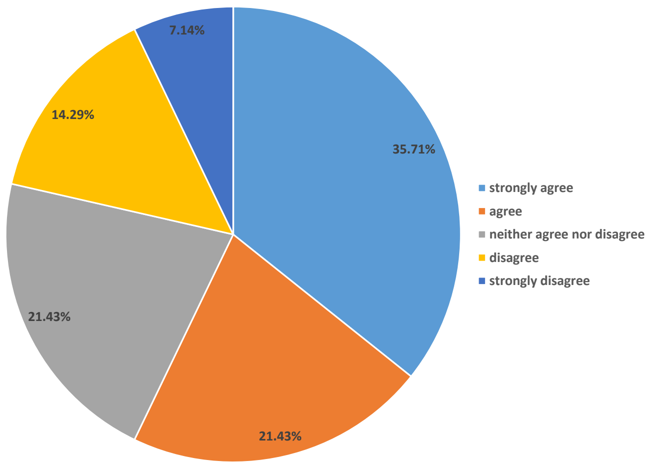


Fig. 7.15 The participants' responses to "making the system responsible of generating the rules on my behalf relieved some of the burden on me"

Another possible benefit that is worth investigating the teachers' views about is whether involving the teachers in the operational phase by allowing them to access the rules and alter any of them may enhance their quality. The majority of the teachers agreed with this opinion (50% strongly agreed and 35.71% agreed) while 7.14% were neutral and a similar percentage disagreed (see Figure 7.16).

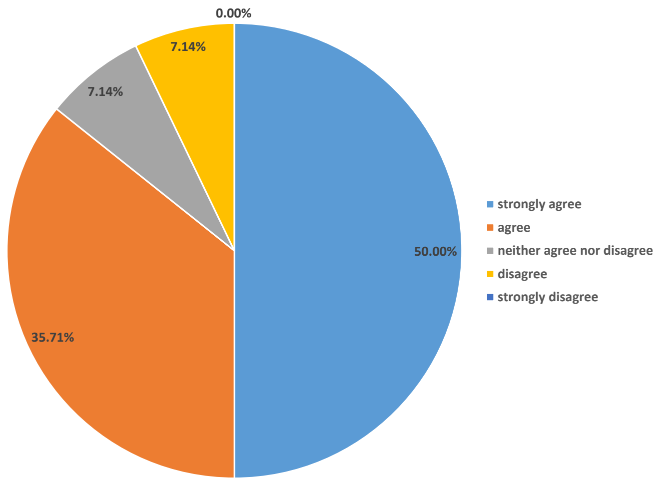


Fig. 7.16 The participants' responses to "giving me the ability to access the rules and alter them enhances their quality"

Exploring the teachers' views regarding the guidance modes

The aim of this section was to investigate the teachers' opinions about giving the students the ability to adjust the autonomy level in general and their views about every level in specific. Although only the students were offered the ability to adjust the autonomy level, exploring the teachers' opinions in this matter may give another angle to this research. It should be noted here that when completing the survey, the teachers did not know about the final results of both experiments, which were reported in Chapter 5 and Chapter 6. The researcher did that to ensure that the teachers would not be influenced while answering the survey. Hence, if the teachers had known about the results, their opinions would probably have been biased towards the idea of giving the students more freedom to adjust their learning to suit their learning needs.

Teachers were first asked if the three autonomy levels offered to the students (full, partial and no autonomy) were enough to fulfil students' needs. The majority of the teachers agreed (42.86% strongly agreed and 35.71% agreed) while 14.29% were neutral and 7.14% disagreed (see Figure 7.17). In addition, some teachers indicated the reasons for their agreement or disagreement. In terms of agreement, one teacher noted, *"I can see that in the learners' behaviours: some learners keep asking me and do whatever I ask them but others learn by themselves and some others want to consult and then take their choice"*. Another teacher commented that *"they cover all the possible guidance situations and preferences"*. Interestingly, one of the teachers agreed that they were enough but he suggested another level: *"the only extra level I can think of is a level of partial autonomy where the system will allow the student to study a unit from the set of units selected by the system"*. This suggestion is worth investigating in the future. Although, at the first stage, the three offered levels fulfil some of the students' learning needs, as has been approved in the above responses, and the three levels lead to enhancing the learning outcomes, as approved by the two experiments, this does not mean that there is no need for more levels. The new suggested level can be located in between the full and the partial guidance levels. It can possibly offer a way of not breaking the dependency constraints of the lessons. Thus, the system in that level can balance between giving the students the ability to follow or disregard the guidance and ensuring that when a student discounts the guidance, (s)he will learn the pre-requisite lessons first. Another possible benefit for adding this level in the future research is to try another method for solving conflicting rules, not to mention the fact that it may also help in enhancing the rules.

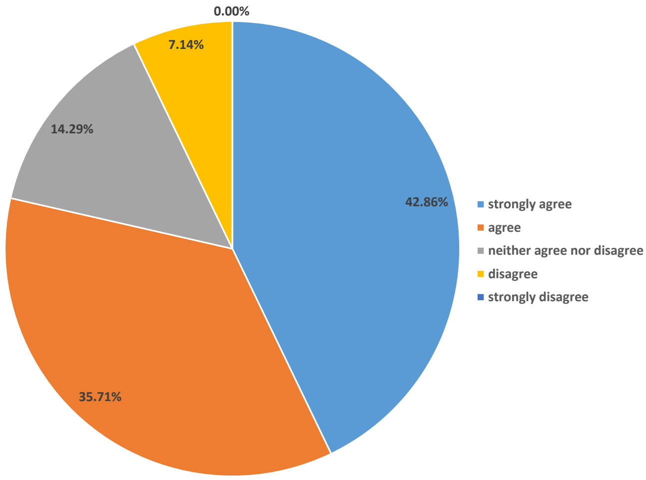


Fig. 7.17 The participants' responses to "the three autonomy levels (full, partial and no autonomy) are enough to fulfil students' needs"

As for the statement "It is a good strategy to give the student the ability to choose the preferred level of autonomy", two thirds of the teachers agreed (28.57% strongly agreed and 42.86% agreed) while 7.14% were neutral, 14.29% disagreed and 7.14% strongly disagreed (see Figure 7.18).

In terms of the reasons behind their opinions, many teachers expressed how advantageous this strategy is. For instance, teachers commented that *"it makes students satisfied and motivated"*, *"increases the interaction"*, *"improves students' learning outcome"*, *'mimics the way people learn"* and *"pays attention to students' individual needs"*. Teachers who disagreed suggested that only teachers should have the ability to decide the level of each student. One teacher reasoned this suggestion by explaining that students usually find the easiest ways not the best ones. Another teacher's reason was that the students would waste their times by exploring the different levels. Teachers were also asked about to whom this service should be offered and a variety of responses were received. One teacher suggested that the highest 10% of students in the class/group can have the ability to adjust the guidance mode. Some teachers suggested to give it to all students, while other teachers suggested that it be given to all postgraduate students, and only some undergraduates. A few teachers suggested that it should be given as a reward to the highly self-motivated students. Finally, one teacher recommended that it should be given to students in the final year of their study.

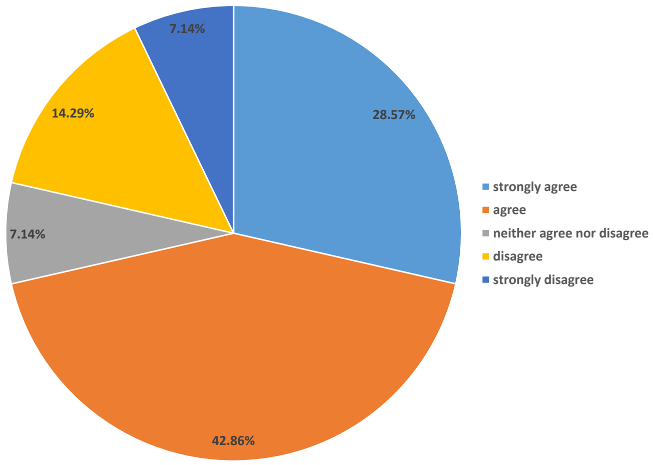


Fig. 7.18 The participants' responses to "It is a good strategy to give the student the ability to choose the preferred level of autonomy"

A further step was taken to focus the questions on each level of the three autonomy levels. To start with the full autonomy level, i.e. whether the teachers agreed that sometimes they want to force some students to learn a lesson, the majority of the teachers agreed (28.57% strongly agreed and 57.14% agreed) while 7.14% were neutral and 7.14% disagreed (see Figure 7.19).

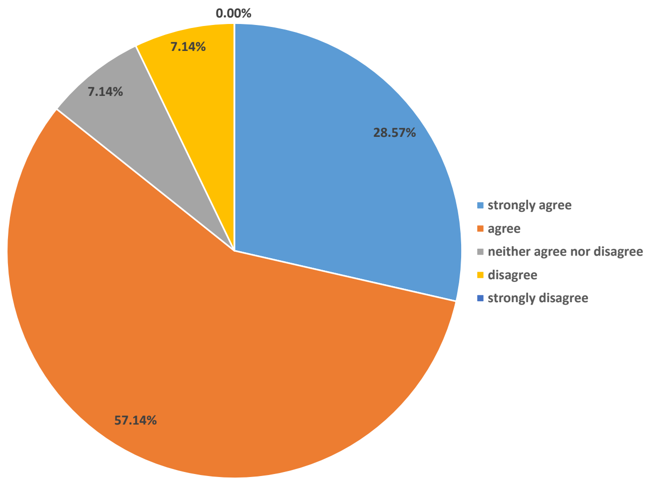


Fig. 7.19 The participants' responses to "sometimes, I want to enforce (oblige) some students to learn a lesson (without giving them the option to study another lesson)"

As for the partial autonomy level, the statement was "there are some students to whom I want to recommend a lesson to study and they are free to study it or study another one". The results indicated that half of the teachers strongly agreed and 35.71% agreed, while 7.14% were neutral and 7.14% strongly disagreed (see Figure 7.20).

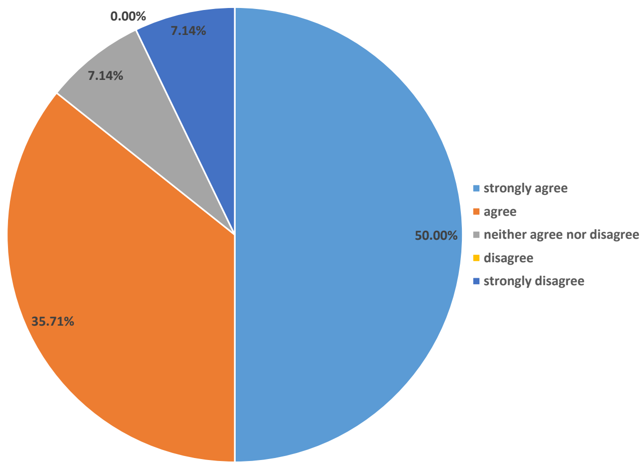


Fig. 7.20 Participants' responses to "there are some students to whom I want to recommend a lesson to study and they are free to study it or study another one"

The last level of autonomy is the no autonomy. The statement which the teachers were asked to rank their agreement with was “It is good to give some students the freedom to choose what they want to study in their preferred sequence”. The results showed that half of the teachers agreed (7.14% strongly agreed and 42.86% agreed) while 21.43% were neutral, 14.29% disagreed and 14.29% strongly disagreed (see Figure 7.21).

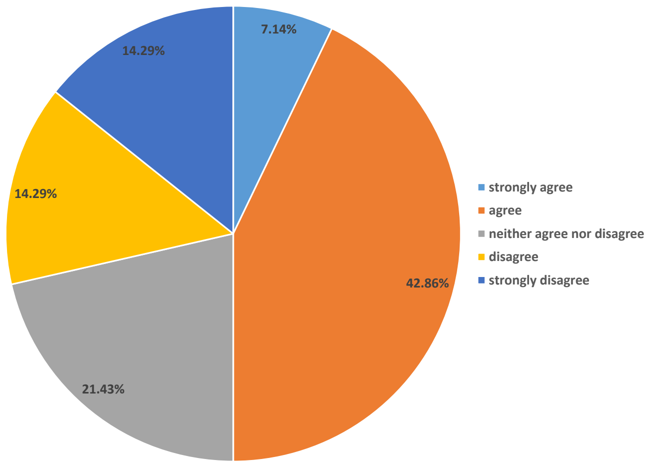


Fig. 7.21 The participants’ responses to “It is good to give some students the freedom to choose what they want to study in their preferred sequence”

Exploring their general view of ACSA and its pros and cons

Teachers were asked if they wanted to use ACSA with their students in the future; hence they were required to rank their agreement with the statement “in the future, I want my students to study in this intelligent system”. More than three quarters of the teachers agreed (half strongly agreed and 28.57% agreed) while 14.29% were neutral and 7.14% disagreed (see Figure 7.22).

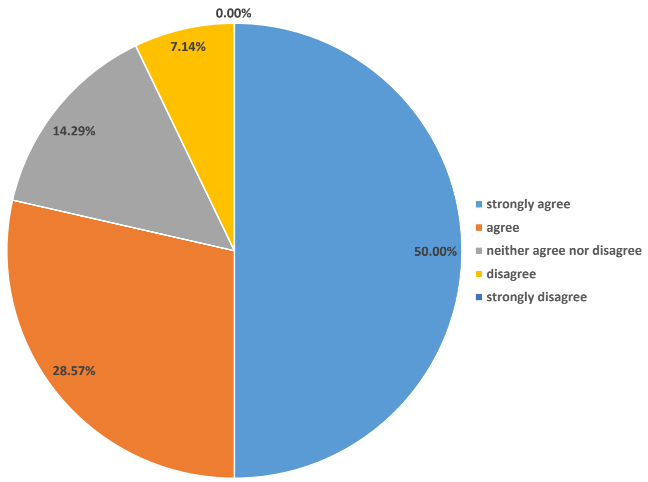


Fig. 7.22 The participants' responses to "in the future, I want my students to study in this intelligent system"

Teachers were also asked about how much they were satisfied with ACSA. The majority of them agreed (half strongly agreed and 35.71% agreed) while 7.14% were neutral and 7.14% disagreed (see Figure 7.23).

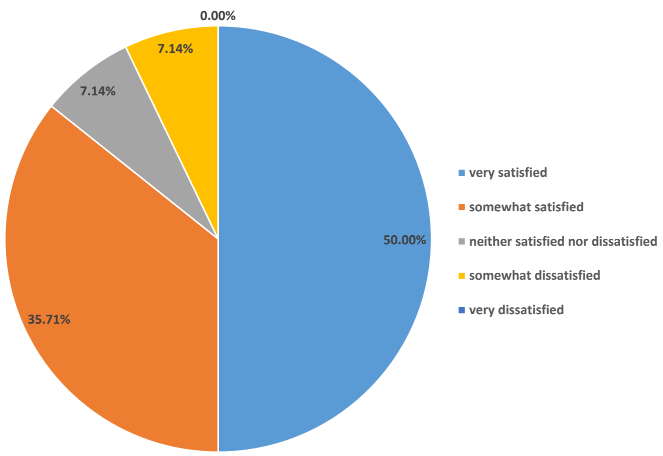


Fig. 7.23 The participants' responses to "In general, to what extent are you satisfied with the system?"

Finally, in response to the question about the advantages and shortcomings of ACSA, the teachers stressed a number of strengths and highlighted a number of weaknesses. In terms of advantages, one of the advantages mentioned by the teachers is that the rules are auto-generated during the learning sessions and can be controlled and amended by them. One teacher noted that *"the rules which are formulated by students allow them to study something based on their level, which may not sometimes be known by the instructor"*; another teacher commented that *"having such a smart system can help discover new information (rules) that humans cannot discover"*. Another strength suggested by the teachers is that students can control the learning process. One teacher highlighted that ACSA *"mimics the way people learn. so the learners can choose how to be taught, and produces the recommendations based on learners' behaviours, which also mimics how people learn from one another's experiences"*. The flexibility of the system was another advantage according to some teachers. This flexibility is manifested in the adjustment of the autonomy levels, in the control of the learning process and in the variety of the teaching styles introduced with effective scaffolding and feedback. One of the participants commented that the system *"is flexible and can accommodate several types of students' bands and different teaching approaches"*. Moreover, creativity is another benefit of utilising agents in the systems. As one of the teachers stated, *"the system gives students the opportunity to learn and discover new subjects and make them able to broaden their horizon"*.

Other advantages stated by the teachers are saving the teachers' time, fulfilling some of their needs and reducing their workload. One teacher commented that this is particularly the case when classifying students based on their knowledge level: *"it eases tracking and monitoring students and their progress"*. Most importantly perhaps, one of the advantages of ACSA is that it seeded some trust of utilising the adjustable autonomy agent in the educational field. One teacher commented, *"It was my first time dealing with such a system that guides the learning process. In the beginning, I was strongly persistent due to my understanding* *that no technology can take the teachers' roles. However, giving the teachers the ability to intervene and alter/delete any rule reduced some of that persistence. Nevertheless, I still believe that it is not good to allow students to decide themselves what to learn"*.

Other suggested advantages are *"the simplicity of the system"*, *"the ease of using it with user-friendly interfaces"*, *"the accuracy of the rules"*, *"the responsive support team"*, *"the reliability of the system"* and *"the interactive and responsive learning units"*. The last two advantages encouraged a teacher, as he noted, to make the final practical exam to be done in the system. A teacher suggested that *"the close observation of students by the agent pushed students to make a great effort in learning"*.

On the other hand, a number of limitations of ACSA were outlined by the teachers. A number of limitations may arguably happen in other intelligent systems such as *"the occurrence of bad rules"*, the data privacy, the need for a *"large number of users (students) to start in order to generate an accurate set of rules"* and the validity time (i.e. expiry date) of relying on the generic rules. This limitation can also happen if the learning objectives of the module/course have been modified. For example, in our case, ACSA taught 12 lessons in M.S. Excel. Now if it was decided to add other lessons or omit some, the question would be, to what extent would the rules be valid and how much could ACSA benefit from these outdated rules? Such questions and concerns are worth more and intense investigation in the future.

On the contrary, some teachers criticised giving all the students the ability to adjust the autonomy levels. They wanted to have control over this; one teacher said *"It does not allow me to control the autonomy level for individual students as some of them may use it for fun"*. Another teacher added, *"the careless student should not be given the opportunity to select the subjects that (s)he wants to study. (s)he should be forced by the instructor since this ability to choose should be given to the distinctive students only"*. Another teacher suggested not to give students this ability as it may disturb them. Another major drawback of the system is the huge amount of the rules which *"sometimes burden the instructor when (s)he tries to assess them"*. One teacher wrote, *"the rules are long and I want to train how to deal with these systems"*. Actually, utilising the intelligent tutoring systems brings new tasks for teachers and they should be trained to deal with these tasks in the future as the agent collaborates with the teachers to minimise the load. Thus they should not scan all the rules. Alternatively, the effective and highly trained agent can present the bad and weak rules to them to seek their help with decisions. Additionally, involving the students to "explicitly" vote for the validity of the rules will enhance the rules and that may in turn lead to reducing the load on the teachers.

Other limitations of the systems included *"no deep analysis for students' progress presented for teachers, but only their marks in details"*. The fact that only one module was taught in the system is another drawback, as indicated by a teacher. What's more is that *"the system should have a discussion forum, so learners will raise questions and reply"*. At this first stage, ACSA adopts only personalised learning and perhaps communication between students can be offered in the future. A teacher did not believe that involving students in deciding what to learn is not a good technique. Finally, one teacher had a reservation about the simplicity of the design of the user interface, which, from his point of view, *"needs more work to attract students"*.

7.3 Discussion

The core aim of this chapter was to explore the teachers' opinions which could help in validating some functionalities of the ACSA's conceptual architectural model. Five objectives were created to aid in achieving this aim: 1) identifying the teachers' opinions towards the generated rules, 2) investigating their views about allowing them to control the learning process, 3) exploring their opinions about making the agent collaborate with them in generating and optimising the sequence rules, 4) exploring their views regarding giving the students the ability to adjust the guidance level in general and their opinions about every level of guidance in specific, 5) clarifying their satisfaction with ACSA in general and its advantages and disadvantages.

A mixed research method (qualitative and quantitative) was followed to meet these objectives by designing an online questionnaire with open-ended and closed question and administering it with teachers. 43.75% of the teachers responded to the survey and the results showed that many of the teachers were satisfied with the system's auto-generated rules and introduced some reasons behind their answers. Moreover, they indicated that these rules were sufficient to teach students. This demonstrates how reliable machine is in learning from the students' learning behaviours. The results also indicated that many teachers interacted with the agent by altering some of the generated rules and they described the characteristics of the bad or weak rules which may inspire the researchers in intelligent environments and tutoring systems fields in the future.

As for their satisfaction with the two offered methods, which allow them to control the rules with more flexibility, the results indicated that many of them were satisfied and they followed-up their answers with reasons. The majority of the teachers stated that creating adaptive and personalised sequencing rules needs more effort and time. However, many of them did not agree to give all the responsibility for generating and applying rules to the agent without their control. The majority of them said that they wanted the help from the agent but under their own control, and some from them indicated that this relieved some of the burden on them. The majority of the teachers approved that giving them the ability to access the rules and alter them improves the quality of the rules. Regarding allowing students to adjust the autonomy level, the majority of the teachers stated that the three offered levels of guidance are enough to meet students' needs. They also stated that it is a good strategy to give the student the ability to adjust the guidance. They agreed in majority that using the full or partial guidance level only for cretin students is a good strategy while half of the teachers agreed that the no-guidance level is good for some students. The majority of the teachers were satisfied with ACSA in general and more than three quarters of them agreed to use ACSA again in the future, which means that they trusted the systems and indicates that the conceptual model is valid to be adopted in the educational field.

Chapter 8

Conclusions and Future Work

This thesis aimed to bring more adaptability, flexibility, creativity and controllability to the intelligent online tutoring systems. This was achieved by designing and implementing a conceptual architectural model that utilised adjustable autonomy mechanisms. The model allows teachers, students and the tutor agent to collaborate in optimising the learning process, offers students the ability to control the amount of assistance received from the tutor agent and help them find a better alignment for their changeable individual learning needs. The thesis focused on the adaptive course sequencing as an example approach to online tutoring systems. At the first step towards designing the conceptual model, the literature on the related issue was reviewed in Chapter 2. Then, this was followed by exploring the students' learning needs regarding personalising and adapting the learning path, and the preferred pedagogical guidance mode while learning (Chapter 3). After that, the thesis described the design of the conceptual model and presented the implemented prototype system I called the adaptive course sequencing approach (ACSA) (Chapter 4). This approach was trailed twice in two experiments, once via the use of the teacher-driven method (Chapter 5) to explore the pedagogical benefits of adjustable autonomy and another through the use of the collaborative-driven method (Chapter 6) to explore the pedagogical benefits of machine learning. In addition, the teachers' views about the ACSA conceptual model were surveyed and discussed in Chapter 7.

8.1 Reminder of the Thesis' Aims and Hypotheses

The aims of this thesis were classified into pedagogical and technical aims. Pedagogically, the first aim was to understand some of the students' learning needs and preferences related to adapting and personalising the lessons' sequence in online tutoring systems, which involved studying the need for adjustable autonomy in these systems. Technically, the research also aimed to devise a conceptual architectural model for adjustable autonomy online tutoring systems. This involved identifying the individual agents' roles in the proposed multi-agent system and defining a conceptual architectural model with its components and functionalities. In addition, one aim was to implement the conceptual architectural model in the adaptive course sequencing approach (ACSA), as an example of online tutoring systems, to make this type of systems more adaptive, agent-collaborative and controllable. This entailed finding a suitable way to encode the learning experiences in fuzzy rules.

The last aim was to explore adjustable autonomy in ACSA through implementing ACSA based on the conceptual architectural model, comparing between the outcomes of the students in each level (full, partial and no autonomy) and the results of those who can adjust their autonomy level, and comparing between the teacher-driven method and the collaborative method, where machine learning is utilised. In other words, I wanted to provide answers to these research questions: 1) does adjustable autonomy improve students' learning outcomes?, 2) does adjustable autonomy achieve teachers' requirements?, and 3) what level of teacher intervention is required to create an effective rule set?.

Following setting up the aims, I hypothesised that:

- *"students using online tutoring systems differ in their individual desired level of autonomy. Moreover, this level sometimes differs between students and over time for an individual student depending on factors such as the student's learning-needs and preferences as well as the current lesson and subject. Therefore, equipping online tutoring systems with adjustable autonomy mechanisms will allow the student to control the amount of assistance and choose the preferred level of autonomy, which will bring a better alignment of learning needs and lead to optimising the learning gain"*.

- *"It is possible to devise a conceptual architectural model capable of adapting the sequence of learning content, allowing students to personalise the way of receiving the sequence, making the tutor agent capable of producing sequencing rules and giving the teachers the ability to control the learning process"*.

- *"Machine learning has the ability to produce sequencing rules which can be used to guide students to learn better and are similar to the rules generated by teachers"*.

- *"Giving the teachers the ability to control the generated rules will enhance the rules and will satisfy the teachers."*

8.2 Contributions

The main novelty of this work stemmed from the application of adjustable autonomy mechanisms to online tutoring systems. A number of primary contributions flowed from this vision which included:

1. Developing a novel theoretical model of adjustable autonomy for education.

2. Translating the theoretical model into a unique technical and pedagogical implementation.

3. Conducting two extensive trials of adjustable autonomy in education, leading to a large sample of quantitative and qualitative data, which, upon analysis, unveiled valuable and unique findings.

The process of achieving these contributions had multiple facets. For example, investigating the effectiveness of adjustable autonomy was fulfilled through proposing and then constructing a conceptual architectural model as a way of delivering the required functionalities that cover the adaptive and personalised pedagogical needs for students. This involved finding the possible practical solutions such as utilising the adjustable autonomy (to allow students to adjust the autonomy level to find a better alignment to their individual learning needs), fuzzy logic (to generate human readable rules and handle the uncertainty of some of individual students' characteristics) and mixed initiative (to give the teachers the ability to control the agent).

Beyond the main contributions there were many secondary, but important contributions arose through supporting work such as:

1. Completing a pre-design survey concerning students' views about their preferences on sequencing lessons and controlling the amount of assistance they require from their teachers. The findings of this survey is valuable in itself.

2. A thorough review of literature that underpinned the ideas underlying the theoretical model of adjustable autonomy.

3. Proposing and building a conceptual architectural model to cover the students' personalised pedagogical needs.

4. Assigning more informative value to the sequencing rules in the system to enable the teacher and the tutor agent to define the active rules from the set of all the automatically generated rules.

5. Allowing for multi-agent collaboration in creating and optimising the sequencing rules.

6. Making online tutoring systems more adaptable and flexible by involving teachers in the design and operational phases.

7. Making the tutor agent services accessible to other e-learning systems, which facilitates the construction of new online tutoring systems in the future through utilising the pedagogical decisions of other tutor agents.

The theoretical models and experimental trails were realised through a computational architecture that took a web-based asynchronous adaptive course sequencing approach (ACSA) that was capable of serving the functionalities identified in the conceptual model. The implementation of the ACSA resulted in numerous technical contributions and pedagogical contributions. The technical contributions can be summarised as follows:

- Assigning additional informative value to the sequencing rules such as the number of students who follow or do not follow a particular rule, whether the rule is modified by a teacher or not, the identity of the modifier and the date of modification. This information enables the teachers and the tutor agent to define the active rules from potential ones. Moreover, the teachers can make this definition unique for every kind of autonomy level, which gives more flexibility to the learning process in that teachers may be stricter in defining active rules in the full autonomy level and be more tolerant in the partial autonomy level.

- Enabling tutor agent services to be accessible from other e-learning systems. This encourages the development of new online tutoring systems in the future via utilising the pedagogical decisions of other tutor agents, which can save time, effort and financial resources that would be required for establishing a new online system from scratch. This can be achieved when pedagogical decisions and recommendations are shared publicly amongst educational institutions.

The pedagogical contributions and findings can be summarised as follows:

- The construction of the ACSA conceptual architectural model that enhances the learning outcomes through adjustable autonomy mechanisms. This allows students to follow their preferred or personalised learning path and control the amount of help or guidance they receive from the tutor agent. It draws on O'Neill and McMahon's continuum [159], giving students the opportunity to adjust their position on the teacher-centred and student-centred learning continuum.

- As the tutor agent monitors the learning behaviour of large numbers of students (big-data), it opens up the possibility to mine this data to both improve the learning sequencing and provide hitherto hidden insights that could lead to better lesson design and contributing to understanding students' learning needs and concerns regarding sequencing lessons and the level of assistance they demand from their teachers.

- This work included an in-depth investigation of teachers' opinions regarding the ACSA functionalities and services producing valuable insights into how such a system might be improved moving forward.

- The model adopts a novel type of crowd sourced intelligence whereby it facilitates multi-agent collaboration in creating and optimising the sequencing rules, which is particularly advantageous when the number of students is massive. As a result, teachers are not required to take the whole responsibility for generating the rules as the task is accomplished by the interaction between the tutor agent, teachers and the students. In other words, the teacher will only have a supervisory role, which reduces their workload, enabling them to focus on other teaching tasks. Besides, the multi-agent collaboration contributes not only to the generation phase but also to the consumption phase, where the teacher defines the active rules for each level of autonomy, allowing the tutor agent to identify the appropriate rules for a given student.

- The model affords a great deal of adaptability enabling the online tutoring system to serve a large and diverse set of multicultural students, as adjustable autonomy offers a variety of autonomy levels that are required to fulfil the diverse and changing personal needs of students.

- As educational environments vary in terms of their policies, curricula, and objectives, adopting a single large-scale online tutoring system by institutions will save the human and financial resources required to develop individual systems with different curricula and objectives. The high levels customisation that are inherent to adjustable autonomy schemes make ACSA particularly well suited to providing such a single solution for an institution. It also fits established practice well as it mirrors and augments traditional teaching processes closely but in its metered delivery of guidance and its involvement of teachers in the design and operational phase. In other words, individual institutions can utilise the system using their own teaching curricula and the teacher can still adjust the rules.

8.3 Summary of Achievements

In addition to the aforementioned contributions, the analysis of the data generated from the students' survey, the two empirical experiments and the teachers' survey contributed to disclosing a number of significant and intriguing findings.

Regarding the students' survey, the results show that many students wanted to be involved in controlling the learning process and have the ability to decide their learning path. The results also indicate that many students restudied lessons or part of them in various courses, and many students expressed negative feelings when repeating lessons. However, some of them believed that this could be a good technique for learning. An interesting finding is that, for many students, the most important factor which made them decide to learn a lesson or not was the prior knowledge about that lesson. Some students had concerns about having the skills needed for deciding the learning path. Thus, in general, students appreciated the teachers' help in choosing the suitable lessons' sequence. Moreover, they valued sharing experiences with other students, specifically those who had similar levels of knowledge. In terms of the autonomy levels (i.e. full guidance, partial guidance and no-guidance), many students agreed that these three levels were sufficient for them to achieve their learning objectives and that their preferences for any of these three levels might vary according to the context. Based on these findings, it is inferred that involving students and teachers in the design and operational phase of the system is worthwhile as it may contribute to improving the process of fulfilling the students' learning needs. In addition, offering students a way to adjust the received amount of guidance helps them to find a better alignment for their learning needs.

Following the construction of the ACSA based on the conceptual architectural model, the two experiments resulted in interesting findings in terms of the advantages of applying adjustable autonomy mechanisms and machine learning.

Starting with the first experiment, in order to overcome the problem of "cold start", the teachers were required to create the sequencing rules (teacher-driven method). Since the number of rules was massive, the hierarchical fuzzy logic classification was adopted, which dramatically reduced the number of sequencing rules in a way that ensured their sufficiency and effectiveness. The results of the first experiment showed that the adjustable autonomy group significantly outperformed the other three groups (full, partial and no autonomy). Moreover, a deeper analysis of the adjustable autonomy group data revealed that students who made full use of the adjustable autonomy mechanism by changing their autonomy level more than once performed slightly better than those who chose an autonomy level and did not change it. The first findings in the first experiment suggested that the ITS which adopted only one of the guidance mode: full, partial or no autonomy guidance mode such as [56],

[69], [71], [72], [73] to consider adopting adjustable autonomy mechanisms. Hence, the ITS will be more adaptable, controllable and creative, and the students' learning outcomes will be enhanced.

As for the second experiment, it studied how machine learning can help the tutor agent generate sequencing rules from the gathered dataset and how the teachers, the tutor agent and the students can collaborate to enrich the learning experiences and enhance the learning process (i.e. collaborative-driven method). It also measured the pedagogical impact of this method based on the students' learning outcomes and the teachers' feedback. The analyses of the students' learning gains displayed that there was no statistically significant difference between the collaborative-driven method and the teacher-driven method. The similar performance of the collaborative driven method to that of the teacher-driven method validates the effectiveness of the former as it reduces the burden on the teachers, promotes the users' feeling of responsibility and creativity, and speeds up the time needed to create an online tutoring system and meet the changing learning needs.

Finally, the teachers' survey, where the teachers were asked to introduce their opinions about ACSA and its functionalities, showed that many of them were satisfied with the generated rules and saw that these were enough to teach students, which may validate the accuracy and practicality of the conceptual model. Despite the fact that the majority of the teachers believed that the ACSA did reduce the time and energy needed to create the rules, many of them insisted that teacher intervention was sometimes necessary and that the two introduced control methods satisfied them. The teachers' responses regarding giving students the ability to adjust the autonomy levels showed that the majority of them saw this as a good strategy and that the three autonomy levels were enough to suit students' needs. Finally, the majority were satisfied with ACSA and said they wanted to use ACSA again in the future.

8.4 Future Work

The limited time available for the research made us focus on achieving the aims and try to verify the hypotheses within the system. This has resulted in leaving some aspects uncovered, which can be areas for investigation in the future. These can be summarised as:

- Making the teachers decide whether to allow a student to have the ability to adjust the autonomy level or not. This proposal was suggested by some teachers, who argued that allowing the students to have the ability to adjust the autonomy level might distract them.
- Investigating the ACSA application to other learning topics.
- Utilising some technical solutions to optimise the rules' form as some teachers criticised its length in the IF-part. A solution that can be considered in this matter is through using the hierarchical fuzzy logic system to minimise the rules' antecedents (inputs).
- Applying the conceptual model for another type of adaptation, for example, adapting the learning design. In this case, the three offered autonomy levels should be revised in accordance with learner variables, such as personality traits, learning style, social skills, perceptual skills, etc., where some students may need more levels than others and some may be allowed to access the rules to create or alter their own rules.
- Studying how the conceptual model can be utilised in different pedagogical environments (e.g. adapting the learning path in 3D immersive spaces or mixed reality systems).
- Utilising the teachers' descriptions of the bad and weak rules to automatically recognise them and then make decisions of altering, (de-)activating or deleting any bad or weak rules.

- Investigating the effect of temporal learning as an influence on the performance of the tutor agent and the teachers' and students' opinions.
- Since the definition of the knowledge level may differ between people and even between countries, future research may consider utilising Type-2 Fuzzy Logic to handle the uncertainty in this matter.

It is important to note that the success of the two experiments in this thesis by no means suggest that the construction of the adjustable autonomy system is an ideal and faultless system that should be blindly used. It is, however, a stepping stone towards reaching such a perfect system that everyone can trust and is no more than a little piece of evidence in a promising research area.

References

[1] A. Gulz, M. Haak, A. Silvervarg, B. Sjödén, and G. Veletsianos, "Building a social conversational pedagogical agent: design challenges and methodological approaches," in *Conversational agents and natural language interaction: Techniques and effective practices* (D. Perez-Marin and I. Pascual-Nieto, eds.), pp. 128–155, Hershey, PA: IGI Global, 2011.

[2] K. Mathieson, "Predicting user intentions: comparing the technology acceptance model with the theory of planned behavior," *Information Systems Research*, vol. 2, no. 3, pp. 173–191, 1991.

[3] T. Govindasamy, "Successful implementation of e-Learning: Pedagogical considerations," *The Internet and Higher Education*, vol. 4, no. 3–4, pp. 287–299, 2001.

[4] A. Jones, "ICT and Future Teachers: Are We Preparing for E-learning?," in *Information and Communication Technology and the Teacher of the Future* (C. Dowling and K.-W. Lai, eds.), no. 132 in IFIP — The International Federation for Information Processing, pp. 65–70, Springer US, 2003.

[5] "What is e-Learning? A short introduction." [Online]. Available: http://www.virtual-college.co.uk/elearning/elearning.aspx.

[6] "Learning Management Systems (LMS) Market - Global Forecast to 2020.." [Online]. Available: http://www.marketsandmarkets.com/PressReleases/learning-management-systems.asp.

[7] J. Self, "The defining characteristics of intelligent tutoring systems research: ITSs care, precisely," *International Journal of Artificial Intelligence in Education (IJAIED)*, vol. 10, pp. 350–364, 1998.

[8] J. Bourdeau and M. Grandbastien, "Modeling Tutoring Knowledge," in *Advances in Intelligent Tutoring Systems* (R. Nkambou, J. Bourdeau, and R. Mizoguchi, eds.), no. 308 in Studies in Computational Intelligence, pp. 123–143, Springer: Berlin & Heidelberg, 2010. DOI: 10.1007/978-3-642-14363-2_7.

[9] B. Woolf, *Building Intelligent Interactive Tutors: Student-centered strategies for revolutionizing e-learning*. Morgan Kaufmann, July 2010.

[10] J. A. Self, "Student models in computer-aided instruction," *International Journal of Man-machine studies*, vol. 6, no. 2, pp. 261–276, 1974.

[11] J. A. Self, "Concept teaching," *Artificial intelligence*, vol. 9, no. 2, pp. 197–221, 1977.

[12] J. Self, "A perspective on intelligent computer-assisted learning," *Journal of Computer Assisted Learning*, vol. 1, pp. 159–166, Dec. 1985.

[13] J. R. Carbonell, *Mixed-Initiative Man-Computer Instructional Dialogues. Final Report.* PhD thesis, Massachusetts Institute of Technology, Cambridge, MA, 1970.

[14] J. R. Carbonell, "AI in CAI: An artificial-intelligence approach to computer-assisted instruction," *IEEE transactions on man-machine systems*, vol. 11, pp. 190–202, Dec. 1970.

[15] W. J. Clancey, *Transfer of Rule-based Expertise Through a Tutorial Dialogue*. PhD thesis, Stanford University, Stanford, CA, USA, 1979.

[16] W. J. Clancey, *Knowledge-based Tutoring: The GUIDON Program.* Cambridge, MA, USA: MIT Press, 1987.

[17] W. J. Clancey and R. Letsinger, "Neomycin: Reconfiguring a Rule-based Expert System for Application to Teaching," tech. rep., Stanford University, Stanford, CA, USA, 1982.

[18] R. Crowley, O. Medvedeva, and D. Jukic, "SlideTutor: A Model-Tracing Intelligent Tutoring System for Teaching Microscopic Diagnosis," in *Artificial Intelligence in Education: Shaping the Future of Learning Through Intelligent Technologies*, (Sydney, Australia), IOS Press, 2003.

[19] "ITS 2016 International Conference On Intelligent Tutoring Systems." [Online]. Available: http://its2016.its-conferences.com/.

[20] "AIED 2015." [Online]. Available: http://perseo.lsi.uned.es/aied2015/.

[21] E. Wenger, *Artificial Intelligence and Tutoring Systems: Computational and Cognitive Approaches to the Communication of Knowledge*. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 1987.

[22] C. R. Eliot, K. A. Williams, and B. P. Woolf, "An intelligent learning environment for advanced cardiac life support.," in *Proceedings of the AMIA annual Fall symposium*, p. 7, American Medical Informatics Association, 1996.

[23] A. Corbett, "Cognitive tutor algebra I: Adaptive student modeling in widespread classroom use," in *Technology and Assessment: Thinking Ahead. Proceedings from a Workshop. National Academy Press, Washington, USA*, 2002.

[24] I. Arroyo, J. E. Beck, B. P. Woolf, C. R. Beal, and K. Schultz, "Macroadapting Animalwatch to Gender and Cognitive Differences with Respect to Hint Interactivity and Symbolism," in *Intelligent Tutoring Systems* (G. Gauthier, C. Frasson, and K. VanLehn, eds.), vol. 1839 of *Lecture Notes in Computer Science*, pp. 574–583, Springer: Berlin & Heidelberg, 2000.

[25] Y. Zhou and M. Evens, "A practical student model in an intelligent tutoring system," in *Proceedings 11th International Conference on Tools with Artificial Intelligence*, pp. 13–18, 1999.

[26] G. Hunter, D. Livingstone, P. Neve, and G. Alsop, “Learn Programming++: The Design, Implementation and Deployment of an Intelligent Environment for the Teaching and Learning of Computer Programming,” in *2013 9th International Conference on Intelligent Environments (IE)*, (Athens), pp. 129–136, IEEE, July 2013.

[27] R. Stathacopoulou, G. D. Magoulas, M. Grigoriadou, and M. Samarakou, “Neuro-fuzzy knowledge processing in intelligent learning environments for improved student diagnosis,” *Information Sciences*, vol. 170, pp. 273–307, Feb. 2005.

[28] K. VanLehn, “Student modeling,” in *Foundations of intelligent tutoring systems* (M. Polson and J. Richardson, eds.), pp. 55–78, London: Lawrence Erlbaum, 1988.

[29] B. du. Boulay and R. Luckin, “Modelling human teaching tactics and strategies for tutoring systems,” *International Journal of Artificial Intelligence in Education*, vol. 12, no. 3, pp. 235–256, 2001.

[30] R. Nkambou, J. Bourdeau, and R. Mizoguchi, “Introduction: What Are Intelligent Tutoring Systems, and Why This Book?,” in *Advances in Intelligent Tutoring Systems* (R. Nkambou, J. Bourdeau, and R. Mizoguchi, eds.), vol. 308 of *Studies in Computational Intelligence*, pp. 1–12, Springer: Berlin & Heidelberg, 2010.

[31] A. Alzahrani, V. Callaghan, M. Gardner, and A. Alzahrani, “Towards Personalised and Adaptive Learning Paths in Immersive Educational Environments,” *Proc. 3rd European Immersive Education Summit*, p. 259, 2013.

[32] M. Grandbastien, “Teaching expertise is at the core of ITS research,” *International Journal of Artificial Intelligence in Education (IJAIED)*, vol. 10, pp. 335–349, 1999.

[33] N. Major, S. Ainsworth, and D. Wood, “REDEEM: Exploiting symbiosis between psychology and authoring environments,” *International Journal of Artificial Intelligence in Education*, vol. 8, no. 3/4, pp. 317–340, 1997.

[34] S. Ainsworth, J. Underwood, and S. Grimshaw, “Formatively evaluating REDEEM – an authoring environment for intelligent tutoring systems,” in *Computers & Education*, (Amsterdam), pp. 93–100, IOS Press, 1999.

[35] S. Ainsworth, S. Grimshaw, and J. Underwood, “Teachers implementing pedagogy through REDEEM,” *Computers & education*, vol. 33, pp. 171–187, Sept. 1999.

[36] H. S. Nwana, “Intelligent tutoring systems: an overview,” *Artificial Intelligence Review*, vol. 4, pp. 251–277, Dec. 1990.

[37] R. Freedman, S. S. Ali, and S. McRoy, “Links: What is an intelligent tutoring system?,” *Intelligence*, vol. 11, pp. 15–16, Sept. 2000.

[38] A. S. Gertner and K. VanLehn, “Andes: A coached problem solving environment for physics,” in *Intelligent Tutoring Systems*, pp. 133–142, 2000.

[39] K. Almohammadi, H. Hagras, B. Yao, A. Alzahrani, D. Alghazzawi, and G. Aldabbagh, “A type-2 fuzzy logic recommendation system for adaptive teaching,” *Soft Computing*, pp. 1–15, Aug. 2015.

[40] H. Lee, A. Weerasinghe, J. Barnes, L. Oakden-Rayner, W. Gale, and G. Carneiro, "CRISTAL: Adapting Workplace Training to the Real World Context with an Intelligent Simulator for Radiology Trainees," in *Intelligent Tutoring Systems*, (Zagreb, Croatia), pp. 430–435, Springer, Cham, June 2016. DOI: 10.1007/978-3-319-39583-8_52.

[41] N. Omheni and A. H. Kacem, """i-Read": A Collaborative Learning Environment to Support Students with Low Reading Abilities," in *Intelligent Tutoring Systems*, (Zagreb, Croatia), pp. 221–226, Springer, Cham, June 2016. DOI: 10.1007/978-3-319-39583-8_21.

[42] C. Brooks, J. Greer, E. Melis, and C. Ullrich, "Combining its and elearning technologies: Opportunities and challenges," in *Intelligent Tutoring Systems*, pp. 278–287, 2006.

[43] S. C. Shapiro, *Encyclopedia of Artificial Intelligence*. New York, NY, USA: John Wiley & Sons, Inc., 2nd ed., 1992.

[44] K. Almohammadi, B. Yao, and H. Hagras, "An interval type-2 fuzzy logic based system with user engagement feedback for customized knowledge delivery within intelligent E-learning platforms," in *2014 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, (Beijing), pp. 808–817, IEEE, July 2014.

[45] A. S. Gertner and K. VanLehn, "Andes: A Coached Problem Solving Environment for Physics," in *Intelligent Tutoring Systems* (G. Gauthier, C. Frasson, and K. VanLehn, eds.), no. 1839 in Lecture Notes in Computer Science, pp. 133–142, Springer: Berlin & Heidelberg, June 2000. DOI: 10.1007/3-540-45108-0_17.

[46] I. Arroyo and B. P. Woolf, "Inferring Learning and Attitudes from a Bayesian Network of Log File Data," in *Proceedings of the 2005 Conference on Artificial Intelligence in Education: Supporting Learning Through Intelligent and Socially Informed Technology*, (Amsterdam, The Netherlands, The Netherlands), pp. 33–40, IOS Press, 2005.

[47] J. Johns and B. Woolf, "A Dynamic Mixture Model to Detect Student Motivation and Proficiency," in *Proceedings of the 21st National Conference on Artificial Intelligence - Volume 1*, AAAI'06, (Boston, Massachusetts), pp. 163–168, AAAI Press, 2006.

[48] K. Almohammadi, H. Hagras, D. Alghazzawi, and 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, no. 2, pp. 81–101, 2016.

[49] J. Beck, B. P. Woolf, and C. R. Beal, "ADVISOR: A machine learning architecture for intelligent tutor construction," *AAAI/IAAI*, vol. 2000, pp. 552–557, 2000.

[50] R. Luckin and B. du Boulay, "Capability, Potential and Collaborative Assistance," in *UM99 User Modeling* (J. Kay, ed.), no. 407 in CISM International Centre for Mechanical Sciences, pp. 139–148, Springer, 1999. DOI: 10.1007/978-3-7091-2490-1_14.

[51] P. Baffes and R. Mooney, "Refinement-based Student Modeling and Automated Bug Library Construction," *J. Artif. Intell. Educ.*, vol. 7, pp. 75–116, Jan. 1996.

[52] S. J. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*. Englewood Cliffs, NJ, USA: Prentice-Hall, Inc., 1995.

[53] C. Stewart, A. I. Cristea, T. Brailsford, and H. Ashman, "Authoring Once, Delivering many: creating Reusable Adaptive Courseware," *Web-based Education*, pp. 21–23, 2005.

[54] K. Frankola, "Why online learners drop out," *Workforce*, vol. 80, pp. 53–59, Oct. 2001.

[55] J. Meister, "Pillars of e-learning success," *New York: Corporate University Exchange*, 2002.

[56] P. Brusilovsky and J. Vassileva, "Course sequencing techniques for large-scale web-based education," *International Journal of Continuing Engineering Education and Life Long Learning*, vol. 13, no. 1-2, pp. 75–94, 2003.

[57] P. Brusilovsky, E. Schwarz, and G. Weber, "ELM-ART: An intelligent tutoring system on world wide web," in *Intelligent Tutoring Systems* (C. Frasson, G. Gauthier, and A. Lesgold, eds.), no. 1086 in Lecture Notes in Computer Science, pp. 261–269, Springer: Berlin & Heidelberg, June 1996. DOI: 10.1007/3-540-61327-7_123.

[58] V. J. Shute and D. Zapata-Rivera, "Adaptive educational systems," *Adaptive technologies for training and education*, vol. 7, pp. 7–27, 2012.

[59] G. Weber and P. Brusilovsky, "ELM-ART: An adaptive versatile system for Web-based instruction," *International Journal of Artificial Intelligence in Education*, vol. 12, no. 4, pp. 351–384, 2001.

[60] P. Brusilovsky and C. Peylo, "Adaptive and Intelligent Web-based Educational Systems," *Int. J. Artif. Intell. Ed.*, vol. 13, pp. 159–172, Apr. 2003.

[61] P. Brusilovsky, "Ilearn: An intelligent system for teaching and learning about unix," in *Proc. of SUUG International Open Systems Conference, Moscow, Russia, ICSTI*, pp. 35–41, 1994.

[62] P. Capell and R. B. Dannenberg, "Instructional design and intelligent tutoring: Theory and the precision of design," *Journal of Interactive Learning Research*, vol. 4, no. 1, pp. 95–121, 1993.

[63] A. Barr, M. Beard, and R. C. Atkinson, "The computer as a tutorial laboratory: the Stanford BIP project," *International Journal of Man-Machine Studies*, vol. 8, pp. 567–596, Sept. 1976.

[64] D. McArthur, C. Stasz, J. Hotta, O. Peter, and C. Burdorf, "Skill-oriented task sequencing in an intelligent tutor for basic algebra," *Instructional Science*, vol. 17, no. 4, pp. 281–307, 1988.

[65] V. Brusilovsky, "Task sequencing in an intelligent learning environment for calculus," in *in Proc. of Seventh International PEG Conference*, (Edinburgh), pp. 57–62, 1993.

[66] A. Rios, E. Millán, M. Trella, J. L. Pérez-De-La-Cruz, and R. Conejo, "Internet based evaluation system," in *Artificial Intelligence in Education: Open Learning Environments*, (Amsterdam), pp. 387–394, IOS Press, 1999.

[67] P. L. Brusilovsky, "A framework for intelligent knowledge sequencing and task sequencing," in *Intelligent Tutoring Systems* (C. Frasson, G. Gauthier, and G. I. McCalla, eds.), no. 608 in Lecture Notes in Computer Science, pp. 499–506, Springer: Berlin & Heidelberg, June 1992. DOI: 10.1007/3-540-55606-0_59.

[68] J. Vassileva, "Dynamic CAL-courseware generation within an ITS-shell architecture," in *Computer Assisted Learning* (I. Tomek, ed.), no. 602 in Lecture Notes in Computer Science, pp. 581–591, Springer: Berlin & Heidelberg, June 1992. DOI: 10.1007/3-540-55578-1_101.

[69] N. Idris, N. Yusof, and P. Saad, "Adaptive course sequencing for personalization of learning path using neural network," *Int. J. Advance. Soft Comput. Appl*, vol. 1, no. 1, pp. 49–61, 2009.

[70] T. Kohonen and P. Somervuo, "Self-organizing maps of symbol strings," *Neurocomputing*, vol. 21, pp. 19–30, Nov. 1998.

[71] P. Karampiperis and D. Sampson, "Adaptive instructional planning using ontologies," in *in proIEEE International Conference on Advanced Learning Technologies, 2004. Proceedings*, pp. 126–130, 2004.

[72] Y. Semet, E. Lutton, and P. Collet, "Ant colony optimisation for E-learning: observing the emergence of pedagogic suggestions," in *Proceedings of the 2003 IEEE Swarm Intelligence Symposium, 2003. SIS '03*, (Indianapolis), pp. 46–52, IEEE, Apr. 2003.

[73] D. Vassileva, "Adaptive e-learning content design and delivery based on learning styles and knowledge level," *Serdica Journal of Computing*, vol. 6, no. 2, pp. 207–252, 2012.

[74] B. P. Woolf, H. C. Lane, V. K. Chaudhri, and J. L. Kolodner, "AI Grand Challenges for Education," *AI Magazine*, vol. 34, pp. 66–84, Dec. 2013.

[75] C. Castelfranchi and R. Falcone, "From Automaticity to Autonomy: The Frontier of Artificial Agents," in *Agent Autonomy* (H. Hexmoor, C. Castelfranchi, and R. Falcone, eds.), no. 7 in Multiagent Systems, Artificial Societies, and Simulated Organizations, pp. 103–136, Springer US, 2003.

[76] M. Ball and V. Callaghan, "Explorations of Autonomy: An Investigation of Adjustable Autonomy in Intelligent Environments," in *2012 8th International Conference on Intelligent Environments (IE)*, (Guanajuato), pp. 114 –121, IEEE, June 2012.

[77] H. Hexmoor, C. Castelfranchi, and R. Falcone, "A Prospectus on Agent Autonomy," in *Agent Autonomy* (H. Hexmoor, C. Castelfranchi, and R. Falcone, eds.), no. 7 in Multiagent Systems, Artificial Societies, and Simulated Organizations, pp. 1–10, Springer US, 2003. DOI: 10.1007/978-1-4419-9198-0_1.

[78] M. Wooldridge and N. R. Jennings, "Agent theories, architectures, and languages: A survey," in *Intelligent Agents* (M. J. Wooldridge and N. R. Jennings, eds.), no. 890 in Lecture Notes in Computer Science, pp. 1–39, Springer: Berlin & Heidelberg, Aug. 1994. DOI: 10.1007/3-540-58855-8_1.

[79] P. Maes, "Agents That Reduce Work and Information Overload," *Communications of the ACM*, vol. 37, pp. 30–40, July 1994.

[80] J. C. Brustoloni, "Autonomous agents: characterization and requirements," tech, Carnegie Mellon University, 1991.

[81] R. Beale and A. Wood, "Agent-based interaction," in *in People and Computers IX: Proceedings of HCI'94*, pp. 239–245, 1994.

[82] K. S. Barber and C. E. Martin, "Agent Autonomy: Specification, Measurement, and Dynamic Adjustment," in *Proceedings of the autonomy control software workshop at autonomous agents*, pp. 8–15, Citeseer, 1999.

[83] C. L. Isbell and J. S. Pierce, "An IP Continuum for Adaptive Interface Design," in *Proc. HCI International*, 2005.

[84] T. B. Sheridan and W. L. Verplank, *Human and computer control of undersea teleoperators (Man-Machine Systems Laboratory Report).* Cambridge: MIT, 1978.

[85] R. Parasuraman, T. Sheridan, and C. Wickens, "A model for types and levels of human interaction with automation," *IEEE Transactions on systems, man, and cybernetics-Part A: Systems and Humans*, vol. 30, pp. 286 –297, May 2000.

[86] N. S. Board, *Autonomous vehicles in support of naval operations.* Washington D.C: National Academies Press, 2005.

[87] R. W. Proud, J. J. Hart, and R. B. Mrozinski, "Methods for determining the level of autonomy to design into a human spaceflight vehicle: a function specific approach," in *Performance Metrics for Intelligent Systems*, DTIC Document, 2003.

[88] B. Brehmer, "The dynamic OODA loop: Amalgamating Boyd's OODA loop and the cybernetic approach to command and control," in *Proceedings of the 10th international command and control research technology symposium*, pp. 365–368, 2005.

[89] J. Bradshaw, M. Sierhuis, A. Acquisti, P. Feltovich, R. Hoffman, R. Jeffers, D. Prescott, N. Suri, A. Uszok, and R. Van. Hoof, "Adjustable Autonomy and Human-Agent Teamwork in Practice: An Interim Report on Space Applications," in *Agent Autonomy* (H. Hexmoor, C. Castelfranchi, and R. Falcone, eds.), no. 7 in Multiagent Systems, Artificial Societies, and Simulated Organizations, pp. 243–280, Springer US, 2003.

[90] J. Bradshaw, G. Boy, E. Durfee, M. Gruninger, H. Hexmoor, N. Suri, M. Tambe, M. Uschold, and J. Vitek, "Software Agents for the Warfighter. ITAC Consortium Report," *Cambridge, MA: AAAI Press/The MIT Press.(14] Bradshaw*, vol. 1, pp. 89–95, 2002.

[91] G. Dorais, R. P. Bonasso, D. Kortenkamp, B. Pell, and D. Schreckenghost, “Adjustable autonomy for human-centered autonomous systems,” in *Working notes of the Sixteenth International Joint Conference on Artificial Intelligence Workshop on Adjustable Autonomy Systems*, Aug. 1998.

[92] J. Bradshaw, P. J. Feltovich, H. Jung, S. Kulkarni, W. Taysom, and A. Uszok, “Dimensions of Adjustable Autonomy and Mixed-Initiative Interaction,” in *Agents and Computational Autonomy* (M. Nickles, M. Rovatsos, and G. Weiss, eds.), no. 2969 in Lecture Notes in Computer Science, pp. 17–39, Springer: Berlin & Heidelberg, 2004.

[93] J. Brookshire, S. Singh, and R. Simmons, “Preliminary results in sliding autonomy for assembly by coordinated teams,” in *IROS 2004*, vol. 1, pp. 706–711, IEEE, Sept. 2004.

[94] J. Brookshire, S. Singh, and R. Simmons, “Preliminary results in sliding autonomy for coordinated teams,” in *Interaction between humans and autonomous systems over extended operations*, pp. 127–132, 2004.

[95] M. B. Dias, B. Kannan, B. Browning, E. G. Jones, B. Argall, M. F. Dias, M. Zinck, M. M. Veloso, and A. J. Stentz, “Sliding autonomy for peer-to-peer human-robot teams,” in *Proceedings of the Intelligent Conference on Intelligent Autonomous Systems*, p. 332, 2008.

[96] M. Ball, V. Callaghan, M. Gardner, and D. Trossen, “Exploring Adjustable Autonomy and Addressing User Concerns in Intelligent Environments,” in *Intelligent Environments*, pp. 429–436, 2009.

[97] M. Ball, V. Callaghan, and M. Gardner, “An Adjustable-Autonomy Agent for Intelligent Environments,” in *2010 Sixth International Conference on Intelligent Environments (IE’10)*, (Kuala Lumpur, Malaysia), pp. 1–6, IEEE, July 2010.

[98] M. Ball and V. Callaghan, “Introducing Intelligent Environments, Agents and Autonomy to Users,” in *2011 7th International Conference on Intelligent Environments (IE)*, (Nottingham, UK), pp. 382 –385, July 2011.

[99] M. Ball and V. Callaghan, “Perceptions of Autonomy: A Survey of User Opinions towards Autonomy in Intelligent Environments,” in *2011 7th International Conference on Intelligent Environments (IE)*, pp. 277 –284, July 2011.

[100] M. Ball and V. Callaghan, “Who is in control of intelligent environments? a question of autonomy,” in *10th International Conference on Pervasive Computing*, 2012.

[101] M. Ball and V. Callaghan, “Managing Control, Convenience and Autonomy,” in *workshops proceedings of the 8th International Conference on Intelligent Environments*, vol. 13 of *Special Issue on Agent-Based Approaches to Ambient Intelligence and Smart Environments*, pp. 159–196, IOS Press, June 2012.

[102] R. Cohen, C. Allaby, C. Cumbaa, M. Fitzgerald, K. Ho, B. Hui, C. Latulipe, F. Lu, N. Moussa, and D. Pooley, “What is initiative?,” *User Modeling and User-Adapted Interaction*, vol. 8, no. 3-4, pp. 171–214, 1998.

[103] G. Ferguson, J. Allen, and B. Miller, "TRAINS-95: Towards a mixed-initiative planning assistant," in *Proceedings of the Third Conference on Artificial Intelligence Planning Systems (AIPS-96)*, pp. 70–77, 1996.

[104] M. H. Burstein and D. V. McDermott, "Issues in the development of human-computer mixed-initiative planning," *Advances in Psychology*, vol. 113, pp. 285–303, 1996.

[105] J. Bih, "Paradigm shift - an introduction to fuzzy logic," *IEEE Potentials*, vol. 25, pp. 6–21, Jan. 2006.

[106] L. A. Zadeh, "Fuzzy sets," *Information and control*, vol. 8, no. 3, pp. 338–353, 1965.

[107] C. Martinovska, "A Fuzzy-Based Approach to User Model Refinement in Adaptive Hypermedia Systems," in *Adaptive Hypermedia and Adaptive Web-Based Systems* (P. D. Bra, P. Brusilovsky, and R. Conejo, eds.), no. 2347 in Lecture Notes in Computer Science, pp. 411–414, Springer: Berlin & Heidelberg, May 2002.

[108] S. Maleki-Dizaji, Z. A. Othman, H. O. Nyongesa, and J. Siddiqi, "Evolutionary reinforcement of user models in an adaptive search engine," in *IEEE/WIC International Conference on Web Intelligence, 2003. WI 2003. Proceedings*, (Halifax, Canada), pp. 706–709, IEEE, Oct. 2003.

[109] A. Jameson, "Numerical uncertainty management in user and student modeling: An overview of systems and issues," *User Modeling and User-Adapted Interaction*, vol. 5, pp. 193–251, Sept. 1995.

[110] A. Kavcic, R. Pedraza-Jimenez, H. Molina-Bulla, F. J. Valverde-Albacete, J. Cid-Sueiro, and A. Navia-Vazquez, "Student modeling based on fuzzy inference mechanisms," in *EUROCON 2003. Computer as a Tool. The IEEE Region 8*, vol. 2, (Ljubljana, Slovenia), pp. 379–383 vol.2, IEEE, Sept. 2003.

[111] J. Mendel, "Fuzzy logic systems for engineering: a tutorial," *Proceedings of the IEEE*, vol. 83, pp. 345–377, Mar. 1995.

[112] Y. Bai and D. Wang, "Fundamentals of Fuzzy Logic Control—Fuzzy Sets, Fuzzy Rules and Defuzzifications," in *Advanced Fuzzy Logic Technologies in Industrial Applications*, pp. 17–36, Springer, 2006.

[113] C. C. Lee, "Fuzzy logic in control systems: fuzzy logic controller. I," *IEEE Transactions on systems, man, and cybernetics*, vol. 20, pp. 419–435, Mar. 1990.

[114] L. A. Bryan and E. A. Bryan, *Programmable Controllers: Theory and Implementation*. Marietta, Ga: Industrial Text Co, 2nd edition ed., Oct. 1996.

[115] W. V. Leekwijck and E. E. Kerre, "Defuzzification: criteria and classification," *Fuzzy Sets and Systems*, vol. 108, pp. 159–178, Dec. 1999.

[116] H. Hagras, V. Callaghan, M. Colley, and M. Carr-West, "A behavior based hierarchical fuzzy control architecture for agricultural autonomous mobile robots," in *Int. Conf. Computational Intelligence for Modeling, Control, and Automation*, vol. 2, (Vienna, Austria), pp. 172–177, 1999.

[117] E. Tunstel Jr, T. Lippincott, and M. Jamshidi, "Behavior hierarchy for autonomous mobile robots: Fuzzy-behavior modulation and evolution," *Intelligent Automation & Soft Computing*, vol. 3, no. 1, pp. 37–49, 1997.

[118] F.-l. Chung and J.-C. Duan, "On multistage fuzzy neural network modeling," *IEEE Transactions on fuzzy systems*, vol. 8, pp. 125–142, Apr. 2000.

[119] G. Raju and J. Zhou, "Adaptive hierarchical fuzzy controller," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 23, pp. 973–980, July 1993.

[120] G. Raju, J. Zhou, and R. A. Kisner, "Hierarchical fuzzy control," *International journal of control*, vol. 54, pp. 1201–1216, Nov. 1991.

[121] J. S. Shieh, D. Linkens, and J. Peacock, "Hierarchical rule-based and self-organizing fuzzy logic control for depth of anaesthesia," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 29, pp. 98–109, Feb. 1999.

[122] T. Gedeon, K. W. Wong, and D. Tikk, "Constructing hierarchical fuzzy rule bases for classification," in *The 10th IEEE International Conference on Fuzzy Systems, 2001*, vol. 3, (Melbourne, Vic), pp. 1388–1391, 2001.

[123] R. Holve, "Rule generation for hierarchical fuzzy systems," in *Fuzzy Information Processing Society, 1997. NAFIPS '97., 1997 Annual Meeting of the North American*, (Syracuse, NY), pp. 444–449, IEEE, Sept. 1997.

[124] L. Castillo, A. González, and R. Pérez, "Including a simplicity criterion in the selection of the best rule in a genetic fuzzy learning algorithm," *Fuzzy Sets and Systems*, vol. 120, pp. 309–321, June 2001.

[125] M. G. Joo and J. S. Lee, "Universal approximation by hierarchical fuzzy system with constraints on the fuzzy rule," *Fuzzy Sets and Systems*, vol. 130, pp. 175–188, Sept. 2002.

[126] O. Cordon, F. Herrera, and I. Zwir, "Linguistic modeling by hierarchical systems of linguistic rules," *IEEE Transactions on fuzzy systems*, vol. 10, pp. 2–20, Feb. 2002.

[127] V. Torra, "A review of the construction of hierarchical fuzzy systems," *International journal of intelligent systems*, vol. 17, pp. 531–543, May 2002.

[128] M. Brown, K. M. Bossley, D. J. Mills, and C. J. Harris, "High dimensional neuro-fuzzy systems: overcoming the curse of dimensionality," in *Fuzzy Systems, 1995. International Joint Conference of the Fourth IEEE International Conference on Fuzzy Systems and The Second International Fuzzy Engineering Symposium., Proceedings of 1995 IEEE Int*, vol. 4, pp. 2139–2146, Mar. 1995.

[129] A. Bonarini, "Anytime Learning and Adaptation of Structured Fuzzy Behaviors," *Adaptive Behavior*, vol. 5, pp. 281–315, Jan. 1997.

[130] A. Saffiotti, "The uses of fuzzy logic in autonomous robot navigation," *Soft Computing*, vol. 1, no. 4, pp. 180–197, 1997.

[131] A. Safiotti, “Fuzzy logic in autonomous robotics: behavior coordination,” in , *Proceedings of the Sixth IEEE International Conference on Fuzzy Systems, 1997*, vol. 1, (Barcelona), pp. 573–578 vol.1, July 1997.

[132] H. Hagras, V. Callaghan, and M. Colley, “Prototyping design and learning in outdoor mobile robots operating in unstructured outdoor environments,” *IEEE international robotics and automation magazine*, vol. 8, pp. 53–69, Sept. 2001.

[133] H. Hagras, V. Callaghan, and M. Colley, “Learning and adaptation of an intelligent mobile robot navigator operating in unstructured environment based on a novel online Fuzzy–Genetic system,” *Fuzzy Sets and Systems*, vol. 141, pp. 107–160, Jan. 2004.

[134] H. Hagras, “A hierarchical type-2 fuzzy logic control architecture for autonomous mobile robots,” *IEEE Transactions on Fuzzy systems*, vol. 12, pp. 524–539, Aug. 2004.

[135] T. Mahmood and F. Ricci, “Improving Recommender Systems with Adaptive Conversational Strategies,” in *Proceedings of the 20th ACM Conference on Hypertext and Hypermedia*, HT ’09, (New York, NY, USA), pp. 73–82, ACM, 2009.

[136] P. Resnick and H. R. Varian, “Recommender Systems,” *Communications of the ACM*, vol. 40, pp. 56–58, Mar. 1997.

[137] R. Burke, “Hybrid Web Recommender Systems,” in *The Adaptive Web* (P. Brusilovsky, A. Kobsa, and W. Nejdl, eds.), no. 4321 in Lecture Notes in Computer Science, pp. 377–408, Springer: Berlin & Heidelberg, 2007. DOI: 10.1007/978-3-540-72079-9_12.

[138] F. Ricci, L. Rokach, and B. Shapira, “Introduction to Recommender Systems Handbook,” in *Recommender Systems Handbook* (F. Ricci, L. Rokach, B. Shapira, and P. B. Kantor, eds.), pp. 1–35, Springer US, 2011. DOI: 10.1007/978-0-387-85820-3_1.

[139] M. J. D. Powell, *Approximation Theory and Methods*. Cambridge University Press, Mar. 1981.

[140] J. S. Armstrong, *Principles of Forecasting: A Handbook for Researchers and Practitioners*. Springer Science & Business Media, 2001.

[141] G. Salton, *Automatic Text Processing: The Transformation, Analysis, and Retrieval of Information by Computer*. Boston, MA, USA: Addison-Wesley Longman Publishing Co., Inc., 1989.

[142] E. Rich, “User modeling via stereotypes,” *Cognitive science*, vol. 3, no. 4, pp. 329–354, 1979.

[143] G. L. Lilien, P. Kotler, and K. S. Moorthy, *Marketing Models*. Prentice-Hall, 1992.

[144] B. P. S. Murthi and S. Sarkar, “The role of the management sciences in research on personalization,” *Management Science*, vol. 49, no. 10, pp. 1344–1362, 2003.

[145] M. Balabanović and Y. Shoham, “Fab: Content-based, Collaborative Recommendation,” *Communications of the ACM*, vol. 40, pp. 66–72, Mar. 1997.

[146] D. Jonassen and S. Land, eds., *Theoretical Foundations of Learning Environments*. Mahwah, N.J: Routledge, Jan. 2000.

[147] A. Collins, J. Greeno, and L. Resnick, "Cognition and Learning," in *Handbook of Educational Psychology* (L. B. Resnick and R. Calfee, eds.), NY: Simon & Schuster Macmillan, 1996.

[148] T. Mayes and S. De Freitas, "Review of e-learning theories, frameworks and models," *JISC e-learning models desk study*, no. 1, 2004.

[149] A. Collins, "Cognitive Apprenticeship," in *The Cambridge Handbook of the Learning Sciences*, Cambridge Handbooks in Psychology, Cambridge University Press, 1st ed., 2005.

[150] A. C. Graesser, K. VanLehn, C. P. Rose, P. W. Jordan, and D. Harter, "Intelligent Tutoring Systems with Conversational Dialogue," *AI magazine*, vol. 22, p. 39, Dec. 2001.

[151] N. T. Heffernan, *Intelligent Tutoring Systems Have Forgotten the Tutor: Adding a Cognitive Model of Human Tutors*. PhD thesis, School of Computer Science, Carnegie Mellon University, USA, 2001.

[152] S. P. Lajoie, S. Faremo, and J. Wiseman, "Tutoring strategies for effective instruction in internal medicine," *International Journal of Artificial Intelligence and Education*, vol. 12, no. 3, pp. 293–309, 2001.

[153] M. Virvou and M. Moundridou, "Adding an instructor modelling component to the architecture of ITS authoring tools," *International Journal of Artificial Intelligence in Education*, vol. 12, no. 2, pp. 185–211, 2001.

[154] A. Misirli and V. Komis, "Robotics and Programming Concepts in Early Childhood Education: A Conceptual Framework for Designing Educational Scenarios," in *Research on e-Learning and ICT in Education* (C. Karagiannidis, P. Politis, and I. Karasavvidis, eds.), pp. 99–118, Springer New York, 2014.

[155] "Teacher-Centered vs. Student-Centered Education." [Online]. Available: http://education.cu-portland.edu/blog/classroom-resources/which-is-best-teacher-centered-or-student-centered-education/.

[156] M. Weimer, *Learner-centered teaching*. San Francisco: Wiley Co., 2002.

[157] P. Burnard, "Carl Rogers and postmodernism: Challenges in nursing and health sciences," *Nursing & Health Sciences*, vol. 1, pp. 241–247, Dec. 1999.

[158] P. G. Taylor, "Changing expectations: Preparing students for flexible learning," *International Journal for Academic Development*, vol. 5, pp. 107–115, Jan. 2000.

[159] G. O'Neill and T. McMahon, "Student-centred learning: What does it mean for students and lecturers," in *Emerging issues in the practice of university learning and teaching* (G. O'Neill, S. Moore, and B. McMullin, eds.), All Ireland Society for Higher Education, 2005.

[160] S. J. Lea, D. Stephenson, and J. Troy, "Higher Education Students' Attitudes to Student-centred Learning: Beyond 'educational bulimia'?," *Studies in higher education*, vol. 28, pp. 321–334, Aug. 2003.

[161] M. Huda and J. Freed, "Learner-centered assessment on college campuses: Shifting the focus from teaching to learning," in *Shifting the focus from teaching to learning*, Needham Heights, MA: Allyn & Bacon, 2000.

[162] M. J. Allen, *Assessing academic programs in higher education*. Bolton, MA: Anker Publishing Company, 2004.

[163] K. Lonka and K. Ahola, "Activating instruction: How to foster study and thinking skills in higher education," *European journal of psychology of education*, vol. 10, pp. 351–368, Dec. 1995.

[164] J. Hall and P. Saunders, "Adopting a student-centred approach to management of learning," in *Implementing Flexible Learning* (C. Bell, M. Bowden, and A. Trott, eds.), London: Kogan Page, 1997.

[165] "Teacher-Centered, Learner-Centered or All of the Above." [Online]. Available: http://www.facultyfocus.com/articles/teaching-professor-blog/teacher-centered-learner-centered-or-all-of-the-above/, Jan. 2013.

[166] D. A. Wiley, "Connecting learning objects to instructional design theory: A definition, a metaphor, and a taxonomy." [Online]. Available: http://www.reusability.org/read/chapters/wiley.doc, 2003.

[167] P. Polsani, "Use and Abuse of Reusable Learning Objects," *Journal of Digital Information*, vol. 3, no. 4, 2006.

[168] "IEEE Learning Technology Standards Committee." [Online]. Available: https://ieeeltsc.wordpress.com/.

[169] V. M. Sue and L. A. Ritter, *Conducting Online Surveys*. Thousand Oaks, Calif: SAGE Publications, Inc, second edition edition ed., Jan. 2012.

[170] M. Galesic and M. Bosnjak, "Effects of Questionnaire Length on Participation and Indicators of Response Quality in a Web Survey," *Public opinion quarterly*, vol. 73, pp. 349–360, June 2009.

[171] M. C. Carnes, "Setting Students' Minds on Fire," *The Chronicle of Higher Education*, Mar. 2011.

[172] H. H. Friedman and L. W. Friedman, "Crises in Education: Online Learning as a Solution," *Creative Education*, vol. 02, no. 03, pp. 156–163, 2011.

[173] "UCLA: Statistical Consulting Group. SPSS FAQ: What does Cronbach's alpha mean?." [Online]. Available: http://statistics.ats.ucla.edu/stat/spss/faq/alpha.html.

[174] J. Gallagher, C. C. Harradine, and M. R. Coleman, "Challenge or boredom? Gifted students' views on their schooling," *Roeper Review*, vol. 19, pp. 132–136, Mar. 1997.

[175] L. Kanevsky and T. Keighley, “To produce or not to produce? Understanding boredom and the honor in underachievement,” *Roeper Review*, vol. 26, pp. 20–28, Sept. 2003.

[176] “IEEE SA - 1484.12.1-2002 - IEEE Standard for Learning Object Metadata.” [Online]. Available: https://standards.ieee.org/findstds/standard/1484.12.1-2002.html.

[177] X. Wei and J. Yan, “Learner Profile Design for Personalized E-Learning Systems,” in *International Conference on Computational Intelligence and Software Engineering, 2009. CiSE 2009*, pp. 1–4, Dec. 2009.

[178] J. E. Greer and G. I. McCalla, eds., *Student Modelling: The Key to Individualized Knowledge-Based Instruction*. Springer: Berlin & Heidelberg, 1994.

[179] B. Shneiderman and P. Maes, “Direct Manipulation vs. Interface Agents,” *interactions*, vol. 4, pp. 42–61, Nov. 1997.

[180] D. Burnham, *The Rise of the Computer State*. New York, NY, USA: Random House Inc., 1983.

[181] O. H. Gandy, “The Surveillance Society: Information Technology and Bureaucratic Social Control,” *Journal of Communication*, vol. 39, pp. 61–76, Sept. 1989.

[182] J. C. Augusto and C. D. Nugent, “Smart Homes Can Be Smarter,” in *Designing Smart Homes* (J. C. Augusto and C. D. Nugent, eds.), no. 4008 in Lecture Notes in Computer Science, pp. 1–15, Springer: Berlin & Heidelberg, 2006. DOI: 10.1007/11788485_1.

[183] F. K. Aldrich, “Smart Homes: Past, Present and Future,” in *Inside the Smart Home* (R. Harper, ed.), pp. 17–39, Springer London, 2003. DOI: 10.1007/1-85233-854-7_2.

[184] J. Vassileva, “Goal-Based Autonomous Social Agents: Supporting Adaptation and Teaching in a Distributed Environment,” in *Intelligent Tutoring Systems* (B. P. Goettl, H. M. Halff, C. L. Redfield, and V. J. Shute, eds.), no. 1452 in Lecture Notes in Computer Science, pp. 564–573, Springer: Berlin & Heidelberg, Aug. 1998. DOI: 10.1007/3-540-68716-5_62.

[185] G. Cumming and A. McDougall, “Mainstreaming AIED into education?,” *International Journal of Artificial Intelligence in Education (IJAIED)*, vol. 11, pp. 197–207, 2000.

[186] I. Hatzilygeroudis, J. Prentzas, and J. Garofalakis, “Personalized learning in web-based intelligent educational systems: technologies and techniques,” in *11th International Conference on Human-Computer Interaction (HCII-2005)*, (Las Vegas, Nevada, USA), 2005.

[187] R. S. Baker, “Stupid Tutoring Systems, Intelligent Humans,” *International Journal of Artificial Intelligence in Education*, vol. 26, pp. 600–614, Feb. 2016.

[188] M. C. Mozer, “Lessons from an Adaptive Home,” in *Smart Environments: Technologies, Protocols, and Applications* (D. J. Cook and S. K. Das, eds.), ch. 12, pp. 271–294, Hoboken, NJ, USA: John Wiley & Sons, Inc., Jan. 2005.

[189] M. Ball, V. Callaghan, M. Gardner, and D. Trossen, “Achieving human-agent teamwork in eHealth based pervasive intelligent environments,” in *Pervasive Computing Technologies for Healthcare (PervasiveHealth)*, (Munich), pp. 1–8, IEEE Xplore, Mar. 2010.

[190] D. J. Bruemmer, D. D. Dudenhoeffer, and J. L. Marble, “Dynamic-Autonomy for Urban Search and Rescue.,” in *AAAI Mobile Robot Competition*, pp. 33–37, 2002.

[191] J. Domaszewicz, S. Lalis, A. Pruszkowski, M. Koutsoubelias, T. Tajmajer, N. Grigoropoulos, M. Nati, and A. Gluhak, “Soft actuation: Smart home and office with human-in-the-loop,” *IEEE Pervasive Computing*, vol. 15, pp. 48–56, Jan. 2016.

[192] M. A. Goodrich, D. R. Olsen, J. Crandall, and T. J. Palmer, “Experiments in adjustable autonomy,” in *Proceedings of IJCAI Workshop on Autonomy, Delegation and Control: Interacting with Intelligent Agents*, pp. 1624–1629, 2001.

[193] G. E. Herrera-Almario, K. Kirk, V. T. Guerrero, K. Jeong, S. Kim, and G. G. Hamad, “The effect of video review of resident laparoscopic surgical skills measured by self- and external assessment,” *The American Journal of Surgery*, vol. 211, pp. 315–320, Feb. 2016.

[194] J. J. LaViola and O. C. Jenkins, “Natural user interfaces for adjustable autonomy in robot control,” *IEEE computer graphics and applications*, vol. 35, pp. 20–21, May 2015.

[195] A. Martínez-Tenor and J. A. Fernández-Madrigal, “Smoothly adjustable autonomy for the low-level remote control of mobile robots that is independent of the navigation algorithm,” in *2015 23th Mediterranean Conference on Control and Automation (MED)*, pp. 1071–1078, June 2015.

[196] L. Koczy, K. Hirota, and L. Muresan, “Interpolation in hierarchical fuzzy rule bases,” in *The Ninth IEEE International Conference on Fuzzy Systems, 2000. FUZZ IEEE 2000*, vol. 1, (San Antonio, TX), pp. 471–477 vol.1, IEEE, May 2000.

[197] X.-J. Zeng and G. Singh Madan, “Approximation theory of fuzzy systems-MIMO case,” *IEEE Transactions on Fuzzy Systems*, vol. 3, pp. 219–235, May 1995.

[198] H. Ying and G. Chen, “Necessary conditions for some typical fuzzy systems as universal approximators,” *Automatica*, vol. 33, pp. 1333–1338, July 1997.

[199] L.-X. Wang, “Analysis and design of hierarchical fuzzy systems,” *IEEE Transactions on Fuzzy systems*, vol. 7, pp. 617–624, Oct. 1999.

[200] S. Abe and R. Thawonmas, “A fuzzy classifier with ellipsoidal regions,” *IEEE Transactions on fuzzy systems*, vol. 5, pp. 358–368, Aug. 1997.

[201] D. Nauck and R. Kruse, “A neuro-fuzzy method to learn fuzzy classification rules from data,” *Fuzzy sets and Systems*, vol. 89, pp. 277–288, Aug. 1997.

[202] M. Setnes and H. Roubos, “GA-fuzzy modeling and classification: complexity and performance,” *IEEE transactions on Fuzzy Systems*, vol. 8, pp. 509–522, Oct. 2000.

[203] F. Doctor, H. Hagras, and V. Callaghan, “A fuzzy embedded agent-based approach for realizing ambient intelligence in intelligent inhabited environments,” *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, vol. 35, pp. 55–65, Jan. 2005.

[204] J. Pallant, *SPSS survival manual, a step by step guide to data analysis us-ing SPSS for windows*. Sydney: McGraw Hill, 3 ed., 2007.

[205] A. C. Elliott and W. A. Woodward, *Statistical analysis quick reference guidebook: With SPSS examples*. Sage, 2007.

[206] A. Ghasemi, S. Zahediasl, *et al.*, “Normality tests for statistical analysis: a guide for non-statisticians,” *International journal of endocrinology and metabolism*, vol. 10, no. 2, pp. 486–489, 2012.

[207] D. G. Altman and J. M. Bland, “Statistics notes: the normal distribution,” *Bmj*, vol. 310, no. 6975, p. 298, 1995.

[208] L. Wu and C.-K. Looi, “Incorporation of agent prompts as scaffolding of reflection in an intelligent learning environment,” in *Intelligent and Adaptive Educational-Learning Systems*, pp. 369–391, Springer, 2013.

[209] D. Fossati, B. Di Eugenio, S. Ohlsson, C. Brown, and L. Chen, “Generating proactive feedback to help students stay on track,” in *International Conference on Intelligent Tutoring Systems*, pp. 315–317, Springer, 2010.

[210] “Statistics how to.” [Online]. Available: http://www.statisticshowto.com/tukey-test-honest-significant-difference.

[211] K. Almohammadi and H. Hagras, “An adaptive fuzzy logic based system for improved knowledge delivery within intelligent e-learning platforms,” in *Fuzzy Systems (FUZZ), 2013 IEEE International Conference on*, pp. 1–8, IEEE, 2013.

[212] K. Almohammadi, H. Hagras, D. Alghazzawi, and G. Aldabbagh, “A zslices-based general type-2 fuzzy logic system for users-centric adaptive learning in large-scale e-learning platforms,” *Soft Computing*, pp. 1–22, 2016.

[213] K. Almohammadi and H. Hagras, “An interval type-2 fuzzy logic based system for customised knowledge delivery within pervasive e-learning platforms,” in *2013 IEEE International Conference on Systems, Man, and Cybernetics*, pp. 2872–2879, IEEE, 2013.

[214] L.-X. Wang, “The WM method completed: a flexible fuzzy system approach to data mining,” *IEEE Transactions on fuzzy systems*, vol. 11, no. 6, pp. 768–782, 2003.

[215] L.-X. Wang and J. M. Mendel, “Generating fuzzy rules by learning from examples,” *IEEE Transactions on systems, man, and cybernetics*, vol. 22, no. 6, pp. 1414–1427, 1992.

[216] J. van den Berg, U. Kaymak, and W.-M. van den Bergh, “Fuzzy classification using probability-based rule weighting,” in *Proceedings of the 2002 IEEE International Conference on Fuzzy Systems, 2002. FUZZ-IEEE’02*, vol. 2, (Honolulu, HI), pp. 991–996, IEEE, 2002.

[217] H. Ishibuchi and T. Yamamoto, “Rule weight specification in fuzzy rule-based classification systems,” *IEEE Transactions on Fuzzy Systems*, vol. 13, pp. 428–435, Aug. 2005.

[218] H. Ishibuchi, T. Yamamoto, and T. Nakashima, “Fuzzy data mining: effect of fuzzy discretization,” in *ICDM 2001, Proceedings IEEE International Conference on Data Mining, 2001*, (San Jose, CA), pp. 241–248, IEEE, 2001.

[219] T.-P. Hong, C.-S. Kuo, and S.-C. Chi, “Trade-off between computation time and number of rules for fuzzy mining from quantitative data,” *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, vol. 9, pp. 587–604, Oct. 2001.

[220] H. Ishibuchi, T. Nakashima, and T. Murata, “A fuzzy classifier system that generates fuzzy if-then rules for pattern classification problems,” in *, IEEE International Conference on Evolutionary Computation, 1995, vol.2*, vol. 2, (Perth, WA), pp. 759–764, IEEE, Nov. 1995.

[221] H. Ishibuchi, K. Nozaki, N. Yamamoto, and H. Tanaka, “Selecting fuzzy if-then rules for classification problems using genetic algorithms,” *IEEE Transactions on fuzzy systems*, vol. 3, pp. 260–270, Aug. 1995.

[222] H. Ishibuchi, T. Nakashima, and T. Morisawa, “Voting in fuzzy rule-based systems for pattern classification problems,” *Fuzzy sets and systems*, vol. 103, pp. 223–238, Apr. 1999.

[223] F. Doctor and R. Iqbal, “An intelligent framework for monitoring student performance using fuzzy rule-based Linguistic Summarisation,” in *2012 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, (Brisbane, Australia), pp. 1–8, IEEE, June 2012.

[224] A. G. Fink, *How to Conduct Surveys: A Step-by-Step Guide*. Los Angeles: SAGE Publications, Inc, 5th revised edition edition ed., 2013.