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Fuzzy based computational models of emotion for monitoring students' affective trajectories

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"As you set out for Ithaka
hope your road is a long one,
full of adventure, full of discovery.
....
Keep Ithaka always in your mind.
Arriving there is what you're destined for.
But don't hurry the journey at all.
Better if it lasts for years,
so you're old by the time you reach the island,
wealthy with all you've gained on the way,
not expecting Ithaka to make you rich.

Ithaka gave you the marvelous journey.
Without her you wouldn't have set out.
She has nothing left to give you now.

And if you find her poor, Ithaka won't have fooled you.
Wise as you will have become, so full of experience,
you'll have understood by then what these Ithakas mean."

C. P. CAVAFY

To my wife

And my parents

for supporting me throughout this journey

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Abstract

Affective computing (AC) is an emerging multidisciplinary field, which aims to bridge the gap between the highly emotional human and the emotionally challenged computer, in order to provide a higher level of human machine interaction. This Thesis contributes to AC research by proposing new emotion representations, and by developing novel computational mechanisms and methodological frameworks to be utilised by AC systems. This research is conducted under an educational scope, however it is not limited to an educational context since the methodologies presented can be applied in a number of different areas, thus offering a large potential of future research directions. The contributions of this research fall under the scope of AC, machine learning, and the psychological theories aiming to understand human emotion. A contextualized and personalised version of the Affective Trajectories hypothesis is presented, extending on the original theory, and a framework for its utilization by AC systems is provided. A fuzzy mechanism for knowledge extraction and adaptation is developed, which achieved an improved classification performance compared to the computational methods it relied upon. A novel computational model of emotion, the AV-AT model, is proposed, providing AC researchers with a tool to describe efficiently user's affective state. A custom hierarchical fuzzy method is developed, consisting of a genetically optimized adaptive fuzzy system, and a Fuzzy Cognitive Map. This method incorporates low-level information concerning the basic elements of a student's affective trajectory through time, and high-level information of the affective transitions a student experiences, to model students' affective trajectories during learning tasks. The affective transitions of students are explored in the context of problem based learning pedagogical frameworks. A novel scenario based survey design is introduced to elicit affect information. Finally, an offline adaptation process is presented, to enable the development of pre-trained personalised systems.

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Acronym List

AC	Affective Computing	FLS	Fuzzy Logic System
ALL	Activity Led Learning	FM	Fuzzy Method
AmI	Ambient Intelligence	GA	Genetic Algorithm
ANET	Affective Norms for English Text	GPU	Graphics Processing Unit
ANEW	Affective Norm for English Words	GSR	Galvanic Skin Response
ANS	Autonomous Nervous System	HMM	Hidden Markov Model
AOFIS	Adaptive Online Fuzzy Inference System	HR	Heart Rate
AT	Affective Trajectories	ICT	Information and Communication Technologies
AV	Arousal Valence	IoT	Internet of Things
BLSTM	Bidirectional Long Short-Term Memory	IR	Iterative Reprocessing
CPU	Central Processing Unit	ISTAG	Information Society Technologies Advisory Group
DEA	Dominant Emotion Accuracy	KNN	K-Nearest Neighbor
DT	Decision Tree	ITS	Intelligent Tutoring System
ECG	Electrocardiogram	ML	Machine Learning
EDA	Electrodermal activity	MLP	Multilayer Perceptron
EEG	Electroengephalogram	NN	Neural Network
EMG	Electromyogram	PAD	Pleasure Arousal Dominance
EOG	Electrooculogram	RBF	Radial Basis Function Network
FCM	Fuzzy Cognitive Map	RT	Regression Tree
FFA	Fuzzy FCM Auto system	ST	Skin Temperature
FFE	FUZZY FCM Expert system	SVM	Support Vector Machine
FL	Fuzzy Logic	VR	Virtual Reality

Publications

Karyotis, C., Doctor, F., Iqbal, R., James, A., and Chang, V. (2017) 'A fuzzy computational model of emotion for cloud based sentiment analysis'. *Journal of Information Sciences*. in press. http://dx.doi.org/10.1016/j.ins.2017.02.004

Karyotis, C., Doctor, F., Iqbal, R., and James, A. (2016) ' An Intelligent Framework for Emotion Aware E-Health Care Support Systems'. in IEEE Symposium Series on Computational Intelligence for Human-like Intelligence. held 6-9 December 2016 in Athens, Greece. IEEE

Karyotis, C., Doctor, F., Iqbal, R., James, A., and Chang, V. (2016).' A Fuzzy Modelling Approach of Emotion for Affective Computing Systems'. in The 1st International Conference on Internet of Things and Big Data, Special Session, Recent Advancements in Internet of Things, Big Data and Security (RAIBS). held 23-25 April 2016, Rome, IT

Karyotis, C., Doctor, F., Iqbal, R., and James, A. (2015) 'An Intelligent Framework for Monitoring Students Affective Trajectories Using Adaptive Fuzzy Systems'. in IEEE International Conference on Fuzzy Systems. held 2-5 August 2015 in Istanbul, Turkey. IEEE, 1-8

Doctor, F., Karyotis, C., (2016) 'The Emergence of Affective and Physiological Computing in Ambient User Centred Systems' (Tutorial). in The 12th International Conference on Intelligent Environments - IE'16. held 12-16 September 2016 in London, UK.

Karyotis, C., Doctor, F., Iqbal, R., and James, A. (2017). 'Affect Aware Ambient Intelligence: Current and Future Directions'. in press in Augusto J.C., Goenaga A.A., Orlandinini A. (eds). 'State of the art on AI applied to Ambient Intelligence' of the book series Frontiers in Artificial Intelligence and Applications. IOS Press Book Series.

Chapter 1 Introduction

1.1 Introduction

The promise of a reality where intelligent technologies and unobtrusive networks of interconnected electronic devices support individuals in their daily tasks and activities is delivered by the vision of Ambient Intelligence (ISTAG 2001). In order for this vision to be realized modern technology should possess an understanding of a core aspect of human nature, namely emotion. Humans are social beings who interact with other humans and with their surrounding enviroment. During this interaction they produce emotions, and they are influenced by their emotions. This reciprocal interaction is present eveywhere in their lives, affecting their performance, along with every decision they make during any activity, or task they undertake. It makes no difference if someone is performing a dynamic task such as driving their car, or if they are striving to learn a new skill or aquire knowledge, emotions are always there to affect their decisions and their actions. Affective Computing (AC) is a multidisciplinary scientific field which emerged in order to deliver affect aware computer applications. Affective Computing delivers the promise of achieving a higher level of human machine interaction by developing systems which efficiently detect emotions of their user; systems which are able to express forms of communication which a human would recognize as emotion; and finally systems which would be actually able to feel their own emotions (Picard 1995, 1997). This Thesis contributes to AC research by exploring the notion of emotion, and proposing new emotion representations to be utilised by AC systems. Moreover, novel computational mechanisms are developed, and the necessary frameworks are provided in order for these tools to be utlized by AC applications, so as to model and monitor students affective trajectories during collaborative learning tasks. This research is conducted under an educational scope however it is not limited to an educational context, since the proposed methodology can be applied in a number of different areas, thus offering a large potential of future research directions. Hence this thesis aims to address and improve key aspects concerning the automatic recognition and modelling of emotion for AC systems in order to contribute to the development of more successfull AC applications.

Affective computing can be described as the human-machine interaction where computational approaches are used to recognize human emotion, model its relationship with the surrounding environment, and finally produce an output action in order to influence the user's affective state and move it towards a desired state or behaviour supporting their efforts. For example, students learn better when they are engaged, compared to when they are bored, and as a result the goal of an education oriented AC system could be to detect student's boredom and produce the appropriate output to make them feel more engaged to the learning process. MIT professor Rosalind Picard, who was one of the first to pioneer the idea of Affective Computing, defines Affective Computing as: “computing that relates to, arises from or deliberately influences emotion” (Picard 1995, 1997). Professor Picard points out that in order to construct an intelligent system with a higher level of human machine interaction, we should allow them to successfully recognize and model emotions, or even enable such systems to express their own emotions. Nowadays, with the rapid development of pervasive and ubiquitous computing environments, personalised, wearable, and mobile computing artefacts, it is evident that our interaction with computing devices is becoming more and more profound encrouching on every aspect of our lives. Under the AC scope, in order for this interaction to be effective, the user’s affective state has to be taken into account.

The enormous potential of AC has led to the creation of numerous computer systems containing dedicated components responsible for recognizing the user’s emotional states, and providing the appropriate response corresponding to different application areas, such as medicine, gaming, driving etc. One of the most prominent application areas of AC is education. From the birth of AC, researchers have envisaged the creation of emotion aware systems, which are able to facilitate students' efforts and augment learning experience (Picard 2004). The motivation for developing affective learning systems stems from the close connection between emotion and learning. Emotion and learning are "interrelated, interactive, and interconnected" (Antonacopoulou 2001). Emotion is widely acknowledged as either supporting or hindering learning (Antonacopoulou 200, Boud 1993). As identified by Kolb et al., the ability to understand and appropriately express emotions is a prerequisite for true learning (Kolb 1986). Inspired by the above relation, AC researchers have created a large number of personalised learning systems (Baker 2010). These systems are shown to offer significant learning gains to their users (Baker 2010) (D'Mello and Graesser 2012).

The vast array of existing and newly conceived applications demonstrates the importance of equipping modern computer systems with the ability to recognize and model emotion in a very effective way. But how is it possible for something artificial to recognize and model affect when sometimes it is difficult even for human beings to understand and verbally express their own feelings? Towards achieving this goal, AC applications exploited advances in Machine Learning (ML) and emotion theories. ML techniques provided AC applications with powerful computational tools for discovering hidden patterns and correlations in data, and make predictions concerning their user's affective state based on multiple inputs (Mitchell 1997). The effectiveness of an AC application is equally dependant on the application of the appropriate emotion theory. In the context of an AC system the user's affective state can be represented in several ways such as a set of distinct emotion categories or as a combination of more basic affective elements, such as their arousal (how activated or deactivated someone feels), and valence (how good or bad someone feels) levels. In this research, it is suggested that providing the necessary emotional models and computational tools is the key, in order for computer systems to achieve the desired emotion modelling and recognition level, and become more aware, sensitive, and reactive to their users' needs. The computational tools and ML techniques utilized by AC systems should be accurate, able to deal with the uncertainty concerning a notion like emotion, deliver their results with a reasonable computational complexity, and optimally be able to capture, and represent the underlying affect relations in an interpretable way. The theoretical models of emotion used by these systems should provide them with the ability to successfully represent emotion in a feasible manner for computing devices while at the same time allow computer systems to efficiently identify their user's affective state, and differentiate between different emotion labels by utilizing a variety of different modalities.

One such model, is the Arousal Valence model of emotion (Russell 1980) which has been used extensively for the development of AC systems. The arousal valence model suggests that emotions can be represented as points in a two-dimensional space where the horizontal axis is valence, and ranges from unpleasant to pleasant; and the vertical axis is arousal, and ranges from passive to active. Stress for instance, can be defined as a high arousal and negative valence state. AC systems utilize this model by mapping sensory inputs to arousal and valence values, which in turn are mapped to the corresponding emotion labels. This model provides us with a well-accepted emotion representation, which can be used by itself, or in combination with other emotion models, to provide an efficient emotional modelling approach. The Affective Trajectories (AT) Hypothesis is a simple and promising approach, which can be utilized in conjunction with the AV model. The AT hypothesis is based on the need to explain and interpret the shifts in affect that got a person to a certain affective state.

The fundamental attribute behind the AT hypothesis is that 'emotion arises partly from the evaluations of one's current state, predictions of the future, and the outcomes that one experiences following these predictions' (Cunningham 2010). These processes interact and combine to create an emotional impression (Kirkland 2012). Again, this model is able to provide a sound base for the development of AC systems, as well as merge constructively with other models proposed for AC systems, to provide an effective emotional modelling approach.

Another dimension of emotion is that of time. Affective states evolve dynamically as we move through time. What we feel right now is related to what we were feeling a few moments ago, and to what we are about to feel in the next moment in time. One specific affective state is more or less likely to follow depending on how we are currently feeling. For example, a student is more likely to be frustrated following a state when they were bored, and less likely following a state when they were interested and engaged in a lecture. These affective transitions are especially prominent in education and have been examined and demonstrated by different teams such as the research by D'Mello et al (D'Mello 2007). The affect relations underlying in affective transitions taking place during the learning procedure, can potentially be used to personalize a student's learning experience, and assist in the development of learning systems to facilitate emotion recognition and affect modelling during pedagogical activities.

In order to represent the aforementioned underlying affect relations, concerning the construction of emotions from basic affective elements, and the affective transitions as we move through time, a robust computational machine learning method is required. This computational method should enable interpretable and accurate mapping of emotions from the basic elements, and allow for dynamic modelling of the higher level affect transitions. Emotion is a complex notion containing high levels of uncertainty, existing in the form of both intra-personal and inter-personal uncertainties (Wu 2013). Intrapersonal uncertainty lies in the ambiguity an individual has for their own emotions, while interpersonal uncertainty is attributed to the fact that the perception and expression of a certain emotion differs across different individuals. Hence, there is a need for computational techniques, which are able to handle these levels of uncertainty.

Fuzzy Logic (FL) systems provide a robust data representation and reasoning methodology to deal with imprecise and uncertain data (Wu 2013) which are able to handle and model information uncertainties. Fuzzy Logic was originally developed by

Lotfi A. Zadeh, in the 1960s, to provide fuzzy sets for representing uncertain data and concepts, together with human interpretable fuzzy rules that can be used for inference and decision-making. Fuzzy Logic is a very useful tool for AC systems, as words such as '*low*', and '*desirable*' represented using linguistic quantifiers (fuzzy sets) can be used to model uncertain and data driven notions such as user affective states in the context of particular human centred scenarios. If-Then rules, can be used to provide transparent models, which are interpretable and accountable ("why did user x do y?), thus allowing both modelling, and an explanation of the results produced by a system. Rules could be created from experimental data, and offer valuable theoretical background information by revealing interesting aspects of the domain knowledge they aim to model. This fact could prove very advantageous in modelling emotional theories, for example by unravelling the relations between the different components that combine to create an emotional episode. Additionally FL systems have the ability to adapt effectively to their user's needs when presented for example with new training samples (Faiyaz 2005). The adaptability of the fuzzy sets and rules is an aspect, which could be advantageous to AC systems, since it allows for the development of user friendly systems that are also reflective of individual differences in the construction of emotional processes.

Another ML technique that has been proposed as a tool for emotion recognition and modelling in AC systems is Fuzzy Cognitive Maps (FCM) (Salmeron 2012). FCM have emerged as an alternative tool for representing and studying the behaviour of systems, and people (Kosko 1986). FCM are able to model the behaviour of complex systems by utilizing different data sources including the knowledge and experience of human experts. FCM are represented using signed fuzzy weighted digraphs where the knowledge can be represented as nodes and causal connections within the graph based structure. The FCM nodes indicate the most relevant factors of a decisional environment, and the FCM edges between those factors represent the relationships between them. The inference process of the FCM can then be performed on this structure to draw knowledge, analyse, replicate, and evaluate the impact of parameters and forecast outcomes in complex decision making scenarios (Papageorgiou 2014). FCM provide excellent mechanisms to develop forecasting exercises, especially what-if analysis. Fuzzy Cognitive Maps are a dynamic methodology, which is in accordance with the dynamic nature of human emotion. FCM could be utilized in AC research in order to promote effective emotion recognition and modelling, since it would allow the mapping of dynamic relations, such as the previously described affect transitions, and the incorporation of expert knowledge which would in turn allow additional factors, and multidisciplinary knowledge to be taken into account in the design of complete and effective AC applications.

In this Thesis, the aforementioned emotional models and affect relations are utilized, and the advantages of adaptive Fuzzy Logic systems and Fuzzy Cognitive Maps are exploited towards developing novel computational models of emotions. Special emphasis is given to the interpretability of the fuzzy rule base models, which are extracted, and to the representation of the underlying affect relations. In addition, this research is carried out and evaluated in an educational context, in order to provide an effective framework that uses these modelling approaches and computational tools for developing successful personalised learning systems.

1.2 Motivation

The vast majority of AC systems currently classify emotions into models where emotions are divided into discrete emotion categories, or by relying on simple dimensional models of emotion, such as the Arousal Valence (AV) model of emotion. This type of classification poses certain limitations when choosing a set of emotions to describe the emotional space for any application context. The choice of emotions may be forced by the need to have emotions, which can be easily differentiated in the AV space rather than including emotions, which reflect the user's affective experience during their interaction with a system in a specific context. Nevertheless, if someone decides on a set of emotions that is not perfectly separated in the chosen emotional space, this may result in a system with low recognition accuracy. For example, if we consider the 2D AV space, anger and stress are both emotions with high levels of arousal and negative valence, and as a result, the task of differentiating between them is difficult. This research was driven by the need to develop a simple and applicable model of emotion, which allows for a more accurate representation of our affective state. This model would allow AC applications from different areas to use the appropriate emotion labels, to achieve a better recognition accuracy and more complete representation of their user’s affective state, thus offering an improved quality of human machine interaction. Additionally exploring and testing structural elements of emotion would be beneficial at gaining an insight of the underlying emotion theory and the basic components of emotion. As discussed in Calvo et al., it is important that computer scientists and engineers influence the emotion literature and collaborate in a multidisciplinary effort to understand this complex notion (Calvo 2010).

The motivation for this research was also reinforced by the need to develop a ML technique that allows the successful mapping of inputs, such as basic cognitive and affective elements to the desired output affective states in a simple, accurate, and interpretable manner. Nowadays, research has nurtured a push towards achieving better recognition accuracy, nevertheless it has also led to the development of extremely complex ML approaches and systems, where the computational burden is high, and the interpretability ranges from very limited to nonexistent. Understanding the structure of emotion and providing the necessary tools to exploit this knowledge, is the key for the future design of more successful human centered AC systems. Additionally, the development of computational techniques, which do not require high computational resources, enables the systems to be utilized by devices which do not possess high computational power, such as tablets, smart phones and pervasive computing artefacts. As the infiltration of mobile and interconnected technologies becomes more and more prominent in our lives, the same applies to the need for fast and efficient delivery of services through their utilization.

The final motivational factor that contributed to embarking on this research was the need for efficient AC systems facilitating the educational process. The author was inclined to satisfy this need, and promote students' learning in modern pedagogical settings, by facilitating the creation of affect aware personalised learning systems, which can become useful tools in the hands of students and teachers alike. Therefore, there is a need for systems that do not solely rely on sensory input, such as captured facial expressions, or physiological signals. More specifically, there is a need for systems that are focused in exploiting the structure of modern pedagogical approaches such as activity led learning, taking into account cognitive evaluations provided by the student, as well as other factors, which contribute in the formation of the students affective state.

1.3 Research questions and objectives

The aim of this research is to develop a novel emotional modelling methodology for Affective Computing (AC) systems, and implement the necessary computational tools in order for the model to be realized, utilized, and evaluated in an appropriate application domain. This research aims to address the following research questions:

- Is the AT theory practically applicable in an educational context?

- What is the role of individual differences in the construction of emotion processes under the scope of the AT Hypothesis?
- Can this research provide the necessary computational tools and pedagogical frameworks for applying the AT theory to AC?
- Is it possible to develop novel fuzzy computational tools that are able to produce accurate emotion classification results, and in the same time reflect the underlying emotion theory?
- Is it possible to combine ideas from different constructivist theories of emotion, to be used by AC systems to describe their user's affective state more effectively?
- What are the underlying patterns of students' affective transitions during collaborative learning tasks?
- Is it possible to utilize affective transition information in order to monitor and model effectively the affective trajectories of student's in the classroom?
- Is it possible to develop novel fuzzy machine learning techniques able to incorporate affective transition information, which are easily extendible to include other factors influencing students' emotion in the classroom?
- Can this research provide simple and safe ways to create personalised models of emotion for individual users of AC systems?

In this Thesis, a novel emotional modelling framework/methodology is provided by combining the AV model of emotion with the newly introduced Affective Trajectories (AT) hypothesis. Aiming for successful emotion mapping and enhanced recognition accuracy, the likelihood of the transitions between affective states is also incorporated in the proposed methodology. Harnessing the advantages of adaptive fuzzy logic systems and FCM, the necessary computational methodology and framework are provided in order for this model to be implemented by AC systems. Considering the importance of emotion in the students' engagement and performance, the proposed approach was tested in an educational context during collaborative and activity led learning tasks to model and monitor student affective trajectories. Through these experimental sessions, an insight was provided into the affective trajectories of students over time. Additional tools, such as a novel survey design, and an offline adaptation mechanism are presented to facilitate the construction of computational models of emotion. The research objectives of this Thesis can be summarized in the following points:

1. Examine the nature, and structural elements of emotion.
2. Investigate the ML and affect modelling approaches used by modern AC systems.
3. Study the role and influence of emotion in the learning process, and the elements that contribute to the creation of the student's affective state.
4. Introduce a framework for utilizing the AT theory to AC. This framework includes a fuzzy computational technique; a basic AC system architecture; and a pedagogical approach, to monitor student's affective trajectories.
5. Demonstrate the applicability of the AT hypothesis in an educational context.
6. Extend on the AT hypothesis by demonstrating the role of individual differences in the construction of emotional processes.
7. Present an adaptive fuzzy logic classification system able to deliver accurate emotion recognition results. This system aims to deal effectively with the uncertainties concerning emotion labels selected by users and deliver its results in a way, which is user friendly, not computationally intensive, and most importantly reflects the underlying theory.
8. Propose and test a computational model of emotion which is the combination of the arousal valence model and the AT hypothesis theory (AV-AT model).
9. Extend and optimize the fuzzy classification model in order to create a novel and effective emotional modelling approach that utilizes the AV-AT model.
10. Investigate the transitions between affective states during collaborative and activity led learning tasks.
11. Exploit the advantages of the Fuzzy Cognitive Maps methodology in order to provide a tool for emotional modelling, which takes into account the transitional probabilities along with other factors that contribute to the construction of the student's affect.
12. Propose a novel survey design to elicit affect information in various contexts.
13. Suggest safe and simple ways to develop individualized models of emotion.

1.4 Scope

This research was aimed at developing a computational model of emotion for monitoring student’s affective trajectories. The author proposed emotion representations, and the corresponding computational techniques in order to model and utilize these representations towards emotion recognition purposes. The aim was to develop novel computational models of emotion with reasonable complexity as it concerns the emotion representation, and the corresponding computational mechanism, which are able to differentiate efficiently between emotion labels and represent the underlying affect relations in an interpretable manner. These models could provide AC researchers with useful tools for developing interesting AC applications. In this research, the proposed emotion modelling framework was tested in an educational context, yet it could be extended to various application domain areas, different from education. However, all the proposed models relied on the ability of the system to acquire the user's prediction and evaluation of their experience of the outcome for a specific activity. As a result, the affect modelling approaches presented in this Thesis are limited to applications where the start and end points of an activity can be clearly defined. Given these constraints are met, the proposed methodology can be applied in different contexts by simply adjusting the set of output emotions, to emotions that match the context of the application. Although implementation and testing of rudimentary affective learning systems is presented, this research was not focused on developing a personalised learning system with complex input signals and feedback mechanisms. Rather the focus of the research was to develop a computational emotional modelling approach, which could be used effectively as a tool by future personalised learning and other AC systems in order to model and monitor their user's affective trajectories through time.

1.5 Research contributions

There are a number of contributions arising from this research effort. The research findings are related to AC, ML, and the understanding of human emotion. These contributions are supported by the experimental results presented in the following chapters (chapters 5, 6 and 7) of this Thesis, and discussed in detail in chapter 8. The research contributions to knowledge can be outlined as below:

- Introducing a framework for applying the AT theory to AC research. The AT theory was tested in an educational context, and the framework and computational technique for its utilization in AC applications was provided. Due to its simplicity, the AT could provide a powerful tool in the hands of AC practitioners.
- A novel computational model of emotion, namely the AV-AT model, was presented and tested. The AV-AT proved to be a very effective model for emotion recognition and modelling purposes, as it will be demonstrated from

the results of practical experiments and user studies, conducted in this research.

- A novel hierarchical fuzzy methodology was developed. This methodology incorporates in its design an adaptive fuzzy system responsible for modelling the low level affect relations as they are presented by the AV-AT, and an FCM system responsible for modelling the high level information concerning affective transitions between discrete affective states.
- Based on previous research a new fuzzy adaptive mechanism was developed, which proved to be very efficient when a small number of fuzzy sets was used to describe the input space.
- Based on the experimental results presented in chapter 5, the author extended on the AT theory, as it was introduced by Kirkland et al. (Kirkland 2012). It was demonstrated that every individual may use the basic structural elements, the AT suggests (current state, prediction, and outcome) but they may do so in a personalised way. As a result, the same combination of structural elements may result in a different emotion, or in experiencing the same emotion but with different intensity across individuals.
- A novel scenario based survey was presented. This survey extended on previous research, and potentially enables the exploration of complex affect relations in various application contexts. Moreover the survey responses were utilized in combination with the developed adaptive mechanism to construct a highly personalised learning system through a novel offline adaptation process.
- An insight of the affective state of students was provided. The author explored the relations of eight education related emotions with basic affective elements of the student's affective trajectory through time, and demonstrated the way a student performing collaborative learning tasks transitions from one affective state to another.

1.6 Thesis overview

In the following chapters of this Thesis, the author aims to present the necessary background knowledge, research methodology, proposed approaches, and corresponding results supporting the achievement of the research objectives. An overview of this Thesis is outlined as follows:

- **Chapter 1. Introduction**. In this chapter, introduced the main ideas and basic concepts that were utilized in this thesis were introduced. The motivation, aims, objectives, contributions, and scope of this research were highlighted.
- **Chapter 2. Affective Computing, Emotion and Learning**. In this chapter, the vision of Ambient Intelligence, and the importance of incorporating emotion in order to realize this vision are discussed. The author explores, and investigates different aspects and current research trends of Affective Computing, including application fields, types of input data sources, emotion models proposed by psychologists, and computational models of emotions presented by computer scientists. Previous work on affective transitions is also presented, under the scope of AC. Furthermore, in this chapter the reader can find a study on the relation of emotion and learning, and the factors that influence student emotion during learning related activities. Moreover, a description of the pedagogical frameworks utilized in this research are included, as application contexts and testing grounds for the proposed approaches. Throughout the literature problematic applications, disadvantages and unresolved issues are identified, thus highlighting the motivation of this research.
- **Chapter 3. Fuzzy Logic and FCM**. In the third chapter, FL and FCM computational techniques are discussed in detail, as the basis for the computational methods developed in this thesis. The choice for using these approaches is explained and justified, and basic knowledge for both techniques is provided. Moreover, modern AC applications, which utilize these computational methods, are presented.
- **Chapter 4. Methodology**. In this chapter, the research methodology followed and the different phases of this research are presented and explained. The researcher describes and justifies the choices that were made throughout the different phases of this research in regards to emotion models, computational methods, data collection, evaluation measures and methods, and experimental settings.
- **Chapter 5. Affective Trajectories**. In this chapter, an extended Affective Trajectories model of emotion is proposed and explored. The adaptive fuzzy mechanism developed to represent this model is described. The necessary data was collected in order to construct the proposed model, with the help of an online user-centered survey, and the effectiveness of the proposed affect modelling approach was tested by comparing the results of our fuzzy method

with a selection of other popular ML techniques. Finally, a framework for utilization of this affect modelling methodology for monitoring students' affective trajectories was presented.

- **Chapter 6. AV-AT model**. In this chapter, a novel computational model of emotion called the AV-AT model is presented. The data collection process conducted to create this model is described, and the genetically enhanced fuzzy technique used to represent it is explained in detail. This model is tested by using data from a series of online and offline experiments. The suggested approach is compared with other ML techniques, and the popular AV representation of emotion, and the corresponding results are discussed. The implementation of a personalised learning system is presented. Moreover ideas are suggested towards expanding the AV-AT framework for utilization as part of AC systems, in other application contexts beyond that of education.
- **Chapter 7. Affective Transitions**. In this chapter, the researcher presents a novel methodology for monitoring students' affective trajectories by utilizing high and low level elements of their affective trajectories through time. The methodology for constructing and evaluating this approach is outlined. Furthermore, details of the soft-computing technique used to represent this model are presented. This technique consists of a combination of an adaptive fuzzy technique, and an FCM. The author reports and analyses the results from examining the performance of this model, and from a statistical analysis, aiming to provide an insight concerning the affective transition of students during collaborative learning tasks. Finally, the experimental results and findings arising from this chapter are discussed.
- **Chapter 8. Conclusions**. In this chapter, the contributions arising from this research are highlighted; the limitations of the proposed methodology are discussed; and opportunities for future work extending on the conducted research are presented.

Chapter 2 Affective Computing, Emotion and Learning

2.1 Ambient Intelligence

The concept of a digital environment able to sense, and respond to human presence was envisaged by the Information Society Technologies Advisory Group (ISTAG), part of the European Commission's Joint Research Centre. In an attempt to set the grounds for future developments in Information and Communication Technologies (ICT), the researchers constructed four scenarios to speculate what living in an "Ambient Intelligent" environment might look like in ten years time (ISTAG 2001). Ambient Intelligence (AmI) emerged from the ISTAG report as a newly introduced discipline defining the concept of intelligent systems and networks that are embedded in everyday objects, and communicate with each other in order to facilitate human interaction with the environment, in a seamless and unobtrusive way. This definition envisages a future where AmI systems are integrated in everyday devices enabling them to sense, anticipate and adapt to human needs, in order to improve life experiences and utility of user centered systems and services.

The vision of AmI systems has been supported by computational and electronic advances and more specifically the deployment of sensors, pervasive and ubiquitous computing, and artificial intelligence. Since the birth of computer science, technological breakthroughs have made personal computers available in the public. Moreover, the construction of microprocessors has led to their deployment in everyday objects (such as smart phones, smart TVs, or even washing machines and microwave ovens) introducing intelligent technology in our everyday life. As of 2015, 68% of adult Americans, and 63% of UK adults own a smart phone or a tablet. However, AmI systems go beyond smart phones and tablets as they are currently used for entertainment purposes, in gaming consoles and smart TVs, in portable devices such as satellite navigators and PDAs, as well as in household appliances such as fridges, and ovens, to make our lives easier and safer. AmI also embraces the growth of personal wearables, such as smart watches and activity monitoring devices, which together make up the Internet of Things (IoT) supported by mobile communication, distributed management and information retrieval infrastructures.

The development of Ambient Intelligent systems calls for the cooperation of different disciplines such as artificial intelligence and ubiquitous computing. Moreover, AmI systems need to satisfy a number of key features. According to Cook et al. AmI systems have to be transparent, ubiquitous, and intelligent (Cook 2009). Transparency refers to the integration of systems and networks into everyday objects, so that they operate in an un-obtrusive way to the user. Ubiquity stems from the wealth of applications that AmI can be applied to, and intelligence refers to the decision making process that systems employ in order to satisfy the user's needs. Moreover, in order for AmI systems to aid the interaction between humans and their environment, they need to be sensitive, responsive, and adaptive. These features are highly dependable upon the application context of the AmI system. For example, for sensitivity purposes sensors that are able to understand human presence, and detect context specific features are employed. Responsiveness highlights the ability to respond to human needs, and make desirable changes in the environment. Finally, adaptability is the ability to process and analyze data (extracted from the user, the environment or other sources) in order to make decisions and generate responses that will benefit the user.

Affective Computing (AC) is an emerging discipline aiming towards the realization of the Ambient Intelligence vision through the integration of emotion in human machine interaction. AC can be used in interesting and novel ambient intelligence systems for recognizing, modelling, and eliciting affect information, in order to better understand the intentions, and satisfy the needs of modern users (Doctor 2015). Incorporating emotion in the design of AmI systems will enable the environment to perform the necessary changes in order to meet individual needs and preferences, and produce responses, which influence the users in more effective, intelligent, and personalised ways. Especially in education, AC is able to aid in the construction of affect aware systems to aid students in their effort towards learning. Nowadays these systems can largely benefit students due to the prominent connection between learning and emotion, and due to the enhanced potential of modern pedagogical settings to incorporate this kind of technologies in the learning process. In this chapter, the author aims to guide the reader through the structural elements of Affective Computing systems and applications, in order to provide an overview of this broad scientific field and highlight the limitations and existing gaps of methods and models, to be further addressed in this thesis. For clarity purposes, it should be noted that this literature review, is not exhaustive, since that would not be realistic, considering the broad and multidisciplinary spectrum of Affective Computing applications.

In section 2.2, the concept of AC is discussed and a basic architecture for AC systems is presented. In section 2.3, different application areas are identified, where the concept of AC has been applied. In section 2.4, a number of potential inputs for utilization by AC systems are highlighted. In section 2.5, different computational techniques used in AC systems are presented and compared. In section 2.6, different models of emotions provided by a variety of psychological theories are discussed. In section 2.7, the notion of a computational model of emotion is described, and some indicative examples are provided. In section 2.8, the close relation between emotion and learning is explored in detail. In section 2.9, recent AC research efforts focused in the area of education are presented. In section 2.10, AC literature where affective transitions are investigated is presented. In section 2.11, the factors contributing to the creation of students' emotions are discussed. In section 2.12, the pedagogical frameworks under which this research was conducted are described. Finally, in section 2.13, the challenges and conclusions arising from this literature review are summarized.

2.2 Affective Computing

In 1950, one of the pioneers of computer science, the British mathematician and genius Alan Turing suggested the famous Turing test (Turing 1950). During the Turing test, a human evaluates a conversation conducted between a human and a computer. Their task is to differentiate the responses of the human to the ones produced by the machine. The conversation is limited to text. In order for the machine to pass the Turing test, its responses should be similar to that of a human. The Turing test is considered a reliable measure to assess the ability of a machine to mimic human's mental activity. Humans are emotional creatures and their responses are highly influenced by their affect. Hence, it is logical to infer that in order for the emotionally challenged computer to be able to duplicate human responses, and pass the Turing test, it should be able to understand and express emotions.

Affective computing is at the heart of the challenge to bridge the gap of the deeply emotional human, and the emotionally deprived computer. Affective computing is “computing that relates to, arises from, or deliberately influences emotion”, which delivers the promise of achieving a higher level of human machine interaction by developing systems which efficiently detect emotions of their user; systems which are able to express forms of communication which a human would recognize as emotion; and finally systems which would be actually able to feel their own emotions (Picard 1995, 1997). Nowadays, artificial intelligence and agent based technologies have extensively infiltrated our everyday lives, and since emotions greatly impact on our decisions and actions, our interaction with the machines will be greatly improved with the incorporation of emotion regulation.

In order for Affective Computing applications to serve their purpose of promoting the user's wellbeing, they should contain three main elements following Wu's proposal (Wu 2010). Firstly, they must be successful in recognizing the present state of the user from input signals. This can be achieved by utilizing a number of different signals such as facial recognition, physiological signals, text, etc. which are related to the users affective state. Secondly, the system should be able to model effectively the relation of the user's affect with the surrounding environment. For instance, a system created to aid in the educational process should be aware of the factors affecting the student's affective state. Finally, the system should be able to output the necessary signals, and perform the necessary actions to influence or align its user's affective state towards a more beneficial state in order to achieve their goals. For example, the system may decide to play some classical music to an angry driver to calm him down. These three basic principles are demonstrated in the architecture proposed by Wu et al., which comprises of three elements: affect recognition, affect modelling, and affect control.

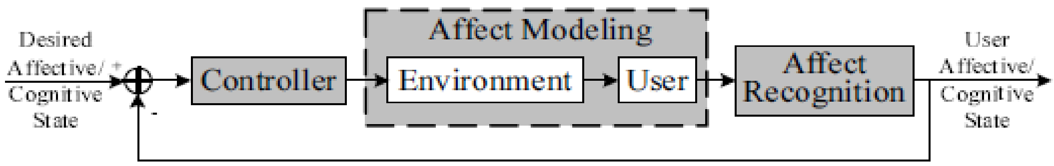


Figure 2.1 Wu's affective Loop (Wu 2012).

2.3 Affective Computing application areas

Developing new systems, or enriching already existing ones, by adding the emotional aspect has produced a number of interesting applications across completely different scientific fields, ranging from education to medicine. This fact resulted in the development of a large number of affective computing applications, and the increased focus of the scientific community, which has dedicated a number of conferences and journals to Affective Computing research. This broad spectrum of application areas demonstrates the growing importance of Affective Computing in modern computer science and Ambient Intelligence.

A thriving and promising application field of AC is promoting health and wellbeing. It is known and proven that emotions influence our mental and physical health either in a positive or negative way (Cacioppo 2003). For example, laughter and happiness can strengthen our immune system (Bachorowski 2001), while stress and depression can weaken it (Glaser 1994). This prominent connection between an individual's health, and emotional state has encouraged researchers to produce applications and interventions in order to aid patients and therapists. Tele-home healthcare, ubiquitous monitoring, virtual communities with emotionally expressive characters for elderly or impaired people are only a few areas where the potential of AC has been realized and applications have emerged. One indicative example of such an "affective medicine" application was suggested by Lisetti et al.’s research, where an avatar-based system is operated in order to help people abandon unhealthy habits, such as excessive drinking (Lisetti et al. 2012). A very recent example of an affective computing application in medicine concerns the work by Bian et al., where the researchers developed a Virtual Reality (VR) based driving environment in order to train teenagers with autism spectrum disorder to drive independently. The affect recognition was performed through several channels of physiological signals, which via a variety of classifiers were mapped to four categories of affective states (engagement, enjoyment, frustration, boredom) (Bian 2015).

AC’s potential is also utilized in enhancing game play experience, in the field of affective gaming. Games with the ability to recognize human emotion are consequently able to adapt appropriately to the user's state, offering a unique gaming experience. Research from Gilleade et al. proposes the design principal “assist me, challenge me, and emote me”. According to the research team, an affective gaming system should have the ability to detect frustration, in the first place, and adjust aspects of game play to improve gaming experience of the user. After detecting the player's arousal level, the level of challenge of the game could be altered to better match the individual gamer’s profile. Finally, the game content could be modified to induce an intended emotional state (Gilleade et al. 2005). Another example that can be considered as a benchmark for modelling and monitoring emotions during interaction with play technologies is the work presented by Mandryk et al. in 2007 (Mandryk 2007). The researchers used a two stage hierarchical approach to map physiological data to emotion labels. Originally, a fuzzy logic system utilizes data from galvanic skin response, heart rate, and electromyography physiological signals to provide estimates of arousal and valence values, and then a second system maps those values to five emotional states relevant to computer game play, namely: boredom, challenge, excitement, frustration, and fun. Another recent example of work in affective gaming is the work of Broekens et al. where two experimental games were developed. These games used an emotion engine for games called GAMYGDALA, in order to simulate non-player character emotions, and were used to highlight the novel game play experience achieved because of emotion simulation (Broekens 2015).

A modern and intriguing application area is the development of systems aimed to assist drivers. Research and experience informs us that being in a good mood is the best precondition for safe driving, and that happy drivers produce fewer accidents (James 2000). This can be described with the statement “happy drivers are better drivers” (Eyben 2010). On the contrary, when the driver experiences aggressiveness and anger, this affects their attention, and prevents them from concentrating on the road ahead, which can increase the risk of an accident (Wells-Parker 2002). From the exact opposite perspective, other states like sadness and fatigue can also have negative impact because of the very low arousal levels associated with them. These very low activation levels lead to reduced attention as well as prolonged reaction time, and therefore impair driving performance (Eyben 2010). Nowadays the driver's attention and performance can also be influenced by their stressful modern life, or the confusion caused by malfunctioning devices such as a SAT-NAV. In order to develop a successful "affective driving application", a researcher should be able to answer the following questions: How the driver feels; how their feelings affect their driving; how the features available in the car, and the cabin’s configuration can affect how they feel. One of the most influential works that can be used as a guide in the area of "affective driving" is the work by Nasoz et al. (Nasoz 2010). The researchers presented an approach to promote and enhance driving safety, through the deployment of multi-media technologies in order to identify and adapt to the drivers’ affective state by using multi-modal intelligent car interfaces. The team utilized the data from signals (galvanic skin response, heart rate and temperature) collected form an experiment conducted in a VR environment to find physiological patterns of emotions and ultimately map those signals to three emotion states (panic/fear, frustration/anger, boredom) with the help of different classification systems. Bayesian belief networks were then used in order to help the team develop a user model that takes into account user specific factors like personality traits and preferences, in order for the most appropriate feedback response to be delivered.

Affective Computing also boasts a number of applications in the educational field, due to the very close relation between human emotion and learning (this relation will be presented in detail in section 2.8). The ultimate goal of these applications is to facilitate learning through emotional experience. One way applications have utilized affective computing is by enriching Intelligent Tutoring Systems (ITS) with the ability to recognize student's affect, and then use this additional information to help in the learning process. Possibly the most famous ITS is AutoTutor, which plays the role of a human tutor and holds a conversation with the student (Graesser 2005). Other interesting education related areas where applications have been developed include the utilization of AC prospects to e-learning (Shen 2009), mobile learning (Qoussini 2014), smart classrooms (Song 2014) and virtual environments (Potkonjak 2016). As this research was conducted under an educational scope, recent affective computing applications in education are reviewed in more detail later in this chapter (section 2.9).

The potential of the AC technology to identify affective states can also be exploited for e-business and marketing purposes, in order to discover and utilize customers' feelings towards different products and services. In Ren's work, an emotion recognition system was built to measure customer satisfaction. This system was able to detect and identify a number of different emotions of the customers. The results demonstrated that incorporating emotion recognition could provide more appropriate follow-up for customer relationship management (Ren 2012). Another interesting business related field for AC applications, as identified by Wu (Wu 2013), is Kansei/affective engineering that is related with product design. Kansei engineering is defined as "translating technology of a consumer's feeling and image for a product into its design elements" (Nagamachi 1995).

2.4 Affect recognition and input signals for AC systems

Regardless of the context of the application, the ability to sense and recognize emotion is the first step towards the development of a complete and effective AC system. In order for an AC system to respond to human emotion, there is first a need for creating an affect-sensitive system, able to capture and understand a wide spectrum of human emotions. This task is achieved through the deployment of affect recognition systems that collect data of the user’s physical or psychological state. A variety of different modalities has been used as inputs to AC systems including: facial expression; voice; body language and posture; physiology; brain imaging and EEG; text; and multimodal data. The usability and value of these modalities as possible affect detection channels is measured against a number of factors that are consistent for each modality (Calvo et al 2010). Firstly, the validity of the signal used in order to capture the user’s affect. Secondly, the reliability of the signals that are extracted from real world environments to represent accurately user’s affect. Thirdly, the temporal resolution of the signal in comparison to the needs of the application, and lastly, the cost and obtrusiveness of the device, responsible for capturing the signal, in the user's life and everyday activities.

The way different modalities have been utilized by AC systems for affect recognition purposes is explored below. This list is indicative of the numerous methods, and aims to highlight the advantages and disadvantages of the modalities per se, and the methodological challenges that computer science researchers have to overcome when creating an AC system. For example when choosing to employ facial expression, as a means to collect emotion data from the user, a number of requirements need to be satisfied. Firstly, the different emotions under exploration need to correspond to distinct facial expressions in order to be identified and categorized. Secondly, facial expressions need to be analyzed according to the context they were expressed in for them to be meaningful. Finally, analyzing facial expression in real time requires video segmentation and processing which can be a very time consuming and costly endeavour, compared to analyzing a static image. Hence, AC systems utilizing facial expressions as inputs may struggle in terms of applicability in real time environments (Zeng et al. 2009).

Utilizing voice as input for AC systems includes two core aspects: the words used to communicate a message (linguistic content), and the way the message is communicated from the individual, i.e. the prosody of language (paralinguistic content) (Calvo 2010). As far as the linguistic content is concerned, affective word dictionaries have been developed in order to match the meaning of words towards specific emotions (Whissell 1989, Plutchick 1980). However, the literature shows that linguistic content can be a very ambiguous source of information in terms of matching an individual's choice of words with their emotional expressions. Moreover, the emotion burden of words is bound to cultural and language constraints and thus generalizing from one language to another is still a concept under investigation (Zeng et al. 2009). With regard to the paralinguistic aspect, from Russell et al.'s review it is evident that pitch plays an important role into detecting arousal (Russell 2003). However, the exact mechanisms behind decoding prosody are yet to be discovered, and even though it is known that emotion information is encoded in speech, using audio as input in AC systems, to detect specific sets of emotion, yields results of lower accuracy when compared to using video. This is prominent for the set of emotions identified by Paul Ekman through facial expressions experiments (anger, disgust, fear, happiness, sadness, and surprise), which is one of the most frequently used sets of emotions in

AC applications. Nevertheless, utilizing voice as input for AC systems is low cost, offers fast time resolution and at the same time, it can be realized in an unobtrusive way. More specifically, it is possible to record human voice with the use of a voice recorder placed anywhere near the source.

Body language and posture can be utilized to provide emotion information that is sometimes overlooked by the aforementioned modalities. For example, keeping a distance from other people and being withdrawn are aspects of human behaviour that can be inferred neither from facial expression, nor from voice recognition (Walk 1988). One of the greatest advantages of postured-based affect detection is that body language and movement is genuinely unconscious and non-intentional, and therefore it is not bound to any social or contextual interference (Calvo 2010).

Measuring the physiological activity of humans may provide AC systems with a valuable input in order to detect emotion. The scientific field of psychophysiology explores the physiological features of behaviour by measuring electrical signals produced by the brain (electroengephalogram, EEG) the heart (electrocardiogram, ECG) the muscles (electromyogram, EMG), skin conductivity (galvanic skin response, GSR), and eye movement (electrooculogram, EOG). All these signals are found to relate strongly not only with expressing emotions, but also with higher functional cognitive processes, such as focus of attention, perception, memory, and problem solving. A very recent study on emotion recognition utilizing physiological signals was conducted in the work by Li et al. (Li 2015). In this work, the emotion recognition process from physiological signals is described in detail and critical topics concerning relevant databases, feature extraction, selection and several classification techniques were studied. AlZoubi et al. highlight in their research the potential of EEG signals to be utilized for the development of affect recognition systems (AlZoubi et al. 2009). In terms of methodological constraints, brain imaging and other neuroscience techniques require strict and complex experimental protocols to be followed in order to reflect realistic activities. Moreover, they require specialized and expensive equipment to carry out the experiments, which is still a disadvantage towards building practical applications. Developments in signal processing and classification algorithms are working toward this direction to utilize EEG signals for affect recognition in AC systems. (Bashashati et al. 2007, Lotte et al. 2007). Recent research on emotion recognition using EEG signals was conducted by Lokannavar et al. (Lokannavar 2015) and Vijayan et al. (Vijayan 2015). Lokannavar et al. utilized a pre-processed dataset of EEG signals in order to construct an emotion recognition system which classifies the EEG signals to four emotions (happy, relax, sad, fear). In Vijayan et al.'s work, an emotion recognition approach based on the EEG signal utilizing Shannon entropy, cross correlation, and autoregressive modelling was presented. Excitement, happiness, sadness, and hatred were classified achieving a very high accuracy (94%). Both researchers relied on support vector machine (SVM) based classifiers to achieve their goals.

Writing is a form of communication across cultures and geographical boundaries barring not only a linguistic message, but also expressing the emotions of the author and evoking emotions of the reader. Therefore, it is not surprising to utilize written text in AC systems in order to detect the writer’s affect. Research strands work around different methodologies including: mapping emotion words in multidimensional space according to their “evaluation”, “potency” and “activity” values, similarly to the well-known arousal valence model of affective experience (Osgood 1990, and Russell 2003); lexical analysis including dictionary based categorization; and developing dictionaries by normatively rating common affective words. One such approach is the Affective Norm for English Words (ANEW) (Bradley 1999) and Affective Norms for English Text (ANET) (Bradley 2007).

Humans experience and express their emotions in different ways with an immediate impact not only upon their brain activation and cognition, but also in their facial expressions, body language, tone of voice and the words they choose to use. All these implications are interconnected helping humans to naturally decode and understand the emotional expressions of others. Moreover contextual information plays a major role in identifying and distinguishing among different emotion expressions. Therefore when creating emotion sensitive AC systems it is only logical to suggest that a system, which takes into consideration different input channels, would be more advantageous, compared to a system processing information from only one source (Sharma 1998). The inherent difficulty in utilizing multimodal input in AC systems lies in the integration of affect information and fusion of different signals in order to produce a meaningful outcome.

2.5 Computational techniques in AC systems

After the corresponding input signals are captured (video, audio, text, posture, physiological signals etc.) and the relevant features are extracted, a classification system would be responsible for mapping the values of the extracted features to specific emotions or values of affective elements. The success of an AC application relies on the success of its emotion recognition part. As a result, success is largely dependent on the choice of the appropriate ML technique. The classification method selected, would constitute the computational backbone of the AC application affecting a number of different important aspects. For instance: classification accuracy, user friendliness, software and hardware specifications, time performance, personalization, and adaptability are all aspects of an AC application, which are affected by the choice of the ML technique.

A large number of ML techniques have been used towards performing effective emotion recognition. In this section, examples of basic ML approaches utilized by AC systems are provided. A very popular ML approach is the biologically inspired Neural Networks (NN) (Cambria 2013), which has been used extensively in Affective Computing systems (Lee 2005, Caridakis 2008, Banda 2015, Zeng 2015). An NN is an interconnected assembly of simple processing elements that loosely mimics the neurons of the human brain. The processing ability of the NN is stored in the values of the weights connecting the artificial neurons, and these are obtained either by adaptation, or by learning from training data (Gurney 1997). In this Thesis, two of the most commonly used Neural Network types namely the Multilayer Perceptron (MLP) and the Radial Basis Function network are used for comparison purposes. The MLP is an NN, which has a feed forward architecture of multiple layers of nodes. There are no loops and the signals are transmitted from the input layer, through a number of hidden layers to the output layer. MLP is trained through backpropagation, which is a supervised learning technique. The idea of backpropagation lies in the updating of the weights after a training datum is presented to the network in order to minimize an error function. The MLP is able to differentiate between data, which are not linearly separable. A standard MLP architecture can be seen in figure 2.2 (Popescu 2009). RBF is another type of feedforward NN, which is used extensively for pattern recognition. RBFs can be considered as two-layered NN where the hidden layer contains neurons that utilize radial basis functions as activation functions, and the output is a linear combination of the output of the hidden units (Bors 1996). Most commonly used radial basis function is the Gaussian function. RBF are proven ML techniques for solving complex problems. For the same problem, an MLP would require a large number of hidden layers. An example RBF architecture for a classification problem can be seen in figure 2.3. In recent AC research, state of the art NN based approaches have been used in a variety of AC related tasks. In Zheng et al. the researchers utilized deep belief networks in order to investigate critical frequency bands and channels towards developing emotion recognition models based on the

EEG signal for three emotion categories: positive, negative, and neutral (Zeng 2015). In Banda et al. the use of a "Nonlinear AutoRegressive with eXogenous inputs Recurrent Neural Network" (NARX-RNN) was proposed in order to learn emotional patterns from a dataset to tackle the challenging task of successfully recognizing continuous dimensional emotion representation, and modelling of emotions as temporal processes (Banda 2015).

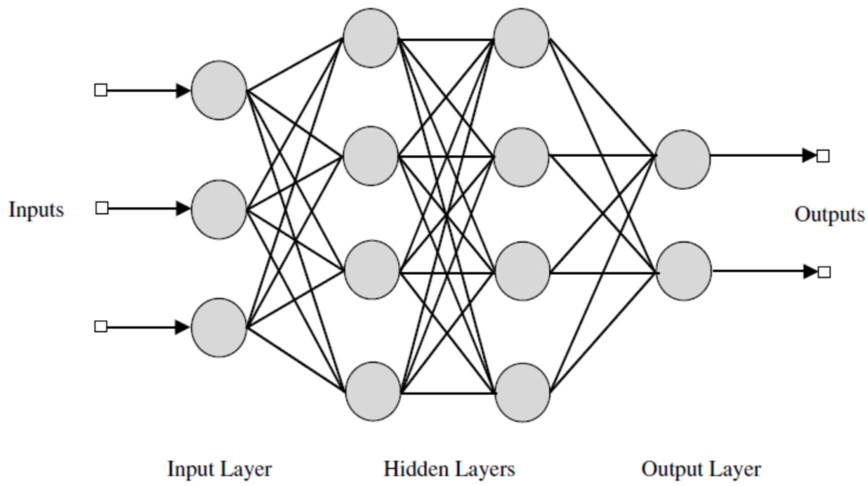


Figure 2.2 Architecture of an MLP (Virtual Lab).

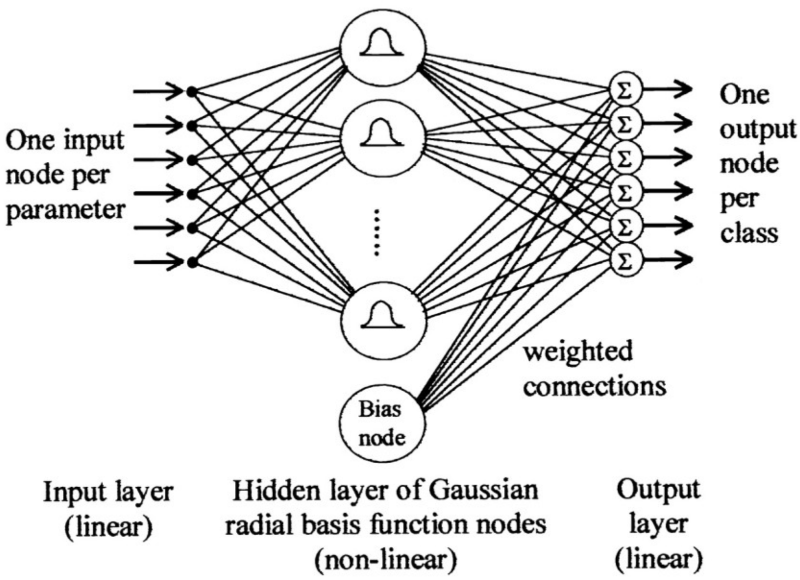


Figure 2.3 Example RBF architecture for classification (Wilkins 1999).

Support Vector Machine (SVM) is another modern and robust ML technique widely utilized by modern AC systems (Lokannavar 2015, Vijayan 2015, Pan 2012, Tseng 2013). The basic concept of SVM is to maximize the "margin" which corresponds to the distance between a hyper plane separating classes, and the instances of each class. Lokannavar, Vijayan and Tseng have utilized SVM based approaches in order to recognize emotion categories from the EEG signal (Lokannavar 2015, Vijayan 2015). SVM have also been utilized by other AC research teams (Pan 2012, Kumar 2015) towards emotion recognition with the help of speech signals.

Other AC emotion classification systems are based on Fuzzy Logic. Fuzzy Logic is an established methodology to deal with imprecise and uncertain data, that provides a set of mathematical rules and functions for approximate reasoning and control (Zadeh 1965) for various human centered systems such as in (Doctor 2016). It has been claimed by a number of researchers to be a very promising approach in modelling and recognizing emotions due to its ability to handle uncertainties and permit natural language queries (Wu 2013). Fuzzy logic is the core computational methodology used throughout this Thesis. Its use is justified in detail in Chapter 3 where a number of recent AC applications that utilize fuzzy logic based techniques towards for a variety of affective computing tasks are also presented.

Decision Trees (DT) are non-parametric supervised learning methods with a tree-like graph structure, which are used for classification and regression. DT have been utilized by a number of research teams for AC applications (Bogomolov 2014, Lee 2011, Cichosz 2007). Every node in a DT represents an instance of a feature that needs to be classified, and every branch represents a value, which the node can assume. Instances are classified based on the values of their features, starting from the root node and moving down the tree structure (Kotsiantis 2007). A recent example of a state of the art decision trees based technique utilized in AC can be found in the work by Bogomolov et al. In (Bogomolov 2015) the researchers aimed at recognizing stress levels through the use of human behaviour metrics extracted from mobile phone data such as sms log, call log etc. The team utilized a random forest based model, which has demonstrated a better bias-variance trade-off compared to other modern machine learning methods.

Hidden Markov models (HMM) are another technique that has been extensively utilized in recent years by AC researchers (Quan 2016, Sikka 2015, Chen 2015, Metallinou 2012). An HMM is a stochastic finite state automaton, that generates an observation sequence, under the assumption that this sequence is produced as a result of successive transitions between states. The transitions between states are governed by an underlying stochastic process which is not observable, and can only be inferred, hence the name hidden. HMM have been used for recognizing emotions with the help of a variety of different inputs. In Quan et al., weighted high order HMM were utilized for emotion recognition from text and they were proven very efficient to identify sentence emotions compared to other state of the art ML techniques (Quan 2016). Sikka et al have utilized HMM for emotion recognition from facial expressions in videos (Sikka 2015). Chen et al. performed automatic emotion recognition with the help of multimodal physiological signals by utilizing HMM, and their results have shown significant performance accuracy compared to other techniques (Chen 2015). Finally, HMM have also been utilized by a number of applications, towards emotion recognition from speech (Fink 2014).

AC researchers have also utilized a number of other simpler ML techniques, which can prove useful tools when there is a need for low complexity, or there are strict restraints of limited delivery time of the results, or of confined computational resources. Naive Bayes classifiers are simple probabilistic classification systems based on Bayes' theorem, which were also used in past AC research (Sebe 2002, Cohen 2002) because they are proven to have a performance comparable to more sophisticated classifiers despite their simplicity, and assumption for feature independence (Rish 2001). Classification in these systems is performed by assigning the most likely class to the training sample based on the values of its features (Rish 2001). K-Nearest Neighbor (KNN) is another simple pattern recognition algorithm, where classification happens by locating the object in the feature space, and comparing it with its K nearest neighbors. KNN has also been used by AC researchers (Khalili 2008, Rieger 2014, Murugappan 2011). Other simple classification systems used in AC research are Linear Discriminant Classifiers (LDC) (Lee 2001). In modern AC systems, these types of classifiers are not popular, and they are mostly used as comparative measures in AC research, in order to demonstrate the efficacy of more sophisticated ML techniques.

Another class of algorithms that have been used towards the development and optimization of AC classification systems is the class of evolutionary algorithms. These algorithms can be considered as optimal solution search methods that mimic natural processes such as biological evolution or social behaviour (Elbetagi 2005). One of the most popular and widely used evolutionary algorithms is the Genetic Algorithm (GA). GA's philosophy is based on the Darwinian theory of evolution where the survival of the fittest in a population of a species is promoted. A usual solution to a problem where GA is applied is represented with a chromosome which is a string consisting of genes that represent different values of variables of the optimization problem. The GA starts form an initial population and for every chromosome an objective function (e.g. values of the error that need to be minimized) representing the fitness of the individual is calculated. The fitness value of each member of the population is calculated and the fittest chromosomes (the ones with the best fitness value) are combined together to produce new offsprings. This process is repeated through a number of generations till a desirable solution to a given problem is reached. A demonstrative example of a GA's workflow can be seen in figure 2.4. GA's have been used successfully by recent AC research in order to optimize the performance of systems and models. In Yu et al's research, a GA was used to construct an emotion recognition system that utilized heart rate variability, in order to recognize the user's affective state among four emotions (stress, sadness, happiness, and neutral). The researchers implemented an SVM based classifier, and a GA was utilized for feature selection. The team's experimental results showed that the recognition accuracy of the proposed method was massively improved when the GA was used, compared to the recognition accuracy achieved without feature selection (Yu 2015). In 2014 Fung et al presented a guided search GA that was used in order to identify the optimal solution to the design attributes of products, which are able to satisfy the emotional needs of customers (Fung 2014). In another very recent example of AC research, Karyotis et al. proposed the use of a GA algorithm for calculating the optimal parameters of a fuzzy model that was used to represent a computational model of emotion (Karyotis 2017).

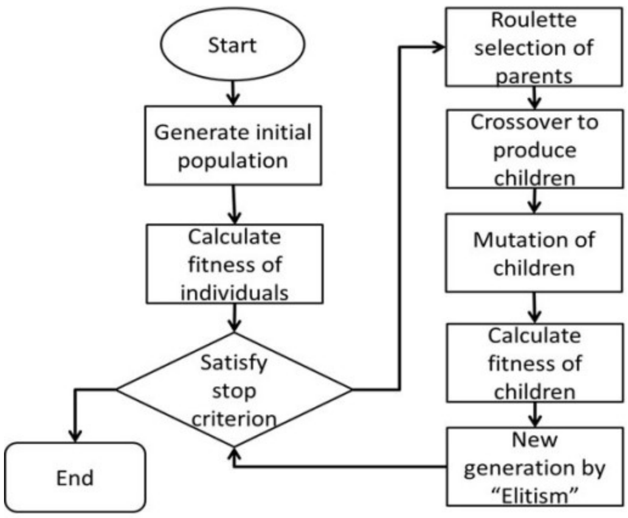


Figure 2.4 Flowchart a GA workflow (Kang 2011).

Defining an emotion classification approach as "effective" is highly dependent on the context or the goals of the application. Obviously, the overall emotion classification accuracy is a major factor influencing the choice of the ML technique. In other applications, there is a need for data to be processed quickly and provide the classification results in a reasonable amount of time, thus showcasing the classification speed as a prominent factor. Additionally training the machine learning classification systems involves dealing with databases, which include noisy, and outlier data points along with high levels of uncertainty. Despite the obvious reasons that could be attributed to sensor malfunctions or inaccuracies, these aspects are also very closely related with the inherent uncertainties associated with the notion of emotion. As stated in Wu et al., emotions include both intrapersonal and interpersonal uncertainty. Intrapersonal uncertainty refers to the uncertainty a person has about an emotion at different times and scenarios whereas interpersonal uncertainty can be due to different individuals having different perceptions and expressions of the same emotion (Wu 2012). As a result, the classifier should optimally be able to handle noise and these uncertainties concerning emotions. Another factor to be taken into account is the classifier's tolerance to irrelevant, redundant, or interdependent attributes. Emotion is a notion that still is not fully understood or explored and as a result, its relevance with all specific input signals or with the large number of features extracted from those signals for training a model is not clear. Some features extracted from the input signals may be completely irrelevant, while others may account for the same variance in the final constructed model and as such, they add complexity without offering any benefits. Another aspect that should be taken into account is the ability of the classifier to adapt and perform the necessary changes in order to reflect individual differences and satisfy the user's needs. It is possible that an AC application would be based on a classifier trained from data taken from a general population, and as such, it would not account fully for personal characteristics. Even the same person as it was stated before may adjust or vary their perception of the label they provide to describe their affective state, given the overall context they are in, for example time of the day, their location and environment. Consequently, the model should be adaptive and versatile at handling new incoming training data. Finally, it is also possible that for certain research efforts the main objective would not only be the construction of an accurate classifier, but also the extraction of knowledge from data, in order to reveal the underlying affect relations, and gain an insight on emotion theory. Comparative studies were conducted by Kotsiantis et al. and Bhavsar et al. in order to compare the performance of a variety of basic ML techniques in different aspects of the machine learning process (Kotsiantis 2007, Bhavsar 2012). The results have demonstrated that there is not a single ML algorithm outperforming all others, in all the aspects described above (Bhavsar 2012), and that the key question to be answered, in every case, is under which conditions a particular method can achieve better performance when compared to others, on a given application problem (Kotsiantis 2007).

In this Thesis, novel ML techniques based on Fuzzy Logic, Genetic Algorithms and Fuzzy Cognitive Maps are developed and presented. These custom techniques are tested against a number of other popular ML techniques in order to demonstrate their potential for deployment in an AC system. The ML techniques used for comparison include NN based approaches (MLP and RBF), decision trees, linear regression, and others. Aiming to satisfy the requirements of an effective AC application the developed techniques were designed and implemented to be robust, accurate, and reflective of the underlying emotion theory. The systems, which relied to the custom ML techniques constructed in this Thesis, generated scalable values for different emotions. These values demonstrated the degree to which a user of the system is feeling an emotion at a specific moment in time (form 0 to 100). The classification performance of the suggested ML techniques was evaluated by utilizing two different measures. The first measure was the ability of the system to identify the dominant emotion, meaning the emotion with the highest values among all emotions in the set used by the system. The second measure was the Normalized Mean Square Error (NRMSE). NRMSE is a measure, which is utilized extensively for evaluating the classification performance of ML techniques and represents the standard deviation of the differences between the predicted values of the systems, and the real observed values. NRMSE is a scale dependant measure able to demonstrate classification performance of different systems for a specific variable (Hyndman 2006).

2.6 Emotion models in Affective Computing

One of the first and most important choices to consider in the development of an affective computing application is which emotional model to use in order to describe the user's affective state. AC researchers should possess a clear understanding of emotion theories in order to construct effective AC applications. According to Calvo et al., "It is not only informative, but arguably essential for computer scientists to more expertly integrate emotion theory into the design of AC systems. Effective design of these systems will rely on cross-disciplinary collaboration and an active sharing of knowledge" (Calvo 2010). It should also be noted that the way an individual chooses to describe and define the complex notion of emotion, not only affects many aspects concerning the construction of AC applications, but it also depicts their understanding of the concept itself. Truly, if we grasp the nature of the structural components of emotion and understand the underlying emotion theory, our ability to recognize, model, and exploit the user's emotion to promote their wellbeing will be enhanced. The author therefore proceeds to investigate different emotion models utilized in AC systems under a perspective, which reflects a debate among psychologists as to the way in which emotions are cognitively processed and represented. On one side of the debate there is the idea that emotions can be classified into discrete, basic emotions, while on the other side, also called psychological constructivism, the suggestion is that emotions emerge from the combination of more basic affective elements.

2.6.1 Basic Emotion Models

In 1884 William James, an American philosopher and psychologist, asked the question: “What is an emotion?” (Gendron 2009) and this question has triggered a debate among researchers, which is still active today (Gendron & Barrett 2009). Perhaps the most common answer to James William's question is that emotions are mental states provided by the structure of the nervous system, which result in consistent and specific patterns of physiology, such as movements of the facial muscles, feelings, and behaviour (Lindquist 2013). If we accept this definition, and describe emotions as mental states, which are products of the activation of the human nervous system, then we instantly make certain assumptions about the nature of emotions. One such is that linguistic emotion categories like "excitement", "boredom", "fear", "anger" etc. are physiologically and biologically fundamental states. This fact translates into the idea that emotions can be "natural kinds". As "natural kinds", we would describe elements (i.e. distinct emotion categories), which exist in nature and can be identified independently of human perception (Lindquist 2013).

During the early days of psychology, the perception of emotions as "natural kinds" was predominant. Consequently, the linguistic labels used to describe one's emotions correspond to distinct affective states. When someone uses the word anger to describe their emotions, this word represents a biological process of anger happening in the human body, which cannot be divided any further. According to the supporting theories of "natural kinds" specific and discrete emotion categories evolved independently to aid humans to adapt and survive in their environment (Ekman 1992).

Disgust, for example, comes from the need to reduce the input (e.g. the air someone breaths) from a potential dangerous source (e.g. a deadly poison), and as a result it is accompanied by movements of the facial muscles towards that direction (like narrowing the nostrils, closing the eyes etc.). Basic emotion theories are closely related to Evolution theory. Darwin argued that certain mammalian behaviours reflect inherited mental states, which he named using English emotion categories (Darwin 1965).

The most famous basic emotions theory was developed in the 1970's, when Paul Ekman identified six basic emotions (anger, disgust, fear, happiness, sadness, and surprise) by using cross-cultural facial expressions experiments (Ekman 2003). These emotions are known as the "Big Six" and they are considered the most widely accepted entries to be acknowledged as basic emotions. Ekman expanded his basic emotion list in 1999, to include: amusement, contempt, contentment, embarrassment, excitement, guilt, pride in achievement, relief, satisfaction, sensory pleasure, and shame. Another attempt to classify emotions was conducted by Robert Plutchik who identified eight primary emotions (joy, trust, fear, surprise, anger, sadness, anticipation, and disgust). Each of these primary emotions has its opposite, and they can be combined to create more complex, affective experiences (Plutchik 1980). Plutchik's model is analogous to a colour wheel. Basic emotions can combine to form the full spectrum of human affective experience in the same manner as primary colours combine to create the full colour palette. For example, joy and trust could blend and combine to form love. Other emotion models which categorize emotions into discrete categories are the ones presented by Arnold (Arnold 1960), Grey (Grey 1982), Fridja (Fridja 1986), Izard (Izard, 1971), James (James 1884), McDougall (McDougall 1926), Mower (Mower 1960), Panksepp (Panksepp 1982), Tomkins (Tomkins 1984), Watson (Watson 1930). A detailed description of the sets of emotions used in each work and the basis of this categorization can be found in the review study by Ortony et al. (Ortony 1990).

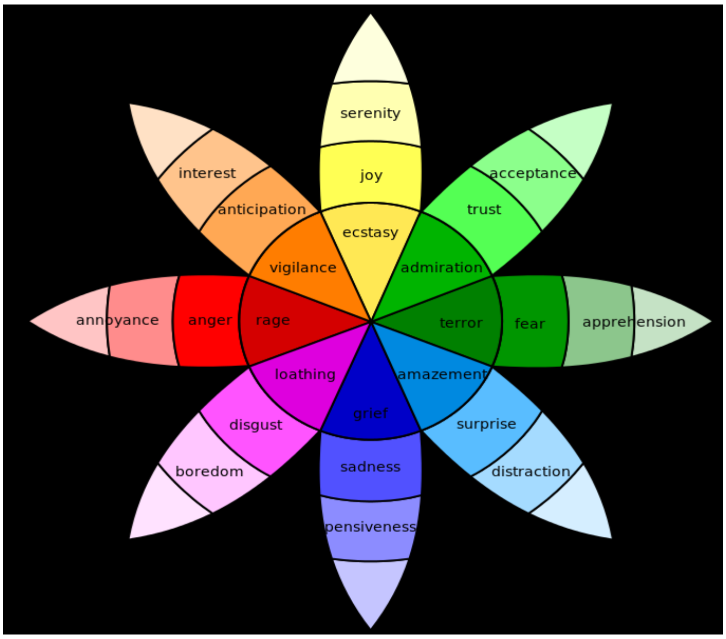


Figure 2.5 Plutchik's wheel of emotions (Plutchik 1980).

Numerous AC applications utilize basic emotion models, and the most popular basic emotion model among AC researchers is Ekman's. As pointed out in D'Mello et al. the predominant use of the basic emotions, in AC applications, is demonstrated by a number of different review studies (D'Mello 2013). For example, Zeng conducted a review on a large number of vision-based affect detection methods, indicating that the majority of systems were aiming at detecting the six basic emotions (Zeng 2009). A similar conclusion can also be drawn by the audio-based affect detection community, although they sometimes also focus on stress, irritation, and frustration (D'Mello 2013). Additionally a meta-analysis of thirty AC systems utilizing multimodal affect detection carried out by D'Mello, also pointed out that most of the systems were targeted at recognizing the Ekman's Big Six (D'Mello 2012). For the research purposes of this Thesis the following set of emotions was chosen: flow, excitement, calm, boredom, stress, confusion, frustration and neutral. These emotions are shown to correlate strongly with the educational process and this choice is explored and justified in detail in section 4.2.

2.6.1.1 Basic emotion models discussion

One major disadvantage for this kind of models arises from the fact that there is an almost infinite number of different affective states which could be used in order to describe the user's affective state. Emotions in real life come naturally and are limitless, thus it does not seem appropriate to restrict the user of an application in labelling their affective sate by using a small set of emotions. This becomes more obvious if someone considers the fact that there are three thousand words in English language alone, which describe emotions. Additionally, emotion theory has shown that the emotion labels, an individual utilizes to describe their affective state, are highly dependent of their cultural background (Tsai 2007). This means that emotion labels are not cross lingual, i.e. the names used to describe emotions do not have direct translations in different languages. For example despite the wealth of the English language, there are still some emotion words from other cultures that do not have a direct translation in English. For example: “Forelsket” (in Norwegian) is: the euphoria you experience when you fall in love for the first time. In a very recent study Lomas identified 216 words pertaining to wellbeing (also including words describing positive and complex feelings), which have no translation in English (Lomas 2016). As a result an AC application utilizing a set of English words (even all of them), would exclude people from other cultures to express their own feelings in the way they prefer, and most importantly the way they experience them.

Research has also demonstrated that the context an individual is currently in, also affects which emotion words they use (Barrett 2011). The relation between emotion and context can be demonstrated through an example. If an emotion recognition system, which is based on facial recognition, used the player's expression in figure 2.6 to predict the athlete's affective state, without accounting for the context of a tennis match (or if it was trained on data irrelevant of the context), which label would it produce as output? Would it be pain, disappointment, excitement, or ecstasy? As a result, it can be inferred that it is close to impossible to accumulate the necessary data in order to train classification systems to reflect adequately the massive number of emotion labels, and at the same time account for cultural and contextual differences. This argument is irrespective of the input signal used in order to construct the emotion recognition part of the system. It does not matter if an AC application utilizes video, audio, physiological signals, posture, or text etc. There would always be the need for incredibly large databases that include a sufficiently large number of combinations of input signals, which are labelled to an almost infinite number of affective states.

Figure 2.6 Emotion and context relation (Barrett 2011).

Of course, someone may argue that this limitation would always apply, no matter what kind of emotion model is used. And since some emotional models have been identified to be cross-cultural, their sets of emotions would be a very good starting point for an application, and a reasonable compromise to describe the user's affective state. The author argues that applications are constrained to use sets of emotions, which do not necessarily reflect the spectrum of their user’s affective states, when in a specific context, and as a result, these applications would not be able to have a positive influence to their users (Zeng 2009). As discussed above maybe the most famous basic emotion model utilized in AC applications, is Ekman's Big Six model. Most AC systems utilizing Ekman's set of emotions have been based on facial recognition, since the basic emotions are associated with discrete facial expressions. For example in Zeng et al. most of the systems reviewed, relied on facial recognition and used Ekman's Big Six to describe their user's affective state (Zeng 2009). However, their choice to utilize Ekman’s Big Six emotions, as Calvo et al. pointed out, was independent of the fact that Ekman's emotions where not relevant with the context of their application (Calvo 2010). To illustrate the impact of using non context-related sets of emotions in research, let us consider AC applications developed in the context of education. As D'Mello (D'Mello 2007) mentions, many studies have shown that Ekman's emotions do not play a significant role in learning (Craig et al. 2004, D’Mello et al. 2006, Graesser et al. 2006, Kort, Reilly & Picard 2001). Therefore, it can be concluded that utilizing Ekman's emotions in AC personalised learning systems, would not be beneficial to their users, since the "Big Six" emotions themselves do not have a significant impact on the learning process. Additionally, as it was stated in (D'Mello 2013) "basic emotions" (e.g. anger, disgust, sadness) have been emphasized in AC systems at the expense of other "non-basic" emotions. Through the analysis of data from five different studies, the team have demonstrated that this emphasis can be questioned since the team's results showed that other "non basic" emotions, such as engagement, boredom, confusion, and frustration occurred at a much larger scale (five times the rate of basic emotions) after generalizing across tasks, interfaces, and methodologies (D'Mello 2013).

2.6.2 Constructivists-dimensional models

These emotion models propose that emotions are not unitary modular phenomena, but instead they arise and reflect the interaction of more general processes, that stem from more basic affective and cognitive representations. This approach can be considered as an analogue of the human visual recognition system. The human brain is calibrated to recognize basic elements, such as simple geometrical shapes, while the recognition of more complex objects is based on the initial recognition of these simple shapes (Biederman 1987). An illustration of this operation would be the visual perception of a coffee cup and a bucket; they are both different configurations of a cylinder and a curved handle. Of course, the final image perceived is of the bucket, or the cup itself, and not of the curved handle or the cylinder. Applying the same principle for human emotion responses, with the correct configuration of simple affective cues, it is possible to obtain the final notion of a perceived discrete emotion category.

In contrast to basic emotion models, psychological constructionism hypothesizes that emotions are not natural kinds; instead, it claims they are formed from more elemental psychological processes. These basic structural ingredients or "psychological primitives" (Ortony & Turner 1990) can combine in numerous ways in order to produce a variety of mental and affective experiences, such as emotion. This constructionist emotional modelling idea remains to this date a very important theoretical approach in emotion literature (Gendron & Barrett 2009). This approach dates back in the late 19th century, when William James stated: “The trouble with emotions in psychology is that they are regarded too much as absolutely individual things. But if we regard them as products of more general causes ... then the mere distinguishing and cataloguing becomes of subsidiary importance” (James 1890, p. 449).

One of the most famous constructionist's models of emotion state is that emotions originate from a core affect, which is a two-dimensional space comprising of two axes. The first axis, ranging from activation to deactivation, represents arousal (how passive or active someone is), and the second axis, ranging from unpleasant to pleasant, represents valence (how positive or negative someone feels). Core affect is not the sole component of emotion, but it provides emotion with its hedonic and perceived energy (Russell 1980). Core affect can be converted to emotions through cognitive elaboration (Russell 2003). For example, someone being negatively valenced and highly aroused can be described as stressed. This approach may also enable the successful differentiation between emotions. For example, sadness and anger may have similar negative valence, but they are significantly different in arousal levels (sadness is a negative valence and low arousal state, while fear is a negative valence and high arousal state). Another dimension, which is used in combination with arousal and valence, is dominance. This 3-dimensional representation is used in the PAD (pleasure, arousal, dominance) model, which measures and describes affective states (Mehrabian 1995). The arousal valence (AV) representation is one the most commonly used emotion representation approaches in AC systems. A large number of AC applications exist based on this approach, along with a number of publicly available databases. These include pictures (IAPS, (Lang 2008)), sounds (IADS, (Stevenson 2008)) or English words (ANEW, (Bradley 1999)) that have been rated on these dimensions. These datasets can potentially be used for training purposes, or for designing experimental settings to elicit a user's emotional responses. However, this kind of representation, which describes emotions in relation to two or three dimensional references, is inevitably sensitive to the selection process and context. AC researchers may be bound to describe their user's affective state by utilizing sets of emotions that are not necessarily reflective of the measured affective state or easily separable in the emotional space utilized. The nature or number of the basic structural elements of emotion is still under investigation (Cunningham 2013), and as a result, the same applies to the dimensional representation of emotion in AC systems.

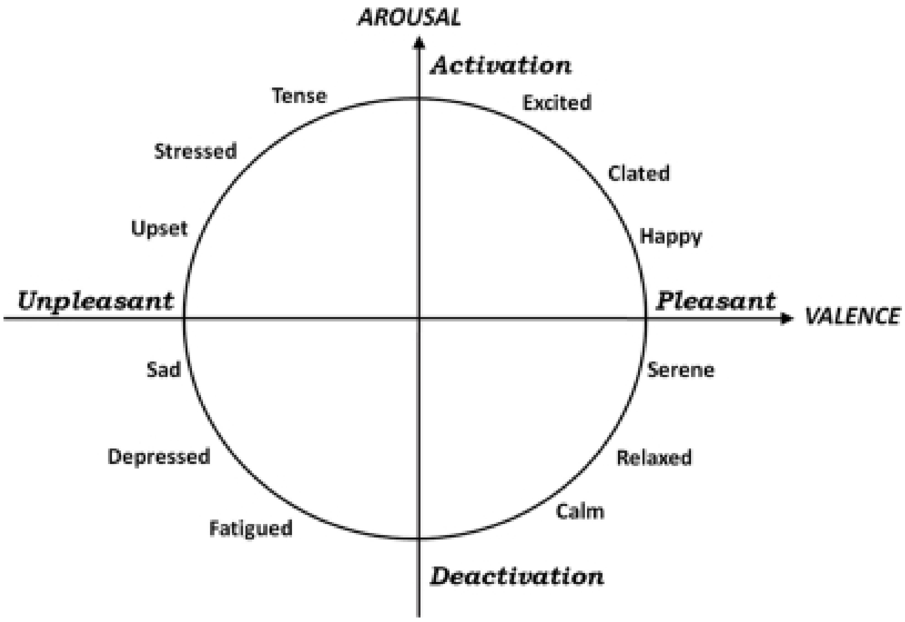


Figure 2.7 Russell's Core Affect (Russell 1980).

Other models propose that events are appraised on a number of goal relevant dimensions and the resulting emotion is a function of these interpretations. Lazarus suggests that emotion theories include a relational, a motivational, and a cognitive aspect (Lazarus 1991). The relational aspect involves the relation between a person and the environment, and suggests that emotions are always shaped by human-environment interaction (Lazarus 1991). The motivational aspect involves the evaluation of a situation in regards to one's goals (Lazarus 1991). Finally, the cognitive component involves one's appraisal of the situation, or an evaluation of how relevant and significant a situation is to one's life (Lazarus 1991). An alternate model of appraisal is Scherer's multi-level sequential check model. This model is made up of three levels of appraisal processing, including sequential constraints at each level of processing that create a specifically ordered processing construct (Scherer 2001). Furthermore, Scherer constructs a strict, ordered progression by which the appraisal processes are carried out. There are various evaluation checks throughout the processes, which allow for observation of stimuli at different points in the process sequence, thus creating a sort of step-by-step appraisal process (Scherer 2001). Such checks include: a relevance check (novelty and relevance to goals); followed by an implication check (cause, goal conduciveness, and urgency); then coping potential check (control and power); and finally there is a check for normative significance (compatibility with one's standards). OCC is another famous appraisal related emotion model, which has been used in AC applications, especially for simulating emotion in virtual emotion characters (Ortony, Clore und Collins 1988). The OCC describes a hierarchy, which is able to differentiate successfully between 22 emotion categories by evaluating consequent events (e.g., joy and pity), actions of agents (e.g., pride and reproach), and aspects of objects (e.g., love and hate) (Steunebrink 2009). In order for appraisal theories to be applied in AC applications, the proposed appraisal dimensions should be related (and consequently automatically estimated) to different aspects of the human-AC application interaction. For example, evaluations of an event could be extracted explicitly through text, during the interaction of a user with a virtual agent. However, automatically extracting this kind of information, without obstructing the user, or without oversimplifying aspects such as relevance, significance, or evaluations of the occurrence of certain events, is a very challenging task.

2.6.3 IR model and Affective Trajectories hypothesis

A different and very interesting approach in emotion modelling is the Iterative Reprocessing Model (IR model) of emotion. IR model suggests that when an individual experiences environmental or internal changes, they process the newly received information through repeating iterative cycles, and ultimately reach a new cognitive/affective state. Through processing the presented stimuli, more detailed evaluations of the incoming information are created, and complex mental states such as affect, arise (Cunningham 2013). It is important to note that the formation of these new more detailed states is dynamic, occurring through neural loops, which happen continuously, multiple times per second. These multiple mental systems serve as a way of tracking our affective trajectories through time. When we are presented with new information, at any point of time, we process the new data by making comparisons with the information already possessed, and predictions concerning what is about to follow in the future. As a result, a current affective state is constructed. As stated in (Kirkland 2012) "Emotion categories depict a way to label and differentiate the various affective trajectories we experience as we move continuously through time". From an AC perspective, the utilization of the IR model involves a high degree of complexity, arising from the inherent difficulty of monitoring and utilizing computationally, very brief cognitive processes.

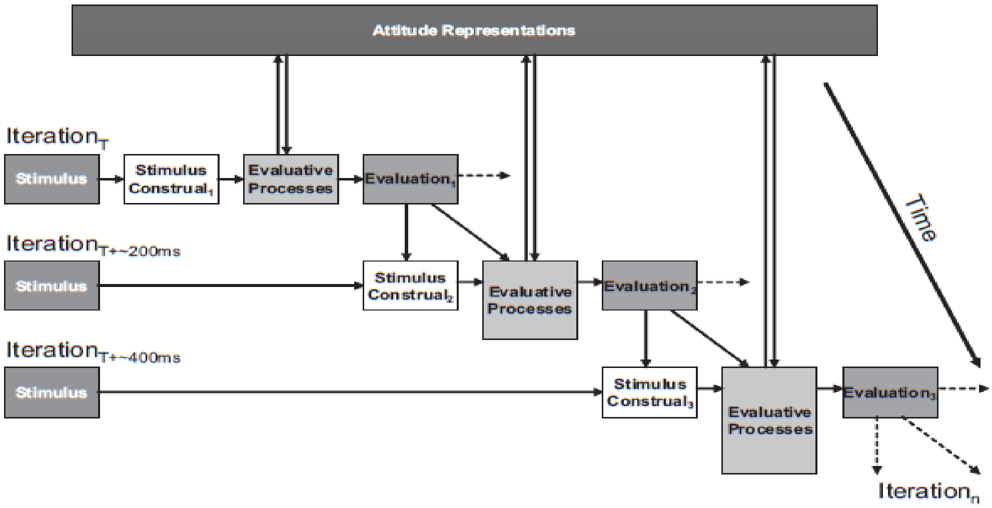


Figure 2.8 IR model (Cunningham 2013).

The IR model is the basis for The Affective Trajectories (AT) hypothesis. The Affective Trajectories (AT) hypothesis proposes that emotion arises partly from the interaction of the evaluations of one's current state, predictions of the future, and the outcomes that one experiences after these predictions (Cunningham 2010). These processes interact, and combine with each other to create an emotional experience (Kirkland 2012). The AT hypothesis is based on the IR model, and it is motivated by the need to explain and understand the shifts in affect that got a person to a certain affective state. The AT theory has been evaluated based on results from experimental sessions (Kirkland 2012), where participants were presented with 18 different combinations of current state, prediction and outcome. Originally they were asked to imagine themselves as feeling 'good', or 'bad', and make a prediction that something would happen (ranging from 'no prediction', to 'great', or 'terrible'). Then they were asked to choose from a list of emotions, the one describing the scenario best. Finally, the outcome ('better', 'worse' or 'as expected') was presented and they were asked to choose again, from the same list, another suitable emotion reflecting their revised affective state. Kirkland's team conducted two studies: in the first one, only one emotion could be chosen, while in the second one, the subjects also rated the degree to which more than one emotion words were describing the scenario. Their results demonstrated that a person is capable of comprehending different emotion labels by using unique combinations of basic elements of their affective trajectory through time, namely their current state, prediction, and outcome (Kirkland 2012). From their results it can be seen that some emotions are in close relation to certain elements of an affective trajectory, and that different emotions can emerge from different combinations of the AT hypothesis basic elements. For example, fear is mostly related with the prediction element of an affective trajectory (we predict something bad is going to happen so we feel 'fear'), while anger, on the other hand, is related to the outcome element, and arises when a combination of a positive prediction and a worse than expected outcome is experienced (Kirkland 2012). There are certain limitations concerning the AT framework since it was tested in a context free environment, and despite the fact that these basic cues demonstrated some predictive power, it is necessary that the oversimplified AT hypothesis structure should be enriched in order to be able to differentiate efficiently between different emotion labels in the context of an AC application. A first attempt to utilize the AT hypothesis under the AC scope was performed in Karyotis et al's work (Karyotis 2015) and it is presented in detail in this Thesis towards modelling and monitoring students' affective trajectories.

2.7 Computational models of emotion

AC researchers and computer scientists have utilized the different emotion theories proposed by psychologists in order to develop their own models of emotions, which would allow the successful incorporation of emotion in computer applications in a realistic and feasible manner. As defined by Reisenzein, a computational model of emotion is a runnable version of a cognitive-affective theory, which can produce predictions based on emotion theory, and as a result, it can be used to produce responses that mimic human emotion in virtual agents, or investigate the mechanisms, which the emotion theory aims to understand (Reisenzein 2009). Some indicative examples of computational models of emotion are described in this section.

The Acting Affectively Affecting Acting project (ActAffAct) (Rank and Petta 2005, 2007) has been used in the field of interactive narrative storytelling. ActAffAct is based on appraisal theory of emotion in order to create virtual agents able to simulate human emotion and interact with each other through the concept of a virtual story world by minimizing external control (thus enabling the agents to make decisions and let the story unravel without human guidance). Rank and Peta's research utilizes an appraisal based architecture, accounting for the cognitive and motivational aspect of emotions (Scherer 2010), and dealing with emotions as labels.

Fuzzy Logic Adaptive Model of Emotions (FLAME) (ElNasr and Ioerger 2000) has been used as a guide for virtual pet simulations. FLAME is based on the cognitive appraisal theory of emotion, and categorizes emotions in regards to their arousal (intensity), and valence (pleasure or displeasure) (Ortony 1988). In FLAME emotions account for the behaviour of the agent, yet they are not responsible for modifying their needs or goals. A fuzzy logic method is adopted to map emotional states in existing events. FLAME models emotion-based learning through employing four different principles: conditioning, reinforcement, probabilistic approach, and heuristic learning (ElNasr and Ioerger 2000).

Fearnot AffecTIve Mind Architecture (FAtiMA Modular) is an updated version of the FAtiMA Core architecture, which has been used to allow for emotional expression of a virtual agent. FAtiMA Modular incorporates a set of components into the core architecture, aiming to create a complex appraisal process able to account for different appraisal theories (such as the OCC, Roseman's and Scherer's) in order to influence the behaviour of a virtual agent, given a specific scenario. This flexible and dynamic approach towards emotion modelling allows different emotion theories to be implemented in a series of scenarios, highlighting their strengths and limitations (Dias et al. 2014).

EMA (Emotion and Adaptation) is a computational model that has been used in order to simulate human behaviour in a virtual training setting. EMA is based on appraisal theory and takes into account different variables that influence the judgment of an outcome, and subsequently the behaviour that follows this event, according to beliefs, desires, or goals (Gratch and Marsella 2004, 2005). The development of EMA is founded over three major dimensions of emotion: the cognitive aspect of behaviour, the interconnection of emotion in a temporal continuum (past, present, and future), and the influence emotion has in determining beliefs and goals in life. As a result, EMA model takes the shape of a closed loop where emotion both influences and is influenced by appraisal.

ParleE is a computational model of emotion developed for a conversational agent in a multi agent environment capable of multimodal communication (Bui 2002). ParleE enables the agent to produce responses directed towards the user and the environment using emotional expressions of different intensity. ParleE relies on previously proposed computational models of emotion (FLAME, Cathexis and Emile), and the psychological basis of this model is the OCC model, and Rousseau's model of personality (Rousseau 1996). In ParleE appraising events rely on learned behaviour and a probabilistic algorithm. ParleE is also able to model personality and motivational states, and the roles these components play in the way the agent experiences emotion (Bui 2002).

Soar-Emote (Marinier and Laird 2008, 2009) makes use of appraisal theories (Scherer 2001) and the PEACTIDM theory of cognition, utilizing the Soar cognitive architecture (Newell 1990). This model accounts for the interaction between emotion and learning reinforcement. In contrast to other models, which work towards creating believable agents (such as EMA), Soar-Emote aims to incorporate the functional components of emotions in Artificial Intelligence. Soar – Emote argues that emotions drive reinforced learning, thus when for instance an agent completes a task, not only do they learn it is good, but they also feel good. Moreover Soar – Emote offers an insight on how the agent's expectations and actions impact upon the intensity of their emotions (Marinier and Laird 2008, 2009).

WASABI Affect Simulation Architecture for Believable Interactivity has been used in different contexts including gaming (virtual agent- human interaction), small talk, learning, and tour guiding. WASABI extends upon the idea that emotions and mood are interconnected over time influencing each other (Becker et al. 2004), thus mapping emotions in a three dimensional pleasure, arousal, and dominance (PAD) space. The structure of WASABI allows two parallel processes to run simultaneously, one for emotional and one for cognitive processing, which provide feedback to the overall interaction and facilitate the simulation of emotion dynamics in the PAD space. Even though WASABI is based on appraisal theory, it also allows external stimuli to influence the agent's emotions, and/or emotions to develop and change over time. However, this change is reflected in the communication of the agent (the way they talk) and their behaviour remains unaffected (Becker–Asano 2013).

As it can be seen by the aforementioned computational models presented in this section, most of their research was oriented towards developing virtual agents with realistic human-like emotion responses. The same conclusion can be reached by utilizing the results from the reviews by Marcella (Marcella, 2010) and Kowalcuzk (Kowalcuzk 2016). Attempts to develop computational models of emotion with more affect recognition oriented goals are rare, and usually they are conducted under the scope of developing successful applications, rather than proposing new models of emotion (Karyotis 2017). The author argues that the development and testing of computational models, with more affect-recognition oriented goals, will reveal useful basic affect components. These will in turn aid AC systems to fulfil their goals, and facilitate efforts into better understanding emotional processes and unmasking the structural elements of emotion, and how they manifest themselves in different contexts, and applications. Observing and estimating the parameters, or affect dimensions of emotion is a problematic task impacting upon the ability of an AC application to provide accurate emotion labeling. As Calvo states "Identifying the appropriate level of representation for practical AC applications is still an unresolved question" (Calvo 2010). In order for this problem to be addressed, researchers across the fields of psychology and computer science should collaborate in an interdisciplinary effort to explore the basic elements of emotion. In this Thesis, it is attempted to provide an emotion representation with a reasonable trade-off between accuracy and complexity, through utilizing novel dimensional models of emotion under an AC scope. The suggested computational models are presented and tested in their ability to monitor and model student's affective trajectories.

2.8 Emotion and learning

This research was conducted under an educational scope since emotion and learning are very closely linked together. Thus incorporating emotion in computing systems, aiming to aid in the learning process, would result in a large improvement in promoting student's wellbeing. Emotion plays a vital role in learning, as the classroom is an emotional place, where the students emote, and they are affected by their emotions. Emotions influence, and are being influenced by almost every cognitive process unfolding in the human brain. Their close relation with motivation, decision-making, performance, communication, memory, perception, and many other processes, which affect human learning, has been demonstrated in numerous studies (Colquitt 2000, Goleman 1995, Bower 1981, Damasio 1994, Birdwhistle 1970, Chovil 1991).

The close relation between emotion and learning can be beautifully illustrated in the statement by English writer and novelist Enoch Arnold Bennet."There can be no knowledge without emotion. We may be aware of a truth, yet until we have felt its force, it is not ours. To the cognition of the brain must be added the experience of the soul" (Dyrek 2009). Leading research in the area of neuroscience demonstrates the relation of emotion and learning through the interconnected pathways of emotion and cognition in the human brain. Learning as a high-level mental activity includes both cognition and emotion (LeDoux 2000). Psychologist Antonio Damasio provides one of the most demonstrative examples to this relation through his famous patient Eliot. Eliot suffered extensive damage to his brain because of a brain tumor. After undertaking a serious surgery, Elliot recovered. His language and intelligence were left untouched. Despite this fact, Elliot was unable to concentrate, manage an organizational task, or arrange his schedule. As it was proven later, through experiments with picture imaging designed to cause an emotional response, Elliot's injury caused damage to centers in his brain responsible for emotion regulation. This damage was the reason for Elliot's inability to concentrate and organize his tasks (Morse 2006, Damasio 1994). It can be concluded from this example that emotions have a detrimental effect on higher and complex cognitive functions, such as learning.

Emotions can either promote or hinder learning, considering the strong neural connections between emotion and mental processes in the brain (Hendel-Giller 2011). Zulll has visualized emotion as the mineral, which fuels the learning process (Zull 2002). Neuroscience research provided evidence to support and enhance Zull's ideas by studying the human brain. More specifically in Cozolino et al.'s research, it has been demonstrated that arousal, a fundamental element of emotion, enhances neural connectivity in the brain (neural pathways transmitting information from different areas of the brain) thus facilitating learning (Cozolino 2006). As shown in cognitive psychology and neuroscience research, the human brain is hardwired to minimize threat (e.g. by exhibiting negative emotions, as disgust, to minimize new input, from a polluted source) or maximize reward (e.g. feeling positive emotions such as contentment, happiness and safety) (Gordon 2000). During learning, an individual is presented with new information which they either assimilate or reject. This learning process is influenced positively or negatively by emotions, which either promote or hinder the assimilation of new input. Research also suggests that it is easier for an individual to choose to avoid new input, rather than engage with it. Similarly, to being in an unknown territory students/learners are alert to the changes of the environment and input, being mindful of potential threats. When the threat is identified, the human brain is wired to respond imminently (fight or flight response) and thus any opportunity for learning is heavily suppressed. This is due to the increased arousal levels generated in the centers of emotion in the human brain (Baumeister 2001). Therefore, emotion has a profound effect on learning.

Emotion and learning are interconnected in a reciprocal relationship. Emotion can be considered as both an ingredient and a product of learning (Antonacopoulou 2001). Famous theorists in the field of pedagogy have investigated this connection. Swiss psychologist Jean Piaget, who was a pioneer in child development, emphasized that emotion is the driving will for learning and development. More specifically, he suggested that the sense of achievement (e.g. feeling proud or successful) or failure (e.g. feeling shameful or anxious) could either support or hinder learning. He viewed emotion to be tightly connected with human mental ability and learning, since emotion is involved in the organization and storage of existing knowledge, and motivates oneself towards deep understanding and assimilation of new information (Piaget 1981). Moreover, according to More, learning has three dimensions: the cognitive, the affective and the behavioural one. More claims that in order for learning to be achieved the student needs to acknowledge all three dimensions. The affective dimension is deeply involved in challenging and evaluating existing knowledge, in order to lead to the assimilation of the new one. Thus, emotions such as curiosity, excitement, fear, and anxiety can facilitate, promote, or suppress learning (More 1974, Antonacopoulou 2001).

Evidence of the link between learning and the emotions of an individual can also be found in the research conducted by Stein and Levine (Stein and Levine 1991). Stein's model utilizes a problem solving and goal directed approach. As with other theories of emotion that incorporate a hedonic principle, people prefer to be in certain positive states (such as happiness), whereas they avoid other negative states (such as sadness). Stein and Levine's model makes the assumption that people strive to grasp new input by assimilating it into existing schemas, which are packages of world knowledge, such as stereotypes, scripts, frames and other categories of generic knowledge. Stein and Levine also assume that emotional experience is in most cases associated with attending to, and making sense of incoming information (Craig 2004). When novel information is presented, a mismatch with already existing schemas is created producing arousal in the Autonomous Nervous System (ANS). During this phase of ANS activation and cognitive processing, an emotional episode occurs (Levenson 1988). Consequently, it can be concluded that learning which is the accumulation of new information schemas, takes place when an emotional episode is unfolding.

Another model accounting for the relation of affect and learning was proposed by Kort et al. Their model is a spiral structure, which comprises of four quadrants (figure 2.9). According to this model, emotion changes occur while a student is moving up the spiral. The model contains two axes with the horizontal axis representing affect and ranging from negative to positive, and the vertical axis representing learning, and ranging from "Un-learning" to "Constructive learning" (Kort 2001a, 2001b). Constructive learning refers to the successful assimilation of new knowledge into schemas, while Un-learning depicts misconceptions and removal of knowledge from schemas. In the upper right quadrant, the learner has positive affect, and they are in the process of constructing learning, which means that they are dealing effectively with the learning challenges. In the upper left quadrant, the student is experiencing negative affect and constructive learning. The student in this case, may be confused while trying to solve some problems they encounter. The quadrant in the bottom left corner consists of un-learning and negative affect. For example, here the student can experience emotional states such as frustration. Finally, the bottom right quadrant consists of un-learning and positive affect. Someone may picture a learner moving from quadrant I where they are working effectively through their material, to quadrant II where they start to have some misconceptions and doubts, then proceeding to III as they strive to discard their misconceptions, after this stage the misconceptions begin to be discarded and the student moves to quadrant IV where they engage into new research towards developing new ideas. Finally, after producing a new idea, they start again from the first quadrant. The student through iterative circles achieves their learning goals and acquires the necessary knowledge.

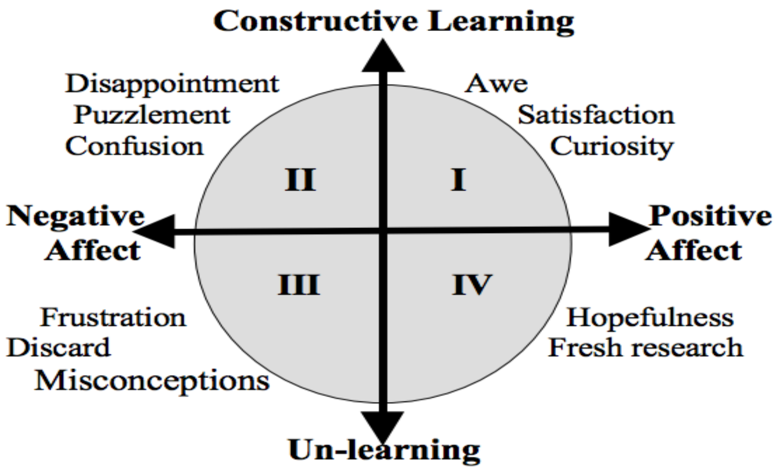


Figure 2.9 Kort's Spiral (Kort 2001a).

The strong relation between affect and learning can also be seen in the book "Emotional Intelligence" written by Daniel Goleman, where the author argues that non-cognitive skills and IQ are of equal importance in determining the individual's success in the workplace (Goleman 1995). This includes the challenges presented in both the professional, and the academic life of the individual. Emotional intelligence can be defined as the capacity to identify the meanings of emotion and their relationships, and the capability to reason and problem-solve on the basis of them. Emotional intelligence is involved in the ability to perceive emotions, assimilate emotion-related feelings, understand the information of those emotions, and manage them (Mayer 1999). Goleman reported that experienced teachers where able to identify the affective states of their student, and provide the necessary feedback, to influence positively their learning (Goleman 1995).

Research has identified a number of discrete emotions, which play a significant role in learning. The "Big Six" (anger, disgust, fear, happiness, sadness, and surprise) proposed by Ekman have been utilized in a generic environment therefore some of those emotions do not account for learning. Other emotions have been identified and utilized towards this goal. In 1990, Csikszentmihalyi described a state called flow, which can be defined as an optimal learning state, where the learner is thoroughly concentrated and interested in the learning procedure (Csikszentmihalyi 1990). During this "Zone of flow", the learner is fully engaged to the activity, and nothing else seems to matter, while time and fatigue tend to disappear (Csikszentmihalyi 1990). Being in this zone could be perceived as the opposite of being bored, or frustrated. Boredom and frustration have been identified by Craig to have a negative impact to the students' effort towards achieving their goal of true learning (Craig 2004). Another important affective state is confusion. Confusion can be described as the state where the student has a lack of understanding and they feel hesitant to act, or decide on a course of action. Research has shown that confusion is an indicator of cognitive disequilibrium, which has a positive correlation with learning (Craig 2004). Cognitive disequilibrium arises when the student confronts obstacles, uncertainty, contradictions, and/or inconsistencies. If the learner tries to restore the cognitive equilibrium through cognitive activities like reflection, problem solving, and thought, only then will deep comprehension and true learning occur. Additionally, learning includes a sense of achievement, therefore positive emotions such as enjoyment of learning, or pride, as well as negative emotions such as stress, anger, or shame correlate with the student's performance. Finally, since the classroom is a place of intense social interaction among students and/or the educator, social emotions such as contempt, envy, or admiration may also influence learning (Pekrun 1992).

Previous research literature includes several studies that further support the prominent impact of emotions to learning. Baker et al. conducted extensive studies where one of the research objectives was to explore the impact of students' emotions to learning. Their experiments included the deployment of different learning environments (ITS, dialogue tutor, problem-solving game) to students of different ethnic origins. The experimental results demonstrated the persistent occurrence of specific emotions and their significant impact to learning (e.g. boredom was correlated with problematic learning performance and behaviour). Based on these results, the researchers argued that special care should be given in the detection and response to emotions such as boredom and confusion. In Pardos et al.'s research, the team explored the relation between students' emotions and learning outcomes. The experimental results have shown significant correlations of different emotions (boredom, engaged concentration, confusion, and frustration) to learning. Very interestingly, the researchers have demonstrated that it is important to highlight the context of the educational setting, since the same emotions may produce different learning outcomes. For example, as it concerns boredom or frustration, it would be useful to recommend interventions to teachers when the student is engaged on original questions, but not if the student experiences these emotions during scaffolding (Pardos 2013). In Cassady et al's research, the impact of cognitive test anxiety, emotionality, and test procrastination were subsequently evaluated on three course exams for a large number of undergraduate students. From the team's results, the negative impact of stress to learning and academic performance was inferred. High-test anxiety was strongly related with lower test scores, while lower levels of physiological arousal were related with improved exam performance (Cassady 2002). In the review study by Moridis et al., the researchers have discussed how specific positive emotions (such as acceptance, joy, satisfaction) and negative emotions (such as anxiety, anger, fear, sadness) affect mental states that significantly influence learning. The researchers summarized on their discussion in the results presented in figure 2.10 (Moridis 2008).

	Impact on learning			
	Positive		Negative	
Emotions	Focuses mind	Broadens thoughts	Blocks thinking and memory	Mind easily distracted
Positive emotions				
Acceptance		x		x
Joy		x		x
Satisfaction		x		x
Negative emotions				
Anxiety	x		x	
Anger	x		x	
Fear	x		x	
Sadness	x		x	

Figure 2.10 Emotions and mental states that influence learning (Moridis 2008)

The close relation between learning and emotion can also be demonstrated by adopting a constructivist approach. This can be achieved with the help of the famous Yerkes-Dodson Law, presented by the psychologists Robert M. Yerkes and John Dillingham Dodson in 1908 (Yerkes and Dodson 1908). According to the Yerkes-Dodson Law, the performance of an individual in simple mental tasks is an almost linear function of their arousal levels, and a U-shaped curve for difficult tasks. Learning is a difficult and complex mental task and arousal is, as mentioned before, a generally accepted basic element of emotion, consequently we can infer the relation of emotion and learning. As it can be seen in figure 2.11, performance during difficult tasks rises at the beginning as arousal is increasing. Then a maximum performance is reached at a certain arousal level, after which performance gradually decreases again, while arousal continues to rise. For example, an overexcited or overstressed (high arousal level) student struggles to concentrate, and thus their performance is hindered. Consequently, emotions which are characterized from significantly low arousal levels (such as boredom), or emotions which comprise of very high arousal levels (such as stress) have a negative influence in the learning process, due to lack of interest or lack of concentration. The desired optimal performance is achieved when the learner reaches a level of arousal, which indicates motivation and involvement in the task, without the negative consequences of excessive arousal.

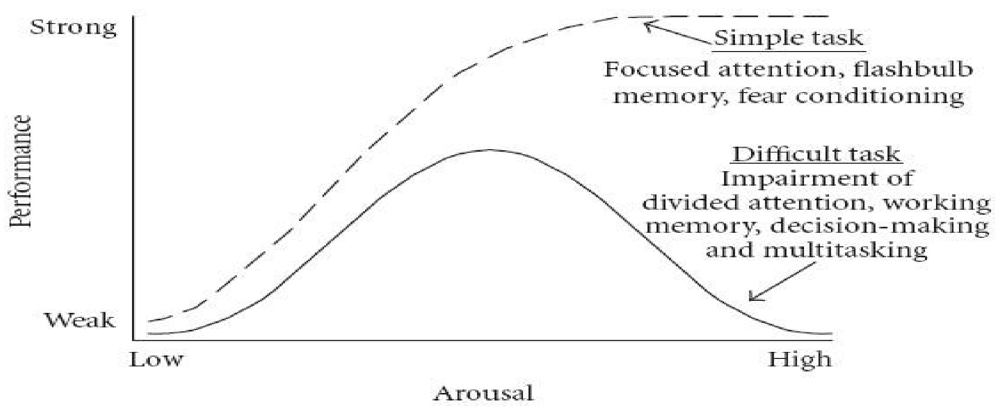


Figure 2.11 Yerkes-Dodson Law (Yerkes and Dodson 1908).

2.9 AC applications in education

The close relation between emotion and learning as highlighted in the previous section has led to the development of a large number of affective computing applications that aim to facilitate the learning process. In this section, recent examples of AC research in education related areas are presented.

An intelligent tutoring system (ITS) can be defined as an application aiming to promote learning through the delivery of instant, personalised, and customised feedback to the students, without the intervention of a human tutor. As D'Mello and Grasser have shown in (D'Mello & Graesser 2012) an ITS is capable of modelling the cognitive, emotional, and motivational processes of the student, thus offering remarkable learning gains for the students. D'Mello and Grasser developed and tested two ITS, namely AutoTutor, and Affective AutoTutor. AutoTutor processes its user's responses and builds a cognitive model of the user's knowledge. The constructed model is then utilized to dynamically adjust the interaction of the user with the ITS. Affective AutoTutor was the extension of AutoTutor with the ability to automatically identify the emotion of its user, and provide tailored feedback. The team has conducted a large number of experiments in order to test the ITS AutoTutor, and Auto Tutor's enhanced version Affective AutoTutor. The team's results demonstrated that Affective AutoTutor achieved "dramatic" improvements in learning with even greater impact compared to the benefits provided by the original AutoTutor system. This was especially prominent when their applications were used by students with limited background knowledge in the domain under investigation. In 2012, D'Mello et al. developed another ITS called Gaze tutor, which was focused at providing the appropriate feedback to students by automatically detecting if the student was bored, or disengaged. This was achieved by utilizing a commercial eye tracker that was responsible to monitor the user's gaze patterns. When the student looked away from the screen for a long period of time Gaze tutor assumed that the student became disengaged. If the student was disengaged, or bored, Gaze tutor provided feedback to the user by outputting dialogue moves, which guided the learner to rearrange their attentional patterns. The researchers have evaluated the performance of the ITS by deploying two versions of the tutor in an experimental session, where students were taught biology related topics. The first version of the tutor was gaze reactive, and the second was not. From the team's experimental results, it was concluded that the feedback dialogs produced by the ITS were effective at guiding the learner's attentional patters. The gaze reactive version of the tutor did not have a significant impact on the learner's motivation or engagement. However, there were significant gains concerning the student's performance in demanding learning tasks (D'Mello 2012). Another very recent example of an ITS is the work by Wiggins et al. where the researchers presented a demo of an ITS called Java Tutor. Java Tutor was developed in order to facilitate learning of basic computer science concepts. Java Tutor aided the student by providing skill-based, cognitive-based, and emotion-based feedback (Wiggins 2015).

Nowadays technology is available and accessible to a large percentage of the population in modern societies; this fact along with the continuous growth of mobile technologies has resulted to a large number of recent applications on e-learning and mobile learning. These applications have utilized AC principles so that they can benefit from incorporating emotion in their design, and produce tailored feedback in order to promote their user's strive for learning. Recent examples of Affective Computing research related to e-learning are the works by Tian et al. (Tian 2014) and Ashwin et al. (Ashwin 2015). In 2014 Tian et al. presented a framework for identifying emotion by utilizing text interaction, and proposed an emotion model specifically designed for e-learning students. Their emotion model consisted of fourteen emotions, which comprised of interpersonal states (e.g. love, anger) and intrapersonal states (e.g. pride, shame). The team applied a large number of ML approaches to data obtained from two experiments to assess the emotion classification accuracy of their approach. Their results support Random Forests as the most efficient technique to accurately classify emotions. A Random Forest comprises of a number of simple decision trees, which are used to produce a final decision. The researchers also introduced active listening as a method, which can be applied in an e-learning environment for emotion regulation of the student user when negative emotions are detected (Tian 2014). Ashwin et al. presented an e-learning system, which supports emotion recognition through face detection of multiple users simultaneously. Their approach was tested on four publicly available databases and the results demonstrated a high recognition accuracy concerning the detection of seven emotion categories, by utilizing an SVM based computational technique. The system was also able to deliver the results in very competitive times through a combination of CPU (Central Processing Unit) and GPU (Graphics Processing Unit) processing. The team also proposed the utilization of the analyzed group emotions in order to adjust the teaching strategy appropriately (Ashwin 2015). Examples of mobile learning applications, which fall under the scope of AC can be found in the work by Shen et al., and Pham et al. (Shen 2014, Pham 2015). Shen et al. presented a non-obtrusive mobile learning model, which relies on multi-modal emotion detection. More specifically, the researchers proposed the utilization of wearable sensors, and of modalities already present in modern mobile phones, in order to detect the user's affective state through data related to facial expression, speech, physiological signals and contextual information. This mobile learning model aimed to provide learning services tailored to the students' needs by aiding a learning system to adjust to a user's status, and as a result augment the overall learning experience (Shen 2014). Pham et al. have presented AttentiveLearner, which is a mobile learning system specifically designed for utilizing video-lectures for massive open online courses. From a study conducted by the team, it was shown that AttentiveLearner was able to extract the heart rates of participants from video frames, which in turn could be utilized to provide predictions about a user's "mind wandering", and of their question answering performance in follow up quizzes. It is important to note that AttentiveLearner can be implemented in standard smart phones without any significant hardware modifications, and as a result, it shows great potential to be utilized in order to enhance real life mobile learning (Pham 2015).

Game based learning environments are another category of computer based learning tools, where the principles of AC can be adopted in order to promote student's engagement and motivation. For example, in the work by Hamari et al., the researchers explored the outcomes of flow, engagement and immersion on learning occurring in game based learning environments. The data for this research was obtained by a survey study using players of two educational games. The experimental results demonstrated that the elements of engagement in the game, and challenge of the game itself, positively influenced learning (Hamari 2016). In the work by Molins-Ruano et al., game design was utilized as a test-bed, where teams of students with academic backgrounds in either computer science or history, collaborated towards designing a video game with a historical theme. The results demonstrated a significant improvement of the student's motivation levels when they were engaged in this kind of activities, compared to other more traditional learning methods (Molins-Ruano 2014). Sabourin et al. have explored the interactions of students in the game-based environment (CRYSTAL ISLAND) in order to provide an insight on the relation of learning with the student's affective state, and engagement in game-based environments. Crystal Island is a game based narrative-centered learning environment. Sabourin et al.'s results highlighted that this kind of environment can promote learning, and positively influence their user's affect, and engagement levels (Sabourin 2014).

2.10 Affective transitions during learning

The affective state of a student is a dynamic psycho-physiological construct that evolves through time. During the progress of an educational session, a student moves from one affective state to another. This sequential progression from one affective state to another can be defined as an affective transition. There have been attempts to monitor and explore these affective transitions, providing evidence that some affective transitions are more or less likely to occur than others. Hence, an individual is more likely to transition to a certain affective state from currently being in a specific affective state. This fact can potentially provide AC researchers with a useful tool in order to model and predict a student's affective state. AC systems could utilize the additional information through advanced modelling and ML techniques in order to recognize and monitor their user's emotion more efficiently. In this section, previous AC research targeted at exploring the affective transitions of students during learning tasks is discussed.

In 2007, D'Mello et al. have monitored and recorded the affective transitions a student experiences during their interaction with the learning environment AutoTutor. College students were tutored in computer literacy while they were video recorded. These recordings were later used by the students to judge their own affective states. The affective states under investigation were: boredom, flow, confusion, frustration, delight, and surprise. The team calculated the relative likelihood of transitioning from one affective state to another. The transitions from the state of boredom into confusion, flow into frustration, and confusion into boredom occurred significantly below chance levels. Some transitions also revealed trends, which were not statistically significant, including the unlikely transition from flow into boredom and the more likely transitions from flow to confusion, and frustration to boredom. The transition from boredom into frustration occurred significantly above chance levels, which suggests the high possibility that a bored student will soon become frustrated. Finally, the transition from frustration into confusion occurred rarely, not being significant, and had a high degree of variability. This triggers speculation about how personal differences might influence this affective transition. Some students may disengage when they feel frustrated, while others may become more active and focused in the face of additional challenges (D'Mello 2007).

Baker, Corbett, Koedinger, & Wagner were able to replicate many of D’Mello et al.’s (D'Mello 2007) findings when they calculated the likelihood of affective transitions in a simulation based learning environment called the Incredible Machine (Baker et al. 2007). Their results also showed that some affective states such as flow, frustration and boredom tend to endure over a long period of time. Another attempt to monitor affective transitions was conducted in 2010 when McQuiggan et al. presented their findings regarding common affective transitions observed in the narrative-cantered learning environment CRYSTAL ISLAND (which was presented in section 2.9). They used an in-game self-report dialogue to capture the participants' affective state. Their set of emotions included ten affective states (anger, anxiety, boredom, confusion, delight, excitement, fear, flow, frustration, and sadness). They concluded that frustrated students were more likely to remain frustrated, or transition to either confusion or fear. When in flow, students were most likely to remain in the flow state followed by confusion, anxiety, and delight, while excitement, and frustration were below chance levels. Finally, when in a state of confusion, students were more likely to remain in the same state followed by excitement, boredom, frustration and finally flow in the aforementioned order (McQuiggan 2010).

Evidence towards the importance of affective transitions in learning can also be provided by the aforementioned cognitive disequilibrium. Deep learning occurs when the student faces obstacles and contradictions. At that point, students through their effort try to change this state of cognitive disequilibrium and restore cognitive equilibrium, thus resulting in learning gains. Some affective states like confusion and frustration are more likely to be reported during the cognitive disequilibrium phase; on the contrary, others like boredom, or flow occur more often during the cognitive equilibrium phase (Kort Reilly and Picard 2001). This allows for some predictions concerning affective transitions, since certain transitions are expected to occur more often than others (D’Mello 2007). One such being a transition from a negative cognitive disequilibrium state, such as frustration, to a negative cognitive equilibrium state such as boredom.

As it can be seen from the above research, previous attempts that targeted the exploration of affective transitions were limited to the specific context of their environments, such as the interaction with the AutoTutor, or with other virtual or simulation based environments. These attempts however, were not monitoring students interacting with other students, or the tutor, in the context of the modern classroom. Additionally the aim of previous research reviewed so far was to investigate affective transitions, and other aspects of human machine interaction, and not to utilize affective transition information towards emotion recognition, or modelling purposes. In this Thesis, an insight is provided into the affective transitions of students performing learning tasks under modern pedagogical frameworks, and this affect information is incorporated in the mechanism of the presented computational approach in order to improve the emotion modelling and recognition process. Previous work, conducted under the broader scope of affective computing, has shown that the affective content of previous and future observations could provide contextual information to be used in order to classify the emotional context of an observation (Metallinou, 2012). Metallinou et al. utilized a multimodal and multi-subject database of dyadic interactions between actors (IEMOCAP (Busso 2008)), and Bidirectional Long Short-Term Memory (BLSTM) neural networks, hierarchical Hidden Markov Model classifiers (HMM), and hybrid HMM/BLSTM classifiers. Their results demonstrated that incorporating long-term temporal context in the classification process is beneficial for emotion recognition systems. There are however certain limitations concerning this research. Firstly, future observations are included as input parameters in the system. This is understandable since it strengthens the argument of including contextual information. However, it has no practical value since future observations cannot be obtained in advance in real life. Additionally, the team used a context free database that contained interactions among actors. This also affects the real life implementation of the system, since professionals provide clearer responses compared to the reactions of ordinary people in real life situations. Finally, the researchers utilized 3 and 4 clusters in the AV space as targets, which is a relatively small set of emotion categories to describe the affective state of users. In the research process followed in this Thesis, a customised fuzzy computational technique was developed, which combines low-level affect information, along with affective transition information, in an education context, and by only acknowledging the previous affective state of students. Moreover, the presented approach was tested in a modern educational setting, and used a set of emotions that can be utilized by a personalised learning system, aiming to promote the student's wellbeing. As shown in this section, and as it will be demonstrated in the following chapters of this Thesis, certain affective states are more, or less likely to follow others (for example a bored student can easily become a frustrated student), and this likelihood can be used to facilitate in providing an emotion label to describe the user's affective state.

2.11 Factors influencing students' emotions

In the previous section, the potential of incorporating affective transitions in the design of an AC application was discussed. However, students' emotions are also influenced by a number of other factors, which could also be considered as potential inputs for personalised learning systems. The construction and the intensity of student's emotions are regulated by all the factors, which primarily influence emotion.

Research has shown that gender, personality, culture, power, social role, and status, even situational variables are all factors, which contribute to the emotions experienced by people. Before focusing on the factors influencing students' emotions, a brief reference in the general factors affecting emotions is discussed.

Kring et al. assessed emotional responses of men and women, using emotional films, and found that women were more expressive than men. Women also demonstrated different patterns of skin conductivity, which is a physiological response known to correlate strongly with the arousal levels of an individual (Kring 1998). The fact that emotions may differ between men and women, is reinforced by social conventions and the view of femininity and masculinity in their culture (Wester 2002). Another factor affecting emotion is culture. Its impact includes social gender roles, as mentioned before, and extends to determine which emotions can be expressed, and which are good or bad. As an example in Western cultures the dominant view is to try to maximize your positive, or minimize your negative emotions, while in certain Eastern cultures, the leading view is to find a balance between positive and negative emotions (Kityama 1999). Personality features are also associated with individual differences in daily emotion life, such as negative and positive affectivity (how individuals experience positive or negative emotions), affect variability, and affect reactivity (Komulainen 2014).

A student's affective state is largely influenced by all the aforementioned factors. Moreover, research indicates that situational variables such as the time of the day and/or year, also influence the student's affective state. The time of year is found to regulate cortisol levels and mood. As seen in King et al.'s, and Walker et al.'s research, cortisol levels appear to be higher during fall and winter, and lower during spring (King et al. 2000, Walker et al. 1997). Higher cortisol levels are proven to be in association with shyness (Schmidt et al. 1997), anxiety and depression (Schulkin et al. 1998). Cortisol levels are also affected by the time of day, being higher in the morning, and then gradually decreasing throughout the day, reaching the lowest levels during night (King et al. 2000, Van Cauter 1989). Mood is more likely to be depressive during fall and winter rather than spring (Oyane et al. 2008) and is influenced by the circadian cycles (a daily rhythmic activity cycle, based on 24-hour intervals, that is exhibited by many organisms including humans). Mood is more likely to be negative in the morning, and as the day progresses it becomes more positive (Wirz-Justice 2005).

Along with the general factors, which influence students' emotions, there are specific in-classroom factors that contribute greatly in shaping the students' affective state. Research shows that student emotions are related to the cognitive and motivational quality of instruction. If the learning material is presented to the students lacking structure, task demands are heavily burdened or exams lack clarity and transparency, this will have an effect of elevating the students' anxiety levels (Zeidner 1998). On the other hand, if the student is motivated and their needs are met, then the student is more likely to move towards more positive emotions. Moreover if the teacher is energetic and conveys their enthusiasm to the students, this also results in the student adopting positive emotions more easily, as it was supported by observational learning and emotional contagion (the tendency for two persons to converge emotionally) (Hatfield, Cacioppo, & Rapson 1994).

The student's perceived control over the learning process and the consequent positive emotions accompanying this experience are enhanced by learning environments, which support autonomy, and self-regulated learning. These environments increase the students' positive emotions by satisfying their need for autonomy. Of course the teacher should always account for the individual competencies and needs, otherwise the students may feel that they are losing control, and experience the corresponding negative emotions (such as anxiety). Similarly, the students may feel overwhelmed by the demands of excessively high achievement expectations, leading again to the experience of negative emotions. Hence, another factor that greatly impacts students' emotions is achievement expectations during the educational process. Research shows that elements such as being in a competitive classroom, combined with the expectance to achieve, positively correlate with test anxiety (Johnson & Johnson 1974). Therefore taking emotions into consideration teachers should create classroom environments, which promote cooperation as a means to facilitate learning objectives.

Finally, another factor is the feedback provided to the student and the consequences of achievement. Research has shown that student anxiety is closely related to receiving repeatedly negative feedback (Zeidner 1998). When the student experiences success, their perceived control is enhanced along with the related positive emotions. On the contrary, when the student experiences prolonged negative feedback and failures, their perceived control declines, and the related negative emotions arise. In addition, the perceived consequences of success and failure are important. The educator must try to provide success experiences and treat academic misfortunes and mistakes, more like opportunities for change rather than personal failures.

From all the above, it can be concluded that there are numerous factors, which have been identified to influence student emotions. All these factors could be potentially utilized by AC systems to aid them in monitoring the students' affective state. In this Thesis, the author aims to develop a computational mechanism with the ability to expand easily in order to be able to accommodate a number of these diverse factors.

2.12 Pedagogical Frameworks

During the research process outlined in this Thesis, personalised learning systems have been developed, utilizing novel models of emotion. These models were tested by applying the developed systems to learning sessions conducted under the scope of two modern pedagogical frameworks: Problem Based Learning (PBL) (Barrows 1996) and Activity Led Learning (ALL) (Wilson 2008). PBL and ALL are modern frameworks that can accommodate new technologies and interventions and as a result, they can be good platforms for applying and testing personalised learning systems. These frameworks allow students to experience a wide range of emotions by taking part in different activities, and learning tasks (such as games, discussions, presentations, problem solving exercises etc.). Moreover, the activity-based structure of PBL and ALL is a suitable test bed for monitoring emotions, since there are discrete activities with start and end points for emotion values to be obtained. This start and end point structure is in accordance with the emotion modelling techniques proposed in this Thesis. Therefore, PBL land ALL were chosen as a basis for designing the experimental learning sessions conducted to evaluate the developed computational emotion modelling frameworks. A brief description for both pedagogical frameworks is provided below.

2.12.1 Problem Based Learning

Problem Based Learning (PBL) is a modern pedagogy where students are actively involved in learning through engaging in real life, problem-solving activities. PBL is different from traditional instruction as it takes an active approach towards learning, where small groups of students, facilitated by their tutor, employ analytical skills to find solutions in open-ended, and ill-structured problems. During PBL the teacher/ tutor engages in the role of mediator/ facilitator clarifying discussion and guiding the students towards new information. Thus in PBL, the tutor is not the source of knowledge, but they are rather facilitating the leaning process by providing means for active enquiry and exploration, and harnessing group dynamics (Wilkerson and Gijselaers 1996). Through processing ill-structured and real-life problems, students engage in a cycle of active enquiry (figure 2.12). Firstly, the problem is stated and existing knowledge is elicited and used to form a hypothesis, then missing information is acknowledged and strategies are employed to access what the students do not know. Once new information is gathered, it is then applied to the problem in search of a solution. For this reason, the most suitable means to apply PBL is open-ended problems, where multiple answers are possible. PBL promotes group discussion and collaboration, and allows for the deployment of different methods and strategies to reach a solution, thus enhancing the students' independent learning skills (Shelton & Smith 1998, p. 21).

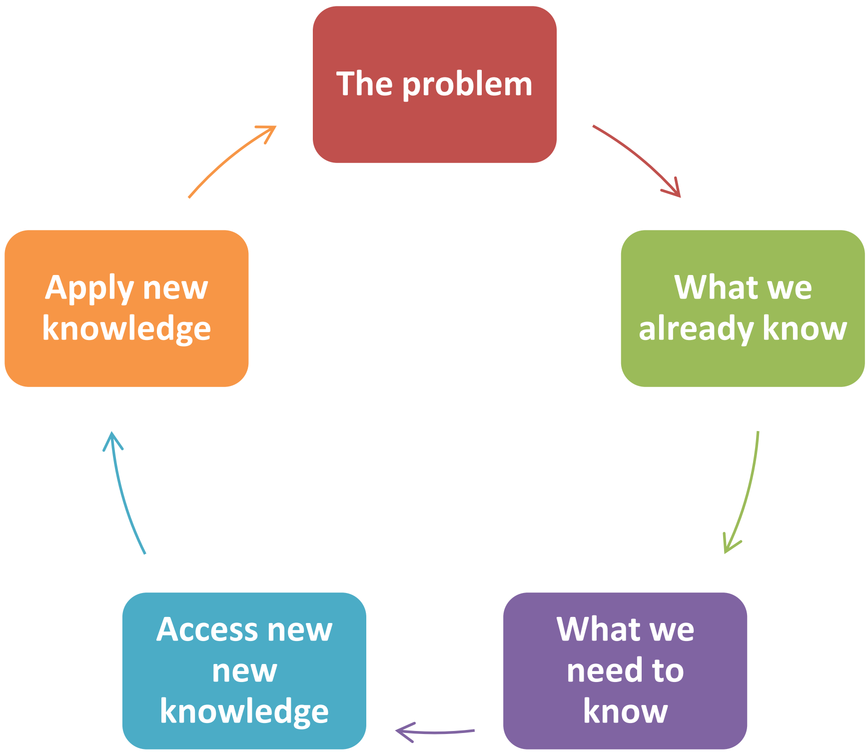


Figure 2.12 Active enquiry circle in PBL.

2.12.2 Activity Led Learning

Activity Led Learning (ALL) is a modern pedagogical approach, which embraces learning as an active process, and seeks to enrich the students' learning experiences through active involvement in stimulating activities. An activity can be defined as any structured task where scientific methods can be employed. Thus, a case study, a research question, a work based laboratory exercise, a problem, or a scenario are suitable for ALL implementation (Wilson-Medhurst 2008). ALL falls within the Problem Based Learning framework (PBL) where the learners, form small groups and actively seek new information, guided by their academic tutor. ALL has been developed and thoroughly researched at Coventry University, both at undergraduate and postgraduate levels, and its benefits have been demonstrated through longitudinal studies across different disciplines (Cooke 2014, Iqbal 2013). Amongst the advantages of ALL is student engagement and academic attainment. Moreover, due to the nature of ALL, students have had the opportunity to advance their oral presentation and group collaboration skills, thus developing a highly desirable skill set for future employment.

2.13 Literature review Summary and Conclusions

Initially in this literature review, the author explored the concepts, and provided background information on Ambient Intelligence, and Affective Computing. Moreover, an overview of the different application areas, inputs, and machine learning techniques used in affective computing systems was presented. Additionally the importance of choosing the appropriate model of emotion for an Affective Computing application, in order to describe its user's affective state was highlighted. The difficulties arising from utilizing basic emotion models, dimensional models, and appraisal models were demonstrated. More specifically, disadvantages concerning basic emotion models emerge from the relation of emotion with the context of an application, or/and the cultural background of each user, along with limitations concerning the emotional labels to be used, or the affect recognition techniques to be utilized. The author also considered the problems arising from utilizing constructivist models with low dimensionality, such as the Arousal Valence model, or with very high complexity, such as the IR model. Furthermore, challenges, and practicality issues concerning the applicability of appraisal models in real life applications were discussed. Additionally previous research attempts to create computational models of emotion were presented and discussed, highlighting the fact that already existing models focused on mimicking human emotion for virtual agents, and did not account for emotion recognition. In this Thesis, new representations of emotion are proposed and tested, towards the development of a model, which is capable of differentiating efficiently between emotions, while at the same time, retains a reasonable degree of complexity. In the following chapters, these emotional models are tested through implementing, and applying novel personalised learning systems, which are based on AC architectures specifically designed to utilize these models. Lastly, in this chapter previous literature exploring affective transitions during learning tasks was discussed, and evidence of the potential integration of affective transition information in an affective computing system was provided. Previous attempts in the area of personalised learning systems focused on exploring affective transitions on virtual, or simulation environments. In this Thesis, the author explores the affective transitions occurring during collaborative learning tasks in a real educational context, and in the same time develops a system that utilizes this affective information to achieve improved emotion recognition performance. As argued in this chapter, students' emotions are influenced by a variety of factors, which may be exploited as potential inputs for AC systems. This research addresses this challenge by proposing a technique, which has the potential to be easily extended to incorporate all these factors into the design.

Chapter 3 Fuzzy Logic and Fuzzy Cognitive Maps

3.1 Introduction

In this chapter, a short tutorial for the two main soft computing techniques utilized in this Thesis is provided. Namely, the ideas and basic principles of Fuzzy Logic, and Fuzzy Cognitive Maps (FCM) are described, since both methodologies were applied throughout the different phases of this research. Fuzzy Logic was utilized mostly towards the goal of modelling low-level affect relations, and representing the proposed models of emotion, while the FCM was used in order to create a dynamic representation of affective transitions, and model affective trajectories through time. In this section, the author describes the basic concepts of the aforementioned methodologies, in regards to their mechanism, and highlights the traits, which make them suitable for our research domain. Moreover, examples and applications of both methodologies in Affective Computing are presented.

3.2 Fuzzy Logic introduction

The fundamental principle, which led to the growth of the digital age and the development of modern electronics, and programming languages, was the development of Boolean algebra (Bool 1854). In Boolean algebra, a variable can be either true or false, and it relies on the logical approach stating that an expression is either true or false. This approach can be traced back in Greek philosopher Aristotle who states that "No one can believe that the same thing can (at the same time) be and not be". This kind of logical representation was challenged even in Ancient times. The famous Epimenides' Paradox demonstrates how this representation can run into trouble. The Ancient Cretan Epimenides stated that "All Cretans are liars". Epimenides says that Cretans always lie, but Epimenides is a Cretan so he lies, so Cretans always speak the truth, but then Epimenides should speak the truth etc. The fact that truth and reality cannot be reliably depicted into two-valued variables is also congruent with every day experience. Let us consider a hard limit of 1.80m is defined to categorize people as tall and short. Consequently, a person with a height of 1.79m would be categorized as short, and a person with a height of 1.81m as tall. A fact that contradicts with common sense, since in real life those two people would be considered of almost equal height. Of course, the precision of the height's measurement is not the problem here, actually the more precise the measurement, the more inaccurately this hard limit classification begins to show. This fact may be attributed to our concept of "tall" or "short" being inherently fuzzy. In every-day life, this balance between precision and true is something, which has been mastered by humans. This relation can be easily demonstrated in figure 3.1.

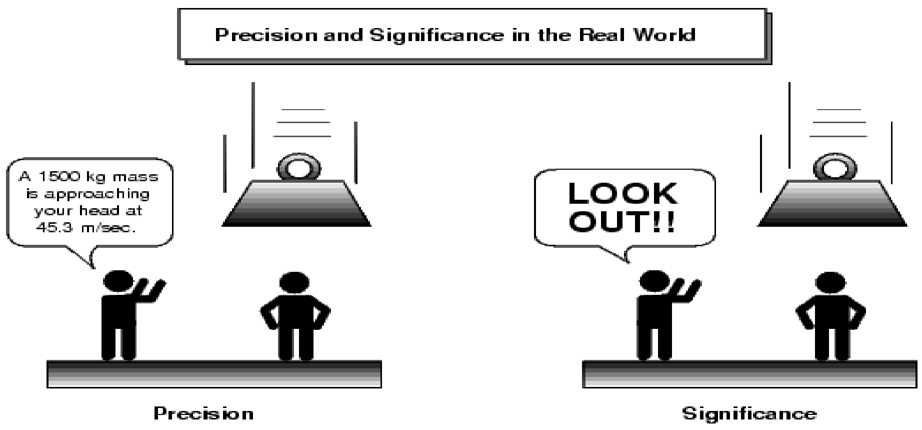


Figure 3.1 Precision vs Significance in the real world.

Contrary to Boolean logic, which allows for two values, Fuzzy Logic is multi valued. An expression is not true or false, but it can be both partly true and false at the same time. Fuzzy Logic is the equivalent of seeing things with the entire colour palette instead of just black and white. Lotfi A. Zadeh introduced Fuzzy Logic as an extension of the Boolean logic (Zadeh 1965). Fuzzy Logic makes use of the theory of fuzzy sets, and introduces the notion of the degree of verification of a condition. It is a set of mathematical rules and principles allowing for partial membership in a set, and for knowledge representation based in natural language rules. These mathematical rules and functions allow successful uncertainty handling, and natural language queries. The advantages of Fuzzy Logic stem from the facts that it allows partial membership in a category, and uses natural language. As a result, Fuzzy Logic is a suitable approach to computationally model and represent emotion, which is fuzzy by nature. Precision loses its meaning when describing a notion that is so vague. In addition, the use of natural language makes Fuzzy Logic easy to understand, and even allows it to incorporate expert knowledge, and common sense which can be beneficial to emotion modelling. Furthermore, the utilization of natural language fuzzy rules enables the creation of computational models of emotion, which reflect the underlying emotion theory and affect relations.

Another advantage of Fuzzy Logic is that it offers a very low computational complexity and many times, given a certain application context, it has similar or better performance compared to other far more complex computational techniques. As the founder of Fuzzy Logic Lotfi Zadeh, stated: "In almost every case you can build the same product without fuzzy logic, but fuzzy is faster and cheaper". This aspect makes Fuzzy Logic suitable for supporting the online deployment of affective computing systems by achieving a very satisfying trade-off between performance, and delivery time of the results/feedback, or software and hardware requirements. Fuzzy Systems are also able to adapt in a very efficient way to the needs and individual preferences of their users. Adaptive Fuzzy Logic systems have delivered a number of successful applications in different domains demonstrating their ability to extract knowledge and model successfully a number of different problems (Doctor 2005). In AC, reflecting individual differences in the construction of emotion is of paramount importance. The way every individual is influenced by their environment, or the manner they express themselves to describe their affective state are both highly personalised. Fuzzy Logic is a proven technique that can aid at achieving this goal thus creating successful personalised and user-friendly Affective Computing applications.

3.3 Crisp sets vs. fuzzy sets

At the heart of fuzzy logic lies the concept of a fuzzy set. Fuzzy sets are a natural extension and generalization of crisp sets. In fact, it would be valid to say that classical set theory is a subset of fuzzy set theory. At first, we need to recall the notion of a crisp set S. A crisp set S can be defined either by noting all the elements belonging to this particular set, or by identifying the condition/conditions for which an element would be a member of this set. The notion of belonging can be represented with a mathematical function called a membership function, which can be defined for the crisp set S as follows:

$$\mu_S(x) = \begin{cases} 1, if\ x \exists S \\ 0, if\ x \nexists S \end{cases} \qquad (3.1)$$

In contrast to a crisp set were an element is either a member of non-member of a set, a fuzzy set *F* does not have hard-defined limits of membership and allows partial membership of an element in a set. For fuzzy sets, the membership function may take values in the interval [0, 1]. This value would represent the degree of membership of an element to the fuzzy set *F*. The membership function can take the following values.

- $\mu_F(x) = 0$, if element x does not belong in fuzzy set F.
- $\mu_F(x) = 1$, if element x totally belongs in F.
- $0 < \mu_F(x) < 1$, if element x partially belongs in F.

A demonstrative example of a crisp set versus a fuzzy set can be seen in figure 3.2. In the first picture, the set of tall people is depicted as a crisp set with a hard boundary between membership and non-membership at 1.80 meters. In contrast, the second picture shows the set of tall people represented as a fuzzy set where the boundary between membership and non-membership is graduated to represent partial memberships to the set.

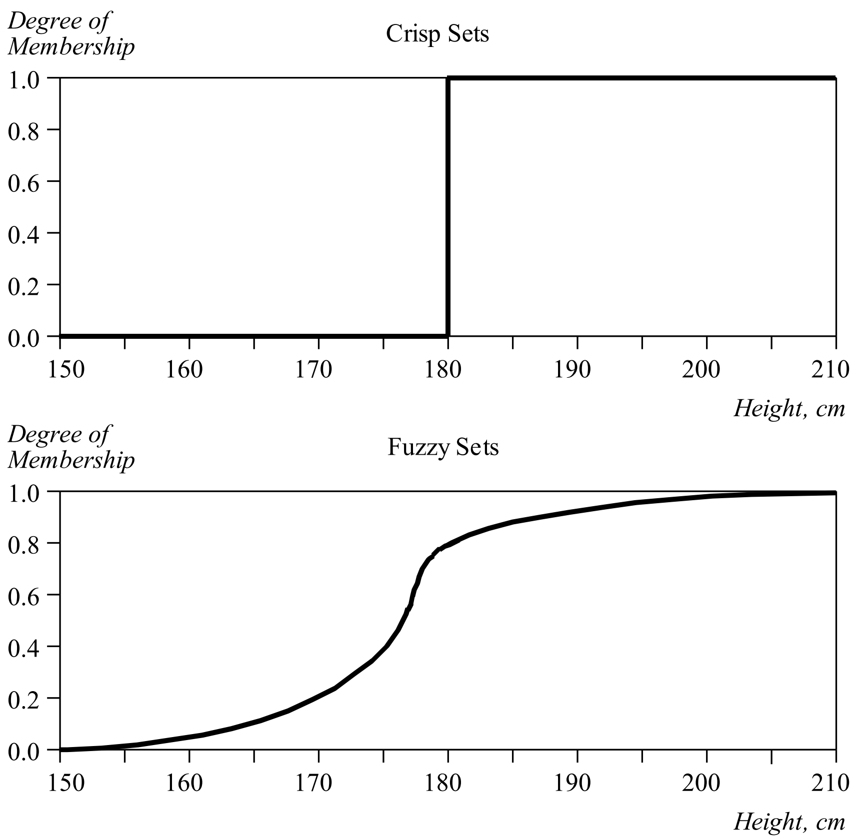


Figure 3.2 Crisp and fuzzy set representing "tall" people.

3.4 Fuzzy Logic Inference Process

A Fuzzy Logic System (FLS) provides a nonlinear mapping of inputs to outputs by converting linguistic information into mathematical information (Doctor 2005). An FLS, which can be described in terms of type-1 fuzzy sets, is called a type-1 FLS. The main parts of the type-1 FLS are shown in figure 3.3.

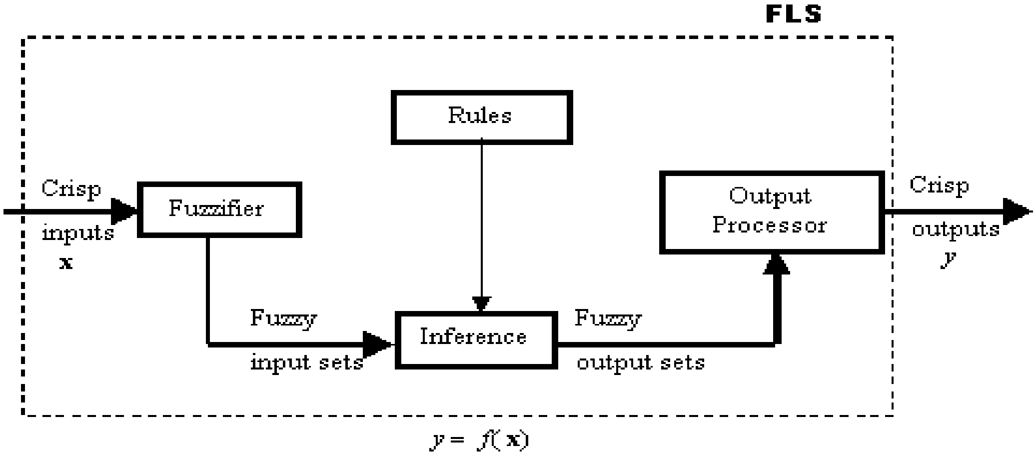


Figure 3.3 Type-1 Fuzzy Logic System (Mendel 2000).

A type-1 FLS contains four basic components: the fuzzifier, the inference engine, the rules, and the output processor. The fuzzifier is responsible for mapping a crisp measurement into a fuzzy number. The inference engine is responsible for the way the fuzzy rules are fired and combined to map input fuzzy sets to output fuzzy sets. Rules are if-then statements, which are provided by domain experts, or derived from numerical data. Finally, the output processor is the part of the system responsible for the defuzzification of the output fuzzy sets. Defuzzification is the production of a crisp output from a fuzzy set, and is crucial since, in the majority of applications, a crisp output needs to be obtained in order to be utilized in practical settings.

3.5 Fuzzy Logic in recent AC research

Fuzzy Logic has been extensively used in AC systems towards a variety of research purposes. The literature review in section 2 reveals a large number of AC related publications, which utilize Fuzzy Logic as the computational backbone of their research in order to recognize, model, or generate human-like artificial emotion expressions. In this section, we present recent examples of AC applications in several diverse AC domains.

Fuzzy Logic has been utilized as a tool by recent AC systems in order to recognize the user's affective state from a variety of different input signals. In the work by Nicolai et al., a facial emotion recognition system based on Fuzzy Logic was presented. This system utilized a two-stage approach comprising of an image processing, and an emotion recognition stage. Initially the system extracted the user's face, facial features and identifying points, relevant to each facial feature. These points were utilized in order to identify the strength of the user’s facial expressions. This strength was finally used to recognize the user's emotion (Nicolai 2015). A recent example of affect recognition from speech is the work by Ram et al. (Ram 2016). In their work, the team presented a fuzzy system for recognizing the emotional content of speech and their results yielded that hybridization of features using the proposed fuzzy inference system, can achieve better emotion classification accuracy, compared to other approaches. Gesture is another signal utilized as input by modern Fuzzy Logic based AC systems. In the work by Kar et al., the researchers presented an approach for recognizing emotion from gestural information. The team, with the help of a professional actor, trained their system to recognize different gestures, and also using the same actor, trained different individuals to perform gestures with a strong emotional expression. Their results were based on utilizing Microsoft's Kinect equipment and illustrated that their Fuzzy Logic based approach had a state of the art performance in gesture recognition, while at the same time retained minimum complexity (Kar 2013). As discussed in chapter 2, another input signal used by AC systems is the EEG signal. In a recent attempt to utilize the EEG signal, Matiko et al. developed a Fuzzy Logic algorithm to utilize EEG for classifying positive and negative emotions. They utilized previous work in the field of neuroscience stating that there is a correlation between positive and negative emotions and activation of the left and right hemispheres of the human brain (Matiko 2014) in order to construct the fuzzy rules of their model. They achieved an accuracy of 64%, which is notable compared to other computational approaches utilizing the EEG signal. Their algorithm also proved to be a lot faster than other popular approaches (Bayes and SVM based classifiers), thus making Fuzzy Logic a very logical choice for real time emotion recognition (Matiko 2014). Fuzzy Logic systems have also been used for affect recognition systems utilizing combinations of input signals. In Sokolova et al.'s work, an intelligent fuzzy decision making technique was used in order to perform multimodal emotion recognition. The team implemented a multi-agent architecture in order to capture different inputs such as: physiological signals from sensors (EDA, ECG, HR, ST); facial expressions captured by a vision agent monitoring the participant; and human behaviour and activities captured by a second vision agent monitoring the participant from above. The final emotion describing the user's affective state was a collaborative decision produced by the three agents (Sokolova 2015).

Fuzzy Logic has also been used by state of the art AC research as a means to represent emotion words in an emotional space, thus creating interesting models of emotions. In the work by Ayesh et al. the researchers tried to interpret computationally, different emotion theories and create generic, and application independent models. Namely, they have utilized Fuzzy Logic to computationally interpret the psychological theories of Sherer and Millenson (Ayesh 2015). Another attempt to create Fuzzy Logic models for representing emotion words was done by Kazemzadeh et al. (Kazemzadeh 2013). The issue that this paper addressed was the development of a computational model to represent the intentional meaning of emotional words. This resulted in mapping emotion words between vocabularies of the same or different languages. The researchers' approach to the problem was to construct two models, both using Interval type-2 fuzzy sets. In their models, an emotion word was represented by an emotional variable, and this word was mapped through an evaluation function to a region of an emotion space. This space for the first model was the valence, activation, and dominance space, and for the second model, the word was a vector of affirmation values over propositions. The team used different combinations of similarity and sub-sethood measures to translate from one vocabulary to another. The evaluation of the model's performance was done by comparing it with the performance of humans asked to perform the same task. The results demonstrated Fuzzy Logic's ability to capture, and model the inherent uncertainty concerning human emotion. In a similar work, Cakmak et al. utilized interval type-2 fuzzy sets in order to analyze a set of Turkish words related to emotion. In order to construct the necessary fuzzy sets, the researchers gathered data from users provided which arousal, valence, and dominance ratings describing each of the emotion words (Cakmak 2012).

Fuzzy Logic's potential has also been utilized in recent AC related work towards simulating and generating human emotions for virtual agents and robots. In the work by Leu et al., a robot was designed to be empowered with Ekman's Big Six set of emotions. When a new sentence was used as an input to the robot, the robot used the voice signal along with Google speech recognition to identify the sentence. The robot then produced an output to reveal its affective state. Every sentence caused changes to the six variables, which represented each of the Ekman's emotions, and a fuzzy algorithm determined the most significant emotion among the six, as the dominant emotion. Given this decision, an output sentence was chosen from the robot's database to match the detected emotion. This research simulated successfully how emotions can be influenced by input voice signals from the outside world (Leu 2014). In other recent AC research, Nanty et al. utilized the Pleasure Arousal Dominance (PAD) model of emotion, in order to simulate human emotions for a robot. The team used a Fuzzy Logic system responsible for controlling the emotions of their robot. The researchers achieved this by feeding the system with internal and external stimuli, and utilizing the system's output to define attractors in the PAD space. The experimental results of the team demonstrated that the emotion state of the robot evolved smoothly, and was congruent with the different situations occurring when the robot interacted with humans. Another interesting aspect of their work was that, by easily adjusting the fuzzy rules, it was possible to adjust the robot's personality (Nanty 2013).

3.6 Fuzzy Cognitive Maps introduction.

Many real world problems and applications consist of multiple components that interact and relate with each other in complicated ways. Through this dynamic interaction, real life problems grow and evolve continuously through time. Classical modelling approaches cannot support a successful modelling of real life problems and environments due to the inherent complexity and dynamic nature of these problems (Salmeron 2012). Modelling the affective trajectories of students in a dynamic environment, such as the modern classroom, is an example of such a problem. The imprecise and uncertain nature of emotion, along with the dynamics of affective transitions, as an individual moves through time, call for a methodology that allows effective dynamic representations. Fuzzy Cognitive Maps (FCM) are a combination of the principles and ideas of Fuzzy Logic and Cognitive Maps. By realizing this combination, FCM are able to model dynamic and complex systems with high degrees of uncertainty.

Fuzzy Cognitive Maps is a soft computing technique, which has been introduced in 1986 by Southern California university professor Bart Kosko as a tool for modelling and studying the behaviour of people and systems (Kosko 1986). Fuzzy Cognitive Maps are a modified version of the Cognitive Maps, which was proposed by American Psychologist Edward Tolman in 1948 (Tolman 1948). Cognitive Maps were a form of mental representation which allowed a person to obtain, code, store, recall, and decode information about the relative location and attributes of phenomena in their everyday, or metaphorical spatial environment. Fuzzy Cognitive Maps are modified Cognitive Maps, which enable their concepts to take fuzzy values, and to be connected with fuzzy degrees of interrelationships. The concepts of an FCM are usually the factors, which contribute to the behaviour of a system, and the connections between them represent their relations. Therefore, an FCM is a Cognitive Map with two important aspects. Firstly, the causal relations among concepts can be represented by a positive or negative number illustrating the intensity of a positive or negative relationship. Secondly, the system is a dynamic structure where the change in one concept can affect other concepts, which in turn can affect the initial concept. This fact provides FCM with a very important temporal aspect. An FCM is a signed directed weighted graph where the concepts affecting the behaviour of a system are the graph's nodes, and the relations between them are represented by the graphs weighted edges (Salmeron 2010). The weight of each edge is the number, which represents the type and intensity of the relation. It can take a positive or negative value in the [-1, 1] interval representing a negative or positive causal relation between the concepts connected. Where -1 would be a perfect negative and 1 a perfect positive relation respectively. As an example we can see in figure 3.4 one of the simple FCM models constructed by Lin et al. to represent the causal relations between the user's emotional status with play time, and achievements during their interaction with an educational game (Lin 2012).

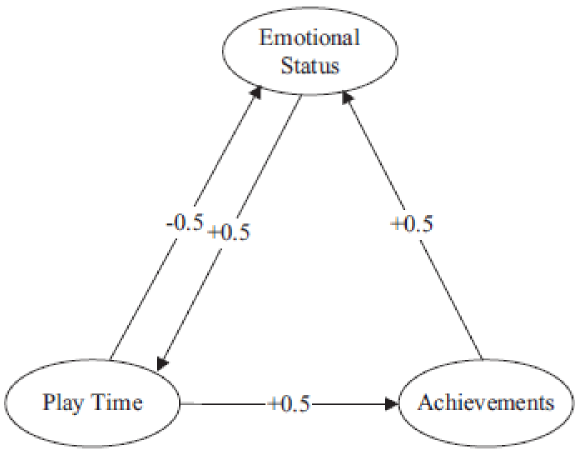


Figure 3.4 A simple FCM structure example (Lin 2012).

The structure of an FCM model can benefit from expert opinion, and human knowledge on the context of the system. Experts can define the concepts to describe the problem and the initial conditions of the FCM, based on their individual experience and knowledge of the subject. Fuzzy methods allow the selection of nodes and the assignment of the weights of the graph's edges to be exported from the combination of opinion, and knowledge of different individuals. A crucial advantage of the FCM methodology, flowing from integrating expert knowledge into the design of the FCM, is the simple and straightforward updating of the constructed FCM structure. This can be done easily by adding, or removing edges and nodes in the graph. Experience from the implementation and application of a system can be incorporated into its existing structure by simply adding or removing nodes/concepts or edges/relations, thus offering a better modelling approach of a problem. These features are very suitable for modelling student's affective trajectories in our research, since they allow opinions of individuals with different scientific backgrounds, to be taken into account in the construction of a system. Knowledge from different fields such as psychology, education, or computer science facilitates a better representation and integration of concepts and relations into the system at different stages of its construction. In addition, the FCM structure as previously mentioned can be easily extended to include factors that influence the students' affective trajectories, which may not be taken into account in the design of the original system.

An FCM structure contains N concepts (c_i is concept i) and is usually represented by a $N * N$ matrix. Let us call this matrix weight matrix W. Each element w_{ij} of this matrix is the weight of the edge of the graph connecting concept node c_i with concept node c_j.

$$W = \begin{array}{c} \\ c_1 \\ \vdots \\ c_n \end{array} \begin{array}{c} \begin{array}{ccc} c_1 & \cdots & c_n \end{array} \\ \begin{bmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{bmatrix} \end{array} \tag{3.2}$$

For example, the FCM model depicted in figure 3.4 has a weight matrix:

$$W = \begin{bmatrix} 0 & 0.5 & 0 \\ -0.5 & 0 & 0.5 \\ 0.5 & 0 & 0 \end{bmatrix} \tag{3.3}$$

The FCM inference procedure starts by providing a vector C that includes the values of the concept nodes at the first step of the algorithm $C^1 = (c_1^1, c_2^1, \ldots, c_n^1)$. Where c_n^s is the value of concept *n* in step *s*. Each concept's value in step *s*+1 is calculated by taking into account the influence of all other concepts at step *s*. This is achieved through equation 3.4, where f is a function responsible for scaling the values of the concept to the desirable interval. This process will continue until $c_i^{s+1} == c_i^s$ or until a threshold value is satisfied.

$$c_i^{s+1} = f(\, c_i^s + \sum_{\substack{j=0 \\ j \neq i}}^{N} w_{ji}\, c_j^s) \qquad (3.4)$$

Most commonly used activation functions are either the sigmoid function ($\mathrm{f(x)} = \frac{1}{1+\mathrm{e}^{-\lambda \mathrm{x}}}$, where λ is a constant representing the function's slope) and the values of the concepts may fall in the [0,1] interval, or the hyperbolic tangent ($\tanh(\mathrm{x})$) where the values of the concepts are allowed to take values in the [-1,1] interval (Salmeron 2012, Papageorgiou 2013).

The inference process of the FCM may terminate by reaching one of three possible final states. Firstly, the FCM can reach a state of equilibrium where the values of its concepts remain the same. This is called hidden pattern, or fixed point attractor. Secondly, the FCM can fall between several states when its nodes keep cycling through a loop of numerical values, this is called limited cycle. The third possible case is where the FCM will exhibit chaotic behaviour with each node's value changing in a random way. This state is called a chaotic attractor (Salmeron & Lopez 2011).

3.7 FCM applications in Affective Computing

The Fuzzy Cognitive Map soft computing methodology has been used as a modelling tool for a number of different applications in completely different fields. The diversity of applications demonstrates the dynamic and flexible nature of the methodology. FCM have been utilized in order to develop a number of different applications in: engineering and control (Salmeron 2010, Papageorgiou 2013); software engineering (Xiangwei 2009, Papageorgiou 2013); energy industry (Amer 2013); agriculture (Makrinos 2007); business and management (Lazzerini 2010); medicine (Froelich 2012); social sciences (Carvalho 2010); education (Georgiou and Botsios 2008); pattern recognition (Papakostas and Koulouriotis 2010); and time series forecasting (Homenda 2014). Towards affect modelling and Affective Computing purposes, a limited number of applications and models that utilize FCM have been proposed.

In Salmeron et al.'s research the use of FCM was proposed as a method for predicting artificial emotions and constructing an affective recognition system. The team used the Thayer's emotion model and tested their proposed approach with three simulated scenarios. The aim of their research was not to provide a modelling solution to a real world problem. Instead, the researchers focused at proposing a theoretical framework to enable future AC researchers to incorporate FCM as an emotion recognition tool in their applications (Salmeron 2012). In 2012, Lin et al. utilized an FCM based method in order to forecast student's affective state during their interaction with an educational game. In order to evaluate their model and observe the desired affect relations, the team ran simulations using different configurations of the FCM structure. In their paper, the team proposed an FCM based method to calculate student’s emotions by taking into account the dynamic interactions between student emotions, game time, and achievements during playing an educational game (Lin 2012). From the team's results, it was concluded that FCM can be utilized for modelling complex systems which contain reciprocal influences. The simulation process of the FCM demonstrated that emotions experienced by a player can be computed and predicted by this method. Extending on this work, Lin et al. presented another model in 2013, which used the FCM methodology and the OCC emotional model, in order to predict the user's feelings towards specific game actions and calculate their intensity. Internal goal desirability of the user, and external event consequence in the game world was used to predict the user’s affect (Lin 2013). It must be stated that their results were based by running scenarios where the FCM automatically produced a series of results to simulate an interaction between the system and the user. The construction of the FCM was based on a user study where the participants described what their feelings would be in respect to specific actions in the game world. In both cases (Lin 2012) and (Lin 2013) the constructed FCM models aimed at creating a simulation environment which allowed observations to be made, rather than producing emotion recognition results.

In the work by Akinci et al., an emotion modelling technique was presented, using the FCM approach to calculate arousal and valence values. In order to develop their model the researchers utilized the Big Bang - Big Crunch learning method. The results from different simulations, where the DEAP database was utilized, demonstrated that FCM is an effective methodology for modelling emotion (Akinci 2013). DEAP is a database containing the recordings of physiological signals from people watching video clips and reporting their emotions. In the paper by Buche et al., FCM were used in order to model affective states (Buche 2010). Each emotion was modelled by an FCM towards simulating the behaviour of autonomous entities in virtual environments. The results of the research team highlighted the usefulness of the FCM as a tool to specify and control individual agents, and supported the FCM as an effective methodology for modelling behaviour. Another attempt to use FCM in the area of Affective Computing was the development of a pedagogical Agent's affective interface by Torres et al. (Torres 2013). Their research was based on the design of a cognitive affective model, which was implemented by utilizing the FCM machine learning technique. Their model provided answers to what happens in the environment in respect to the cognitive and affective state of the user, thus resulting in an augmented human machine interaction.

3.8 Summary and conclusions

In this chapter the principles of Fuzzy Logic and FCM were presented as the core computational methodologies used in this Thesis. Recent research efforts conducted under the scope of AC, which utilized these methodologies, were reviewed. Moreover, the characteristics making these methodologies suitable for our research purposes were discussed in detail. More specifically, it was argued that Fuzzy Logic is a computational methodology able to handle uncertainty efficiently; has a low computational cost; reasonable accuracy; accounts for individual preferences; and permits the use of natural language thus allowing the development of interpretable models which reflect the knowledge hidden in data. This research deals with the inherent uncertainties concerning the complex notion of emotion. In addition, this research involves human data collection related to emotion modelling and recognition, which is subject to high levels of noise, uncertainty, and outlier artefacts. In the same time, it is important to construct interpretable computational models of emotion that reveal the underlying affect relations. For these reasons, Fuzzy Logic is a suitable methodology to base the proposed modelling approach. In this chapter, the author also discussed the ability of FCM to create effective representations of dynamically evolving environments and incorporate expert knowledge, thus allowing FCM to easily update and expand. The affective state of the student is a dynamically evolving process. It is affected by various factors that can be accounted for with the use of human knowledge and experience. As a result, modelling student's affective state calls for a robust computational technique, and it can largely benefit from human experience and knowledge. For these reasons and given the methodological advantages of FCM described above, FCM was chosen as a suitable ML technique to model student's affective transitions.

Chapter 4 Methodology

4.1 Introduction

In order to explore the research questions (as specified in section 1.3) the author adopted a positivist research philosophy, where knowledge was obtained through structured data collection and quantitative data analysis. According to positivism the world is external (Carson 1988) and "there is a single objective reality to any research phenomenon or situation, regardless of the researcher's perspective or belief" (Hudson 1988). In this Thesis, the role of the author was to gather and interpret objectively the obtained data with the use of statistical tests and machine learning techniques, which are able to produce observable and quantifiable results. In science, quantitative research can be defined as the systematic empirical investigation of observable phenomena via statistical, mathematical, or computational techniques (Given 2008). These principles guided the research process followed in this Thesis into creating a structured approach that was highly dependent on popular quantitative research methods, including for instance: experiments (online surveys, tutorial learning sessions etc.), correlation and regression analysis methods (Pearson's coefficient, Chi Square statistical tests, Linear Regression etc.), and other ML techniques (custom FL techniques, Neural Networks etc.).

In this chapter, the author presents the research methodology, and provides a detailed overview of the research process followed. The research is divided into three key phases. Each research phase built upon the findings, emotion model, computational approaches, and experimental settings of the previous phase. Moreover, the overall research process is outlined, and all the choices made to achieve the research goals are supported with evidence. In the first phase, the focus was to explore the Affective Trajectories (AT) hypothesis. More specifically, the emotion theory of Affective Trajectories hypothesis as presented by Kirkland et al. (Kirkland 2012) was extended, by proposing a novel personalised AT model of emotion. An adaptive fuzzy computational technique was proposed to model this new representation, which achieved an improved performance compared to the original fuzzy method it relied upon (Online Adaptive Fuzzy System- AOFIS) (Doctor 2005). Finally, during this phase a framework for AC applications was proposed, which offers a new computational model of emotion with a reasonable trade-off between accuracy and complexity. In order to realize the aforementioned goals, an online survey was conducted, which was able to elicit affect related information from the participants. The novel design of the survey extended on the experimental approach of Kirkland et al. by introducing a scenario based structure and providing the participants with tools (sliders) to accurately report their emotions. In the second phase the AT hypothesis was extended by introducing a new representation of emotion, called the AV-AT model. By proposing this novel emotion representation, and by enhancing the computational mechanism of the first phase, the author opted to create a computational model of emotion for AC researchers. This new model aims to overcome the limitations of other emotion representations such as the aforementioned AT, or the AV models of emotion without the overwhelming cognitive burden of complex models of emotion (such as the IR model (Cunningham 2013)). The AV-AT framework was tested through the development of a personalised learning system that was applied in two tutorial sessions. Finally, in the third phase of this research the researcher tested a novel approach which incorporates the AV-AT model, and the affective transitions one experiences during learning tasks, into a design which monitors and models students' affective trajectories. This model extends on previous work by Lin et al. (Lin 2013) since it utilizes affect transition information for online affect recognition, rather than simply running simulation scenarios (section 3.7). Moreover, the proposed model extends on Metallinou et al.'s work (Metallinou 2012), since it takes into account only past observations in a real time educational context (instead of both past and future observations relying on an artificial dataset, as can be seen in section 2.10). The developed model also utilizes a novel hierarchical system that comprises of an adaptive fuzzy rule base system, and an FCM. Every research phase was based on key structural components, which were consistently implemented. These include five steps, which can be seen in figure 4.1: emotion model, data collection, statistical analysis, computational methodology, and AC framework. The methodological steps followed, although unique in order to enable pursuing the research objectives, also relied upon well-established research in the area of AC. In the very influential paper of Kazemzadeh et al., the researchers proposed a similar methodology for developing a vocabulary of emotion words for translating between different languages. The researchers initially proposed two models. The first model was based on valence, activation, and dominance values, and the second model was based on users answering a set of open-ended questions from the game of Emotion Twenty Questions. Following the model's selection, two online surveys were conducted in order to collect the necessary data so as to create the models and study the underlying affect relations. Fuzzy Logic based approaches were then utilized to computationally represent the emotion words. Finally, the constructed models were used to deal with the translation between emotion vocabularies (Kazemzadeh 2013). An overview of the research methodology followed in this Thesis is described below.

The initial step for each one of the three key phases was to propose an emotion model. More specifically, in the first phase of this research process the emotional model was a contextualized and personalised version of the AT hypothesis. In the second phase, the AT hypothesis was enriched to combine with the Arousal Valence representation of emotion, thus proposing a novel emotion representation, the AV AT model. In the third phase, a model of emotion specifically designed for students was proposed, which comprised of inner basic affective elements such as arousal or valence elements, and outer factors of their affective trajectory through time, such as the transitions between affective states. This model combined the previously introduced AV-AT model of emotion, with the affective transitions a student experiences while performing collaborative learning tasks.

The second step, which was also common for each of the three research phases, was to collect the necessary data. For phase 1, data collection was achieved with the help of an online survey. In phase 2, data collection comprised of a second online survey following the design of the first one, along with two tutorial sessions, where groups of students were involved in collaborative learning tasks. The data collected in the second phase were also utilized towards achieving the research purposes of third phase. In the first phase a statistical correlation analysis was performed on the online survey data in order to explore the AT hypothesis' underlying affect relations when used in an educational context. In phase 2, there was no need to perform a separate statistical analysis, since the proposed AV-AT model relied on the already proven affect relations of the AV and AT models. The AV representation is a model already explored in previous research (Russell 1980) (Russell 2003), and the AT was investigated in the first phase of our research. In phase 3, the data collected from the tutorial sessions were used for conducting statistical analysis in order to observe the affective transitions of students while they were engaging in collaborative learning tasks.

A focal point in every phase of the research process was the design of the computational approach used in order to model the suggested emotion representation. In the first phase the personalised version of the AT hypothesis was modelled using an adaptive fuzzy method. This method was a two-stage fuzzy rule base classification system, resulting from the modification of the design and mechanism of well-established fuzzy techniques. In the second phase, the AV-AT model was represented with an enhanced version of the previously developed adaptive fuzzy approach. The fuzzy method's internal parameters were enhanced with the help of a genetic algorithm, in order to improve the fuzzy system's performance when compared to the original version. In the third phase, this enhanced version of the fuzzy method was used in combination with an FCM system to create a computational methodology to model and monitor student's affective trajectory during learning tasks. In every phase, the proposed emotion representation along with the computational approach developed to model it, was tested, and evaluated in terms of its ability to accurately predict values of emotional labels to describe the user's affective state.

Finally, at the end of every phase, a framework for practical implementation of each of the emotional models and computational approaches was provided. An overview of the research process can be seen in figure 4.1 where the different steps for each one of the research phases can be seen. In the following sections of this chapter, the author describes in detail the design choices and methods used in each of these steps for every consequent research phase towards achieving the research objectives.

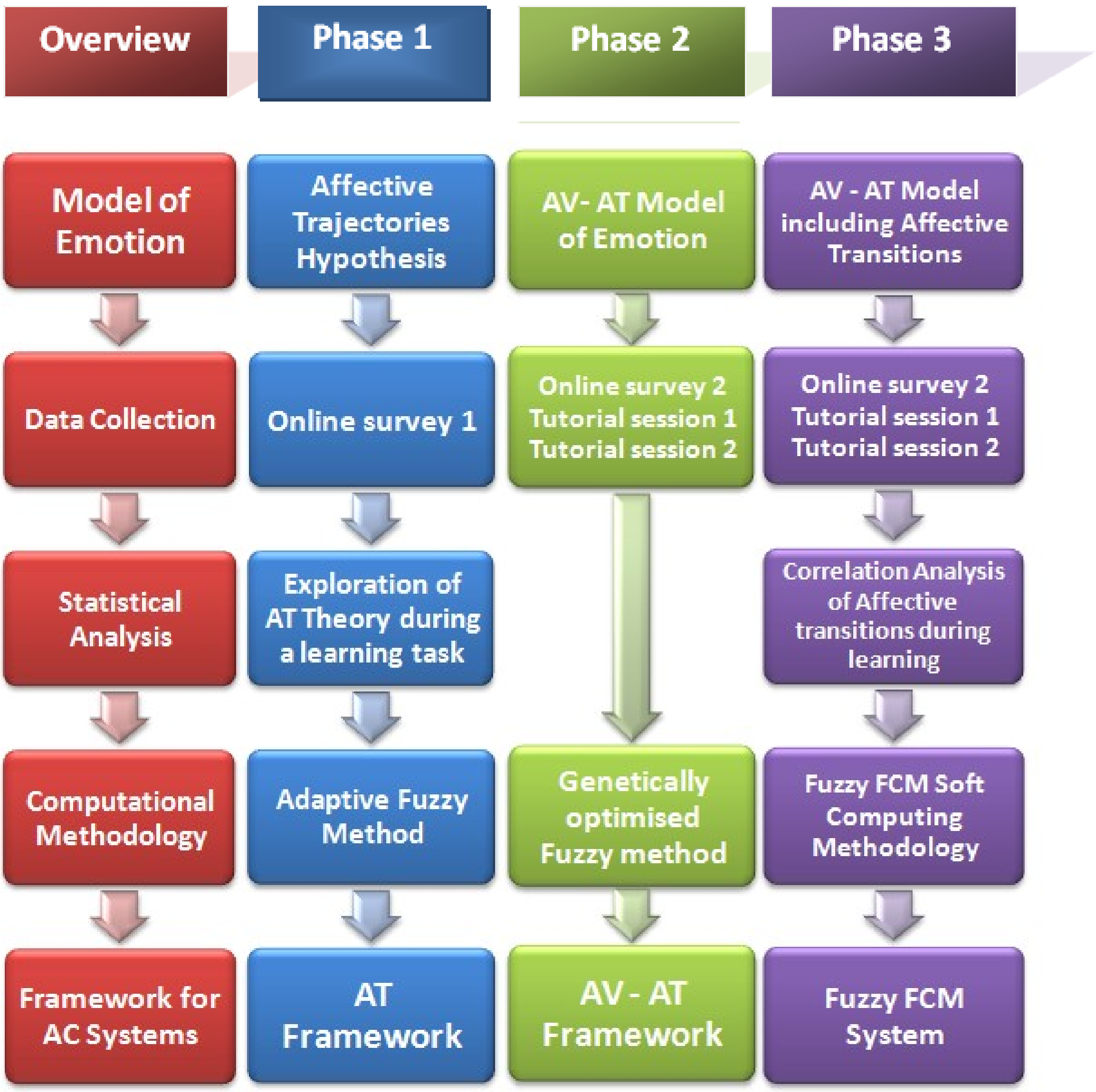


Figure 4.1 Research overview.

4.2 Phase 1-Affective Trajectories Hypothesis Model

The first phase of the research bears the importance concerning the methodology that was followed, and the design choices made during the entire research process. All other phases built upon this phase's basic design choices in terms of emotion representation, data collection methodology, computational approaches and the proposed frameworks for affective computing systems.

The AT hypothesis which was under investigation during this phase, is a relatively new psychological framework offering a new perspective on emotion representation. AT hypothesis relies on the differentiation between emotions through the use of core, and easily comprehensible basic affective elements, such as our current state, predictions about the future, and evaluations of the outcome we experience, after making these predictions. To the best of the researcher's knowledge the AT hypothesis has not been used before in AC systems. Nevertheless, its simplicity is a considerable factor highlighting AT's potential for supporting the development of applications in the area of Affective Computing. Additionally AT is an approach, which fits very well in the education process. Providing predictions and evaluations, what someone expects and what ultimately happens is very closely related to the process of learning and the formation of the student's affective state. As a result, this kind of emotion representation is promising, especially for contributing to the construction of effective personalised learning applications.

However, an extensive research process was needed before reaching the point in time when the AT framework could be applicable in a specific educational setting. " The original work from Kirkland et al. needed to be extended to include various contextual and user specific aspects. Firstly, only a set of emotions related to Ekman's Big Six, was studied under this AT perspective. The team explored how the emotions of ‘fear’, ‘hope’, ‘joy’, ‘sadness’, ‘anger’, ‘surprise’, ‘content’, ‘disgust’ and ‘none’, were formed from combinations of the AT's basic elements. Yet, these emotions are shown not to relate to the educational process, as mentioned before in the literature review chapter (section 2.8), and as a result they are not well suited to be emotions which could be potentially used for promoting the student's wellbeing as part of an AC system. As a result, the researcher opted for a set of emotions, which are suitable for achieving the goals of this research. These emotions should be relevant to the learning procedure, in order to aid at observing the underlying affect relations with the AT's basic elements. Moreover, these emotions could serve as the target emotions in an AC system. A second aspect of Kirkland's work that needed to be modified was that the experiments of the research team were context free, which is logical if we consider that at that point the AT theory was presented for the first time and needed to be validated as a generic emotion modelling approach (Kirkland 2012). However, the context an individual is currently in, is a major factor in the construction of their affective state. For this reason, testing of the theory in a specific context such as education, was a mandatory step before proceeding with modelling and utilizing this theory in a system. Another aspect of previous work, which was extended is personalization. The original theory was extended to include individual differences. The AT elements may be used by individuals to differentiate between emotions but the way every individual combines these elements can be highly personalised. For example, having positive expectations about an upcoming learning activity differs significantly in terms of shaping the levels of engagement across individuals.

The starting point was to select an education related set of emotions, which would support the exploration of the AT hypothesis, and it could be potentially used by a personalised learning system. " The set of emotions that was used during this phase, and was consistently used throughout the entire research process, consists of the following emotions: ‘flow’, ‘excitement’, ‘calm’, boredom’, ‘stress’, ‘confusion’, ‘frustration’, and ‘neutral’. As mentioned in chapter 2, the aforementioned affective states have a strong relation with learning, and therefore are suitable for the purposes of this research. ‘Flow’, for instance, is a state where the student demonstrates high involvement and interest in learning tasks; hence, it is positively correlated with learning (Csikszentmihalyi 1990). Confusion is an emotion that has been identified to occur frequently during learning tasks, indicating a state of cognitive disequilibrium, which has a positive effect in learning (Craig 2004). In Craig's research, boredom and frustration have also been determined as affective states which impact negatively upon the efforts of students. In addition, ‘stress’ is another state, which is frequently associated with students. Numerous reasons account for this, as pointed out in chapter 2, including lack of structure in the delivery of the learning material, the heavy burden of exams, having demanding assignments to complete, receiving cumulative failure feedback, and the consequents of achievement (Zeidner 1998). On the other hand, ‘calm’, is identified as having the opposite meaning of ‘stress’, representing a state of peace of mind for the student. ‘Excitement’ is another emotion in the subset of the selected emotions, and it can be described as a very high arousal positive state, equivalent to delight, as used in D'Mello et al.'s research (D'Mello 2007). The ‘neutral’ state has been used before in Baker et al.'s research (Baker 2007) and it accounts for the diversity of affective states of the student (such as a possible moderate arousal and valence state).

With the help of the chosen set of emotions the AT hypothesis was explored in an educational context. The researcher aimed at illustrating the underlying affect relations to observe the way basic AT elements combine in order for an individual to choose a label to describe their affective state from the set of emotions presented above. It was also important to demonstrate the role of individual differences in the construction of an affective state, since they account for a core part of our research objectives. A computational approach was created to model these affect relations so that they could be used by a personalised learning system. It was also desirable for the proposed computational technique to have a reasonable performance in mapping those basic elements to emotional labels, but at the same time also aid in the exploration goals of this research. Hence, to enable visualizing the underlying affect relations, and to demonstrate the importance of individual differences in the construction of emotional processes. An overview of the methodology followed in this phase can be seen in figure 4.2.

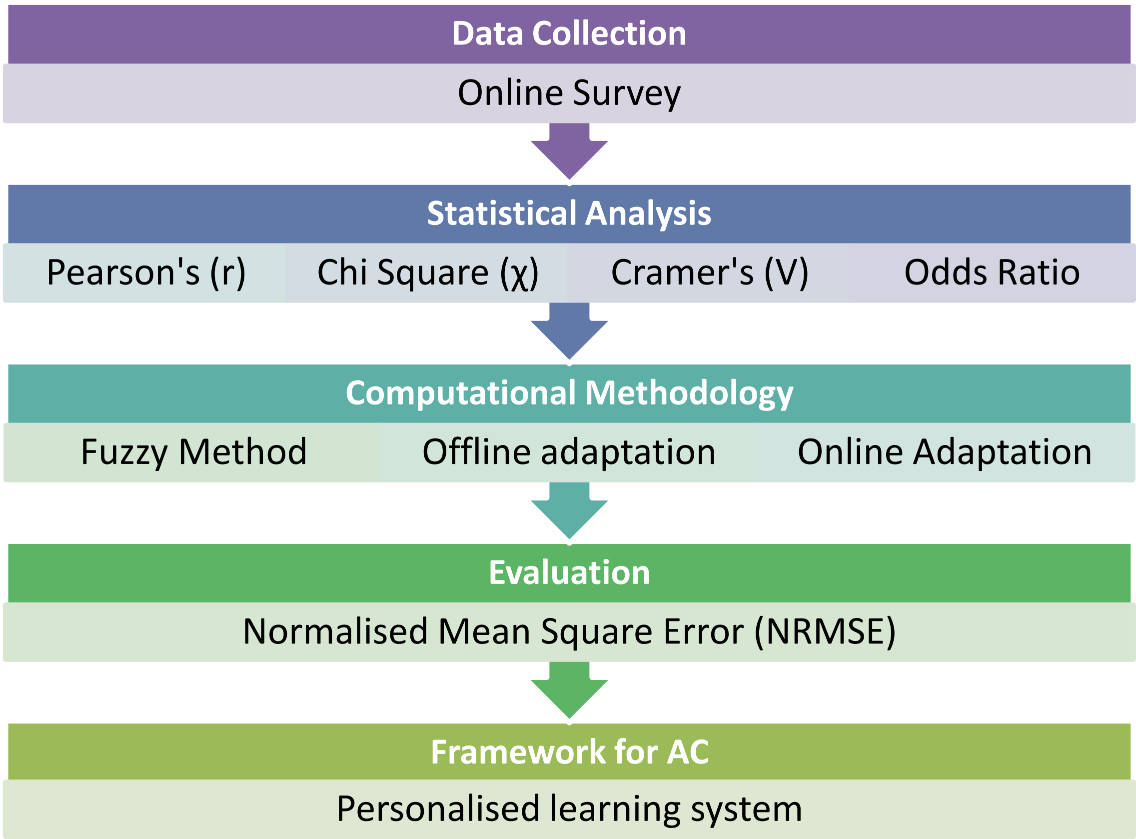


Figure 4.2 Phase 1 Methodology overview.

4.2.1 Phase 1 data collection methodology

In order to achieve the goals of exploring the underlying affect relations and creating a computational model based on the AT theory, data collection was conducted with the use of an online survey. More specifically, the online survey aimed at answering the following research questions.

- Is the AT theory applicable in an educational context?
- Which are the underlying affect relations between the AT's basic elements and the eight emotions chosen in this research?

- Can the AT theory be extended to include individual differences in the construction of emotion processes.
- Is the adaptive fuzzy technique proposed in this phase able to model the affect relations and reflect individual differences?

This survey relied on the previous work of Kirkland et al. on the Affective Trajectories hypothesis, yet the overall design of the online survey was unique in order to fit in an educational context. In their research (Kirkland 2012) the team used two user studies containing very basic and context free lemmas, where the AT's basic elements (current state/valence, prediction, and outcome) varied systematically, and the user was asked to score these different combinations against a list of eight emotions. More specifically, in the first part of Kirkland's experiments, the participant was presented with a combination of their current state and their prediction, and they chose among 8 emotions, while at the second part the outcome was described, and the participant was asked to provide another value to describe their state. A scenario example as used in (Kirkland 2012) was *"You are feeling good. You predict something bad is going to happen.... Instead of what you have predicted, something far better happens"*. Kirkland's team used a total of 18 scenarios, each one representing a different combination of the basic elements (bad/good current state, positive/negative/neutral prediction, and worse/better/as expected for the outcome). During the first study, the participant was able to choose only one emotion, while in the second one they were able to choose more than one emotions to describe the affective state fitting best in the scenario they were presented with.

This design was modified to better simulate a real life situation, in order to aid the user in immersing themselves into the scenario. Additionally, the scenarios were tailored to fit in an educational context, in order to elicit education related affect information. During this survey approach, the participants were presented with scenarios, which described common situations occurring in modern educational settings (e.g. a supervisory meeting, a group project). These scenarios aimed at inducing the eight education-related emotions (flow, excitement, calm, boredom, stress, confusion, frustration, and neutral) which as described in detail in section 4.2 are in close relation with the learning experience. The participants were asked to imagine themselves as taking part in the scenario. The scenarios were divided in two stages. These stages were shown to the participant sequentially. In the first stage, the beginning of the scenario was presented to them, and in the second stage the outcome of the scenario was described. Eighteen scenarios were used in order to represent all the different combinations of the basic elements (current state, prediction, and outcome). Every scenario aimed at representing different combinations of the basic elements. It is argued that the emotions under investigation are more likely to be elicited through scenarios where the participant plays a more active role, or even relives certain scenarios, rather than be presented with context free situations. This way, the participants will be able to provide more objectively an estimate of their affective state.

The online survey was completed by 89 participants and their demographic information can be found in table 4.1. This number of participants is adequate to investigate the research questions considering the fact that is greater than Kirkland's, who used 40 and 31 individuals to validate his studies (Kirkland 2012). Participants were volunteers with a minimum educational experience of undergraduate studies, in order to be able to relate strongly with the scenarios presented in the survey. It is important to note the author managed to obtain a population of individuals with different cultural backgrounds as it can be seen in figure 4.3 were the country of origin of each participant is illustrated. Culture, as mentioned before, is a contributing factor in the construction of emotional processes, therefore having a diverse population sample to account for individual differences at this early stage was favourable for this research. Every participant was given detailed guidelines for completing the survey, which can be found in Appendix A. Since a significant number of the participants were not native English speakers, detailed descriptions for the emotions and the basic elements were essential. The researcher also intended to minimize the effect of triggering, and connecting possible strong positive or negative experiences that may have occurred in the participants' personal lives. Therefore, it was appropriate to avoid mentioning specific subjects (e.g. math).

Table 4.1 Demographic Information for Survey 1.

Demographics		**Frequency**
Gender	Male	50
	Female	37
	Not disclosed	2
Age	18-24	9
	25-34	51
	35-44	15
	Over 44	14
Total Participants		89

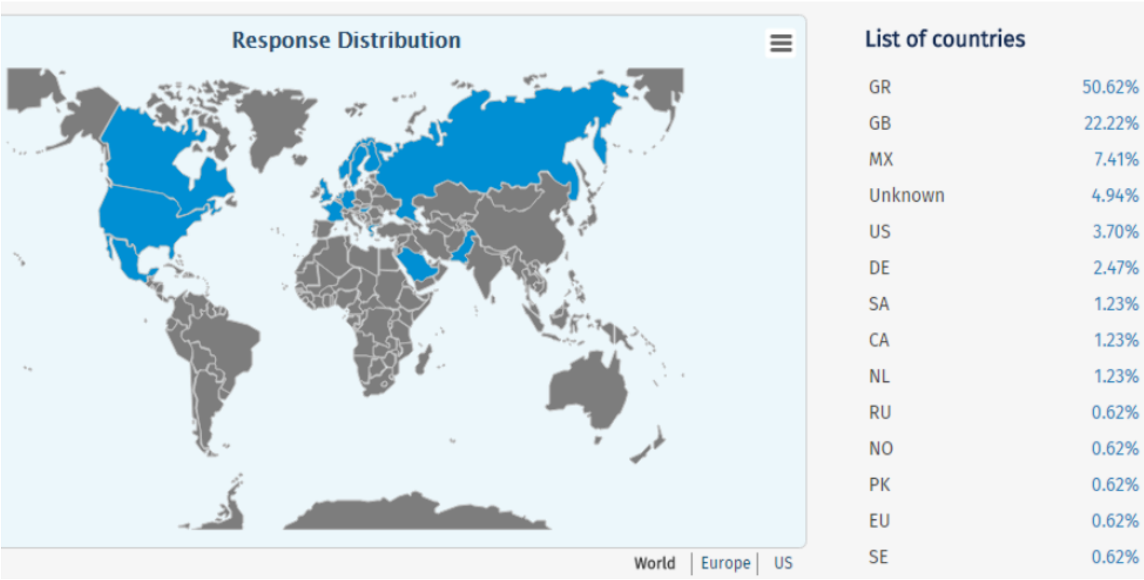


Figure 4.3 Population of the online survey.

During each stage of the survey, the participants rated the basic elements related to the specific stage (current state and prediction for the first stage, and outcome for the second) and the eight emotions by using sliders. In Kirkland's work, in the first study, the participant only chose one emotion using a radio button, and in the second one, they were able to choose more than one emotions, and provide a rating from 1 to 7 (Kirkland 2012). In this research, the participant had the freedom to provide a more accurate estimate of their affective state with the help of the provided sliders. The participants rated the basic elements and the emotions on a scale from 0-100. In congruence with Kirkland's second study, the participant was allowed to choose and rate as many of the emotions as they wished. As suggested by Barrett et al., given a certain emotional state, we impose a label that then allows that state to be consistent with the chosen label (Barrett 2009). However, it is possible that an individual may choose to interpret and describe their affective state with multiple labels. In fact, a student currently in a general positive mood may experience an affective state which includes the elements of flow, excitement, and calm, altogether. This design choice could also be considered in accordance to Plutchik's perspective, where more complex emotions arise from the combination of more basic emotions (Plutchik 1980).

4.2.2 Phase 1 statistical analysis

The research objectives of this phase included the investigation of the AT hypothesis in an educational setting. The author aimed to observe significant relations between the set of the eight aforementioned emotions and the basic AT elements, and explored if some of the emotions were more or less related to specific aspects of the affective trajectory of the student in time. For example, stress can be a prediction related emotion (a negative prediction about the future may cause stress to the individual) and excitement can be a positive outcome related emotion (we are excited when something great happens). If such relations were to be observed and demonstrated, then the utilization of the AT theory as a modelling technique for students' emotions could be justified. Firstly, in order to assess the relations between the AT basic elements (current state/valence, prediction, and outcome) and each of the emotions, the Pearson's correlation coefficient was calculated between values of emotions and values of prediction, current state and outcome provided by the participants in the survey. Pearson's coefficient is a measure of the correlation between two variables and provides values in the interval [-1, 1] where -1 is a perfect negative and 1 is a perfect positive correlation (Field 2013). For example a value of $r = 0.7$ between flow and prediction suggests there is a strong positive correlation between the two, meaning that a student is engaged and interested when making positive predictions about the future. Aiming to provide a better visualization of these affective relations, the scale variables provided in the survey were transformed to categorical ones. In order to perform this transformation, three distinct categories were defined for our three basic elements (current state, prediction, and outcome). The cut points were at 33.3% and 66.6% of the provided values for each element, and the corresponding categories were labelled as ‘negative’, ‘neutral’ and ‘positive’ respectively. Two categories were defined for each of the eight emotions used in this research: either ‘feeling’ or ‘not feeling’ the specific emotion. As "feeling" was considered the case where the participant provided a value for a specific emotion that was above zero, thus demonstrating presence of that emotion, and “not feeling” the case where the provided value for the emotion was zero. For this transformed data, the Chi Square statistic test, the Odds Ratio, and the Cramer's Statistic test (V) were calculated. These statistics are known measures, which demonstrate the strength of the relation between nominal variables. Chi-square test is a statistic that allows the observation of a relationship between two categorical variables and it relies upon the comparison between the observed frequencies and the frequencies expected by chance (Fisher 1922, Pearson

1900, Field 2013). Cramer’s V measures the strength of association between two categorical variables. Cramer is applied when the chosen variables contain more than two categories each. Cramer’s V is an easily interpretable measure, however a simpler way to report effect size for categorical data is the Odds Ratio (Field 2013). This "categorical" view and additional statistics allowed a better observation of the association between emotions and aspects of an affective trajectory.

4.2.3 Phase 1 computational methodology

The role of the suggested computational approach was three-fold. Firstly, a classification system was needed for mapping the AT's basic affective elements to emotions with a reasonable accuracy for the recognition purposes of an AC system. Secondly, this approach needed to be transparent concerning the underlying affect relations, so the application of the AT theory in the educational context could be demonstrated. Finally, the chosen ML approach needed to demonstrate the role of individual differences, which is a critical point in this research. The approach proposed was the development of an adaptive FL method. With the help of the survey data, fuzzy sets and fuzzy rules were extracted in order to depict the affective concepts and demonstrate their interrelations. As mentioned and shown in chapter 3, Fuzzy Logic is a proven methodology for modelling and handling the uncertainties of complex modelling problems, and vague notions, such as human emotion. Thus, Fuzzy Logic is able to account for the intra and inter personal uncertainty concerning the construction of emotion processes, and the inherent vagueness concerning the notion of emotion and its structural elements. In addition, the ability of Fuzzy Logic to model the relations in the data by producing interpretable rules allows the extraction of knowledge concerning the affective relations, thus satisfies the need for a transparent model, which demonstrates the emotion theory. As a result, FL was a logical choice to base the proposed approach.

More specifically the knowledge extraction and adaptation method was based on the adaptive online fuzzy inference system (AOFIS) described in (Doctor 2005). This data driven fuzzy technique was developed and used successfully for supporting the activities of users during their interaction with intelligent inhabited environments. By using the AOFIS, the user's learned behaviours can be adapted online, offering personalised services to the user. The design of the knowledge extraction of this technique relied in two well established clustering and data mining approaches. The first one is the advanced Wang Mendel method (Wang 2003) which is a flexible fuzzy system's approach to data mining. The second one is the Fuzzy C-means clustering algorithm (Bezdek 1981), which is a method of fuzzy clustering, frequently used in pattern recognition. The AOFIS fuzzy modelling methodology was modified in a number of ways in order to fit the research purposes. Firstly, the adaptive mechanism was changed so that individual differences are magnified in the construction of emotional processes. This is a very important choice, in order to highlight the personalised nature of the problem. Secondly, the method for constructing the fuzzy sets and rules from data, and the inference procedure of the developed fuzzy system were modified, so that they rely solely on the position of the centers of the fuzzy sets. This design choice promoted the construction of a model where the level of information is quantified as the number of fuzzy sets used to represent it. For example, if three fuzzy sets are used to describe our predictions about the future, we can observe how an emotional label is formed given a negative, neutral, or positive prediction. Finally, the author suggested the utilization of the modified fuzzy adaptation method in two ways, offline and online. Online adaptation refers to the adaptation process occurring when a user interacted with the fuzzy logic system, and they were able to provide values of the emotions when they were not happy with the results. In addition, there is an offline adaptation process, which was performed by providing the user responses from the online survey to the system as desired changes. This offline adaptation process caused the necessary changes to the system, thus allowing it to be more tailored to the user's preferences, before the system went online.

4.2.4 Phase 1 Evaluation Methodology

The online survey's data were utilized to test the suitability and performance of the fuzzy computational approach to model the AT theory. The performance of the fuzzy technique was evaluated with and without the adaptive part. More specifically, the performance of the fuzzy technique without the adaptive part was tested by comparing it to a number of other popular ML techniques, at mapping values of the basic elements to values of the eight aforementioned emotions. The values provided by each system, were scale variables ranging from 0 to 100. The Normalized Mean Square Error (NRMSE) was chosen as the appropriate measure to evaluate the accuracy of each system. The NRMSE is a measure which is frequently used in order to assess the classification accuracy of different models, and represents the sample standard deviation of the differences between the models predicted values, and the real observed values. In order to assess how the results generalize to independent data, and how this approach performs, the systems' classification accuracy was calculated by using ten-fold cross validation. It is important to remember that one of the research goals was to retain a degree of interpretability so a small number of five sets were chosen to be utilized by the fuzzy method. The smaller the number of fuzzy sets used to describe a problem, the more interpretable the extracted fuzzy rules are.

The stability and performance of the adaptive part of the system were evaluated by using the responses of a participant in the survey as desired changes to the pre-trained systems predicted values. The data samples from a single participant were extracted from the dataset, and presented one by one to the system. Then the system used its adaptive mechanism to make the changes to its fuzzy rule base. Again, by using the NRMSE error, the performance of this approach was compared to the performance of the adaptation mechanism of the AOFIS technique for different numbers of fuzzy sets. Additionally, the performance of the system was also compared with and without its adaptive part. The adaptive mechanism was designed in order to reflect the role of individual differences. As a result, a direct comparison between the two systems would offer an insight in the importance of individual differences and preferences in the construction of emotional processes.

4.2.5 Phase 1 AC Framework and proposed system

In every phase of this research, the author provided a framework for practical utilization of the proposed emotion model, and suggested computational technique. During this initial phase, a basic implementation of a personalised learning system was presented, which utilized the AT theory and the suggested adaptive fuzzy mechanism. This implementation could be used as a benchmark for any personalised learning system willing to use the proposed approach.

This step was essential to accomplish the research purposes because it enabled the identification of a suitable educational context to accommodate the AT hypothesis, and the associated fuzzy mechanism. Collaborative and Problem Based Learning (PBL) (Barrows 1996) were chosen as a suitable educational context. This approach is a student-centered pedagogy, where learning is reinforced through engaging in problem solving activities. In this approach, the tutor acts as a facilitator, supporting and guiding the students' efforts. Additionally collaborative work is promoted, since students work in groups, towards finding feasible solutions to the problematic situation. Modern pedagogical frameworks provide more opportunities for interaction with new intervention technologies where both the student and the tutor are to benefit. Additionally, the structure of the proposed emotional model itself relies in the ability of the system to capture the predictions and evaluations of the students. For this reason, the author suggested the division of the learning sessions, where this kind of system is to be applied, into a number of different activities (a game, a group project, a discussion etc.). The start and the end of each activity are the points in time where the prediction and outcome values can be acquired, and the system is able to provide its results and the necessary feedback. This is consistent with the principals of Activity Led Learning (ALL), which is a pedagogy that falls into the context of PBL while at the same time the focus point of learning is the activity (Wilson-Medhurst 2008).

4.3 Phase2 AV-AT model of emotion

During this second research phase, the AT theory was extended and a novel mixed representation of emotion was presented, called the AV-AT model of emotion. This emotion model is a two stage approach which combines the elements and ideas of the AT hypothesis and Russell's arousal-valence core affect. The AT hypothesis was proven to be a promising approach from the first phase of this research, and the AV representation of emotion is one of the most widely used models in the literature. As a result, the combination of the two models in order to provide a new emotion representation seemed very promising. Main goals and objectives of this phase were to provide evidence of the effectiveness of this novel emotion representation. Moreover, the necessary computational tools were developed, in order to model this representation of emotion effectively. Finally, the goals of this research included presenting a framework utilizing the aforementioned methodology, while at the same time objectively testing, and evaluating its performance. The creation and application of a novel affect modelling approach was a very challenging process. In this section, an overview of the process followed is provided. For consistency purposes, the same set of emotions was used as in the previous phase.

The first step of this phase 2 process was to collect the data in order to explore the model itself, and allow the construction of the computational model. This was achieved through an online survey. The survey data were used in order to observe the affect relations and model them using an enhanced version of the fuzzy technique discussed in the previous phase, into a fuzzy rule base. Initially, a fuzzy rule base was extracted from the online survey's data set, reflecting the preferences of the entire population. This data were then utilized in order to calculate optimal parameters for the constructed fuzzy system. Relying on the findings and suggestions of the first phase of this research, the author aimed at creating a model to reflect individual differences. This was achieved by making use of the adaptation (offline adaptation) capabilities of the proposed fuzzy approach, and thus enabling the system to adapt to the responses of a specific participant of the survey. After this process, a system was developed utilizing the personalised rule base. This system allowed the evaluation of the presented modelling approach in a real educational setting. The system, and consequently the emotion modelling approach were tested through the system's deployment in two tutorial sessions. The first tutorial aimed at exploring the performance, user friendliness, and applicability of the model, while the second was designed to objectively check the classification accuracy of the proposed methodology. An overview of the research process followed during this research phase can be seen in figure 4.4.

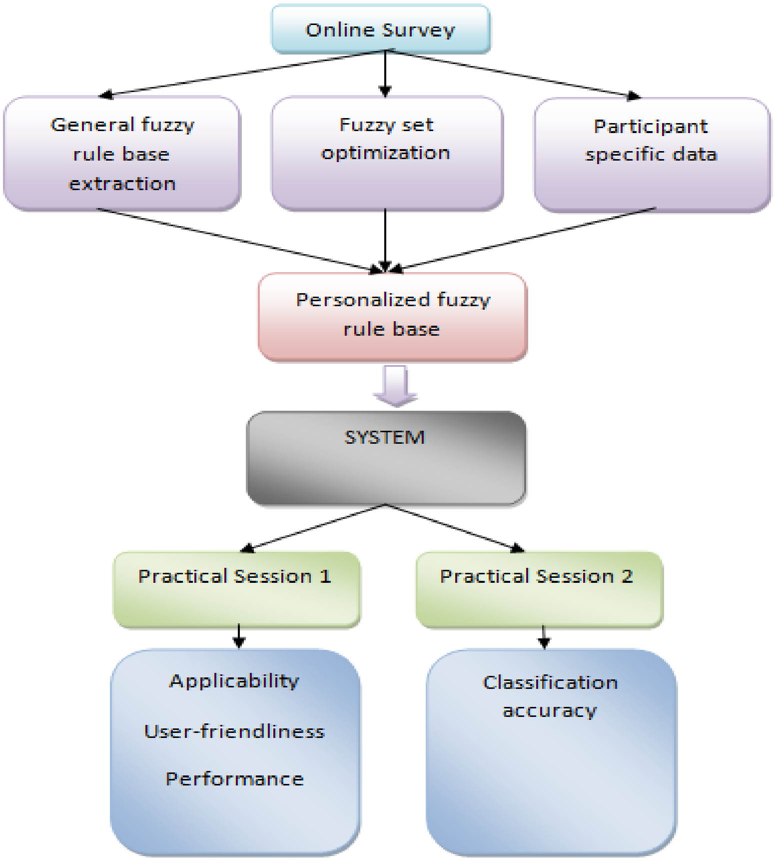


Figure 4.4 Phase 2 Methodology overview.

4.3.1 Phase 2 Data Collection Methodology

The necessary data for phase 2 were provided by an online survey and two practical tutorial sessions. The online survey aimed at answering the following research questions:

- Is it possible to extend the AT theory and introduce a novel emotion representation (AV-AT) to be applied in an educational setting?
- Does the AV-AT enable users and systems to differentiate more effectively among different emotions compared to the AV model of emotion?
- Is the genetically optimized fuzzy technique proposed in this phase more effective at modelling the affect relations of the AV-AT compared to other existing ML methods?

The design of the online survey was the same as that conducted to model the AT hypothesis (in phase1). The new survey made use of the two-stage scenario design of the first survey, where the participants were asked to provide scores of the eight emotions along with scores of prediction, valence and arousal during the first stage of the scenario; and outcome, valence and arousal during the second stage of the scenario.

Table 4.2 Demographic Information for Survey 2.

Demographics		**Frequency**
Gender	Male	40
	Female	39
	Not disclosed	1
Age	18-24	8
	25-34	56
	35-44	10
	Over 44	6
Total Participants		80

The practical sessions were consistent with the design and framework identified in the first phase of the research. They included two tutorial sessions specifically designed to fit the context of collaborative PBL and ALL pedagogical frameworks. Based on the methodology described in this phase, a personalised learning system was developed and deployed in the aforementioned tutorial sessions to evaluate the effectiveness of the system, and draw useful conclusions and ideas concerning the further development of our approach. The proposed personalised learning system was a user-specific version of the general model, as developed from the survey data. The system was tailored to the user by utilizing their responses on the online survey. For this purpose, all the participants, in both tutorials, had previously completed the online survey. The data from every participant were used to create a personalised version of the system for each one of them through the offline adaptation process (feeding the survey responses of the user, to the system, as desired changes). Both tutorials were divided into a number of different activities including class games, lab exercises, group tasks and presentations, quiz etc. The start and end points of every activity served as the moments in time when the participants interacted with the system and they provided estimates of their prediction, valence, arousal, and outcome elements. During the tutorials, the participants were divided into groups and used different versions of the user specific learning system, which was installed in their personal computers.

The first tutorial session offered information on the performance of the proposed system, along with evidence of its user-friendliness and applicability. At the start point of every activity, the participants provided values of their prediction, arousal and valence. At the end point of every activity, the participants provided values of their evaluation of the outcome, arousal and valence. The system utilized these values as inputs to compute values for the eight output emotions. These output values and the corresponding feedback were visible to the participants. The participants either agreed with the results and did not perform any actions, or disagreed and provided their own values for the target emotions. These user provided values resulted in changes in the fuzzy mechanism of the system. All the target emotion values provided either by the user or by the system, at the start and end of every activity, were stored. The stored values were associated with their corresponding basic elements values (prediction, arousal, valence at the start of the activity; and outcome, arousal, valence at the end of the activity), to form the datum in order to evaluate the performance of the system offline. After the end of the tutorial, the participants were debriefed and asked their thoughts and experiences when interacting with the system.

The second tutorial design was focused mostly in evaluating the classification accuracy of the suggested affect modelling methodology. During this tutorial, at the start and end points of every activity, the users provided values for every emotion category, this time however they were not aware of the results calculated by the system, or prompted with feedback provided by the system. This change was induced in the experimental design to provide a more objective measure of how the participants perceived their affective state, and what emotional label they chose to describe it. More specifically, it was considered that, when the participants were able to see the results of the system in the first tutorial, this introduced an amount of bias in favour of the system. However, without having access to the results, the estimates of the emotion labels provided by the participants were more genuine and truthful. As a result, the classification accuracy of this approach could be objectively evaluated by comparing the system's generated emotion values with the unbiased user provided values. It is important to notice that the online adaptation mechanism of the system was present during this tutorial as well, and performed the necessary changes in the fuzzy rule base in the background, based on the emotional values provided by the participants.

Table 4.3 Number of participants for the experiments.

	Online Survey 1	Online Survey 2	Tutorial Session 1	Tutorial Session 2
Number of participants	89	80	21	21

4.3.2 Phase 2 computational methodology

The computational methodology used during this phase was an enhanced version of the one described in phase 1. The technique used was proven effective in modelling affect relations and reflecting individual differences based on the experimental results of phase 1, and for that reason, it was a suitable method for modelling the AV-AT emotion representation. The original fuzzy approach was modified to include the new inputs of the model, and its performance was enhanced by taking advantage of some properties of the original approach. The approach developed in the previous stage relied greatly on some internal parameters of the fuzzy sets and more specifically on the position of the fuzzy set centers used to represent each input and output. With the help of a genetic algorithm, and by using the online survey data the optimal position of the fuzzy set centre points was calculated, offering the best classification results. The optimization of internal fuzzy set's parameters using GA is a proven technique, and has been applied successfully before in order to optimize fuzzy system's performance. In the work carried out by Bernardo et al., the researchers used a genetic algorithm to optimize a fuzzy logic based system for financial prediction. The researchers evaluated their system in two real world financial applications (credit card approval, stock market). Their results showed that the proposed genetically optimized fuzzy system had better performance compared to white box approaches (Evolving Decision Rule financial model) and similar performance to black box approaches (neural networks). It is also important to note that in contrast to the neural network approach the proposed system produced an interpretable model (Bernardo 2013).

4.3.3 Phase 2 evaluation methodology

Initially, the researcher opted to observe the performance of the enhanced fuzzy method and test its suitability at modelling the AV-AT model. In order to achieve this, the performance of the fuzzy method was compared with the performance of other ML systems at mapping the elements of the AV-AT to the eight emotions. The comparison was drawn in terms of the NRMSE, but this time an additional comparative measure was used. It is common practice in AC systems, not to provide scale values for all possible emotions, but instead provide a single emotion for characterizing the users' affective state. In order to evaluate the performance of the proposed affect modelling approach under this perspective, the ability of the system to recognize the dominant emotion was tested. The researcher defined as dominant the emotion with the highest value among the eight emotions. This measure was also a very important indicator of the ability of the system to differentiate between emotions. All comparisons for both NRMSE and dominant emotion accuracy (DEA) were achieved by using ten-fold cross validation. The same measures (NRMSE and DEA) were also calculated to evaluate the system's performance during the practical tutorial sessions, by comparing the values provided by the participants to the ones generated by the system. No data was excluded from our datasets since the data obtained from both tutorial sessions were not used for any training or optimization purposes, and as a result, they were unseen by the system. By comparing the performance of the model constructed from the survey data, to the performance of the system deployed during the tutorial sessions, evidence was provided to support the importance of individual differences, and the effectiveness of the adaptive mechanism. This is attributed to the fact that the personalised learning system used in the tutorial sessions accounted for individual differences through the offline and online adaptation of the implemented approach, in contrast to the generic model extracted from the survey data, which reflected the general trends of the population.

It is pivotal for this research to highlight the importance of the AV-AT, and provide evidence of its ability to enable an AC system to recognize more successfully the user's affective state compared to other emotion representation models. Therefore, the presented approach was tested against the popular AV model for both the survey, and the tutorial data in terms of both NRMSE and DEA. It is common practice in AC research, to map the calculated values of arousal and valence directly to AV space, and assign them with an emotion label. In accordance with this paradigm, this approach was simulated by constructing a minimum distance classifier using the arousal and valence values to choose an emotion label. This was achieved with the help of the Affective Norms for English Words database (ANEW) and details can be found in the corresponding section (6.5). ANEW is a commonly used database, where English words are scored in the affective dimensions of valence, arousal, and dominance. In the corresponding sections of chapter 6 (6.5 and 6.7) a comparison of the AV-AT, with the AT model developed in the first phase of this research, is also provided, to evaluate the progress achieved by using this enhanced approach.

4.3.4 Phase 2 proposed AC framework

The basic implementation of the system used in the first phase was modified to accommodate the new methodology. The developed system using the AV-AT model and fuzzy approach was tested for the first time in a practical setting. This system's architecture can be used as a basis for affective learning systems aiming to utilize the AV-AT model. At the corresponding section (6.8), the author presents ideas and research directions concerning the full automation of the emotion recognition process. An AC design is proposed based on previous research, and on identified relations of the basic affective elements with physiological signals, along with useful conclusions drawn from the interviews with the participants. Moreover, since there are no apparent reasons why the AV-AT model is not suited for different application areas, the necessary modifications are discussed, in order to facilitate the deployment of this model in contexts that are different from education.

4.4 Phase 3 Affective Transitions model

During the third and final phase of our research, a novel methodology for monitoring and modelling affective trajectories of students during learning tasks was created. This approach incorporated low-level information of the basic elements of a student's affective trajectory through time, and high-level information of the affective transitions a student experiences during the educational process. The developed approach presented a new holistic view of the student's affective movement through time. This view included the way a student utilized inner processes to combine basic affective elements to provide an emotion label, and also explored the way the student transitioned from one affective state to another. This approach relied on a novel hybrid hierarchical system consisting of an adaptive fuzzy part, and an FCM part. The adaptive fuzzy part of the system was responsible for modelling and adapting the underlying low-level affect relations as they were presented by the AV-AT model of emotion. The FCM part of the system was responsible for modelling the high-level affective state of the student as a dynamically evolving state, by taking into account the likelihood of transitioning from one distinct affective state, such as boredom frustration etc., to another. As it was shown in the literature review section (section 2.10), some affective transitions are more or less likely to occur than others, and the FCM was responsible to model this affect related information. The distinctive results from each part of the system (adaptive fuzzy part and FCM part) were then combined together with a soft computing technique, which is described in detail in section 7.3.3 in order to produce the final results.

In congruence with the previous research phases, the same set of the eight emotions was used. As pointed out in section 2.10, similar sets of emotions have been used before in research, exploring the affective transitions of students. For example, D'Mello et al. used a set including boredom, flow, confusion, frustration, delight and surprise (D'Mello 2008). In Baker et al. the neutral state was added (Baker 2004) to D'Mello's subset. Finally McQuiggan et al. utilized a set of ten emotions, which comprised of: anger, anxiety, boredom, confusion, delight, excitement, fear, flow, frustration, and sadness (McQuiggan 2010). As a result, the utilization of this set was a logical choice for constructing a computational model of emotion, and it could be used to investigate the affective transitions occurring during collaborative learning tasks.As mentioned earlier in this section, the methodology followed comprises of two main parts: the adaptive fuzzy and the FCM parts. The fuzzy part of the system is the one developed in phase 2, for representing the AV-AT model, and it was constructed with the help of the online survey, as described in the previous section. For simplicity in this Thesis, this part of the system is called the "Fuzzy" part. The FCM part of the system is responsible for monitoring the high-level affective transitions between affective states. Two configurations of the FCM were constructed at this research phase. The first configuration (FCM1) was constructed with the help of domain experts, and the second (FCM2) was developed by utilizing the data obtained from the first practical tutorial session conducted at phase 2. The Fuzzy, and each one of the FCM parts, were combined together to create two versions of the final system. FFE is defined as the version of the final system that uses the expert opinion based FCM1, and FFA as the version of the system, which uses the data driven FCM2. The interaction between the Fuzzy and FCM parts of both systems was optimized by using the dataset obtained in the first tutorial session. The evaluation of all different configurations was performed by using the unseen dataset provided by the second tutorial session. The methodology overview of this phase can be seen in figure 4.5.

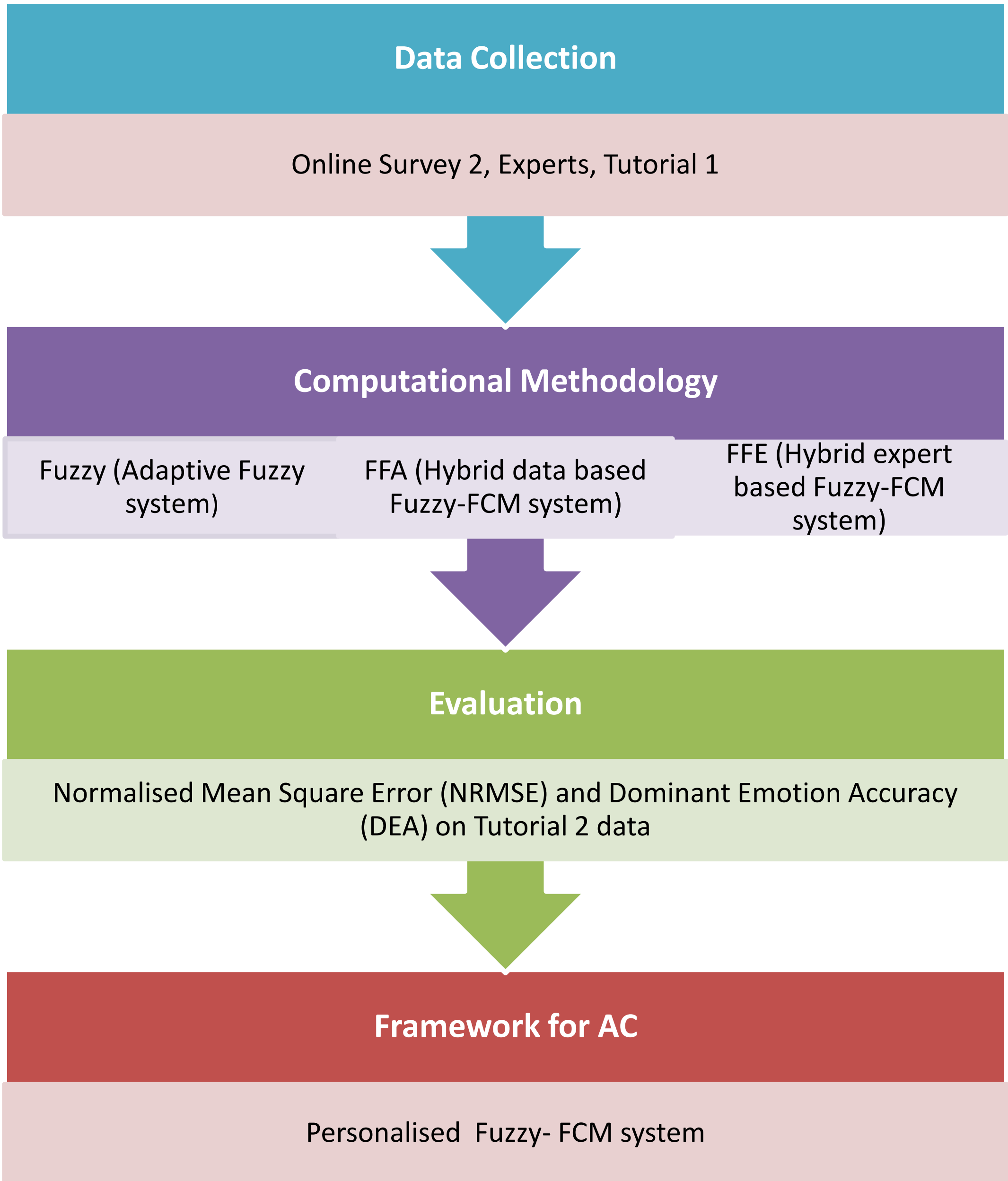


Figure 4.5 Phase 3 Methodology overview.

4.4.1 Phase 3 data collection methodology

All the data required for this phase's purposes were already provided from the datasets obtained from phase 2. The online survey conducted for the AV-AT provided the data for constructing the Fuzzy part of the system. The data from the first tutorial session were used in two ways. Firstly, towards the construction of the data driven FCM2 (FFA), and secondly, for optimizing the interaction of the Fuzzy and FCM parts (FCM1 and FCM2), for each of the finally developed systems (FFA and FFE). During the second tutorial, all different configurations of the system were running at the same time in the background, providing values for the eight emotions and performing the necessary online adaptation. These configurations included: the system without the FCM as this was presented in phase 2 (which in this phase comprises the Fuzzy part of the system); the system with the FCM constructed from data (FFA); and the one constructed with the opinion of experts (FFE). The participants were not able to see the results of the systems, so they were not biased by them, and as a result, they set values, which best represented their affective state. The values of the basic elements and emotions provided by the participants, along with the results produced by each system were stored, in order to assess offline the classification accuracy of each system (Fuzzy, FFA, FFE).

4.4.2 Phase 3 computational methodology

The computational methodology used in this phase, comprised of two core parts the Fuzzy, and the FCM. The Fuzzy part of the system is the genetically optimized adaptive fuzzy system developed in phase 2 of this research and its utilization was justified earlier in this Thesis.

A student's affective state is a dynamic psycho-physiological process and the FCM is a computational methodology capable of providing modelling solutions in problems with a similar dynamic nature. In the implemented FCM, the nodes or concepts of the system were the emotions under investigation, and the edges between them represented the relations between them. Two approaches were developed and utilized in order to provide values for the FCM edges. The first approach was based on the opinion of experts, and resulted in the construction of FCM1. This approach had the advantage of integrating the knowledge of experts from different scientific fields in the FCM design. This approach is a well-established methodology, which was firstly presented in the work of Papageorgiou et al. (Papageorgiou 2003), and has been used since in many applications in order to construct FCM models based in the opinion of experts (Papageorgiou 2009). Using this approach to facilitate the expansion of the FCM model with new concepts is a relatively simple process. This feature is pivotal since it allows the FCM model to include additional concepts in the recognition process. Many factors such as the teachers' affective state, the time of day, and the achievements of the students drastically influence the construction of students' affect, and by using this method, these factors can be easily integrated in a future design of the system. According to the second FCM construction approach, the desired values are automatically extracted from data. The data provided by the first tutorial session, described in the previous phase, were used to realize this data-driven approach. In the first tutorial session it was possible to extract quantifiable relations, which reflected the transitions between affective states, hence this knowledge was used to construct FCM2. Both approaches are described in detail in the corresponding sections (7.3.2.2 and 7.3.2.3).

The final system provided values for each emotion by combining the results from the Fuzzy, and the FCM part. The FCM was utilized as a supervisory and advisory system used to intervene and improve the results provided from the low level Fuzzy system. This was achieved by implementing a soft computing technique, which relied on two parameters. The first parameter regulated "when" the FCM had to intervene, and the second "how much" the FCM should contribute to the outcome. These two parameters were optimized with the help of a Genetic Algorithm. The data obtained from the first tutorial session were used for optimization purposes, in order to calculate the optimal values of these parameters, with the help of a Genetic Algorithm. As mentioned earlier, two versions of the final system were constructed, one that utilized the FCM1 constructed from experts (FFE), and one that utilized the FCM2 constructed from data (FFA). The idea of using the FCM as an intelligent supervisor was introduced in the work of Stylios et al. (Stylios 2000). There a two-levelled approach was proposed in order to model a manufacturing control system. On the lower level, conventional computational methodologies were used, and on the higher level, an FCM part acted as an intelligent supervisor that attempted to simulate a human control capacity (Stylios 2000).

4.4.3 Phase 3 evaluation methodology

The data from the second practical tutorial session (phase 2 data collection) were utilized in order to provide an objective evaluation of the constructed system. This data have not been used either for training, or for optimization purposes. The constructed system's accuracy was evaluated in terms of NRMSE and Dominant Emotion Accuracy (DEA). A direct comparison with other models is provided, including the previously developed AV-AT, in order to demonstrate the performance and potential of the proposed methodology.

4.4.4 Phase 3 statistical analysis

The data obtained from both tutorial sessions were also used for a separate statistical analysis. One of the objectives of this research phase was to explore affective transitions during learning tasks, and by performing this analysis, additional information emerged concerning these affective transitions. In order to achieve this, Pearson's correlation coefficient was calculated between values of emotions obtained at two consecutive steps of the system. Despite the fact that consequent emotion values as captured by the system, had a significant amount of time difference between them, significant relations were still expected to appear since they shared their basic components with longer lasting affective states, such as moods. For example, if a student was in a positive valenced mood and reported flow in the beginning of an activity, which is a positively valenced emotional state, they were then more likely to report an emotion sharing the good valence element of their mood, at the end of this activity, such as to remain interested or become excited.

4.5 Conclusions Summary

In this chapter, the methodology followed in this research was presented. The three different phases of our research were discussed, and the main steps undertaken towards the completion of every phase were outlined. More specifically, the author supported his choices in regards to the emotion theory, the computational approach, the data collection, the evaluation methodology, and finally the application framework for AC. By reading this chapter, the reader is able to gain a deep understanding of the presented methods, and follow the overall approach. Detailed descriptions for all the research steps, along with the corresponding results can be found in the following chapters. More specifically, in chapter 5, 6, and 7 a detailed description of phase 1, 2 and 3 of our research is presented respectively, followed by conclusions in chapter 8.

Chapter 5 Affective Trajectories Hypothesis

5.1 Introduction

The journey of this research into computational models of emotion as tools for Affective Computing applications begins here. In this research phase, the Affective Trajectories hypothesis is explored, as a simple and yet promising approach which has never been used or explored by AC systems before. Moreover, the Affective Trajectories hypothesis was investigated and tested as an emotional modelling approach for Affective Computing. The AT Hypothesis was tested in an educational context, and it was modelled with the use of a set of eight educational related emotions. The analysis was performed by utilizing the results from an online survey designed to capture the combinations amongst the basic elements of the theory. More specifically, the author explored how one's current affective state, prediction of the future, and experienced outcomes were combined in order for them to provide a label to describe their affective state. The emotions under investigation here were 'flow', 'excitement', 'calm', 'boredom', 'stress', 'confusion', 'frustration', and 'neutral'. We evaluated the predictive value of the developed model by using the basic elements as inputs to classifiers based on different machine learning techniques. The role of individual differences was explored in the construction of emotion processes, in the context of the AT model. More specifically, the focus of this research was to explore the way an individual combined the basic elements to manifest their emotional experiences and associate them with emotions. Through this research, the AT theory was extended, and supported the creation of more personalised learning systems. A data driven fuzzy approach was implemented in order to provide a computational representation of the emotional model. By utilizing this approach, the underlying affect relations were represented with the help of interpretable fuzzy rules. Moreover, an adaptive mechanism was developed to account for individual differences. Through implementing a personalised learning system, the author provided a framework for AC systems utilizing the proposed AT emotion modelling and adaptive fuzzy approach.

This chapter is organized as follows: In section 5.2, an online survey is presented. This survey provided the necessary data to conduct the statistical analysis, and train the fuzzy computational model. In section 5.3, the statistical analysis performed on the collected data is described. This analysis was conducted to test the AT theory in an educational context. In section 5.4, the data driven adaptive fuzzy method is described in detail. This method was developed to model the AT hypothesis.

In section 5.5, the performance of the proposed fuzzy method is evaluated by comparing it with other ML techniques. In section 5.6, a personalised learning system is presented, which is responsible for monitoring student's trajectories during collaborative and activity led learning tasks. This system was based on the principles of the AT hypothesis, and the mechanism of the proposed adaptive fuzzy method. Finally, in section 5.7, the findings and conclusions of this stage's research process are discussed.

5.2 Online survey 1

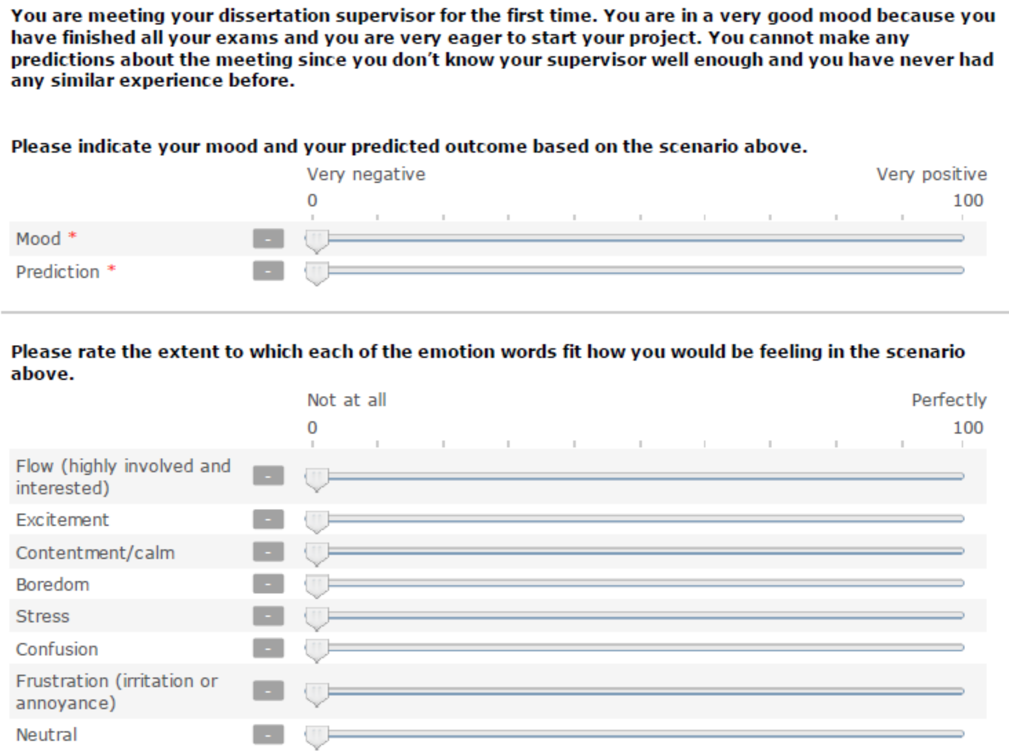
The survey conducted was designed and completed with the use of the online survey tool QuestionPro. The survey aimed at harvesting the necessary data to be used in the construction of our fuzzy model to represent the affective trajectories hypothesis and allow the author to explore the underlying affect relations. The author opted to see how a set of eight education related emotions (flow, excitement, calm, boredom, stress, confusion, frustration, and neutral) are constructed from different combinations of the basic AT's affective elements of: current state, prediction, and outcome. Before commencing the survey, the participants were provided with full instructions, and they were asked to provide their informed consent. The instructions described in detail the overall process for completing the survey, and included definitions for all emotions and basic affective elements. All participants provided information about their age, gender, nationality, and educational level. Eighty-nine participants completed the survey.

The definitions of the basic elements, and the emotions, which were given to the participants were as follows:

- <u>Current state:</u> how positive or negative you feel.
- <u>Prediction:</u> your evaluation of the predicted outcome in the scenario.
- <u>Outcome:</u> your evaluation of the outcome of the story.
- <u>Flow:</u> you are highly involved and interested in performing a certain task, you are fully immersed in a feeling of energized focus in the process of the activity you are performing.
- <u>Excitement:</u> a feeling of high arousal where you feel eager and enthusiastic.
- <u>Calm:</u> a feeling of mild satisfaction, piece of mind.

- Boredom: you are feeling impatient from lack of interest, you do not feel concentrated from lack of interest, you don't feel engaged in the activity and you have trouble concentrating.
- Stress: a feeling of mental tension where you feel worried or anxious.
- Confusion: you have a lack of understanding and an inability of how to act or decide.
- Frustration: a feeling of irritation or annoyance also related to anger and disappointment.
- Neutral: you feel neither good nor bad, neither active nor passive.

The main body of the survey consisted of eighteen different scenarios describing common situations, which are very likely to happen in an educational setting. The participants were asked to relax, and try to imagine themselves as taking part in the scenario. Each scenario represented different combinations of the AT basic elements (current state, prediction and outcome) and was divided in two parts, which were presented in a sequential order to the user. In the first part of the scenario, the participants were presented with the starting point of a scenario, which contained information about their current state and their predictions about the future. Then the participants read the scenario, and proceeded at rating their current state, and prediction in the story by using the sliders provided. Current state and prediction ranged from very negative (0) to very positive (100). After scoring the basic elements of current state and prediction, the participants were asked to choose from a list of eight emotions and rate the extent to which each of the emotion words fitted how they felt in the scenario. This value ranged from 0 (not at all) to 100 (perfectly). After providing scores for the eight emotions, the participants proceeded to the second part of the scenario where the outcome of the story was presented. The outcome of the story was either better, worse, or as the participant has predicted in the first part. To avoid cognitive overload and help the participant remain focused to the story, the first part of the scenario was also presented on the screen formatted in Italics. During this second and final part of the scenario, the participants rated the outcome of the story in relation to their prediction in the first part. The outcome variable ranged from worse than expected, terrible (0) to better than expected great (100). After providing a value for the outcome element, the participants chose a score for the eight emotions as before, and proceeded to completing the next scenario (figures 2.1 and 2.2).



You are meeting your dissertation supervisor for the first time. You are in a very good mood because you have finished all your exams and you are very eager to start your project. You cannot make any predictions about the meeting since you don't know your supervisor well enough and you have never had any similar experience before.

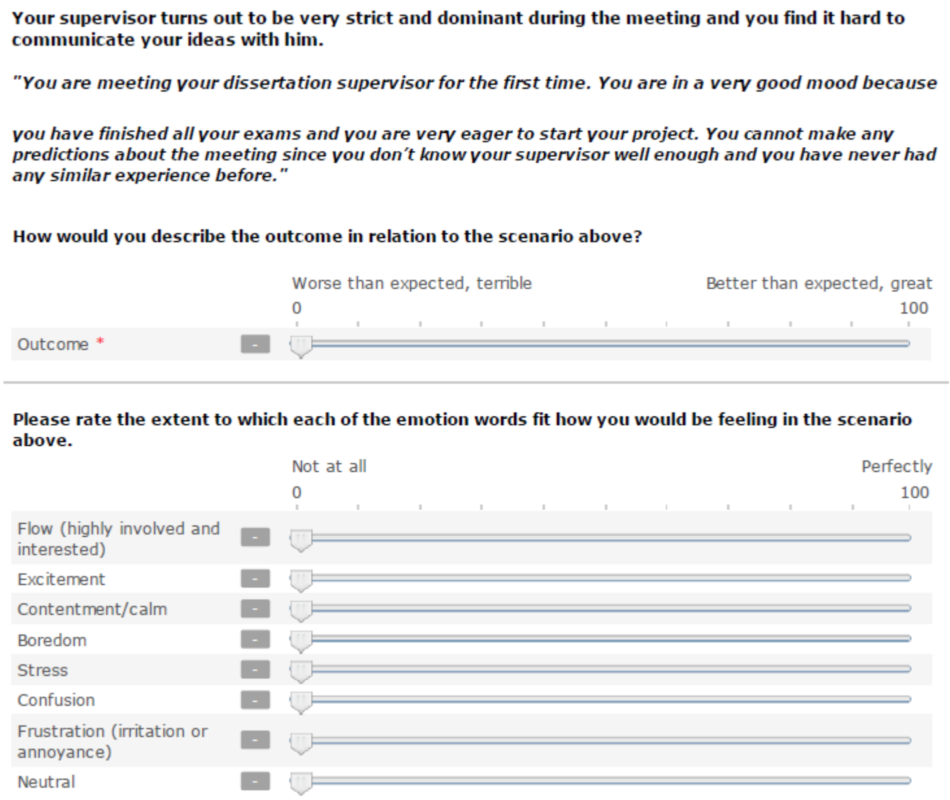
Please indicate your mood and your predicted outcome based on the scenario above.

	Very negative 0	Very positive 100
Mood *		
Prediction *		

Please rate the extent to which each of the emotion words fit how you would be feeling in the scenario above.

	Not at all 0	Perfectly 100
Flow (highly involved and interested)		
Excitement		
Contentment/calm		
Boredom		
Stress		
Confusion		
Frustration (irritation or annoyance)		
Neutral		

Figure 5.1 AT's online survey's first stage scenario example.



Your supervisor turns out to be very strict and dominant during the meeting and you find it hard to communicate your ideas with him.

"You are meeting your dissertation supervisor for the first time. You are in a very good mood because

you have finished all your exams and you are very eager to start your project. You cannot make any predictions about the meeting since you don't know your supervisor well enough and you have never had any similar experience before."

How would you describe the outcome in relation to the scenario above?

	Worse than expected, terrible 0	Better than expected, great 100
Outcome *		

Please rate the extent to which each of the emotion words fit how you would be feeling in the scenario above.

	Not at all 0	Perfectly 100
Flow (highly involved and interested)		
Excitement		
Contentment/calm		
Boredom		
Stress		
Confusion		
Frustration (irritation or annoyance)		
Neutral		

Figure 5.2 AT's online survey's second stage scenario example.

The dataset acquired from the online survey contained 1602 training samples for each part of the scenarios. For the purposes of this research, the part of the scenario where the prediction is made was defined as stage 1, and the part of the scenario where the evaluation of the outcome of the story is made was defined as stage 2. The data collected were used for the statistical analysis presented in the next section, as well as for the training of the fuzzy model.

5.3 Statistical Analysis Results

Initially in order to observe the underlying affect relations between the eight emotions and the basic elements of current state, prediction, and outcome, Pearson's correlation coefficient was calculated. It can be observed from the correlation results in table 5.1 that all emotion categories (except for the neutral state) have significant correlations with the basic AT elements. More specifically:

- "Flow" demonstrated a strong positive correlation with current state, prediction, and outcome. Thus, a student is more likely to experience flow when in a positive mood, making positive predictions or experiencing positive outcomes. For example in figure 5.3 we can observe the strong relation between prediction and flow.
- "Excitement" demonstrated a strong positive correlation with current state, prediction, and outcome. Thus, a student is more likely to become excited when in a positive mood, making positive predictions or experiencing positive outcomes.
- "Calm" demonstrated a medium positive correlation with current state, prediction, and outcome. Thus, a student is more likely to be calm when in a positive mood, making positive predictions or experiencing positive outcomes.
- "Boredom" demonstrated a medium negative correlation with current state, prediction, and outcome. Thus, a student is more likely to be bored when in a negative mood, making negative predictions or experiencing worse than expected outcomes.
- "Stress" demonstrated a strong negative correlation with current state, prediction, and outcome. Thus, a student is more likely to become stressed when in a negative mood, making negative predictions or experiencing worse than expected outcomes.

- "Confusion" demonstrated a medium negative correlation with current state, prediction, and outcome. Thus, a student is more likely to be confused when in a negative mood, making negative predictions or experiencing worse than expected outcomes.
- "Frustration" demonstrated a strong negative correlation with current state, prediction, and outcome. Thus, a student is more likely to become frustrated when in a negative mood, making negative predictions or experiencing worse than expected outcomes.
- As it concerns neutral state, maximum values were observed when average values of AT basic elements were provided, while when the values of the basic elements were either very low or very high then neutral state's values were very low. This is illustrated in figure 5.4 where neutral state and the outcome variable are depicted. The majority of neutral state values were concentrated around a value of 50 for the outcome, while when the outcome was 0 or 100 most of the neutral state provided values were zero. This led to the conclusion that there was no linear relation between the two measures. Therefore, a statistical measure such as Pearson's that is designed to detect linear relations failed.

Table 5.1.Pearson correlation coefficient between the AT's basic elements and the emotion words.

Pearson's Coefficient [confidence intervals], significance p, N=1602			
Emotions/ AT Elements	**Current State**	**Prediction**	**Outcome**
Flow	0.537 [0.497, 0.576] p=0.000	0.665 [0.634, 0.696] p=0.000	0.725 [0.700, 0.750] p=0.000
Excitement	0.585 [0.553, 0.615] p=0.000	0.609 [0.574, 0.639] p=0.000	0.762 [0.740, 0.781] p=0.000
Calm	0.465 [0.427, 0.499] p=0.000	0.347 [0.311, 0.386] p=0.000	0.433 [0.398, 0.470] p=0.000
Boredom	-0.443 [-0.476,- 0.409] p=0.000	-0.346 [-0.384, -0.310] p=0.000	-0.315 [-0.348,- 0.262] p=0.000
Stress	-0.432 [-0.469,- 0.390] p=0.000	-0.554 [-0.586,- 0.519] p=0.000	-0.535 [-0.562,- 0.504] p=0.000

Confusion	-0.278 [-0.313,- 0.242] p=0.000	-0.298 [-0.333,- 0.260] p=0.000	-0.430 [-0.464,- 0.396] p=0.000
Frustration	-0.521 [-0.550, -0.493] p=0.000	-0.513 [-0.542,- 0.478] p=0.000	-0.796 [-0.813, -0.778] p=0.000
Neutral	0.16 [-0.27, 0.054] p=0.512	-0.12 [-0.02,- 0.016] p=0.637	0.09 [-0.24, 0.026] p=0.962

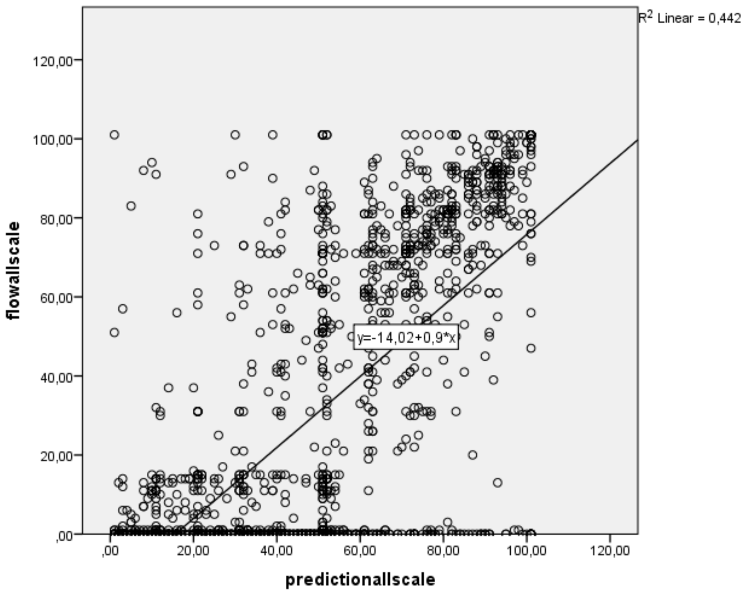


Figure 5.3 Flow vs prediction.

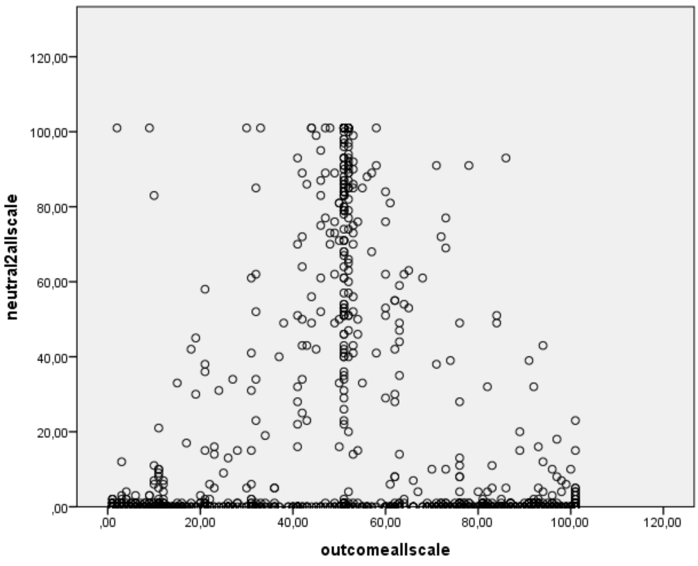


Figure 5.4 Neutral vs outcome.

The survey data samples were also transformed from scale to categorical variables. In order to perform this transformation the current state, prediction and outcome elements were divided into three categories, them being "positive", "neutral", and "negative" for the current state and prediction elements, and "better than expected", "as expected" and "worse than expected" for the outcome elements. The cut points for each category were defined at the 33.3% and 66.6% of the provided values of the corresponding elements. The values of current state, prediction, and outcome, which correspond to each category, can be seen in table 5.2. The emotion variables were divided into two categories namely “feeling” (when the provided value was above zero) or “not feeling” (when the provided variable was zero) the corresponding emotion.

Table 5.2 Basic AT elements categories.

Basic AT elements value (v)	**Categories**		
Current State	$0 \le v \le 35.3$ (negative)	$35.3 < v < 62.7$ (neutral)	$62.7 \le v \le 100$ (positive)
Prediction	$0 \le v \le 30.6$ (negative)	$30.6 < v < 69.6$ (neutral/no prediction)	$69.6 \le v \le 100$ (positive)
Outcome	$0 \le v \le 36.3$ (worse than expected)	$36.3 < v < 63.9$ (as expected)	$63.9 \le v \le 100$ (better than expected)

By utilizing this view, a more clear visualization of the affective relations was achieved, and additionally it became possible to highlight the fact that some of the eight emotions related stronger with specific aspects of an affective trajectory through time. For example in figure 5.5, the total number of survey answers indicating the presence of an emotion in each stage can be observed. For instance, more answers demonstrated the presence of confusion and frustration during the second stage rather than the first one. This signifies that confusion and frustration are emotions mostly related with the evaluations we make after we experience a certain outcome. We feel frustrated when a very negative outcome happens, or we are confused when we are confronted with an unexpected event. Other emotions like stress, flow, or boredom appear to be more related with the point in time where we make our predictions. For example we feel stressed when we expect something bad to happen in the future. Moreover, the results obtained in the first stage of the scenarios for flow indicate that there may be further differentiation between the basic affective elements of current state and prediction. In fact, flow appears to have a stronger connection with the prediction element, compared to the current state element. As it can be seen in figure

5.6, for the first stage of the scenarios where the participants provided values of their current state and prediction, there were more people reporting feeling "flow" when a positive prediction was reported, even in the case that the participants reported negative or neutral current state.

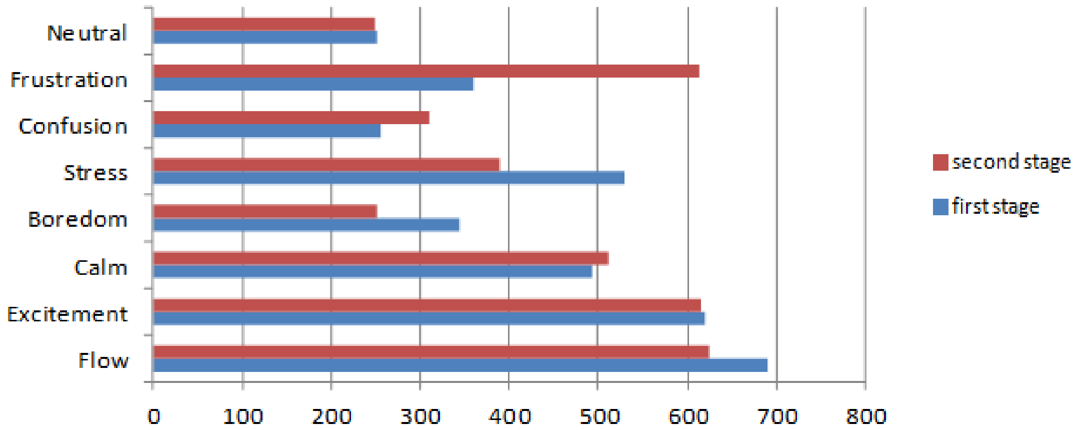


Figure 5.5 Number of survey answers indicating the presence of a specific emotion in each stage of the survey.

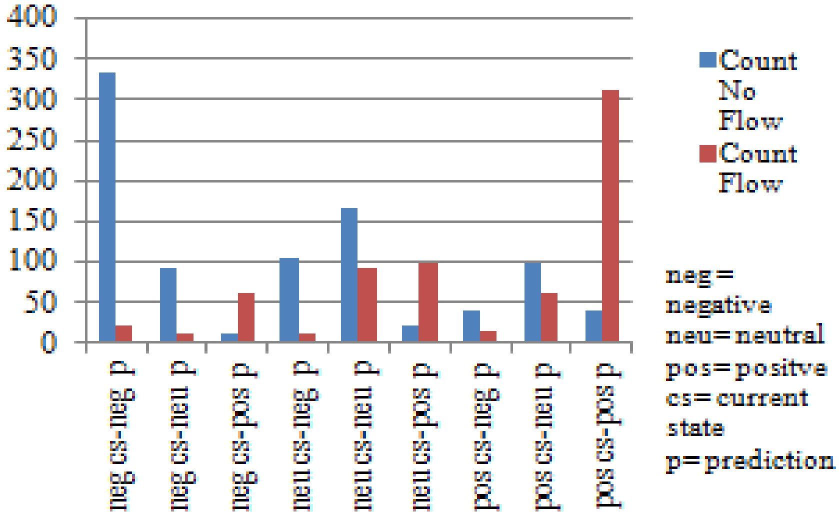


Figure 5.6 Number of survey answers indicating the presence of flow during the first stage of the survey.

The categorical variables were used in a separate statistical analysis in order to observe the relations between the basic elements of the AT and the eight emotions. Initially Chi-Square statistic was computed to investigate the underlying relations.

Cramer's V, which is a well-used measure of association, was calculated as a measure of strength of the relation. A Cramer's V value below 0.3 signifies a week relation, whereas values between 0.3 and 0.5 represent a medium relation, and values above 0.5 represent a strong relation. Finally, Odds Ratio was also computed. Odds Ratio is a very interpretable statistic measure allowing for a practical visualization of the association between two variables. In table 5.3, the results for the Chi-square (x^2) and Cramer's V statistic can be observed. The calculated values show that there are significant (p<0.001) relations between all the elements and all the emotions.

Table 5.3 Chi square and Cramer's V statistics between the AT's basic elements, and the emotions.

Chi square (p<0.001) and Cramer's V			
EMOTIONS/AT ELEMENTS	**Current State**	**Prediction**	**Outcome**
Flow	x^2=293.723 V=0.428	x^2=697.021 V=0.660	x^2=727.730 V=0.672
Excitement	x^2=408.978 V=0.505	x^2=576.797 V=0.600	x^2=892.391 V=0.746
Calm	x^2=281.770 V=0.419	x^2=194.841 V=0.349	x^2=290.570 V=0.426
Boredom	x^2=325.852 V=0.451	x^2=194.382 V=0.348	x^2=155.301 V=0.311
Stress	x^2=246.122 V=0.392	x^2=555.455 V=0.589	x^2=449.886 V=0.530
Confusion	x^2=116.340 V=0.269	x^2=169.602 V=0.325	x^2=322.963 V=0.449
Frustration	x^2=470.726 V=0.510	x^2=467.375 V=0.540	x^2=1061.626 V=0.814
Neutral	x^2=47.872 V=0.173	x^2=149.850 V=0.306	x^2=370.415 V=0.481

With the help of the odds ratio statistic, the following can be concluded for each of the emotions:

<u>Flow:</u> the odds of a participant reporting flow when they were in a positive mood were 3.15 times higher than when being in a neutral mood, and 10.25 times higher

than when being in a negative mood. The odds of a participant reporting flow when they made a positive prediction were 13.67 times higher than when making a neutral prediction, and 63.33 times higher than when making a negative prediction. The odds of a participant reporting flow after a better than expected outcome were 10.51 times higher, than after a neutral outcome and 140.15 times higher, than after a worse than expected outcome.

Excitement: the odds of a participant reporting excitement when they were in a positive mood were 3.60 times higher than when being in a neutral mood, and 22.18 times higher than when being in a negative mood. The odds of a participant reporting excitement when they made a positive prediction were 7.88 times higher, than when making a neutral prediction, and 43.14 times higher than when making a negative prediction. The odds of a participant reporting excitement after a better than expected outcome were 20.41 times higher than after a neutral outcome and 533.84 times higher than after a worse than expected outcome.

Calm: the odds of a participant reporting calm when they were in a positive mood was 2.42 times higher than when being in a neutral mood, and 14.70 times higher than when being in a negative mood. The odds of a participant reporting calm when they made a positive prediction were 1.70 times higher than when making a neutral prediction, and 9.29 times higher than when making a negative prediction. The odds of a participant reporting calm after a better than expected outcome were 1.29 times higher than after a neutral outcome, and 24.52 times higher than after a worse than expected outcome.

Boredom: the odds of a participant reporting boredom when they were in a negative mood were 3.83 times higher, than when being in a neutral mood, and 52.93 times higher than when being in a positive mood. The odds of a participant reporting boredom when they made a negative prediction were 2.14 times higher than when making a neutral prediction, and 15.84 times higher than when making a positive prediction. The odds of a participant reporting boredom after a worse than expected outcome were 1.51 times higher than after a neutral outcome, and 100.33 times higher than after a better than expected outcome.

Stress: the odds of a participant reporting stress when they were in a negative mood were 2.37 times higher than when being in a neutral mood, and 10.11 times higher than when being in a positive mood. The odds of a participant reporting stress when they made a negative prediction were 6.61 times higher than when he made a neutral prediction and 63.86 times higher than when making a positive prediction. The odds of a participant reporting stress after a worse than expected outcome were 7.29 times higher than after a neutral outcome, and 45.60 times higher than after a better than expected outcome.

Confusion: the odds of a participant reporting confusion when they were in a negative mood were 1.63 times higher than when being in a neutral mood, and 10.25 times higher than when being in a positive mood. The odds of a participant reporting confusion when they made a negative prediction were 2.47 times higher, than when making a neutral prediction, and 22.50 times higher than when making a positive prediction. The odds of a participant reporting confusion after a worse than expected outcome were 6.78 times higher than after a neutral outcome, and 21.07 times higher than after a better than expected outcome.

Frustration: the odds of a participant reporting frustration when they were in a negative mood were 5.22 times higher than when being in a neutral mood, and 149.28 times higher than when being in a positive mood. The odds of a participant reporting frustration when they made a negative prediction were 9.01 times higher than when making a neutral prediction, and 49.20 times higher than when making a positive prediction. The odds of a participant reporting frustration after a worse than expected outcome were 52.42 times higher than after a neutral outcome, and 1607.77 times higher than after a better than expected outcome.

Neutral: the odds of a participant reporting neutral when they were in a neutral mood were 2.55 times higher than when being in a negative mood, and 2.60 times higher than when being in a positive mood. The odds of a participant reporting neutral when they made a neutral prediction were 4.87 times higher than when making a negative prediction, and 5.93 times higher than when making a positive prediction. The odds of a participant reporting neutral after a neutral outcome were 21.58 times higher than after a worse than expected outcome, and 19.67 times higher than after a better than expected outcome.

From the results of the Pearson's, Chi-Square, Odds Ratio, and Cramer's V statistics, it can be inferred that the basic affective elements of the AT are strongly connected with the eight aforementioned educational related emotions. It can also be concluded that certain educational related emotions are more connected to specific aspects of an affective trajectory. Some of the emotions (stress, flow) are more connected with our predictions, while others with our evaluations (excitement, confusion, frustration). These conclusions point out to the fact that the AT hypothesis which was tested before in a general and context free manner, can also be applied in a specific context such as education.

5.4 Fuzzy Method

The statistical analysis performed in the previous chapter revealed significant correlations between the selected set of emotions, and the AT basic elements, thus justifying the construction of a computational model which utilizes the AT theory in AC context. This model should be able to extract knowledge from data, in order to capture and model the underlying emotion theory for the general population, but in the same time it should possess the ability to demonstrate the personalised way an individual utilizes the AT elements of current state, prediction and outcome to provide an emotion label to describe their affective state. The role of individual differences is a core aspect in this research. Consequently it was fundamental that the computational approach utilized to model the AT hypothesis was able to reflect and highlight these differences. In order to achieve this, an adaptive fuzzy logic system was developed. As mentioned in the methodology chapter (section 4.2.3) the logic behind the proposed system was based on the Fuzzy C-means clustering algorithm for the creation of the fuzzy sets; on the Wang Mendel method (Wang 2003) for the fuzzy rule extraction; and on the Adaptive Online Fuzzy Inference System (AOFIS) as described in (Doctor 2005) for the adaptation process. The proposed fuzzy system comprised of two fuzzy classifiers. Each of the classifiers modelled a stage in the AT model of emotion. The first one was responsible for the point in time where we make our predictions about the future, and the second one was responsible for the point in time where we make our evaluations of the outcome of a situation. The first classification system used values of current state, and prediction elements as inputs (independent variables) to produce values for the eight output emotions (target variables). The second classifier utilized as inputs values of current state, prediction, and outcome to provide output values for the eight target emotions. The process resulting in the construction of this fuzzy system comprised of the following main steps. Initially the necessary data were collected in order to train the model. With the use of the collected data, fuzzy sets were constructed depicting our input and output variables, and the fuzzy rule-bases for each of the classifiers were developed. Finally, an adaptation mechanism was implemented and applied in order to tailor the developed fuzzy model toward a specific user, and make it more user-friendly.

The data required for the construction of the system were provided by the online user survey described in section 5.2. To accomplish the training purposes of the system the data were divided into two datasets. The first dataset comprised of the values of current state, and prediction as inputs, and the values of the eight emotions that were provided in the first part of the scenario, as outputs. The second dataset comprised of the values of current state, prediction and outcome as inputs, and the values of the eight emotions as provided in the second part of the scenario as outputs. Eighty-nine participants provided answers for each of the eighteen different scenarios, thus each dataset comprised from $\mathrm{D} = 1602$ training datum. Let $\mathrm{x} = (\mathrm{x}_1, \ldots, \mathrm{x}_\mathrm{k})$ be the inputs for each stage, and $\mathrm{y} = (\mathrm{y}_1, \ldots, \mathrm{y}_\mathrm{l})$ the outputs (where l is the total number of outputs) forming each training sample $(\mathrm{x}^{(\mathrm{t})}; \mathrm{y}^{(\mathrm{t})})$ $\text{ where } \mathrm{t} = 1, \ldots, \mathrm{D}$. In the first stage, $\mathrm{k} = 2$ (values of current state and prediction), while in the second stage $\mathrm{k} = 3$ (values of current state, prediction, and outcome). In both stages, $\mathrm{l} = 8$ (values of flow, excitement, calm, boredom, stress, confusion, frustration and neutral). Below the fuzzy set and fuzzy rule extraction method are presented. These methods are used consistently for both stages of the model.

5.4.1 Fuzzy set construction

Initially the Fuzzy C-means was applied on the collected survey data in order to construct the fuzzy sets. The Fuzzy C-means fuzzy clustering algorithm returned a list containing the position of the centers for a predefined number of clusters. This predefined number of clusters is the same as the resulting number of fuzzy sets for each input and output. By utilizing the position of each of the center points, provided by the Fuzzy C-means, the fuzzy sets describing each input, and output were defined. Each fuzzy set had the form of triangular membership functions. Each triangular membership function had a membership grade of unity at the center point calculated by the Fuzzy C-Means. Additionally each membership function's support was defined to be the space between the projections of the previous center, and the next center points on the horizontal axis. For example, the fuzzy sets extracted from the survey data for prediction, when a partition of five fuzzy sets was chosen, can be observed in figure 5.7. By utilizing this approach it was possible to construct a computational model where by changing the number of fuzzy sets used, different levels of interpretability of the knowledge extracted could be provided. In this case for example, if we want to observe how a positive or negative current state affects the way an individual chooses an emotion to describe their affective state, then a partition of two fuzzy sets for the ‘current state’ element will be chosen.

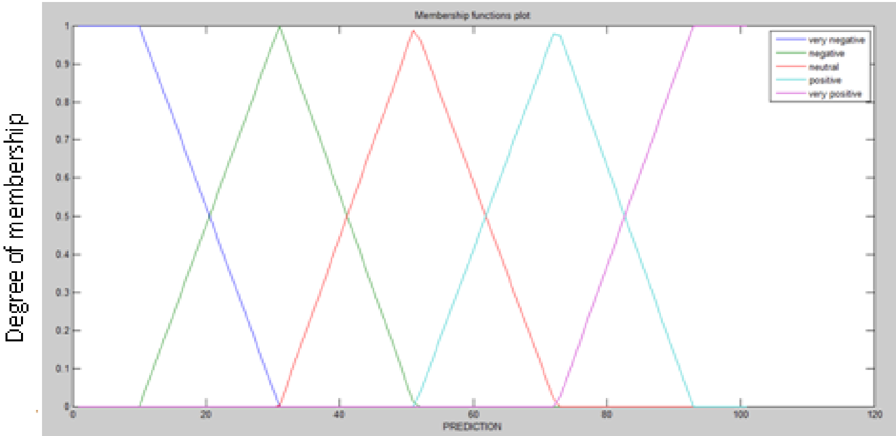


Figure 5.7 Membership functions extracted from the survey data for prediction element.

5.4.2 Fuzzy rules extraction

After the fuzzy set construction, each input and output variable was divided to a number of fuzzy sets. Let n be the number of fuzzy sets used to describe the inputs, and m the number of fuzzy sets used to describe the outputs. Then B_p^c is defined as the fuzzy set for the input p, where $c = 1, \dots, n$ and E_q^d was the corresponding fuzzy set for the output q where *d*$= 1, \dots, m$. The aim was to extract fuzzy rules from the survey data in the form:

$$\text{If } x_1 \text{ is } B_1^c \text{ and... } x_k \text{ is } B_k^c \text{ then } y_1 \text{ is } E_1^d \text{and...and } y_m \text{ is } E_l^d \quad (1)$$

Below the rule extraction for a single output is described, since in the case of multiple outputs the process followed is the same. Every training sample $(x^{(t)}; y^{(t)})$ was used to calculate the corresponding membership values $\mu_{B_p^c}(x_p^{(t)})$ for all inputs $p = 1, \dots k$ and all corresponding fuzzy sets $c = 1, \dots, n$. Then the fuzzy set $\acute{c}$ with the highest membership value was identified:

$$\mu_{B_p^{\acute{c}}}(x_p^{(t)}) \geq \mu_{B_p^c}(x_p^{(t)}) \quad (2)$$

for each set $c = 1, \dots, n$. From the training sample $(x^{(t)}; y^{(t)})$ the following fuzzy rule was generated:

$$\text{If } x_1 \text{ is } B_1^{\acute{c}} \text{ and ... } x_k \text{ is } B_k^{\acute{c}} \text{ then y is centered at } y^{(t)}. \quad (3)$$

At this point, the weight $w^{(t)}$ of corresponding fuzzy rule was computed by using the following formula:

$$w^{(t)} = \prod_{p=1}^{k} \mu_{B_p^{\acute{c}}}(x_p^{(t)}) \qquad (4)$$

By utilizing this method, at this point in time, the generated rules were as many as the training samples. In the following step of the algorithm, all the extracted rules with the same antecedent (If-part) were grouped together. Conceptually each group represented a specific combination of the basic elements. Let this group be group *g* and the total number of groups be *G*. Consequently, the number of fuzzy rules belonging in group g were equal to the training samples belonging to that group. If D_g is the total number of training data belonging in this group (where t_v^g is a training sample of group g and $v = 1, \ldots, D_g$) then a number of D_g rules were also generated from the data in the form of:

If x_1 is $B_1^{(c^g)}$ and ... x_k is $B_k^{(c^g)}$ then y is centered at $y^{(t_v^g)}$. (5)

Then the weighted average $av^{(g)}$ of group g was calculated as follows:

$$av^{(g)} = \frac{\sum_{v=1}^{Dg} y^{(t_v^g)} w^{(t_v^g)}}{\sum_{u=1}^{Dg} w^{(t_v^g)}} \quad (6)$$

The computed weighted average $av^{(g)}$ was mapped to all outputs fuzzy sets E^d $d = 1, \ldots, m$ and the fuzzy set $\acute{d}$ with the highest membership values was identified as follows:

$$\mu_{E^{\acute{d}}}(av^{(g)}) \geq \mu_{E^d}(av^{(g)}) \quad (7)$$

Finally the rules of group *g* were combined together to produce a single final rule for group *g*.

If x_1 is B_1^g and ... x_k is B_k^g then y is E^g (8)

E^g was the fuzzy set with the highest membership value, as it was identified in the previous step. At the end of this process the maximum number of rules that can be generated were n^k. In this research, the number of inputs k was either 2 for the first stage, or 3 for the second stage. Additionally, in order to retain interpretability, a small number of fuzzy sets were chosen to describe each input and output. More specifically, the extracted fuzzy models were tested for a partition of 3, 5, and 7 fuzzy sets per input/output. The final model was constructed for a 5 fuzzy set partition which offers a reasonable trade-off between accuracy and interpretability. Therefore, the total number of possible combinations of inputs (possible fuzzy rules) for every model was relatively small. As a result, the survey data was sufficient since there was at least one rule generated from the data to represent each one of those combinations. Let us consider that the final number of rules contained in each of the fuzzy rule bases for stage 1 and 2 were N and B. Each of these extracted rule bases was utilized by two fuzzy classification systems responsible for providing classification results for stages 1 and 2 of the model respectively. For stage 1 the classifier utilized product inference; singleton fuzzification and centre average defuzzification to map the input $\mathrm{x} = (\mathrm{x}_1, \ldots, \mathrm{x}_\mathrm{k})$ which comprised of the corresponding basic elements' values used (current state, prediction) , to values of an emotion output y as follows:

$$\mathrm{y} = \frac{\sum_{\mathrm{r}=1}^{\mathrm{N}} \mathrm{y}_{\mathrm{ce}}^{(\mathrm{r})} (\prod_{\mathrm{p}=1}^{\mathrm{k}} \mu_{\mathrm{E}_p^{(\mathrm{r})}}(\mathrm{x}_\mathrm{p}))}{\sum_{\mathrm{r}=1}^{\mathrm{N}} (\prod_{\mathrm{p}=1}^{\mathrm{k}} \mu_{\mathrm{E}_\mathrm{p}^{(\mathrm{r})}}(\mathrm{x}_\mathrm{p}))} \quad (9)$$

Where $\mathrm{y}_{\mathrm{ce}}^{(\mathrm{r})}$ was the center of the output fuzzy set E^r of rule (r). The same applied for the stage 2 classifier (where *N*=*B*).

5.4.3 Adaptation

The fuzzy rule base extracted at this point reflected the general trends of the survey population. In order for the constructed fuzzy systems to reflect and account for individual differences, an adaptive mechanism was developed. This mechanism performed changes to the fuzzy rule base when the system was presented with new training data. The changes caused by the implemented adaptive mechanism targeted the fuzzy rule with the highest activation or firing value. Since this rule contributes the most in the calculation of the output, this is also reflective of the user preferences. The utilization of this adaptation method was proposed in two ways, online and offline. Online adaptation occurred when the user was not happy with the results presented to them by the system during their interaction. When this happened, they were able to provide values for the target emotions, resulting in changes to the fuzzy rule base. Offline adaptation was performed by utilizing the participant's responses to the survey before they started using an online version of the system. The participant's responses were presented to the system as desired changes and as a result, they caused the corresponding changes to the fuzzy rule base. In both cases, the mechanism was the same and it was triggered when a new training sample $(x^{(nt)}; y^{(nt)})$ was provided to the system.

When this new sample was presented to the system as a desired change, the membership values $\mu_{B_p^c}(x_p^{(nt)})$ for all inputs $p = 1, \ldots k$ and all corresponding sets $c = 1, \ldots, n$ were calculated. Consequently, the activation value for all fuzzy rules were computed, and all the ones that fired were identified, hence all the rules that had an activation value larger than zero. The activation value of the r_{th} rule that fired was defined as $w^{(r)}$. Let M be the total number of rules with $w^{(r)} > 0$. Initially, the fuzzy rule $\acute{r}$ with the highest activation value among all fired rules was identified. Afterwards the consequent of the rule $\acute{r}$ was replaced, by calculating the value of the 'optimal' position of the centre of the output fuzzy set of the $\acute{r}$ rule, by considering the contribution of all the other $M - 1$ rules that fired, by using the following formula:

$$y_{opc} = \frac{y^{(nt)}(\sum_{r=1}^{M}(\prod_{p=1}^{k} \mu_{E_p^{(r)}}(x_p^{(nt)}) - \sum_{r=1}^{M-1} y_{ce}^{(r)}\left(\prod_{p=1}^{k} \mu_{E_p^{(r)}}\left(x_p^{(nt)}\right)\right)}{\prod_{p=1}^{k} \mu_{E_p^{(\acute{r})}}\left(x_p^{(nt)}\right)} \quad (10)$$

After the optimal position y_{opc} was calculated, we identified among all the output sets E^d where $d = 1, \ldots, m$ the $\dot{d}_{th}$ output fuzzy set for which:

$$\mu_{E^{\dot{d}}}(y_{opc}) \geq \mu_{E^d}(y_{opc}) \qquad (11)$$

After the fuzzy set was identified, the consequent of the rule $\acute{r}$ was replaced with $E^{\dot{d}}$.

5.5 Model evaluation

In this section, the classification performance of the proposed fuzzy approach was tested in terms of its ability to map different combinations of the AT's basic elements to values of flow, excitement, calm, boredom, stress, confusion, frustration, and neutral. Evidence is provided in regards to the performance of the fuzzy method with, and without its adaptation part. The classification accuracy of the fuzzy method was tested without its adaptive mechanism, against a number of classification systems, which were also trained by using the online survey data. For this comparison, various ML methods were implemented. The author used Neural Network approaches such as a Multilayer Perceptron (MLP), and a Radial Basis Function Network (RBF), linear regression (Linear), and a regression tree (RT). For the MLP and the RBF networks, a single layer of ten neurons was used. For the proposed fuzzy method (FM), a number of five sets was utilized to describe the inputs and outputs in order to retain a high degree of interpretability of the obtained fuzzy rules. All systems were tested in both stages of the AT model. In the first stage, the inputs for the systems were the values of current state and prediction elements, as provided by the participants in the survey; and in the second stage, the inputs were the values of the outcome, current state, and prediction elements. In both stages, the outputs were values for the eight emotions, which represented the degree to which the emotion described the participant's affective state. In order to evaluate the classification accuracy of the systems, the NRMSE was calculated. NRMSE was produced based on the values of emotions provided by the participants in the survey, and the ones generated from each of the ML approaches. All results were computed by using ten-fold cross validation, and are presented in table 5.4.

Table 5.4 NRMSE for stage 1 and stage 2 for all static ML approaches.

Emotion	Normalized Root Mean Square Error(NRMSE)									
	Stage 1 Classifier(current state, prediction)					Stage 2 Classifier(current state, prediction, outcome)				
	Linear	MLP	RBF	RT	FM	Linear	MLP	RBF	RT	FM
Flow	0,2684	0,2461	0,2501	0,2701	0,2559	0,2615	0,2428	0,2693	0,2654	0.2359
Excitement	0,2575	0,2355	0,2411	0,2598	0,2432	0,2457	0,2113	0,2606	0,2298	0.2081
Calm	0,2787	0,2738	0,2753	0,2865	0,2763	0,2966	0,2846	0,2858	0,3380	0.2857
Boredom	0,2458	0,2359	0,2390	0,2446	0,2386	0,2240	0,2249	0,2204	0,2760	0.2199
Stress	0,2789	0,2657	0,2702	0,2723	0,2689	0,2657	0,2483	0,2536	0,3156	0.2473
Confusion	0,2170	0,2128	0,2149	0,2212	0,2145	0,2453	0,2363	0,2209	0,2987	0.2331
Frustration	0,2288	0,2133	0,2134	0,2102	0,2174	0,2441	0,2005	0,2680	0,2371	0.2001
Neutral	0,2363	0,2200	0,2243	0,2373	0,2209	0,2566	0,2168	0,2460	0,2386	0.2064
Overall	0,2514	0,2384	0,2410	0,2502	0,2420	0,2549	0,2332	0,2537	0,2749	0.2296

From the results in table 5.4, it can be observed that the proposed fuzzy method (FM) had either comparable or marginally better classification accuracy compared to the other ML approaches. At the same time, given the low-level partition of five sets, the fuzzy rules extracted were reflective of the underlying emotion theory. This is a very important advantage of the FM, since the systems with similar performance, such as the Neural Network approaches, can be considered to be black box approaches, and as such, they do not offer any insight on the underlying affect relations. In addition, it is important to mention that the predictive power of the AT's basic elements can be demonstrated from the ability of very simple classification systems, like linear classifiers to map values of the basic elements to values of the eight emotion words. This is a logical conclusion, since it is extremely difficult, even for an individual experiencing a real situation, to provide an accurate value of the degree they are experiencing a certain emotion. For example, providing a value of 65 instead of 75, to signify the levels of excitement someone experiences, is pointless and it greatly relies upon the personalised way someone chooses to provide a rating for describing their affective state.

The performance of the fuzzy approach, including the adaptation mechanism, was also tested and compared to the performance of the non-adaptive version of the system, and the performance achieved by using the adaptive mechanism of the Adaptive Online Inference System (AOFIS) technique (Doctor 2005). The comparison was performed in terms of the NRMSE generated, and it was repeated for different numbers of fuzzy sets. The comparison was possible by utilizing the proposed offline adaptation approach, thus feeding into the system the values, which the participant provided on the survey for the eight emotions, to be utilized as desired changes to the fuzzy system's produced responses. From the results presented in table 5.5, it can be observed that the adaptive mechanism enhanced the system's performance considerably. This improvement signifies the importance of individual differences in the construction of the emotional processes, since the adaptive mechanism's design enhanced and reflected individual preferences. From the results, it may also be concluded that the proposed adaptive mechanism performed better than the AOFIS adaptation approach for smaller numbers of fuzzy sets. This is important for applications, which represent an emotion model, such as the AT, where the fuzzy rules generated from the data should reflect the emotion theory in an interpretable way.

Table 5.5. NRMSE comparison of the developed system with adaptation (AFM), without adaptation (FM), and the AOFIS technique.

Number of Fuzzy sets	Overall Accuracy (NRMSE)					
	Stage1			Stage2		
	FM	AFM	AOFIS	FM	AFM	AOFIS
3	0,2529	0,2441	0,2957	0,2468	0,2020	0,2992
5	0,2436	0,2035	0,2472	0,2322	0,1639	0,1877
7	0,2386	0,1803	0,2154	0,2243	0,1543	0,1327

As an example of the fuzzy rules interpretability, the following rules are presented. These rules were extracted for flow, both for the survey population, and for a single participant, after they were adapted by using their responses.

Survey population: If current state is neutral and prediction is positive then flow is medium.

Participant: If current state is neutral and prediction is positive then flow is very high.

Survey population: If current state is negative and prediction is positive then flow is medium.

Participant: If current state is negative and prediction is positive then flow is high.

The fuzzy rules extracted for flow are in line with the conclusions drawn for flow from the statistical analysis, supporting the strong bond between the emotion of flow and the prediction element, and highlighting the potential of the fuzzy technique, to linguistically represent the affective relations existing in the data using natural language.

5.6 Framework for AC

In this section, a basic architecture of a personalised learning system is suggested, which utilizes the AT hypothesis and the adaptive fuzzy mechanism described earlier in this chapter. This architecture can be used as a framework for AC systems willing to utilize the AT hypothesis. Congruent with the affective loop design, this system is responsible for identifying the user's emotional state and monitoring their affective trajectory during learning tasks. Based on the results, the system finally produces the necessary output signals to promote engagement and wellbeing of the students. The architecture and implementation of the proposed system demands the learning session in which the system is applied, to be divided into discrete parts with specific goals. In this research, the pedagogical frameworks of collaborative problem based and activity led learning are chosen. In accordance with these frameworks, the educational sessions where the system is applied, are divided into discrete activities (e.g. group project, a presentation, a test, a class discussion etc.)

The architecture of the system can be observed in figure 5.8. The core of the system consists of two classification systems based on the approach described in section 5.4.2. These classifiers utilize as inputs the elements of prediction, current state, and outcome, and provide estimates for the eight emotion categories. The adaptive mechanism described in section 5.4.3 is also present in order to make the necessary changes when the user does not agree with the system's output values. Given the estimated values for the eight emotions, the system proceeds in providing the necessary feedback. All values of the basic elements and target emotions obtained during the interaction of the user with the system can be stored in order to retrain the system in the future, when enough data are accumulated. This configuration of the system could be applied for one or multiple learning sessions containing different numbers of activities. It is suggested that before a single user starts utilizing the system, they should complete an offline version of the survey. By feeding their responses in the survey, an offline adaptation of the system can be performed to allow the classifiers' rule bases reflect the user's preferences before the user starts using the system in real time. This process results to a user tailored system. The system’s computational process remains the same for every consequent activity. A stepwise implementation for a single activity is described in detail below.

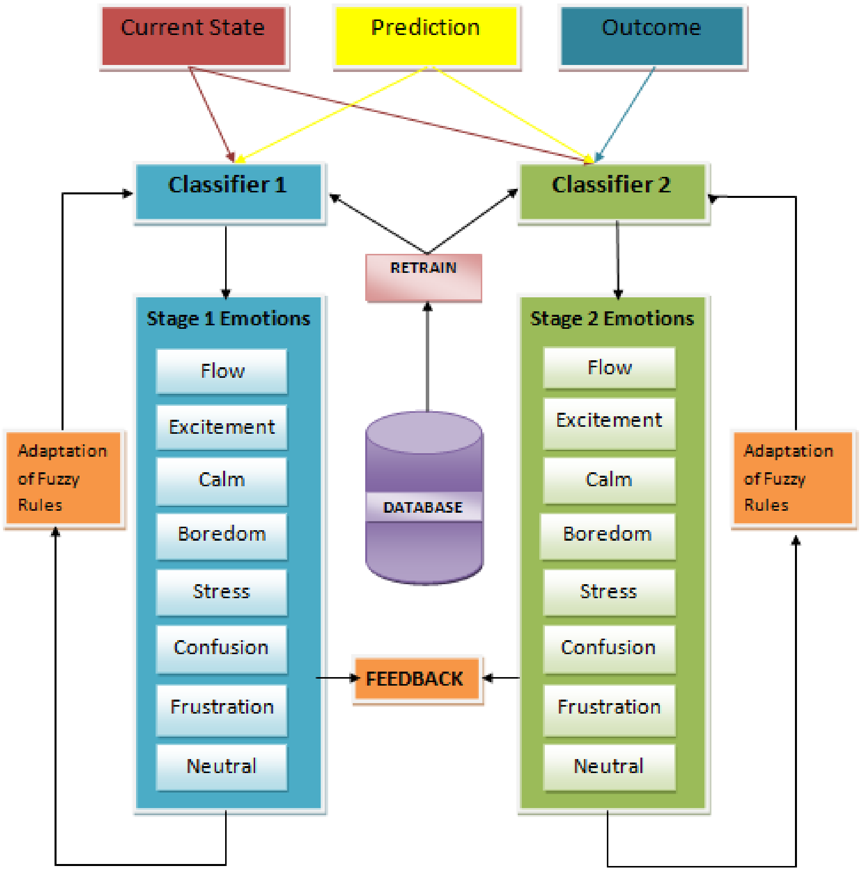


Figure 5.8 Personalised learning system architecture.

At the beginning of the activity, the student is asked to provide an estimate concerning their prediction for the upcoming activity. For example:

[In the next part of this tutorial, we will have a class discussion on quotes from famous scientists on fuzzy logic; How well do you think you are going to do?]

The linguistic labels/answers provided by the user to describe their prediction were transformed to numerical values of prediction (0-100) which were then used by the first stage classifier, along with their current state to calculate values for the eight emotions. The emotion values generated by the system are then presented to the user. In the case that the user is not happy with the system's response, they are able to provide their own values for each emotion category. These values will be used by the adaptive mechanism to make the necessary changes to the first classifier's rule base. Based on the values of the emotions and their positive or negative influence on learning, the system generates feedback to support the student. This feedback is decided based on the emotion with the highest calculated value and is given in the form of small motivational quotes and tips. For example if stress is found to be the dominant emotion, then the following message would be given to the student:

[You appear to be stressed. Why don’t you take a small break and discuss your issues with your group's members and the tutor?].

After the activity ends, the system reminds the user of their prediction in the beginning of the activity, and asks them to provide an estimate of the activity's outcome.

[Your prediction was that you were going to participate and find this discussion very interesting. How would you rate what happened in respect to your prediction?]

The outcome value will be combined with the values of current state and prediction, and will be fed into the second classifier. The stage 2 classifier is responsible for mapping these values to values of the eight emotion categories. As before, the student is able to provide their own values of the target emotions, if they are not satisfied with the system’s results. After the student's values have been obtained, the adaptive mechanism will perform changes at the rule base of the second stage classifier. Again based on the emotion values, feedback is provided to the student. The same process is repeated for every consequent activity. At every start and end point of each activity, the calculated emotion values are stored and can be shown to the student as feedback. By observing their affective trajectory during the learning session, the student can reflect on their performance. Figure 5.9 illustrates the levels of flow, boredom, and frustration as recorded for 2 sessions containing 7 activities. It must be noted that the figure reflects the user's affective state at the start and end points of every activity, and not over the duration of the activity itself, since emotions are short lived episodes which can change in a very small time. Nevertheless, this representation can offer a good picture of the student's affective state when they are performing educational tasks.

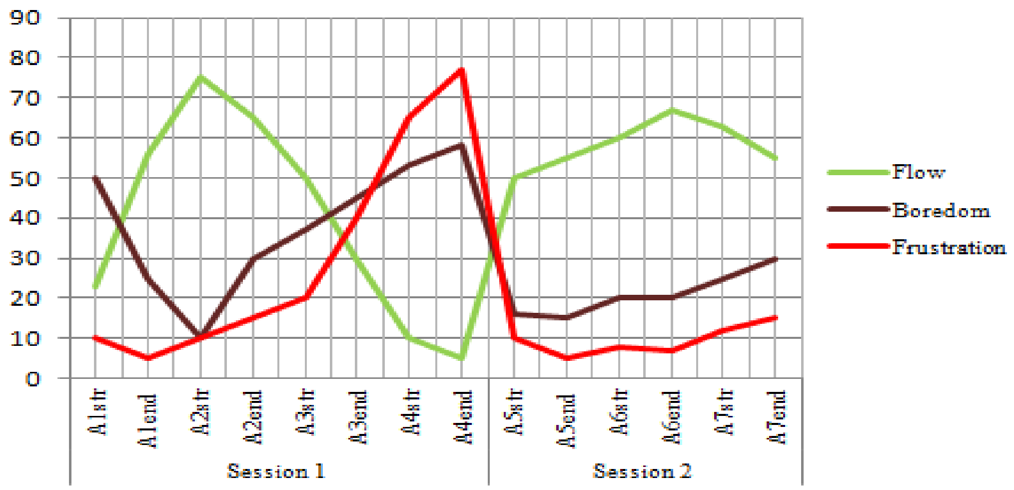


Figure 5.9 A student's flow, boredom, and frustration affective trajectory (Karyotis 2015).

The system could also assist the tutor in their efforts during the learning process. This could be achieved by notifying the tutor when a student requires assistant. In addition, the values of emotions calculated at every stage of each activity, for each of the students, could be used in order to provide an average affective state of the class. This view of the class's affective state will be very useful to the tutor in order for them to reflect on their performance (figure 5.10). Based on these results, the tutor may proceed at adjusting their teaching style, taught material, equipment used, or classroom management. The computational burden of the suggested system is very low. Thus, it could be installed in devices with limited resources such as the smart phones and tablets, which are continuously gaining popularity among students.

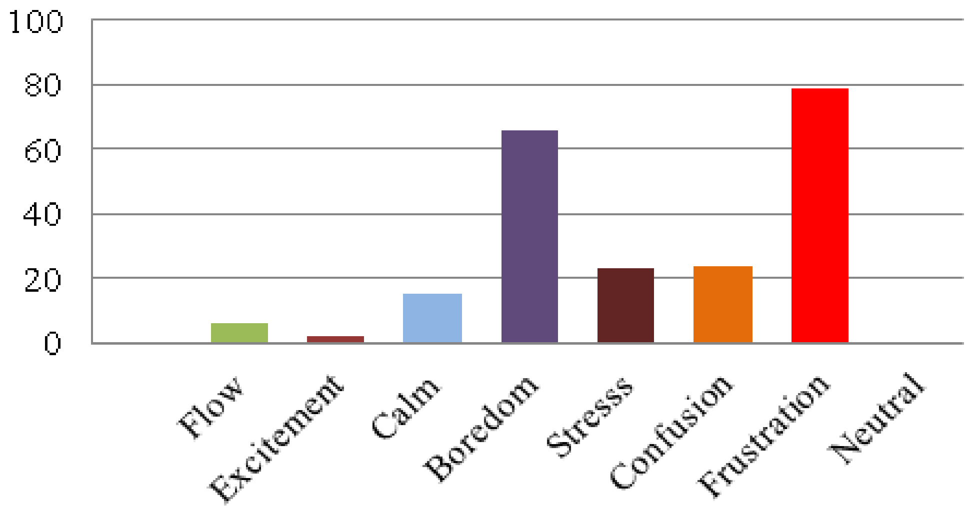


Figure 5.10 Average emotion values of the class presented to the tutor (Karyotis 2015).

5.7 Conclusions

In this chapter the AT hypothesis was explored and utilized for the first time as a modelling approach for Affective Computing systems. Moreover, its applicability was demonstrated in the design of a system responsible to monitor students' affective trajectories. The AT theory was tested using a set of eight education related emotions in a scenario based survey. The experimental results demonstrated the ability to provide emotion labels based only on the basic elements (current state, prediction, and outcome) of one's affective trajectories through time. Furthermore, through the statistical analysis performed in this chapter, the basic AT elements were shown to correlate strongly with the chosen, context related set of emotions, highlighting the underlying affect relationships between them. This statistical analysis offered a new viewpoint of the student's affective state in the classroom.

An adaptive fuzzy logic approach was developed in order to model the aforementioned underlying affect relations. The experimental results supported the proposed fuzzy method in terms of accuracy in mapping basic elements to specific emotions. The performance of the fuzzy method was comparable or able to outperform other ML techniques, such as basic Neural Network configurations, regression trees, and linear regression. The proposed fuzzy method extended the AOFIS method it relied upon (Faiyaz, 2005), and achieved better classification results compared to the AOFIS for a small number of fuzzy sets. The adaptability of the suggested fuzzy method, in terms of incorporating individual differences into the model, enabled the development of two separate models, a generic and a personalised one. The generic one reflected the general population trend, while the more personalised adaptive model, accounted for the idiosyncratic characteristics of the individual. The massive improvement in classification accuracy achieved with the deployment of the adaptive model demonstrated the importance of individual differences in the construction of emotion processes from more basic affective elements. An additional advantage of using the proposed fuzzy method was the ability for fuzzy rules to be extracted from data and expressed in natural language. Thus allowing a clear visualization of the Affective trajectories of an individual, and observe the underlying emotion theory applied to a practical setting.

In this chapter, the foundations of our research were laid. More specifically, having explicitly described the AT emotional representation principles, the author proceeded in designing the data collection method of the online survey, the adaptive fuzzy method of the system, and the proposed AT framework. In the next research phases, the author extends on the AT emotional representation, enhances the fuzzy computational method and AC framework, and finally incorporates in the design other elements contributing for modelling the affective trajectory of students.

Chapter 6 AV-AT Model of Emotion

6.1 Introduction

The findings and methods of the Affective Trajectories hypothesis presented in chapter 5 led to the construction of a novel methodology for incorporating emotion in AC systems. This methodology comprises of three fundamental parts: a novel representation of emotion, namely the AV-AT model; an enhanced fuzzy technique in order to utilize this model; and a framework for deploying this affect modelling methodology in AC systems for tracking and recognizing user's affect through time. The AV-AT model of emotion is a novel concept introduced for the first time in this Thesis, which combines the principles of the AT Hypothesis and the AV model of emotion in order to provide an accurate emotion representation. The computational approach is a modified version of the adaptive fuzzy system used for modelling the AT hypothesis. The previously presented fuzzy model (chapter 5) has been optimized by using a genetic algorithm, thus resulting in augmented classification performance. The AC framework utilizing this affect modelling approach is presented with the help of a personalised learning system. Lastly, an extension of the AV-AT framework is discussed to fit in other contexts and applications of AC.

The concept and structure of the suggested AV-AT model is described in section 6.2. The data collection process is described in section 6.3, through the deployment of an online survey. The data collected were analysed in order to explore the affect relations of the AV-AT model, and construct a generic computational model. Moreover, the online survey provided the necessary data in order to create a personalised fuzzy system, which utilizes the AV-AT model with the help of the genetically optimized adaptive fuzzy techique as presented in section 6.4. The appropriateness of the fuzzy technique to represent the suggested model was tested, and evidence of the AV-AT's potential in AC is provided in section 6.5. This was achieved by comparing the presented computational technique with other popular ML techniques utilizing the AV-AT model, and the popular AV model of emotion, in terms of classification performance. In order to evaluate the emotion modelling methodology, the proposed emotional model and machine learning techique were utilized to develop a personalised learning system, which was tested in two tutorial sessions. The system is presented in section 6.6. The tutorial sessions along with their findings are described in detail in section 6.7. In section 6.8, empowered by the knowledge obtained from the practical implementation of the system, the author discusses ideas for the generalization of the proposed methodology, in various application areas such as driving, gaming etc. Finally, in section 6.9 the research conclusions that arise from this research phase are discussed.

6.2 The AV-AT model of emotion

The AV-AT model is a two stage mixed representation of emotion, which is a direct combination of the ideas and basic principles of the AT hypothesis and Russell's AV Core Affect. The proposed AV-AT model suggests that emotion words used to describe our affective state emerge from the combination of more basic affective elements, during two different stages of our affective trajectory though time. In accordance with the AT hypothesis structure, two stages were defined. The first stage is the point in time where an individual makes their predictions about the future, and the second point is the moment in time where an individual evaluates the outcome of a situation following their prediction. During the first stage of the model an individual provides an emotion word to describe their affective state by combining information concerning the basic affective elements of valence, arousal, and prediction. During the second stage, an individual provides an emotion label based on the outcome they experience after their prediction, and again their arousal and valence levels. Predictions and evaluations of the outcome are the subjective judgements provided by the individuals at the corresponding stage of the AV-AT model. For example, according to the AV-AT emotion representation approach, anger is considered to be an emotion used to describe a person's affective state after they experience an unpleasant and unexpected outcome, accompagned by high arousal levels, whereas stress may arise from the combination of negative predictions about the future, negative valence, and high levels of arousal.

The AV-AT model of emotion is a highly personalised emotion representation. As shown in the previous chapter for the AT model of emotion, individual differences play a major role in the construction of emotional processes from more basic affective elements. Since the AV-AT is based on the ideas and principles of the AT, it is suggested that the way an individual combines the basic elements of prediction, outcome, valence and arousal in each of the stages of the model, is highly personalised. With the utilization of this mixed AV-AT emotion represantaion model, this research aims to provide an applicable way for AC systems to monitor their user's affective state, and allow these systems to differentiate more successfully among the emotion labels they chose to describe their user's affective state. This fact will enable

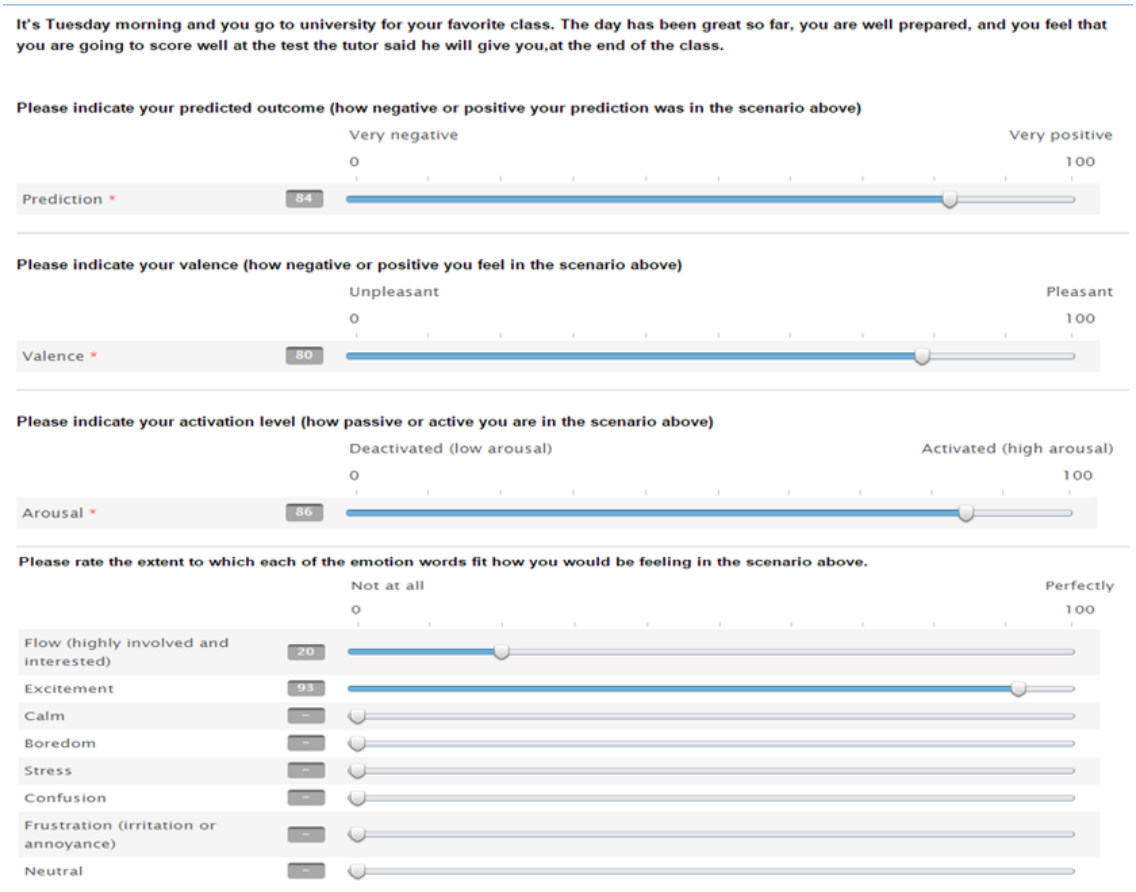
AC researchers to use larger sets of emotions, to cover more adequately their user's affective state description. Moreover, researchers will be able to use sets of emotions that match better the context of the application.

6.3 Online survey 2

The AV-AT introduced an entirely new concept, and in order to explore the underlying emotion theory and model this emotion representation computationally, a new online survey was conducted. The new survey, had the same design as the survey described in chapter 5, and was used to elicit emotions and collect the necessary affective information. The main focus of this survey was to discover and model the relations existing between the AV-AT's basic elements (prediction, outcome, valence, and arousal) and the eight emotion words used thoughout this research process (flow, excitement, calm, boredom, stress, confusion, frustration, and neutral).

The survey was implemented and distributed with the use of QuestionPro online survey software tool, and was completed by 80 individuals. Detailed instructions were given to the participants, including how to successfully complete the survey, and descriptions concerning the basic affective elements and the emotions under investigation. The participants provided their consent and some basic demographic information concerning their age, and gender, and then proceeded with completing the survey. The design and structure of the survey relied on the two-stage scenario design of the AT survey, modified accordingly in order to accomodate the proposed AV-AT model of emotion. The participants were asked to relax and imagine themselves as participating in the scenarios described in the survey. In congruence with the previous survey design, the survey included different educational related scenarios reflecting different combinations of the basic elements, which were presented in a random order to the participants. Similarly to the first survey, the first part of the scenario described a point in time where the participants made a prediction about the future, and the second part of the scenario described what actually happened at the end of this scenario. The two parts of the scenario were presented in a sequential order to the user before they proceeded to the next one. The participants used sliders to provide all their ratings.

In the first part of the scenario the participants were presented with the beginning of a strory. After reading the story the participants provided estimates for the AV AT's basic elements, and for the eight target emotions. More specifically, they rated their prediction of the story by providing a value from 0 (very negative prediction) to 100 (very positive prediction), their valence levels ranging from 0 (unpleasant) to 100 (pleasant), and finally their arousal levels which ranged from 0 (deactivated, low arousal) to 100 (activated, high arousal). After scoring these elements, they provided a score from 0-100 to represent the extent to which each of the emotions fitted their affective state in that part of the scenario (0 being "not at all", and 100 being "perfectly"). An example of a first stage scenario can be seen in figure 6.1.


It's Tuesday morning and you go to university for your favorite class. The day has been great so far, you are well prepared, and you feel that you are going to score well at the test the tutor said he will give you,at the end of the class.

Please indicate your predicted outcome (how negative or positive your prediction was in the scenario above)

Very negative 0 — Very positive 100

Prediction * 84

Please indicate your valence (how negative or positive you feel in the scenario above)

Unpleasant 0 — Pleasant 100

Valence * 80

Please indicate your activation level (how passive or active you are in the scenario above)

Deactivated (low arousal) 0 — Activated (high arousal) 100

Arousal * 86

Please rate the extent to which each of the emotion words fit how you would be feeling in the scenario above.

Not at all 0 — Perfectly 100

Flow (highly involved and interested) 20

Excitement 93

Calm -

Boredom -

Stress -

Confusion -

Frustration (irritation or annoyance) -

Neutral -

Figure 6.1 First stage scenario example of the AV-AT online survey.

In the second part of the scenario the participants were presented with the outcome of the story. After reading the end of the story, the participants provided an estimate representing their evaluation of the outcome of the story, this value ranged from 0 (worse than expected, terrible), to 100 (better than expected, great). After providing their evaluation of the outcome, the participants scored the arousal and valence elements along with the eight emotions as before. During this stage, the first stage part of the story was also presented in Italics to help the participants remain focused in the presented story. An example of a second stage scenario as presented in the survey can be seen in figure 6.2.

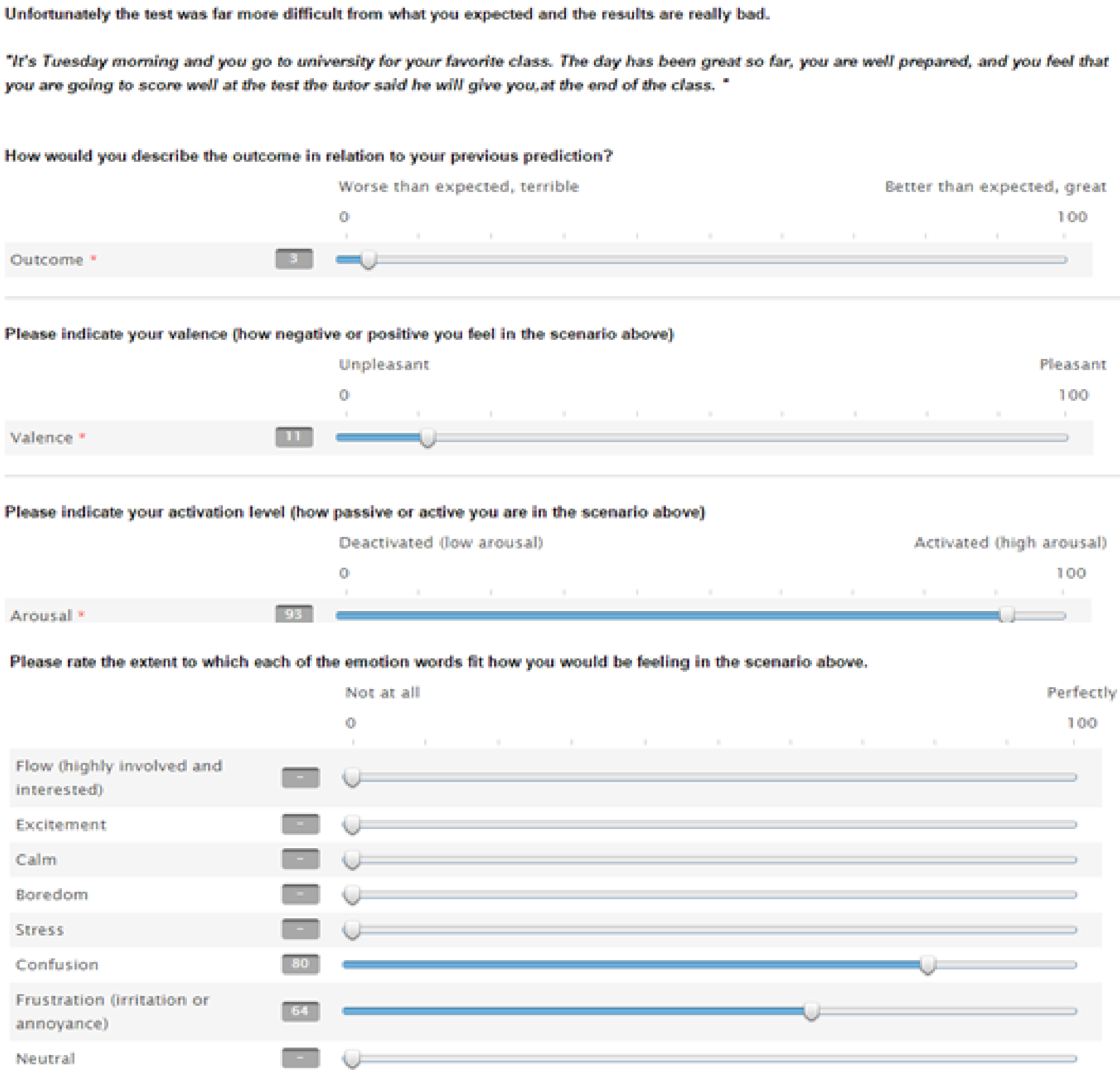


Figure 6.2 Second stage scenario example of the AV-AT online survey.

6.4 Fuzzy method

In this section, the fuzzy mechanism responsible to model the AV-AT is outlined. The stages of our fuzzy set and fuzzy rule extraction method, and adaptation approach, are described briefly, since they are simple modifications of the fuzzy method presented in the previous chapter (section 5.4). Moreover, the genetic optimization technique is presented in detail. This process resulted in the construction of two fuzzy classification systems, corresponding to each stage of the emotional model. The necessary data in order to construct the model were provided by the online survey as described in the previous section (6.3). The training samples contained 3 inputs, and 8 outputs for each stage. In the first stage the inputs were arousal, valence, and prediction, and in the second stage they were arousal, valence, and outcome. In both stages the outputs were values of the eight emotions (flow, excitement, calm, boredom, stress, confusion, frustration and neutral). All variables could take values in the interval [0,100]. Every training sample was in the form of $(x^{(t)}; y^{(t)})$ $t = 1, \ldots., D$. $D = 1440$ since the data samples collected from the new survey were a total of 1440 samples.

The initial fuzzy sets were constructed with the Fuzzy C-Means based method introduced in the previous chapter. For initializing this method, a partition of five fuzzy sets was chosen for the input, and output variables. By using five sets, a good classification performance was achieved, while at the same time a high degree of interpretability of the fuzzy rules extracted from the survey data was retained. It is important to highlight the fact that by utilizing this method, the properties of the constructed fuzzy sets depended solely on the position of the centers. This is attributed to the definition of the triangular membership functions. Each triangular membership function, used to represent the input and output fuzzy sets, was defined as a triangle with the help of the position of the centre points. After the initilazation of the fuzzy sets the fuzzy rule extraction methodology was followed as seen in section 5.4, to extract fuzzy rules from data, which for the first stage classification system, had the following form:

If the user makes a very negative prediction, their valence is negative, and their arousal is very high, then flow is very low, excitement is very low, calm is very low, boredom is very low, stress is very high, confusion is very low, frustration is medium, neutral is very low.

The fuzzy rules extracted for both stages of the model, were used by two fuzzy classification systems that utilized product inference, singleton fuzzification, and centre average defuzzification in order to deliver results for stage 1 and 2 of the proposed AV-AT emotion model. Given this design choice, the calculation of the output emotions was only dependant on the position of the fuzzy set centers. The adaptation method was the same as before, and it was triggered when a new sample was presented to the system. This method was utilized in two ways from the system, both "online" and "offline". This means that the final system was able to make changes when the user was not happy with the results presented to them during their interaction with the system. While at the same time, the system was tailored to the preferences of a specific user, before they started utilizing the system, by presenting the survey responses of this user to the developed system one by one as desired changes.

The extracted fuzzy set and rules, as well as the calculation of the output emotions are dependent on the position of the fuzzy set's center points. A genetic algorithm (GA) was applied, in order to optimize the performance of the constructed system. The performance of the system was evaluated in terms of the Normalized Mean Square Error (NRMSE), which was generated based on a validation set. The validation set comprised of data from the online survey, which was set aside and not used in the training of the classification system. The values for all input and output fuzzy set centers were optimized to produce the minimum value for the NRMSE error, by using the GA. Hence, the objective function of the genetic algorithm that needs to be minimized was defined as the value of the NRMSE calculated in the validation set. Moreover, it was necessary for the produced results to be interpretable. The center points extracted from the optimization process should lead to a reasonable interpretation, and facilitate the visualization of the affect relations existing in the AV-AT emotion model.

As mentioned in the comparative study conducted by Elbetagi et al., there are four basic parameters affecting the performance of the GA: population size, number of generations, crossover, and mutation rates (Elbeltagi 2005). In order to achieve a good trade-off between performance and interpretability, a number of different combinations of the aforementioned parameter settings were tested. As a result, the parameter values that were selected generated small NRMSE, while at the same time the fuzzy set center points corresponded to separate fuzzy terms being represented. As a result, values of parameters that generated non-interpretable results were rejected, since they did not promote an understanding of the proposed AV-AT emotion representation approach. For example, when the GA used a larger population, it generated marginally better results as it concerned the NRMSE, nevertheless the fuzzy set center points were not enabling the construction of an interpretable fuzzy rule base. The GA was implemented by utilizing Matlab's optimization toolbox. In order to use this implementation the algorithm was provided with the following parameters, which generated the most desirable results, and can be seen in figure 2. The optimization process was performed for 55 variables (5 center points for each of the 5 fuzzy sets describing 3 input and 8 output variables). The same procedure was repeated for both stages of the emotion model and it included the following steps:

- Divide the data set to a training, and a validation set.
- The chromosome representing each individual of the population is defined in terms of the position of the fuzzy set center points, for every input and output.
- Initialize the original population (20 individuals) to populate the first generation of the genetic algorithm. In the initial population, the original center points calculated by the FCM are also included as individuals.
- Utilize the method described in the previous section in order to build a fuzzy rule-base for each individual of the population with the help of the training data. Create an instance of the classification system based on the extracted rule base. Calculate the classification accuracy of each fuzzy classifier in the validation set.
- The GA uses the population and the objective function values to produce a new population.
- The selection function of the GA, which chooses the parents for the next generation, is set to be the stochastic uniform function.
- Two individuals of the current generation are guaranteed to survive to the next generation, 80% of individuals of the next generation are produced due to crossover, and the remaining 20% is produced due to mutation.
- The crossover function combines two individuals from the current generation to create a child for the next generation. In our case, the crossover function creates a random binary vector and selects the genes from the first parent where the vector is 1 and the genes from the second parent where the vector is 0 and then combines them in order to construct to the child.
- The Gaussian function is chosen as the mutation function. A random number extracted from a Gaussian distribution is added to each vector entry of an individual. Through these small changes, the necessary genetic diversity is provided and the GA is able to search a larger space.
- The GA evolves until there is no considerable change in the fitness function (e^{-6}) for a consecutive number of generations or until it reaches the maximum number of iterations (100).
- The values of the fuzzy sets' center points for the best individual in the last generation of the GA are used in the construction of the rule base.

The optimization process succeeded at providing a solution that contained a combination of interpretable center points for the fuzzy sets of the proposed model, while at the same time it improved the classification performance of the original fuzzy model that used the center points calculated by the FCM. By utilizing Matlab's 2016 optimization toolbox a basic comparison between the GA and other available optimization techniques was also performed based on classification accuracy of the generated fuzzy classifiers and parameter interpretability. More specifically, the pattern search (direct search), particleswarm (particle swarm), and simulannealbnd (simulated annealing) options, provided by the toolbox, were utilized. The NRMSE results presented in figure 6.3 justify the utilization of the proposed GA based approach in terms of achieving a marginally better performance error compared to the other algorithms. In figure 6.3 it can be observed that the GA optimized fuzzy set center points for the prediction, arousal, and valence elements offer an interpretable solution. In contrast, other methods provided solutions with lower interpretability. These comparisons are by no means exhaustive but justify the design choices that were made for tuning the fuzzy classifiers parameters.

(a) GA parameters

GA parameters	
Number of Variables	55
Lower Bound, Upper Bound	-10,110
Population Type	Double Vector
Population Size	20
Creation Function	Constraint Dependant
Fitness scaling	Rank scales
Selection Function	Stochastic Uniform
Elite Count	2
Crossover fraction	0.8
Mutation function	Gaussian
Crossover function	Scattered
Stopping Criteria	Function tolerance e^{-6}, Stall generations 10, Max generations100

(b) Optimization Performance

NRMSE	No optimization	GA	Pattern Search	Simulated Annealing	Particle Swarm
Stage 1	18.80	17.48	17.74	18.09	17.80
Stage 2	20.60	19.36	19.41	19.80	19.40

(c) Fuzzy center points

Prediction	Arousal	Valence
-0,109 (Very negative)	-0,059 (Very low)	-1,637 (Very negative)
23,986 (Negative)	25,182 (Low)	27,430(Negative)
49,442 (Neutral)	48,088 (Neutral)	50,842(Neutral)
74,083 (Positive)	73,399 (High)	76,422(Positive)
100,871 (Very Positive)	100,249 (Very High)	100,479(Very Positive)

Fig.6.3. (a) GA parameters (b) Optimization performance (c) Fuzzy centers for prediction, arousal, and valence (stage1). (Karyotis 2017)

6.5 Static model performance

In order to test the effectiveness of the proposed fuzzy method to represent the AT-AV model the new survey data were used to compare the fuzzy method's results with the classification results provided from different classification systems. This comparison was drawn for both stages of the emotional model. In the first stage, the inputs were prediction, valence, and arousal, and the values of the eight targeted emotions were the outputs. In the second stage, the inputs were the evaluation of the outcome, valence and arousal and the values of the emotion labels were the targets. Similarly to the previous chapter, the suggested fuzzy method was compared against the same popular ML methods (a Multilayer Perceptron (MLP), a Radial Basis Function Network (RBF), a linear regression model (LNR) and a regression tree (RT)). The comparison was drawn in terms of the Normalized Root Mean Square Error (NRMSE) and the ability of each system to identify the dominant emotion (which was considered to be the emotion for which the participant or the system provided the highest value). The comparisons for each stage were performed using ten-fold cross validation. Additionally, in order to compare the AV-AT model with the AV representation of emotion, the NRMSE and Dominant Emotion Accuracy was provided for all machine learning approaches, when trained by using only the arousal and valence values. To identify the dominant emotion the author simulated the decision an AC researcher would make if they used the AV model, by constructing a minimum distance classifier (D). In order to achieve this, the Affective Norms for English Words (ANEW) (Bradley 1999) database was used to define clusters in arousal-valence space representing each of the eight output emotions. The center of each cluster was defined as the arousal and valence values for that word from the database. Afterwards, using the arousal and valence values provided from the participant, the Euclidian distances from each clusters' centers were calculated. The minimum distance, among the calculated distances, was used to define the dominant emotion. It is important to note that at this point the results were calculated without using the adaptive part of the fuzzy method. This components' performance is evaluated in section 6.7, where the adaptive version of the system is utilized during collaborative learning tasks.

As seen in tables 6.1 and 6.2 the NRMSE values obtained for the Fuzzy Method were smaller compared to the values obtained for all other machine learning methods explored in this research. This applies for both stages, and for both AV and AV-AT models. At the same time, the proposed fuzzy method provided an easily interpretable rule base which allowed the observation of the underlying affect relations, in contrast to black box approaches such as the MLP. Moreover, the fuzzy rules obtained for flow and excitement are provided below, in order to highlight the interpretability of the fuzzy rule base extracted, and how this rule base reflected the underlying affect relations.

If valence is positive, and arousal is high, and prediction is positive, then flow is very high.

If valence is positive, and arousal is high, and outcome is better than expected, then excitement is very high.

The performance and interpretability of FM signifies the appropriatness of this fuzzy technique for emotion modeling and justiifies the researcher's choice for computationally representing the AV-AT model of emotion.

Table 6.1 Stage 1 NRMSE and DEA for survey data.

Emotions	NRMSE and Dominant Emotion Accuracy (stage1 survey)										
	AV - AT					AV					
	FM	MLP	RBF	LNR	RT	FM	MLP	RBF	LNR	RT	D
Flow	16.30	17.92	18.05	21.10	19.89	22.28	23.08	22.52	24.90	25.83	NA
Excitement	15.20	17.11	17.38	21.81	18.09	16.35	18.25	17.20	22.27	18.21	NA
Calm	21.69	24.10	24.06	25.98	26.47	22.16	24.51	24.27	25.97	25.88	NA
Boredom	16.09	17.50	17.09	21.88	19.42	17.03	17.70	17.82	21.98	19.46	NA
Stress	18.73	20.18	19.90	22.15	23.57	20.20	21.57	21.42	23.19	23.80	NA
Confusion	16.04	17.58	17.93	19.60	19.75	16.68	17.88	18.27	19.64	18.87	NA
Frustration	17.97	19.31	19.85	21.67	21.36	19.78	21.43	21.72	22.63	22.65	NA
Neutral	17.85	21.44	19.21	29.65	20.35	19.11	22.22	20.27	29.62	21.31	NA
Overall	17.48	19.29	19.18	22.98	21.11	19.20	20.83	20.44	23.77	22.01	NA
DEA	66.94	64.44	63.68	62.01	59.69	60.56	54.24	58.82	56.25	51.77	54.17

Table 6.2 Stage 2 NRMSE and DEA for survey data.

Emotions	NRMSE and Dominant Emotion Accuracy (stage2 survey)										
	AV - AT					AV					
	FM	MLP	RBF	LNR	RT	FM	MLP	RBF	LNR	RT	D
Flow	19.14	20.87	20.71	22.87	22.79	20.79	21.89	21.89	23.76	24.40	NA
Excitement	15.73	18.52	18.43	21.43	18.86	17.58	19.75	19.17	22.40	20.67	NA
Calm	25.40	29.68	29.53	32.19	31.68	25.71	30.66	30.43	32.17	30.17	NA
Boredom	19.76	21.52	21.65	24.00	24.93	20.28	21.07	21.29	24.03	23.73	NA
Stress	20.12	22.17	21.82	23.04	24.64	20.75	21.74	21.75	23.19	24.38	NA
Confusion	19.79	23.59	23.70	25.57	23.00	20.65	23.67	23.11	25.83	23.69	NA
Frustration	18.15	18.88	19.31	22.22	22.27	19.95	19.57	19.61	22.80	21.53	NA
Neutral	16.81	20.57	19.11	30.33	20.41	33.62	20.88	20.29	30.30	20.67	NA
Overall	19.36	21.97	21.78	25.21	23.57	22.42	22.40	22.19	25.56	23.66	NA
DEA	55.28	49.03	51.04	48.40	45.31	47.01	50.49	51.04	48.13	45.94	43.75

As it can be seen in tables 6.1 and 6.2, for all the systems (FM, MLP,RBF,LNR,RT), the AV-AT model appears to be significantly better in the first stage, and marginally better to comparable in the second stage, compared to the AV model in terms of NRMSE and DEA values. The advantages of utilizing the AV-AT model compared to other emotion models can be demonstrated by comparing the classification results calculated from the utilized ML approaches on the survey data. Stage 1 and stage 2 NRMSE results for all classification systems are improved compared to the results from the previous chapter (table 5.4), where the Affective Trajectories hypothesis and the non genetically tuned fuzzy method was proposed for the emotion modelling approach. These results illustrate the advantages of the new AV-AT emotion model, and highlight the importance of the enhanced fuzzy method used to construct the model. As mentioned in the methodology chapter the online survey step was required for some additional reasons. Firstly, it provided the fuzzy generic rule base and secondly, it allowed for an offline tuning of the system. With the help of the adaptive mechanism, the responses of a specific participant were used as desired changes to the original systems' predicted values. This way, a new participant-specific fuzzy rule base was extracted, which could be used as a starting point for a personalised learning system. This system is presented in the following section. Finally, with the help of the genetic algorithm described above, the optimal positions of the fuzzy sets centres were calculated for each of the input and output variables, using as objective function the NRMSE error. This procedure was performed offline so it did not affect the online version of the system. Therefore the time to deliver the classification results was not affected, and thus the constructed system was suitable for online operation.

6.6 Personalised learning system

The fuzzy mechanism, as described earlier, along with the AV-AT model of emotion were utilized in order to construct a personalised learning system and allow the presented methodology to be tested in real time and in relation to a specific context. Utilization of this system in a real educational setting, offered useful conclusions concerning the applicability and performance of the proposed fuzzy emotion modelling approach. Additionally the system's architecture provided a benchmark for AC systems to intergate and utilize the proposed AV-AT fuzzy affect modelling approach in education, or other application contexts.

The system's architecture was based on the two stage emotion modelling approach as seen in figure 6.4, and it was the extended version of the personalised system presented in chapter 5. It comprised of two fuzzy classifiers which utilized the fuzzy method described in section 6.3. The classifiers used the personalised fuzzy rule base extracted with the help of the online survey, which was unique for every user. Inputs for the classifiers were the prediction, arousal and valence elements for stage 1 and the outcome, valence, and arousal elements for stage 2. The system was also inclusive of the adaptive mechanism in order to provide the necessary changes to the fuzzy rule base, when the user was not happy with the results. The output emotions for each stage comprised of the set of eight output emotions used consistently throughout our research. The system provided the appropriate feedback to improve the user's experience, based on the calculated values of the aforementioned emotions. In this research, the system was applied during educational sessions which were divided in a number of different activities. A basic step by step implementation concerning one activity is described below. The same procedure was repeated for all consequent activities.

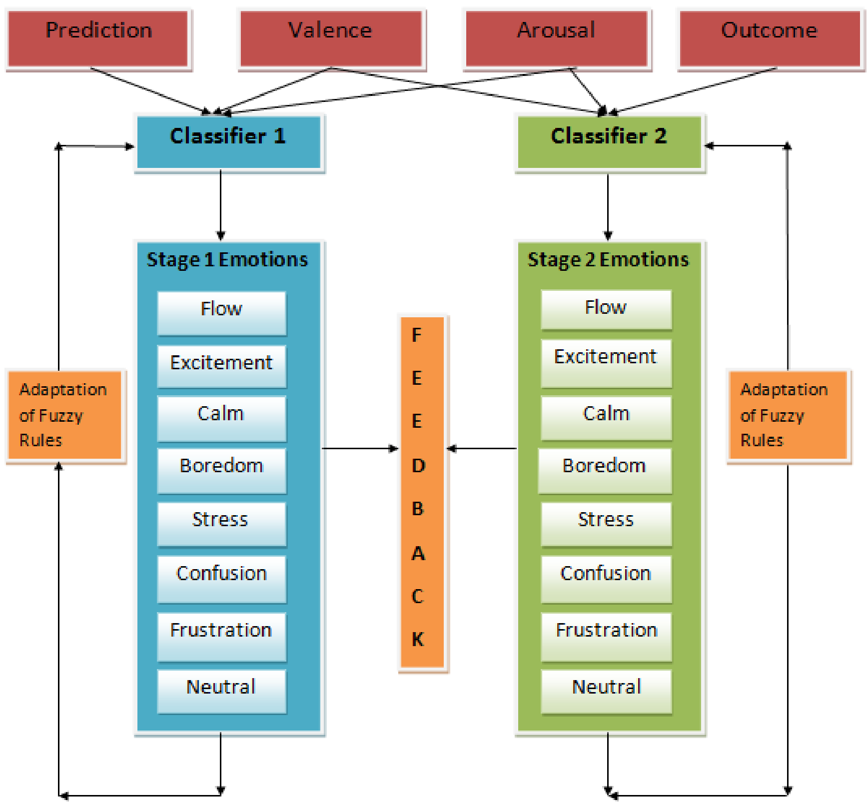


Figure 6.4 Personalised learning system architecture (Karyotis 2017).

Before a new activity started, the participant was asked to provide a value representing their prediction concerning the activity they were about to begin. The prediction along with the values of arousal and valence, which were also elicited from the participant, were then given to classifier 1, which provided values for the eight target emotions. These values were presented to the user in order to reflect on their performance. If the user was not happy with the results, they had the option to provide new values for each of the eight emotions to the system. The adaptive part of the system then processed these values to make the necessary changes to the rule base of the classifier. Given the calculated values of the eight emotions, the system presented tips and short motivational quotes to the user. When the activity ended the user was asked to provide a value which represented their evaluation of the outcome of the activity. This value along with arousal and valence values were then fed into classifier 2, which in turn provided the necessary classification results for the eight output emotions. The system's feedback and adaptation was the same with stage 1. At any point of time the values of emotions, representing the affective trajectory of the user through time, were stored and they were available for viewing. The affective trajectories of two users as provided by the system, over the course of a tutorial session consisting of 4 activities can be seen in figure 6.5.

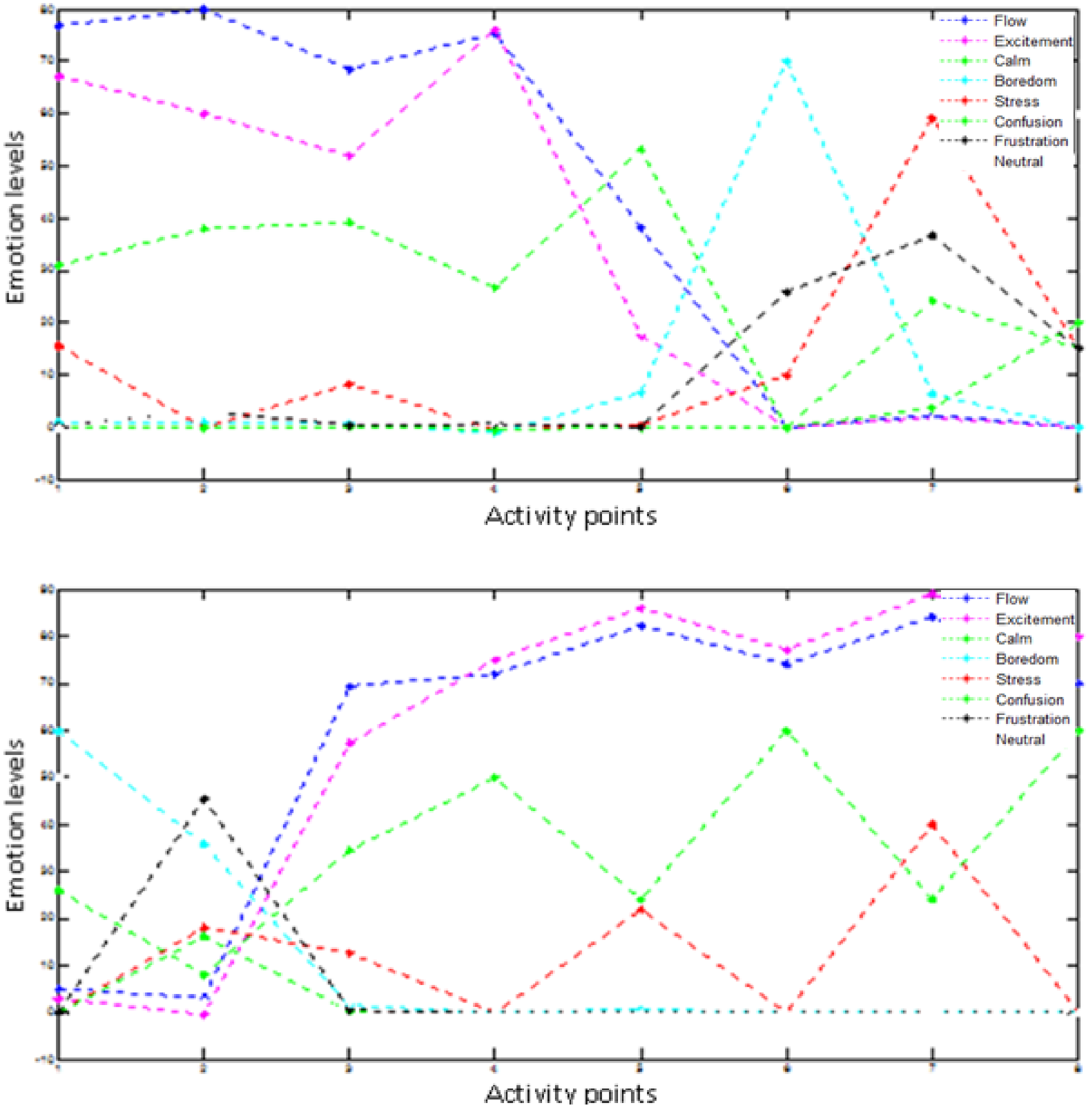


Figure 6.5 System's output of students' affective trajectories during a tutorial session.

6.7 Model evaluation

In order to test the proposed approach two practical experiments were designed and carried out. Twenty one participants, who have previously completed the online survey, participated in two tutorials comprising of two sessions each. The first tutorial was in the area of fuzzy logic, while the second one had a more general machine learning topic, mostly focused on neural networks. Congruent with the proposed architecture and emotion model, the sessions were divided into activities, oriented towards collaborative and Problem Based Learning (PBL), which as mentioned before, is a well structured and modern pedagogical approach able to accomodate the suggested framework. The fuzzy logic tutorial comprised of 2 sessions containing 4 activities each. In this tutorial, the starting session comprised of a lecture on Fuzzy Logic, a class game aiming to familiarize the students with the basic Fuzzy Logic concepts, a discussion on famous quotes related to the subject, and finally a quiz. The second session included a lecture focused on Fuzzy Logic as an ML approach, lab exercises, a group project where the students tried to solve a basic ML problem. Finally, the students presented their developed systems to the rest of the class. The second tutorial also consisted of two sessions with a total of 8 activities. This tutorial's first session included a lecture on ML, a video tutorial, a discussion and a quiz. The second session comprised of a lecture on Neural Networks, a tutorial on Matlab's NN toolbox, a practical exercise and a group based presentation. Participants in both tutorials were divided into groups of three students, and they used their personal laptops where the system was installed. The activities used for both tutorials can be found in Appendices 3 and 4.

In the first tutorial the system was deployed as described above (section 6.6) aiming to explore the applicability, usability and performance of the system, and test the proposed fuzzy modelling approach. The participants were able to see the results and feedback of the system, and they could provide values for the targeted emotional labels to tune the system (based on the adaptation mechanism) if they were not satisfied by the system's values. The values provided by the participants, along with the system's values were stored in order for be used for analysis. In the second tutorial session, the participants were asked to provide values of the target emotions at the beginning and at the end of each activity. During these sessions they were not able to see the results or the feedback of the system's adaptation; hence the values they provided were not biased in any way. Nevertheless the online adaptive part of the fuzzy method was still utilized in the background, making use of the values the participants provided, as desired changes to the system's responses. In both cases the NRMSE was calculated for all emotions, along with the ability of the system to recognize the dominant emotion. In line with the previous experiments, the emotion with the highest value was considered as dominant. Results for both practical sessions, concerning the NRMSE and the Dominant Emotion Accuracy (DEA), are presented in table 6.3. In this table the dominant emotion accuracy achieved when the AV model was used by applying the minimum distance method described in section 6.5 is also included. These classification results are used to provide a direct comparison between the performance achieved by the AV-AT model, compared to the AT, or AV models alone. Additionally, the importance of the role of individual differences in the construction of emotion processes, along with the performance of the adaptive part of the fuzzy method can be observed by comparing the results obtained from the non-adaptive system (section 6.5) with the ones obtained from the adaptive system utilized here.

Table 6.3 NRMSE and DEA for practical experiments.

Emotions	NRMSE and DEA			
	Stage1		Stage2	
	Practical Session 1	Practical Session 2	Practical Session 1	Practical Session 2
Flow	7.32	11.84	8.87	13.41
Excitement	8.31	13.93	7.12	13.64
Calm	9.32	15.52	8.10	15.96
Boredom	7.22	10.03	9.61	11.98
Stress	10.83	11.88	6.55	9.97
Confusion	6.13	7.14	9.68	9.58
Frustration	7.64	9.63	9.58	8.33
Neutral	5.52	9.87	8.67	8.42
Overall	7.79	11.23	8.52	11.41
AV-AT DEA	88.10%	80.94%	80.95%	75.60%
AV DEA	58.93%	64.24%	60.12%	55.95%

From the results in table 6.3 it can be seen that the performance of the model significantly outperformed the survey results presented in table 6.1 and 6.2, for both practical sessions. This was due to the adaptation process which allowed the system to account for individual differences that are proven to play a major role in the AV-AT emotional model in the same manner they do in the AT model. At the same time, it was obvious that it was easier for the participants to provide values in a real setting than when reading an imaginary scenario, and they were also more familiar with the notions of arousal, valence etc. since they had already familiarized themselves with these terms when they completed the online survey. The AV-AT emotion model offered a better approach to recognizing the dominant emotion compared to the AV model for both tutorial sessions and stages. For AV-AT DEA is 88.10% and 80.94% for stage 1 and 80.95% and 75.60% for stage 2, respectively for each of the tutorial sessions. Whereas for AV DEA is 58.93% and 64.24% for stage 1, and 60.12% and 55.95% for stage 2 respectively for both tutorials (table 6.3). The AV model scored around 60% for all stages and sessions, a percentage that was anticipated, considering that the AV is a stage independent model. Specifically, when the AV representation was used, then the emotion was dependant only on the arousal and valence values, and was not affected by the prediction or outcome values. In comparison with the adaptive version of the AT presented in the previous chapter (section 5.5), the results from both practical sessions for the AV-AT model, are significantly better for both stages. In terms of the overall NRMSE the AT model scored 20.35 for the first and 16.39 for the second stage respectively (as it can be seen in table 5.4 for a partition of five fuzzy sets) which are worse compared to the results of the AV-AT model for both practical sessions (overall NRMSE for stage 1 is 7.79 for tutorial 1, and 8.52 for tutorial 2; and for stage 2 the NRMSE is 11.23 for tutorial 1, and 11.41 for tutorial 2). The difference in the results between the first and second practical session was expected since the participants were not able to see the results of the system during the second session, and provided their own values for every case. Moreover, NRMSE and DEA results for both tutorial sessions demonstrate better accuracy for stage 1 compared to stage 2 thus hightlighting the importance of the prediction element, since stage 1 of the AV-AT model is related with the prediction an individual makes about the future.

Once the participants had completed the tutorials they were debriefed, and they were also asked to provide their views concerning their experience of the system in the form of a discussion. A useful remark from the feedback provided, was that participants evaluated the experienced outcomes at the end of an activity, in relation to the predictions they made in the beginning of the activity. In addition, their predictions were influenced by their mood (positive valence was related to a positive prediction), their familiarity with the subject (people more familiar with the subject made more positive predictions), and some personal characteristics such as an optimistic, or a pessimistic stance. Moreover, it was observed that the participants were happy to offer their predictions and evaluations concerning the activities. Providing their evaluations and predictions about the educational process made them more engaged rather than distracted.

6.8 Proposed framework for AC systems

The architecture of the personalised learning system can be easily adjusted to fit into other contexts that are different to education. The only constraint concerning this architecture is the structure of the AV-AT emotional model itself. This structure dictates that no matter the context of the application, the interaction of the user with the system should be divided to segments with clearly defined start and end points. This condition is a prerequisite in order to capture the user's prediction and evaluation of the corresponding outcome, and implement the proposed two stage approach. In education for instance, a session can be divided in different activities (as in the previous section) where the student can provide a prediction for the upcoming activities and an evaluation upon their completion. In a driving assistive application a driver may provide a prediction for the journey ahead when entering the vehicle, and an evaluation of the outcome when leaving the vehicle. Similarly, in a game application, a user may provide their prediction of the upcoming gaming session, and the evaluation of their performance, or of the gaming experience, after they have finished playing.

By considering the above structural limitation in the design of an application, the proposed modelling approach can be applied in different contexts by modifying the set of target emotions to match the context of the application. In an affective driving application for example, the system could use a set of emotions similar to the one used by Nasoz et al. (Nasoz 2010). This set comprised of six emotions namely panic, frustration, anger, boredom, fatigue, fear. In affective gaming a set of emotions such as the one used by Mandryk et al., including boredom, challenge, excitement, frustration, and fun can be utilised (Mandryk, 2007). Whereas, in an affective learning application a set as the one described in this research (containing flow, excitement, calm, boredom, stress, confusion, frustration, and neutral) would fit the purpose. As illustrated by the presented results (sections 6.5 and 6.7), utilization of the proposed model allows researchers to choose more complete and informative sets of emotions to cover the emotional space of their users, since they are able to differentiate more successfully between emotional labels compared to other popular affect modelling approaches.

Affective states have been found to correlate strongly with changes to our physiology. More specifically in the work by Rainville et al. in 2006 it was shown that the heart rate of an individual increases when positive stimuli is presented to them (Rainville 2006). In addition, in the work by McFarland et al., the relation of changes in skin temperature with negative or positive valenced affective state of an individual was explored (McFarland 1985). Dawson et al.'s research demonstrated the close association between arousal levels and the galvanic skin response signal (Dawson 2007). From all the above it can be concluded that estimates of arousal and valence elements can be automatically extracted with the use of the relevant physiological sensors. This can be achieved with the help of non obtrusive wearable devices such as the Autosense, the Empatica E3, or E4 sensors and other available systems.

Additionally, as discussed in the previous section, for the personalised learning system, estimates of the prediction and outcome elements can be provided by a combination of a user profile and specific information relevant to the context of the application. For example, in an affective learning application as the one described earlier, a user profile containing information about the user's psychological characteristics and performance in similar subjects can provide an estimate of their prediction, while the outcome element can be provided through the results of their tests or extracted from their evaluations of the learning process. A two leveled system, such as the one proposed in Mandryk et al.'s research (Mandryk 2007), for the AV model, could be used in order to fully automate the emotion recognition process. The suggested affect modelling approach could be automated by a two-level system where the first level provides estimates of the basic elements through a combination of sensory input, contextual information and a user profile, and the second level maps these values in the AV-AT space.

After the system utilizes the explicitly or implicitly calculated inputs, and provides values for the target emotions, it would then deliver the necessary feedback to move the user to a desired affective state given the context of the application. In a driving context, a system responsible for promoting the driver's wellbeing, could advise a rest stop to a stressed or fatigued driver, or change the car's audio infotainment and cabin lighting, to relax the driver if it detects that they are angry or frustrated. Similarly, in an application designed to enhance game play experience, the system could tailor the difficulty level of the game to match the affective state of the gamer. For example, this can be realised by increasing the difficulty level, if the user is bored from a lack of challenge, or by decreasing the difficulty level of the game, to aid frustrated and inexperienced users. An overview of the proposed AC architecture can be seen in figure 6.6.

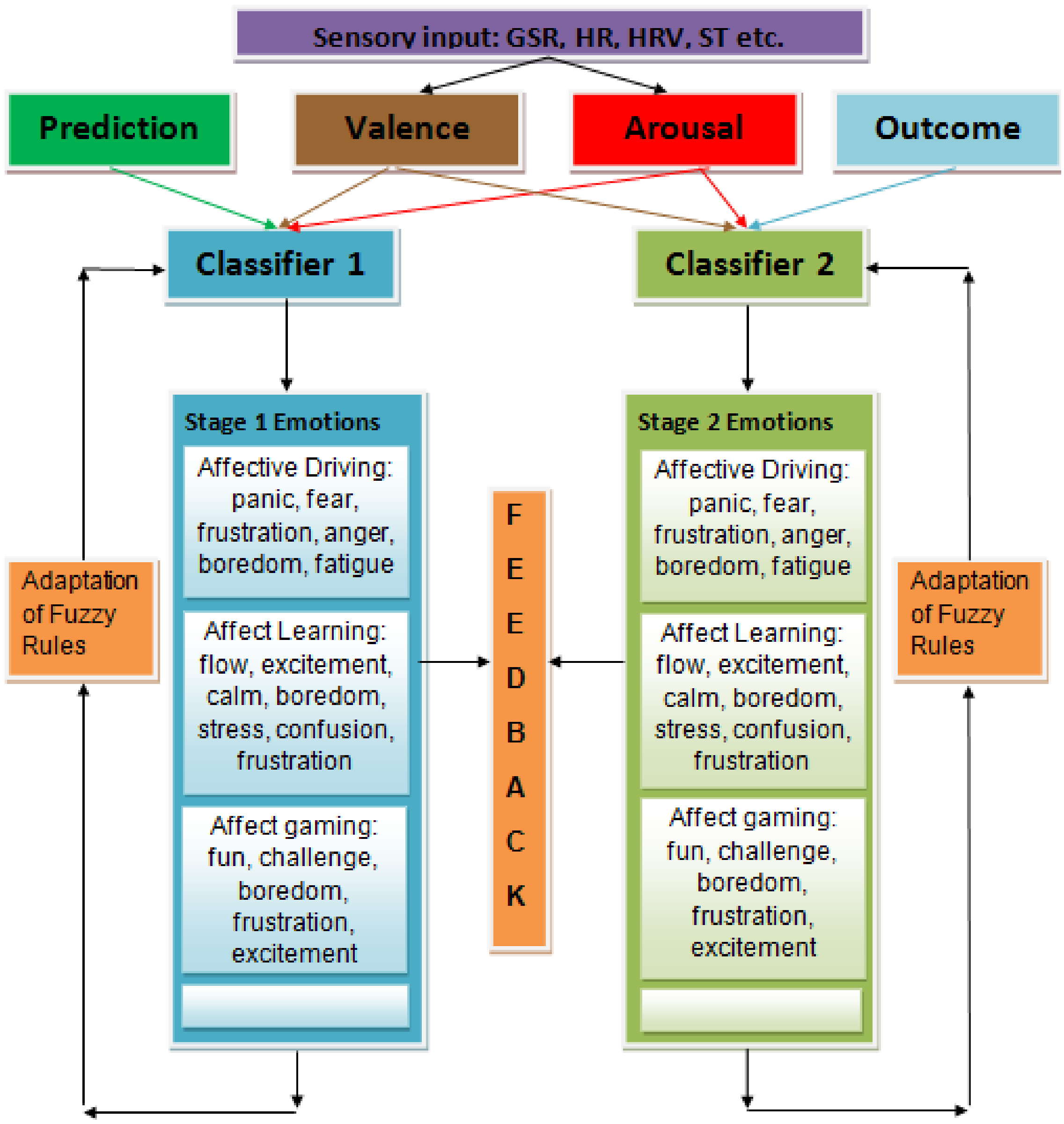


Figure 6.6. Proposed AC system architecture (Karyotis 2016).

6.9 Conclusions

During this research phase, the author introduced a novel methodology for incorporating emotion in the design of intelligent computer systems, and explored its applicability and performance, through carrying out a series of online and offline experiments. The proposed approach, initially established the mixed AV-AT emotional model, which incorporates the arousal valence model of emotion and the Affective Trajectories hypothesis. In order for this model to be successfully utilized, an adaptive fuzzy emotion modelling method was implemented. This method used optimized parameters with the help of a GA. Additionally, the author proposed a framework and basic architecture, which incorporated the presented approach, so that it can be integrated and utilized by AC systems. An online personalised learning system was developed to evaluate the performance of the suggested affect modelling methodology in a real setting while at the same time create a tool which promotes student's learning and engagement in modern pedagogical contexts.

The results obtained revealed the effectiveness and importance of the AV-AT emotional model. Given the application fullfills the structural requirements discussed in section 6.8, the utilization of this model offers high recognition accuracy and additionally allows the researchers to choose sets of emotions for their applications, which describe the emotion space of the user more adequately compared to the AV, or AT models alone. This is due to the fact that the combined model is able to differentiate more effectively between emotions whose representations are close in an alternate emotional space, such as the 2D arousal valence space. The classification results also demonstrated the suitability of the adaptive fuzzy method to represent this approach. Using the survey data it was possible to show that the proposed method had a satisfactory classification performance compared to other well-known ML approaches, while in the same time retained a high degree of interpretability of the underlying affect relations through its use of fuzzy rules. The importance of the adaptive mechanism was demonstrated through the results of practical sessions, where the method's improved performance was attributed to its ability to account for individual user differences. More specifically, the offline and online adaptation process enabled the construction of a fuzzy rule base reflecting the individual's uniqueness in selecting emotions based on the structural elements of the AV-AT model. Finally, the development of the personalised system offered a very interesting insight in the performance of the proposed affect modelling approach, and contributed towards the full automation of the entire process.

By providing a novel computational methodology to represent and model emotion, this research aims to enhance our understanding of the incorporation of emotion in the design of intelligent computing systems, resulting in the improvement of services provided by those systems to their users.

Chapter 7 Affective Transitions model

7.1 Introduction

In this chapter, a novel soft computing technique is proposed in order to monitor and accurately represent students' affective movement through time. The presented soft computing technique is a fuzzy hierarchical hybrid computational technique able to utilize the affective elements of the student's trajectory as time unfolds. The affective state of students is a psycho-physiological construct that evolves dynamically, as the students move through time, and it is formed by the combination and interaction of a variety of different affective elements and factors. As a result, modelling and monitoring an affective trajectory is a taunting and challenging task. This Thesis proposed approach to this task involves a soft computing technique, which is a genetically optimized combination of a fuzzy classification system, and a Fuzzy Cognitive Map (FCM). More specifically the suggested method recreates the students' trajectory through time, by incorporating in the design two central aspects. Firstly, by integrating the inner combinations of basic affective cues, such as predictions about the future, evaluations of the predicted outcomes, and the arousal and valence elements associated with the user's current state. Secondly, by taking into account the way an individual transitions between discrete affective states during learning tasks. Each of the two structural elements of the computational approach is responsible for modelling each of the two aspects. By performing a separate statistical analysis on the data obtained through the experimental sessions, the transitions between affective states in collaborative and problem based learning activities are explored.

This chapter is structured as follows: In section 7.2, the construction and validation process of the proposed affect modelling approach are presented in detail. Moreover, the author explains how the datasets, obtained in the previous stages of this research, along with the previously and newly developed computational tools, and emotion representation ideas, are combined and utilized towards the construction and evaluation of the proposed computational approach. In section 7.3, the computational mechanism that results in the development of a personalised learning system is presented. This system is responsible for monitoring and modelling student's affective trajectories. Special emphasis is given on the development of the newly introduced FCM component, and on the technique used to combine the results of the Fuzzy and FCM subsystems. In section 7.4, evidence is presented supporting the classification performance of the affect modelling methodology. Moreover, results obtained from the statistical analysis of the affective transition data during collaborative learning tasks are provided. Finally, in section 7.5 the research findings and conclusions arising from this chapter are discussed.

7.2 Towards the construction and evaluation of our hybrid Fuzzy-FCM approach

In this section, the process of the suggested affective trajectories modelling approach is described. The by-products of this process are two configurations of hybrid Fuzzy-FCM systems, which are responsible for recognizing student's affective trajectories. Towards the construction of these systems, the data collection ideas, AC frameworks, and computational mechanisms, described in the previous chapters, are utilized. To avoid repetition, the author chose not to describe in detail parts that have already been presented and discussed in previous chapters. However, a brief description is provided on the way these elements are used, and the manner they are combined with the new computational tools and emotion modelling ideas to construct the final systems. The overall process, resulting in the construction and validation of these systems, can be seen in figure 7.1.

The necessary data for constructing and validating the suggested approach, were provided by the following sources: the AV-AT online survey, and the two experimental tutorial sessions described in the previous chapter, together with input from a group of experts. The online survey's dataset was split into two datasets containing training datum, which comprised of three inputs and eight outputs each. Both datasets were used to train a two-stage fuzzy classification system as described in detail in section 6.4. The training process included the extraction, optimization, and personalization of the fuzzy sets and rules, resulting in constructing the adaptive fuzzy part of the final system (Fuzzy). The data from the first tutorial session were also used towards constructing the data driven FCM2 system, and performing a statistical analysis on affective transitions. This time the values of the eight emotions were used, as they were recorded at consecutive points in time, in the first tutorial session. These values, were utilized in order to train the FCM2 using the FCM auto method, which is described in section 7.3.2.3. Another FCM configuration (FCM1) was built from the opinion of three subject experts, with the method described in section 7.3.2.2. This method is very important for future improvement of the system, since it has the potential of being easily extended to include other concepts and affect relations. The two FCM subsystems produced emotion classification results, which were then combined with the results provided by the Fuzzy sub-system using the technique presented in detail in section 7.3.3. The end products of this process were two hybrid fuzzy-FCM systems (FFE and FFA). The performance of those systems was evaluated in terms of the NRMSE and DEA with the help of the second tutorial.

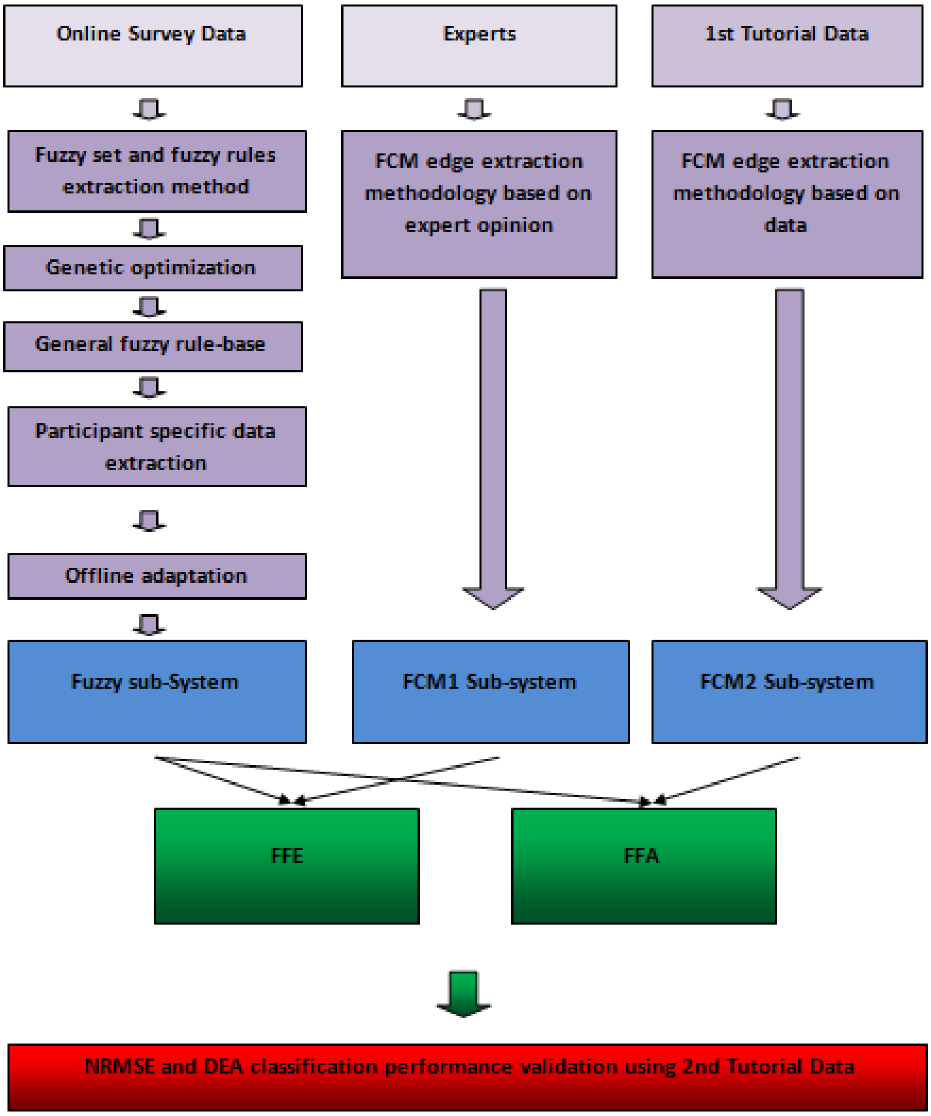


Figure 7.1 The process of constructing and evaluating our affective trajectory modelling approach

During the second tutorial, different configurations of the system (FFE, FFA, and Fuzzy) were running simultaneously at the background, providing values for the eight emotions, and performing the necessary online adaptation. In the second tutorial, the participants were not informed of the results of the systems, and so they were not biased by any external input. As a result, it was possible to obtain values, which best represented the participants' affective state. The basic elements values and the emotion values provided by the participants, along with the results produced by each configuration system were stored, in order to assess the accuracy of each configuration offline. Since the dataset obtained from the second tutorial was not used for any training or optimization purposes, and it was free of the bias in favour of the system, it was deemed appropriate to be used for objectively assessing the classification accuracy of the systems.

7.3 Hybrid Fuzzy-FCM approach

In this section, the computational mechanism of the proposed approach is described. This approach was developed in order to recognize student's affective trajectories during collaborative and activity led learning tasks. The approach resulted in two systems which comprised of two main parts; the Fuzzy part which utilized the AV-AT model to provide values of flow, excitement, calm, boredom, stress, confusion, frustration and neutral, based on values of basic affective elements; and the FCM part which modelled the transitions between these affective states and acted like a supervisory system. Two FCM configurations were developed; one was based on the opinion of experts (FCM1), and one based on the tutorial data (FCM2). Their construction is described in sections 7.3.3.2 and 7.3.3.3 respectively. The values provided by the Fuzzy and FCM subsystems were combined to provide the final classification results as presented in section 7.3.4. The system arising from the combination of the adaptive fuzzy system (FUZZY) with the FCM structure constructed automatically from the tutorial data was defined as Fuzzy-FCM-Auto system (FFA), and the system utilizing the FCM which was constructed based on expert opinion was defined as Fuzzy-FCM-Expert system (FFE).

7.3.1 Fuzzy sub system

The Fuzzy subsystem consisted of the personalised learning system as presented in the previous AV-AT chapter (section 6.6). This system utilized the AV-AT emotion representation model that is computationally represented with the genetically enhanced adaptive fuzzy method as seen in section 6.4. The Fuzzy subsystem utilized two fuzzy classifiers to provide values for the eight target emotions at the beginning and at the end points of every activity. The first classifier used the values of prediction, valence, and arousal, as provided by the participant to calculate the values of flow, excitement, calm, boredom, stress, confusion, frustration, and neutral at the beginning of every activity. The second fuzzy classifier accounted for the second stage of the AV-AT model, and calculated values of the eight target emotions based on values of the user's evaluation of the outcome and the arousal and valence they experienced at the end of each activity. The adaptation mechanism (as presented in detail in 5.4.3), which was developed during this research process was also present, and aided the system to be more personalised and user friendly with its offline and online adaptation process.

7.3.2 FCM sub systems

In this section, the FCM part of the suggested system is described. Initially, the inference process of the FCM is presented. Following that, the two methods used to provide numerical values for the FCM edges are provided. The first method utilized expert opinion while the second extracted the values for the edges automatically from the tutorial data.

7.3.2.1 FCM inference

The FCM structure in the model contained $\mathrm{N} = 8$ concepts ($\mathrm{c_i}$ is concept i). These concepts were the values of the eight emotions. Flow, excitement, calm, boredom, stress, confusion, frustration, and neutral were defined as concepts $\mathrm{c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8}$ respectively. The FCM was represented by an $8 * 8$ matrix W. In this weight matrix, as demonstrated in equation 3.2, each element $\mathrm{w_{ij}}$ is the weight of the edge of the graph, connecting concept node $\mathrm{c_i}$ with concept node $\mathrm{c_j}$.

$$W = \begin{array}{c} \\ c_1 \\ \vdots \\ c_8 \end{array} \begin{array}{c} \begin{array}{ccc} c_1 & \dots & c_8 \end{array} \\ \begin{bmatrix} w_{11} & \cdots & w_{18} \\ \vdots & \ddots & \vdots \\ w_{81} & \cdots & w_{88} \end{bmatrix} \end{array}$$

The FCM inference procedure started by providing an initial vector C to the FCM. This vector included the values of the eight emotions at the first step of the algorithm $\mathrm{C^1} = (\mathrm{c_1^1, c_2^1, \dots, c_8^1})$. In this initial step, the values for the concepts were calculated by the Fuzzy part of the system given the values of prediction, arousal, and valence provided by the participant at the beginning of the first activity. This was done in order to initialize the FCM inference procedure. Let $\mathrm{c_n^s}$ be the value of concept *n* in step *s*. Each concept's value in the next step s+1 was calculated at every consequent step by taking into account the influence of all other concepts. This was achieved through the following equation (7.1), where f was the function responsible for scaling the values of the concept to the desirable interval. In this case, the activation function was the hyperbolic tangent ($\tanh(x)$).

$$c_i^{s+1} = f\left(c_i^s + \sum_{\substack{j=0 \\ j \neq i}}^{8} w_{ji}\, c_j^s \right) \qquad (7.1)$$

The structure of the FCM can be seen in figure 7.2. Every emotion is depicted as a node in the graph. Each node has 14 edges (seven edges leaving from the node, and seven edges arriving to the node).

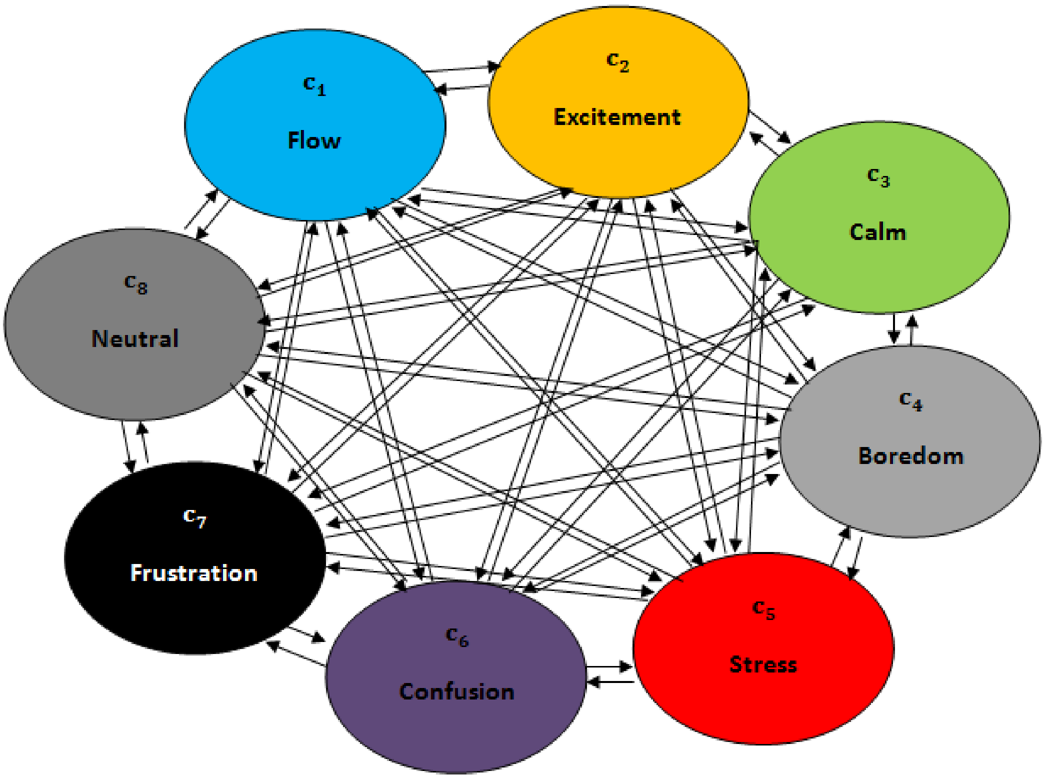


Figure 7.2 FCM sub-system.

7.3.2.2 FCM weights based on opinion of experts

For the purposes of this research, a group of three experts was allocated in order to provide an insight on transitions of the students' affective state, as it unfolds in the classroom. The chosen experts originated from different educational and professional backgrounds, in order to harvest their diverse knowledge and experience on classroom and student psychology. A teacher, an educational psychologist, and a computer science researcher were asked to contribute to this research. Each one of the experts was asked to provide a linguistic label to describe the relation existing between two emotions, each describing the student's affective state at two consecutive points in time.

Every expert was asked to describe 64 affective transitions that represented all the possible combinations of transitions in our set of eight emotions (Appendix 5). Initially, every expert was asked to describe each of the affective transitions as negative or positive. A positive transition between two affective states, which were also the concepts in our FCM structure (e.g. $\mathrm{c_1}$ and $\mathrm{c_2}$), represented the case when a student was in the affective state $\mathrm{c_1}$ they were more likely to transition to the affective state $\mathrm{c_2}$. A negative transition represented the exact opposite, referring to an affective transition between two affective states, which was unlikely to occur. The strength of this transition's likelihood was measured by asking the experts to provide another label stating that this likelihood was either: "non-existent", "weak", "medium", "strong" and "very strong". That way the relation between concepts was declared by utilizing the variable $\mathrm{T(likelihood\ of\ transtition)}$. The variable T comprised of nine variables. $\mathrm{T(likelihood\ of\ transtition)} =$ {Negative very strong, negative strong, negative medium, negative weak, zero or not related, positive weak, positive medium, positive strong, positive very strong} . By using each of these linguistic labels, the experts were able to demonstrate the direction and strength of a certain transition between affective states.

The following semantic rule M was defined to represent each term of the $\mathrm{T(likelihood\ of\ transtition)}$ variable. These terms were represented by the following fuzzy sets and triangular membership functions (figure 7.3):

- M(negative very strong)= The fuzzy set for representing a -1 perfect negative relation (an almost impossible transition) between two affective states at time t and time t+1, with a membership function μ_{nvs}.
- M(negative strong)= The fuzzy set for representing a -0.75 strong negative relation (a very unlikely transition) between two affective states at time t and time t+1, with a membership function μ_{ns}.
- M(negative medium)= The fuzzy set for representing a -0.5 considerably negative relation (an unlikely transition) between two affective states at time t and time t+1, with a membership function μ_{nm}.
- M(negative weak)= The fuzzy set for representing a -0.25 negative relation (a transition that occurs below chance levels) between two affective states at time t and time t+1, with a membership function μ_{nw}.

- M(zero, not related)= The fuzzy set for representing a 0 non-existent relation between two affective states at time t and time t+1, with a membership function μ_z.
- M(positive weak)= The fuzzy set for representing a 0.25 positive relation (a transition that occurs above chance levels) between two affective states at time t and time t+1, with a membership function μ_{pw}.
- M(positive medium)= The fuzzy set for representing a 0.5 considerably positive relation (a transition which is likely to occur) between two affective states at time t and time t+1, with a membership function μ_{pm} .
- M(positive strong)= The fuzzy set for representing a 0.75 strong positive relation (a transition very likely to occur) between two affective states at time t and time t+1, with a membership function μ_{ps}.
- M(positive very strong)= The fuzzy set for representing a 1 perfect positive relation (an almost certain transition) between two affective states at time t and time t+1, with a membership function μ_{pvs}.

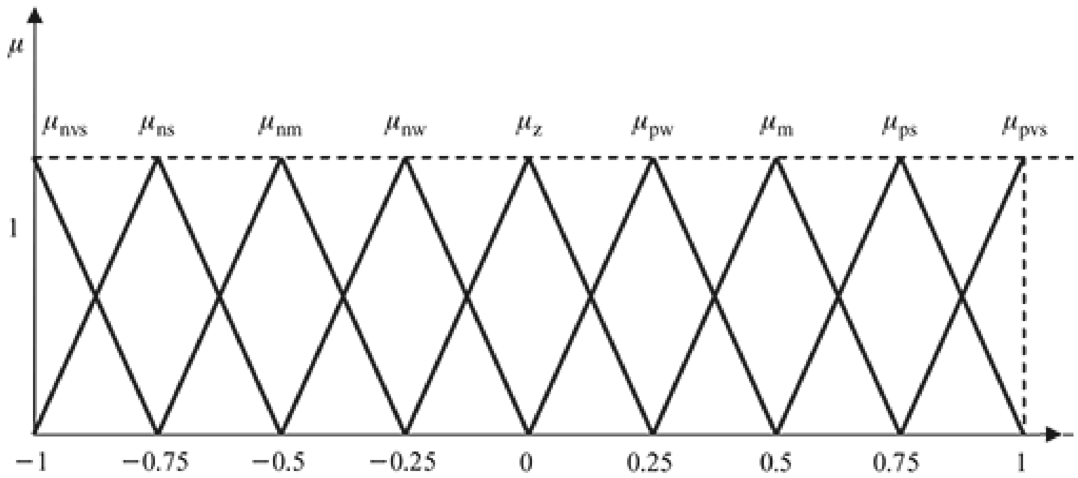


Figure 7.3 The nine membership functions for the fuzzy sets representing each of the labels.

Each of the experts was provided with an 8x8 matrix. The rows of the matrix represented the emotions that students experience at time t, and the columns of the matrix consisted of emotions students experience at time t+1. The experts were then asked to use one of the nine linguistic labels to describe the likelihood of transitioning from one state to the other. As a result, each expert provided a fuzzy linguistic variable for describing the relations existing between the concepts of the FCM. All linguistic variables, provided by each of the experts, describing a transition between affective state (concept) c_i at time t to affective state (concept) c_j at time t+1, were aggregated together by utilizing the SUM operator. Finally, after utilizing the defuzzification method of Centre of Gravity (COG), a numerical value was extracted. This numerical value was then used to define the value of the weight w_{ij} of the corresponding edge of the FCM. The calculated FCM weight matrix can be found in Appendix E.

7.3.2.3 FCM auto

In order to provide values of the FCM edges in an automated way, the collected data, from the first tutorial, were utilized. The weight of an edge of the FCM structure, illustrates the relation between the concepts it connects. The weight of the edge can take values in the interval [-1, 1]. The absolute value is an indication of the relations strength, while the sign is an indication of the relations' direction. In the same manner, the values of Pearson's correlation coefficient demonstrate the relation between two variables and can take values in the interval [-1, 1]. Pearson's correlation coefficients between the values of emotions at two consecutive steps of the algorithm were calculated and utilized as a weight of the edge connecting the two emotions in the graph. All the calculated values can be found at table 7.1 in section 7.4.2.

7.3.3 Combination of the Fuzzy and FCM subsystems

A combination of the values provided by the two sub-systems FCM1 and FCM2 respectively), provided the numerical values representing the degree to which each of the emotions described the student's affective state at every step of the algorithm (start and end points of every activity). As pointed out in the methodology chapter, the FCM played an advisory/supervisory role to the low-level Fuzzy system. This role was simulated by defining two parameters in regards to when and how the FCM should intervene and contribute to the results. The necessity of the FCM to intervene in the system was represented by the difference between the Fuzzy and FCM produced value. If the difference between the values provided by the Fuzzy and the FCM systems was above a threshold ($thres$), the FCM should contribute to the results. The extent, to which the FCM should contribute, was defined by the second parameter, and more specifically by the percentage (per) of the contribution of the FCM to the final results. If we consider $f1$ being the value for one emotion as it was calculated by the Fuzzy system, and $f2$ the value for the same emotion as it was calculated by the FCM (FCM1 or FCM2), for each consecutive step of the algorithm, we then calculate the output value of the system fs for that emotion category by utilizing the following formula:

$$fs = (1 - per) \times f1 + per \times f2 \qquad (7.2)$$

As it can be seen in 7.2 the final output of the system relied on the values of $thres$ and per variables, which represented the interaction of the two subsystems. The genetic algorithm used in order to calculate the optimal position for the fuzzy set centers for modelling the AV-AT (section 6.4), was also utilized here in order to improve this interaction. In this case, the GA was used to find the optimal values for the two aforementioned parameters ($thres, per$).These values minimized the NRMSE generated by running different instances of the final system in the dataset obtained from the first tutorial session. The entire dataset obtained from the first tutorial was used for training, since the validation was performed on the unseen data provided from the second tutorial. The chromosome representing each individual of the population was defined in terms of the two parameters affecting the interaction of the two subsystems. The initial population was set to be 20 individuals. For every individual of the GA a final version of the system was constructed and the classification accuracy of the system was calculated. The GA objective function was set to be the NRMSE of the constructed system calculated by using the second tutorial dataset. All other configuration settings of the GA were the same as the ones utilized by the GA described in the previous chapter (section 6.4). When the last generation of the GA was reached, the best individual was used to define the optimal values of $thres$ and per parameters. By utilizing these values, the final systems (FFA and FFE) were constructed. This process was repeated for each of the two stages of the AV-AT model and for the two different configurations of the FCM (FCM1, which was constructed based on data, and FCM2, which was constructed based on expert opinion). In figures 7.4 to 7.7, the evolution process of the GA for stages 1 and 2 are illustrated, when the data driven and expert driven FCM configurations are used.

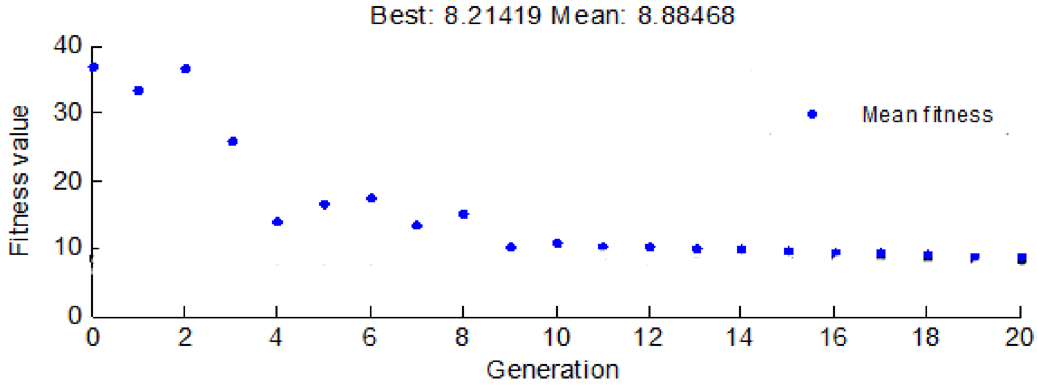


Figure 7.4 Data-driven system stage 1.

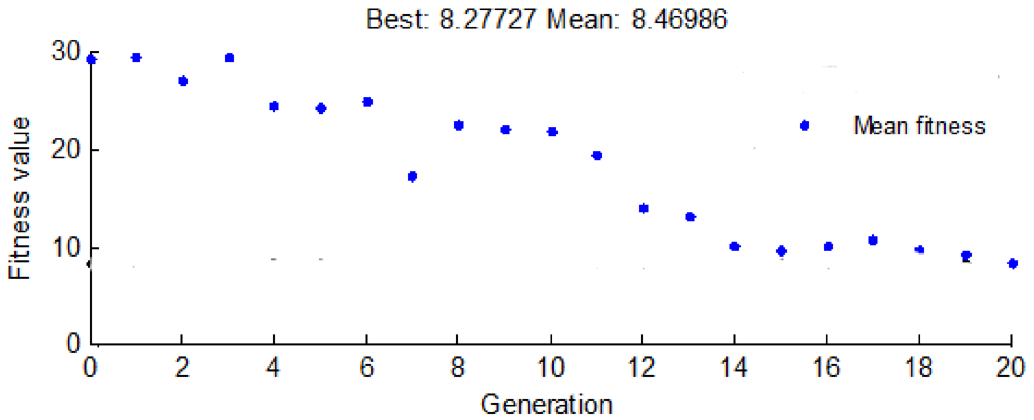


Figure 7.5 Data-driven system stage 2

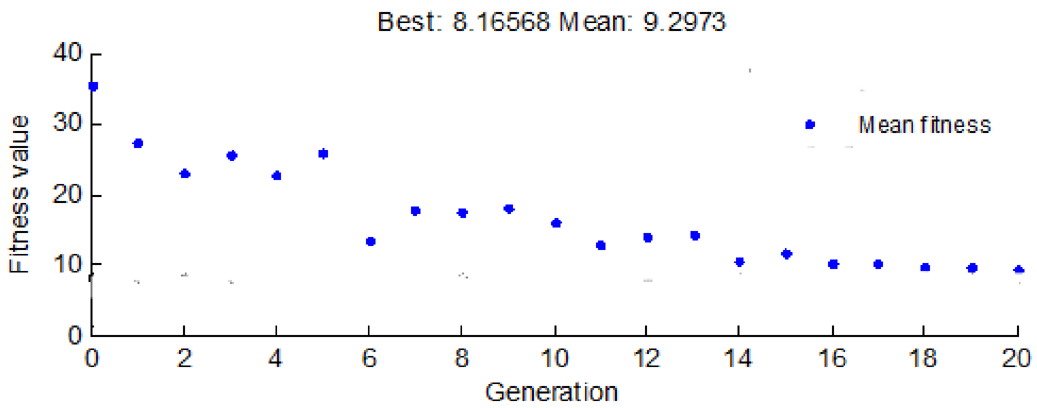


Figure 7.6 Expert-opinion driven system stage 1.

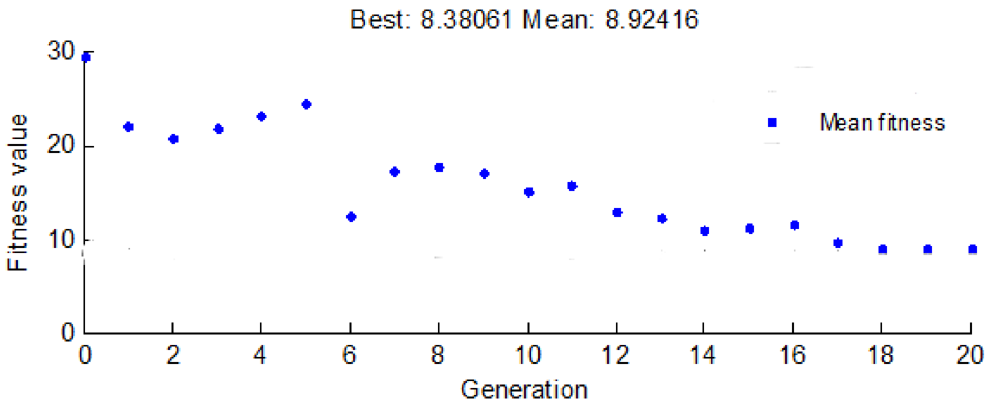


Figure 7.7 Expert-opinion driven system stage 2.

7.4 Model evaluation and statistical analysis

In this section, the classification results obtained from the proposed affect modelling methodology are presented and compared to the ones obtained by the AT model (chapter 5), the AV-AT model (which is the Fuzzy subsystem), and the Arousal Valence (AV) representation of emotion. The statistical analysis performed on affective transitions during collaborative learning tasks is presented and the research findings are compared to the findings of other research teams, exploring affective transitions in different educational settings.

7.4.1 Model evaluation

The classification results obtained in terms of the Normalized Mean Square Error (NRMSE) and the Dominant Emotion Accuracy (DEA) are provided. The NRMSE and DEA calculation was based on the values provided by all systems, and on the values provided by the participants. The procedure followed was the same for both stages 1 (prediction- beginning of an activity) and 2 (outcome- end of an activity). Both NRMSE and DEA were calculated on the data provided by the second tutorial session. This dataset was obtained without introducing any bias to the user, since the participants were unaware of the system's calculated values, and they were not prompted by any kind of feedback. Additionally this dataset had not been used for any training or optimization purposes, by any part of the system. As a result, this dataset was regarded to be an objective validation set for measuring the accuracy of the proposed approach.

The classification results when utilizing the different systems for stage 1 and stage 2 emotions in terms of NRMSE are provided in tables 7.1 and 7.2. The systems that were compared include: the FFE (which is the system utilising the FCM1 trained on the opinion of experts); the FFA (which is the system utilising the data-driven FCM2); the Fuzzy system, (which is the system that utilised the AV AT framework, exclusive of any FCM components); and the AT (the system utilizing the affective trajectories framework as it was presented in chapter 5 for a five fuzzy set configuration for both inputs and outputs). This comparison aimed at exploring whether the suggested approach had a better performance compared to the previous presented models, and evaluating the significance of the introduced FCM component.

Table 7.1 NRMSE for stage 1.

Emotions	**AT**	**FUZZY**	**FFE**	**FFA**
Flow	18.5690	11.8456	10.0698	9.8186
Excitement	17.8589	13.9371	12.9873	12.7654
Calm	20.2164	15.5236	15.4197	15.8745
Boredom	20.0675	10.0378	10.0372	9.6494
Stress	22.0876	11.8800	12.9778	11.8126
Confusion	14.6425	7.1484	7.8283	7.2979
Frustration	16.4462	9.6337	8.7572	8.8126
Neutral	16.7923	9.8717	9.8703	9.8717
Overall	18.3600	11.2348	10.8809	10.7381

Table 7.2 NRMSE for stage 2.

Emotions	**AT**	**FUZZY**	**FFE**	**FFA**
Flow	17.0385	13.4173	11.6636	11.7501
Excitement	16.3430	13.6475	11.8166	11.9466
Calm	18.9163	15.9639	15.6308	15.8675
Boredom	13.9629	11.9808	11.0485	11.0754
Stress	16.4084	9.9761	10.3622	10.3467
Confusion	13.5025	9.5869	10.2588	10.1161
Frustration	14.3604	8.3396	8.0606	8.0276
Neutral	12.3398	8.4263	8.2717	7.7922
Overall	15.3590	11.4173	10.8891	10.8653

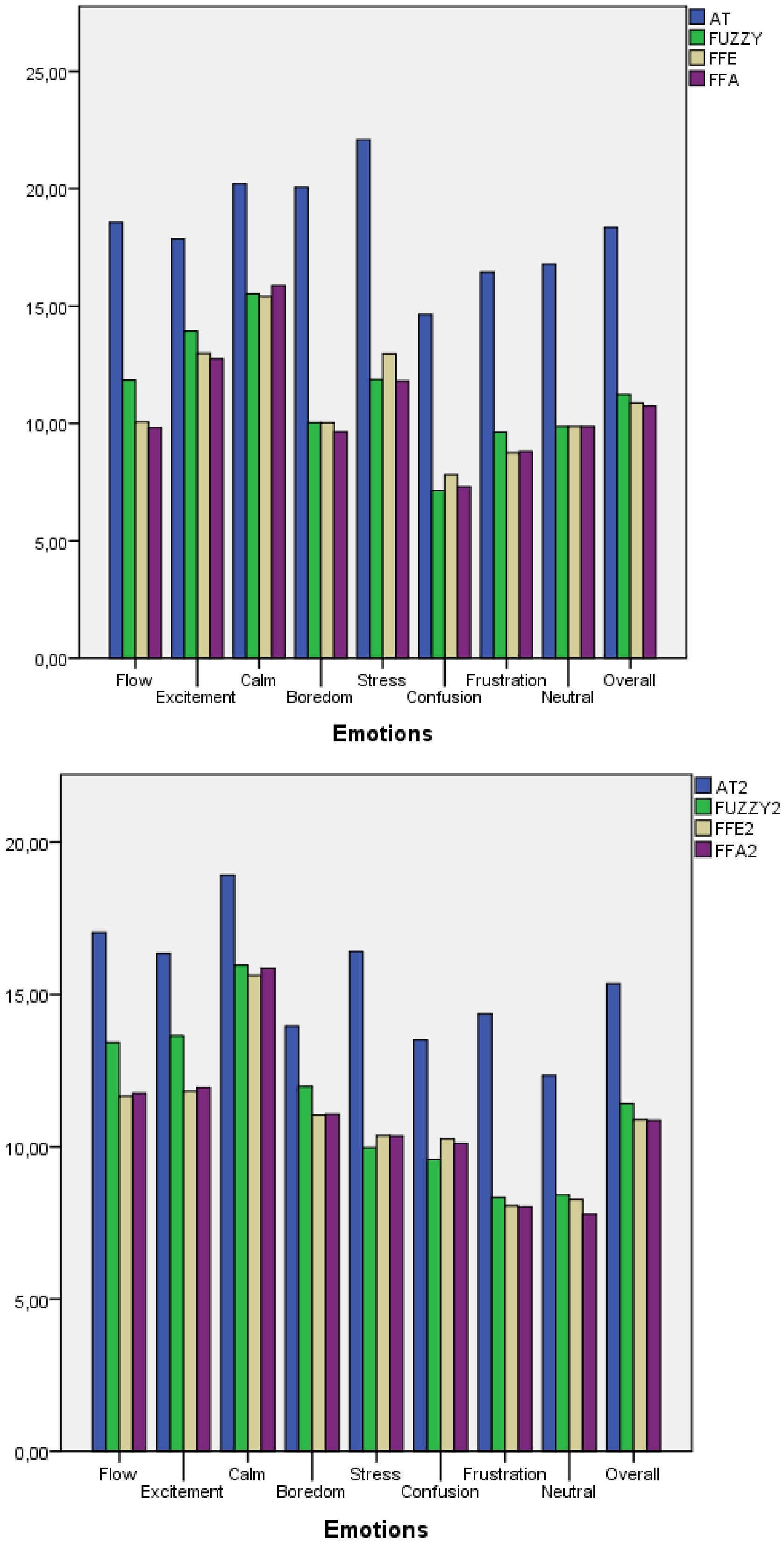


Figure 7.8 NRMSE for stage 1 and stage 2.

In figure 7.9, the corresponding results as calculated for each model, in terms of the Dominant Emotion Accuracy (DEA) are provided. Moreover, the results an AC researcher would have obtained if they had used the very popular Arousal Valence (AV) representation were simulated. As argued in chapter 2, it is a very common practice for AC researchers to use the Arousal Valence representation of emotion as a benchmark to provide an emotion label for their user's affective state. After computing estimates for the arousal and valence elements, an emotion is assigned, based on mapping these values to the representation of an emotion in arousal valence space. This approach was simulated by constructing a minimum distance classifier, which used as inputs the arousal and valence elements as provided by the participants, and computed the dominant emotion. Initially, in order to achieve this, the values for each of the eight emotions from the ANEW database (Affective Norms for English Words database (Bradley 1999)) were used to define clusters in arousal valence space. Each cluster represented one of the aforementioned emotions, and had a center point in the values of arousal and valence provided in the database for the corresponding emotion word, normalized to the interval [0,100]. For example, the cluster of excitement had a center at (83.33, 85.22) which was the normalized mean value calculated for male and female participants in the ANEW database. Given the arousal and valence values as provided by the participant, Euclidian distances from every cluster's centers were computed. The cluster which provided the minimum distance between its center and the values (arousal, valence) provided by the participant corresponded to the dominant emotion.

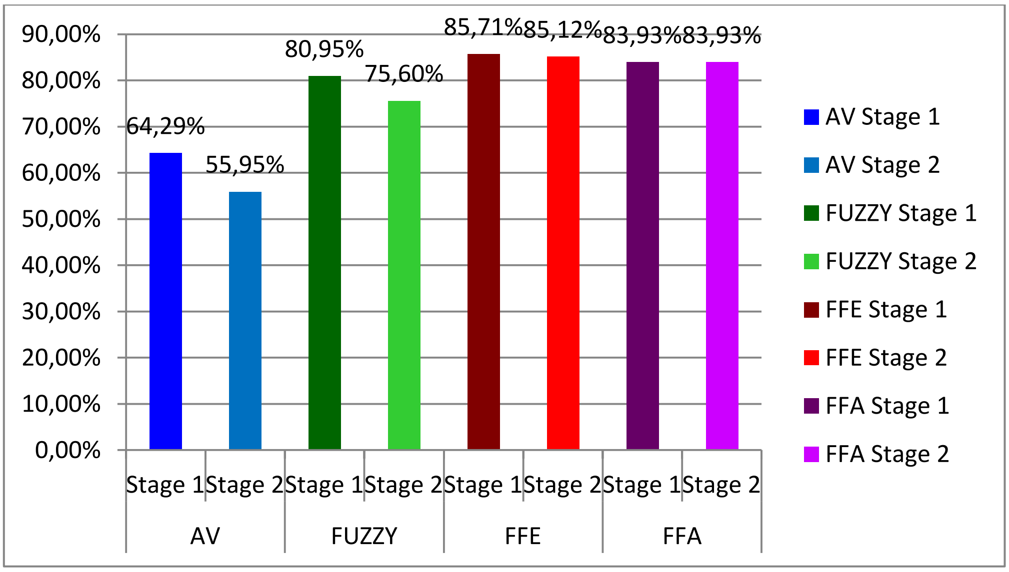


Figure 7.9 DEA for stage 1 and 2.

From tables 7.1 and 7.2 and figure 7.9 it can be observed that both FF systems (FFE and FFA) achieved marginally better performance compared to the Fuzzy model, in terms of the NRMSE, and better performance in terms of the DEA. More specifically, the overall NRMSE for FUZZY was 11.2348 for the first stage, and 11.4173 for the second stage; while for the FF systems the overall NRMSE was: for FFE 10.8809 for stage 1, and 10.889 for stage 2, and for FFA 10.7381 for stage 1, and 10.8653 for stage 2 respectively. DEA values were 80.95% (stage 1) and 75.60% (stage 2) for FUZZY, 85.71% (stage 1) and 85.12 (stage 2) for FFE, whereas for FFA DEA accuracy was 83.93% for both stages. From the above it can be concluded that the hybrid FF systems outperformed the previous FUZZY system (which also reflects the AV-AT model of emotion described in detail in chapter 6) in terms of both NRMSE and DEA. This improvement signifies the importance of adding the higher-level FCM component in the construction of the system. This FCM component accounts for the affective transition information, therefore it allows a more complete modelling approach. Compared to the framework described in Chapter 5 (AT), the Fuzzy-FCM system provides a major improvement for both stages of the AT hypothesis. The NRMSE error was significantly lower for the FF systems, for all emotions and for both stages of the model, compared to the AT. By observing the DEA results, it is also obvious that using the popular AV model de-facto to provide an emotion label poses serious limitations concerning the selection of emotions to describe the user’s affective state. In fact, the very low accuracy achieved by using this AV approach (64.29% and 55.95%), leads to the conclusion that in order for a system to have a reasonable performance, there should be used emotions easily separable in the AV space. This realization may force researchers to select sets of emotions, which provide adequate classification results, but on the other hand, they may not necessarily reflect their user's affective state. Figures 7.10 and 7.11 illustrate the trajectory for each of the eight emotions, as provided by the user (blue), against the trajectory calculated by the system, for the first (figure 7.10) and second participant (figure 7.11) of the tutorial session. This enables better visualization of the system's ability to monitor a student's affective trajectories.

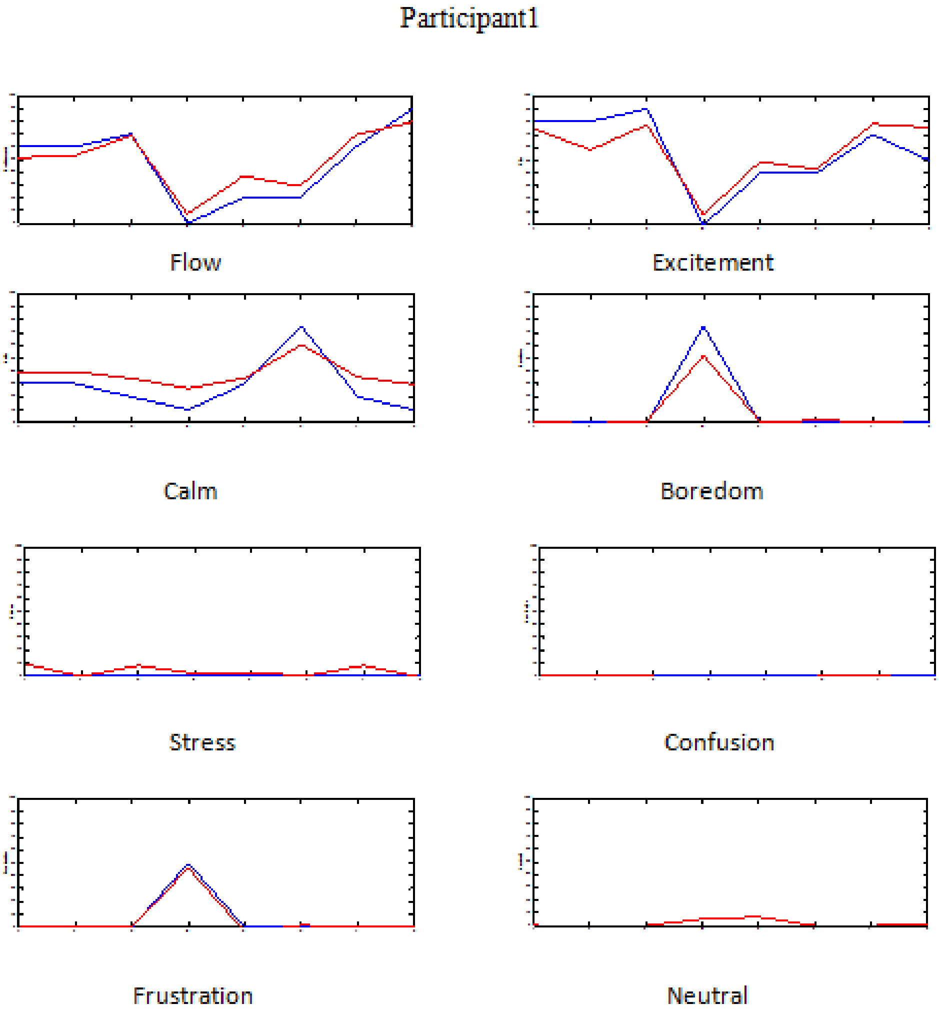


Figure 7.10 Trajectory of emotions as provided by the first participant (blue) against the trajectory calculated by the FFE system, during the first session of the second tutorial (red).

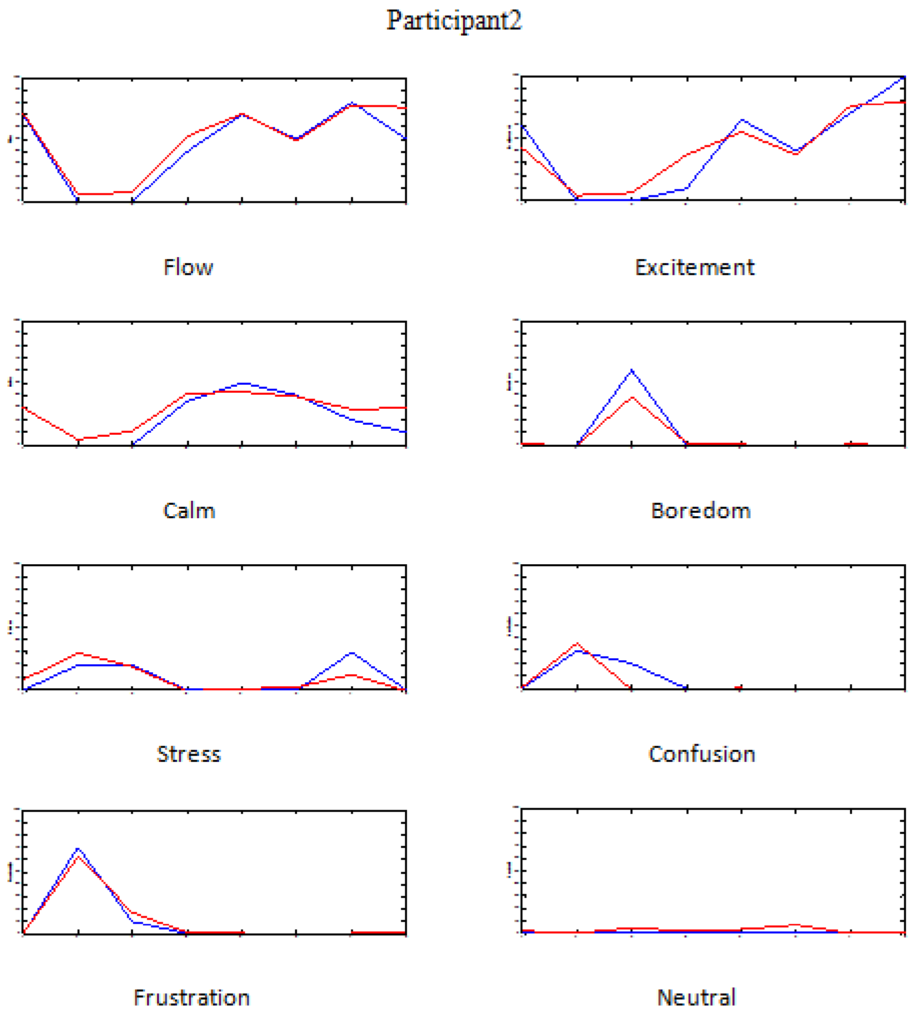


Figure 7.11 Trajectory of emotions as provided by the second participant (blue) against the trajectory calculated by the FFE system (red), during the first session of the second tutorial.

7.4.2 Statistical analysis of affective transitions during collaborative learning tasks

In this section, the correlation results obtained using the datasets from both tutorial experimental sessions are presented. More specifically, Pearson's correlation coefficient was calculated between each emotion values, as they were provided by the participants at time t and time t+1 (indicating the beginning, and end points of each activity). The results can be seen in tables 7.3 and 7.4.

Table 7.3 Correlation Coefficients for affective transitions at Tutorial 1.

Pearson's (Sig)	Flow (t+1)	Excitement (t+1)	Calm (t+1)	Boredom (t+1)	Stress (t+1)	Confusion (t+1)	Frustration (t+1)	Neutral (t+1)
Flow (t)	**0.493 (0.000)**	**0.464 (0.000)**	**0.262 (0.000)**	**-0.306 (0.000)**	**-0.305 (0.000)**	**-0.135 (0.000)**	**-0.482 (0.000)**	-0.063 (0.279)
Excitement(t)	**0.443 (0.000)**	**0.452 (0.000)**	**0.198 (0.001)**	**-0.271 (0.000)**	**-0.244 (0.000)**	-0.099 (0.091)	**-0.398 (0.000)**	-0.086 (0.141)
Calm(t)	**0.332 (0.000)**	**0.253 (0.000)**	**0.308 (0.000)**	**-0.143 (0.014)**	**-0.248 (0.000)**	**-0.194 (0.001)**	**-0.402 (0.000)**	0.026 (0.655)
Boredom(t)	**-0.297 (0.000)**	**-0.253 (0.000)**	**-0.200 (0.001)**	**0.390 (0.000)**	0.064 (0.274)	0.016 (0.786)	**0.298 (0.000)**	0.021 (0.718)
Stress(t)	**-0.282 (0.000)**	**-0.213 (0.000)**	-0.075 (0.203)	0.005 (0.932)	0.087 (0.137)	**0.152 (0.009)**	**0.328 (0.000)**	0.034 (0.561)
Confusion(t)	**-0.215 (0.000)**	**-0.175 (0.003)**	**-0.183 (0.002)**	0.054 (0.359)	**0.272 (0.000)**	**0.170 (0.004)**	**0.251 (0.000)**	-0.048 (0.416)
Frustration(t)	**-0.425 (0.000)**	**-0.344 (0.000)**	**-0.248 (0.000)**	**0.301 (0.000)**	**0.322 (0.000)**	0.101 (0.084)	**0.500 (0.000)**	-0.002 (0.968)
Neutral(t)	-0.038 (0.521)	-.073 (0.211)	0.049 (0.406)	**0.121 (0.038)**	-0.074 (0.204)	-0.059 (0.314)	-0.070 (0.232)	**0.201 (0.001)**

Table 7.4 Correlation Coefficients for affective transitions at Tutorial 2.

Pearson's (Sig)	Flow (t+1)	Excitement (t+1)	Calm (t+1)	Boredom (t+1)	Stress (t+1)	Confusion (t+1)	Frustration (t+1)	Neutral (t+1)
Flow (t)	**0.547 (0.000)**	**0.525 (0.000)**	**0.167 (0.004)**	**-0.437 (0.000)**	**-0.225 (0.000)**	**-0.193 (0.001)**	**-0.461 (0.000)**	-0.027 (0.293)
Excitement(t)	**0.473 (0.000)**	**0.525 (0.000)**	**0.245 (0.001)**	**-0.390 (0.000)**	**-0.198 (0.001)**	**-0.171 (0.003)**	**-0.394 (0.000)**	-0.117 (0.0.45)
Calm(t)	**0.264 (0.000)**	**0.275 (0.000)**	**0.546 (0.000)**	**-0.198 (0.001)**	-0.099 (0.091)	-0.076 (0.192)	**-0.277 (0.000)**	-0.042 (0.477)
Boredom(t)	**-0.455 (0.000)**	**-0.417 (0.000)**	**-0.267 (0.001)**	**0.452 (0.000)**	**0.140 (0.016)**	**0.237 (0.000)**	**0.436 (0.000)**	0.072 (0.219)
Stress(t)	**-0.268 (0.000)**	**-0.214 (0.000)**	-0.009 (0.876)	0.095 (0.105)	0.109 (0.062)	**0.142 (0.015)**	**0.273 (0.000)**	0.020 (0.727)
Confusion(t)	**-0.206 (0.000)**	**-0.215 (0.000)**	-0.041 (0.481)	**0.171 (0.003)**	**0.134 (0.022)**	**0.185 (0.001)**	**0.114 (0.05)**	0.072 (0.222)
Frustration(t)	**-0.463 (0.000)**	**-0.420 (0.000)**	**-0.247 (0.000)**	**0.410 (0.000)**	**0.306 (0.000)**	**0.178 (0.002)**	**0.514 (0.000)**	0.017 (0.772)
Neutral(t)	-0.081 (0.167)	-.0155 (0.008)	0.028 (0.633)	**0.120 (0.041)**	-0.008 (0.888)	-0.005 (0.927)	-0.037 (0.532)	**0.180 (0.002)**

Despite the fact that the experimental setup of the two practical sessions was considerably different, it can be observed that the correlation results from both sessions follow a similar trend concerning the transitions between affective states. Consulting the tables 7.3 and 7.4, it can be seen from the main diagonal (of both tables) that the prominent affective transition, which was present for all emotions, is the one indicating that a student is more likely to remain at the same state, than transition to another. Moreover, flow, excitement, and calm are very likely to follow positive valenced emotions, and they are less expected to appear after negative valenced emotions have been reported. The opposite applies for frustration, since frustration is more likely to follow negative valenced emotions, such as stress or boredom, and less likely to follow positive valenced ones, such as calm, flow, or excitement. From both tables it can be inferred that a student is more likely to become bored, if they are currently bored or frustrated, or when they are in a neutral state. On the other hand, transitions to the emotion of boredom from a student reporting flow or excitement are very unlikely to occur. Furthermore, a student is more likely to feel stressed after they were confused, or frustrated. Confusion has a positive correlation with stress, and a negative one with flow. Pearson's correlation coefficient did not reveal any significant relations concerning the transitions to the neutral state.

The results agree with the main findings provided by other research teams in the past. Indeed in Baker's simulation based environment "incredible machine", the results supported the high likelihood of a student remaining in the same emotional state, namely flow, frustrated, or bored (Baker 2007). The results from this Thesis for both tutorials are in line with these findings. In addition, the correlation results from both tutorials demonstrated strong positive correlations for flow (0.493 and 0.547), frustration (0.500 and 0.514), and boredom (0.390 0.452). The same applied for the results of D'Mello et al. where the team explored the affective transitions of students during their interaction with the intelligent tutoring system "AutoTutor". D'Mello et al. pointed out that affective transitions, such as moving from frustration to boredom, boredom to confusion, and boredom to frustration, were more likely to happen. On the contrary, the researchers concluded that transitioning from being interested to being frustrated was unlikely to occur (D'Mello 2007). As it can be seen in the corresponding tables, the results obtained are in line with these observations. A discrepancy appears in the results suggested for the affective transition of confusion to boredom. D' Mello et al. suggested that this transition is highly unlikely to happen, while in tables 7.3 and

7.4, the correlation appears to be non-significant for tutorial 1 data, or having a week positive relation for tutorial 2 data.

7.5 Conclusions and discussion

In this chapter, a novel soft computing methodology for monitoring and modelling the changes of students' affective state during collaborative learning tasks was presented and tested. Student's affective state was recognized through a combination of different lower (basic affective elements) and higher (distinct affective states) level affective elements of their affective trajectories through time. This methodology led to the construction of a hierarchical personalised learning system, which utilizes different combinations of an adaptive fuzzy rule base system, and a fuzzy cognitive map. Two configurations of this system were built, one based on constructing the FCM part from the opinion of experts (FFE) and the other one based on constructing the FCM part by utilizing the tutorial data (FFA). In order to provide values for the eight emotions, the FFA and FFE systems utilized information about basic affective elements of an affective trajectory through time, with the help of their Fuzzy subsystem, while at the same time they took into account the likelihood of different transitions between affective states through their FCM subsystem. The results from both parts of the system were combined in order to produce the final emotion outputs.

Comparing the Fuzzy-FCM system utilizing the FFE and FFA configurations, with the AV-AT fuzzy system alone, provided results which indicated that the classification performance of the Fuzzy-FCM (in terms of NRMSE), and its ability to differentiate between emotions (in terms of DEA), were improved significantly. Thus these results highlighted the importance of integrating the FCM sub system (either the data or the expert driven FCM), into the final system in order to achieve better classification performance. It is necessary to note that improvement was achieved despite the fact that the FCM only took into account the likelihood of transitioning from one affective state to another. This is important for two reasons. Firstly, it is reasonable to assume that by utilizing an extended version of the proposed FCM model, other factors that influence students' emotions can be easily incorporated in the design (e.g. the teacher's affective state, or the overall group's or class's performance). As a result, the performance of the FCM system would be improved since the additional factors would account for a larger percentage of variance existing in the model, and consequently the performance of the hybrid system that utilizes the FCM element would be improved as well. Secondly, the fact that the FCM system relied solely on the affective transitions, caused massive NRMSE to be produced from the FCM subsystem, when a student changed their affective state to a completely unexpected one (for example this could occur when an activity was extremely engaging or extremely hard/boring). Nevertheless, the combination of the Fuzzy and FCM sub-systems produced lower NRMSE compared to the performance of the Fuzzy subsystem, thus demonstrating that the way the two sub systems were combined was logical and provided a more complete and efficient, affective trajectories modelling approach.

Real time observations of the tutorial session and the results of data analysis pointed out that the effective integration of the two systems enabled the final system to account for underlying affective elements, which lasted longer in time (like moods). Emotions arise from and are highly correlated with these elements, and, as a result, there is a sense of continuation on the affective states themselves. This effect is more prominent whilst referring to the same affective state, meaning that a student is more likely to remain in the same state rather than transition to a different one. The Fuzzy part of the system was not able to cope with this fact by itself. For example, let us consider an interested student with high levels of flow at the beginning of an activity, utilizing the fuzzy rule base system, which used only the basic elements as inputs. When at the end of the activity the student provided negative estimates of the basic elements (e.g. negative outcome) then the Fuzzy system would produce results demonstrating zero levels of flow. However when that was observed, the students in most cases provided emotion values that showed that their flow levels were indeed drastically decreased, but they were not completely zero. The same applied when the user provided emotion values congruent with their previous state (e.g. moving from flow, to flow). When they were asked to provide values for their emotions after an event, which reinforced their previous affective state, they tended to provide a higher value for the same emotions compared to the values provided for those emotions at the previous moment in time, even though the provided values for the basic elements were the same. The FCM subsystem enabled the overall system to deal with both situations, thus providing better classification results.

Finally, the statistical analysis of the affective transitions during the experimental tutorial sessions provided an additional insight of the affective transitions occurring during collaborative and activity led learning tasks, which had not been explored before, under an Affective Computing scope. The results were in accordance with the affective transition results calculated by other research teams (Baker 2007, D'Mello 2007) and showed that certain affective transitions were more or less likely to happen than others.

Chapter 8 Conclusions

8.1 Introduction

This Thesis focused on developing computational models of emotions for Affective Computing applications. The research outcomes extended on already developed emotion theories, such as the AT hypothesis, and included novel emotion representations, such as the AV-AT model and the hybrid affective transition approach. These theories were explored in detail with the help of statistical tools, and they were modelled by utilizing novel fuzzy computational techniques. The main focus of this Thesis was to provide AC researchers with novel affect modelling methodologies, to successfully represent their user's affective state, thus supporting the emotion recognition and modelling process of AC applications. Additionally, through the detailed investigation of the notion of emotion and its underlying structure, the author opted to realize the vision of Calvo et al., so that "computer scientist and engineers inform the emotion research literature" (Calvo 2010).

This research journey started in the first chapter, by outlining ideas and providing the basic background knowledge from all relevant scientific disciplines. Moreover, the aim, research questions and objectives, motivation, and scope of the research were discussed. In the second chapter of this Thesis, a literature review on AC was presented, and all core aspects of this multidisciplinary scientific field were discussed. More specifically, various AC application areas were identified; potential input signals for AC systems were discussed; computational techniques used by AC systems were compared; various emotion theories utilized in AC were presented; the notion of a computational model of emotion was outlined and recent examples were provided; the close relation between emotion and learning was highlighted; modern affective learning applications were presented; previous AC research and AC literature exploring affective transitions of students were discussed; the factors influencing students' emotions were outlined; and finally the PBL and ALL pedagogical frameworks, under which this research was conducted, were discussed. Reviewing the existing literature enabled the author to address the following research objectives. Firstly to expand his understanding of the nature and structural elements of emotions (objective 1). Secondly, to identify machine learning techniques, and computational models of emotion, used in AC systems (objective 2). Thirdly, to explore the influence of emotion on learning and outline the factors affecting students' emotions (objective 3). During this process, the researcher also highlighted the several challenges, and existing limitations, which led to the formation of this research. In the third chapter, the methodological principles of Fuzzy Logic and Fuzzy Cognitive Maps, which are the core computational approaches applied in this Thesis, were discussed, and examples of recent Fuzzy Logic and FCM based AC applications were presented. In chapter four, the overall research methodology was described, offering an overview of the research process followed, and a detailed explanation of the choices made, and methods used during the three phases of this research.

In chapter five, the author tested, modelled, and evaluated an extended version of the AT hypothesis in an educational context. This was achieved with the help of a scenario based online survey. The novel survey design enabled the extraction of rich affect information in an educational context. Moreover, by modifying the content of the scenarios, an AC researcher is able to easily adjust the survey to the desirable field of research (objective 12). A statistical correlation analysis was performed using the survey data to demonstrate the underlying affect relations of the AT theory in an educational context. The medium and strong correlations revealed by the statistical analysis (section 5.3) and the ability of simple classification systems to provide values of emotions based on the AT elements (section 5.5) demonstrated the applicability of the AT theory to education (objective 5). These affect relations were modelled with a novel adaptive fuzzy logic approach (section 5.4). This fuzzy logic approach achieved an improved performance compared to other popular machine learning approaches, while at the same time provided natural language fuzzy rules reflecting the underlying emotion theory (section 5.5) (objective 7). This approach was also inclusive of an adaptive mechanism which through a novel offline adaptation process was able to create personalised computational models of the AT theory (section 5.4.3). Due to the offline and user-friendly nature of this process, offline adaptation can be easily applied in settings were the development of personalised systems can be obtrusive or dangerous (e.g. emotion models for patients) (objective 13). By comparing the classification results of the personalised systems to the models obtained for the general population (section 5.5), the researcher demonstrated the prominent role of individual differences in the creation of emotion processes, thus achieving to extend the original AT theory (objective 6). Finally, a framework for utilizing this approach to monitor student's affective trajectories was provided in section 5.6 (objective 4).

In chapter six, the AV-AT emotion model was introduced. The researcher presented this novel emotion representation, and extended on the developed computational tools by enhancing its parameters with the help of a GA algorithm. The performance of this approach was tested through a second online survey, and through the deployment of a personalised learning system, in two tutorial sessions. The experimental results (tables 6.1, 6.2, and 6.3) demonstrated the ability of the AV-AT model, which is the combination of the AT Hypothesis with the arousal valence model of emotion, to provide more accurate emotion classification results compared to the two models alone (objective 8). Additionally, as shown by the results in sections 6.5 and 6.7, the genetically optimized fuzzy approach outperformed other machine learning approaches and the previous fuzzy method in terms of classification performance (objective 9). Finally, a framework for utilizing the AV-AT approach in a broad AC context was presented.

In chapter seven, a fuzzy computational model was developed that was responsible for modelling low-level information of the basic elements of a student's affective trajectory through time, and high-level information of the affective transitions a student experiences during the educational process (objective 11). With the help of the tutorial data, the ability of this approach to monitor and model student's affective trajectories was tested. This system was more effective at modelling and monitoring students affective trajectories compared to the previous systems. The hybrid system was more accurate in terms of NRMSE and DEA (tables 7.1, 7.2, and figure 7.9) and as discussed in chapter 3, because of its FCM component it is able to extend its structure to incorporate the effect of other factors influencing the student's emotions (objective 11). Moreover, by utilizing the tutorial data to perform a statistical analysis, the affective transitions of students during collaborative learning tasks were explored in modern pedagogical environments such as PBL and ALL (objective 10). The correlation analysis results (tables 7.3 and 7.4) demonstrated that certain affective transitions, especially the ones sharing a common structural element, are more likely to occur than others.

In the following sections, the strengths and limitations of this research are presented, and future research directions are discussed. More specifically, the significant contributions arising from the findings of this research are presented in section 8.2; the limitations are discussed in section 8.3; and finally, future research directions are considered in section 8.4.

8.2 Contributions

The research contributions of this Thesis fall under the scope of AC, Machine Learning, and the psychological theories aiming to understand human emotion. More specifically, the research contributions include: extending on the AT theory (8.2.1); introducing a framework for applying the AT theory to Affective Computing (8.2.2); developing a fuzzy mechanism for fuzzy set construction, fuzzy rule extraction, and online adaptation (8.2.3); proposing the novel AV-AT emotion representation (8.2.4); developing a novel scenario based survey design to elicit affect information (8.2.5); creating personalised computational models by utilizing the survey data to perform an offline adaptation process (8.2.6); implementing a hierarchical fuzzy method for monitoring student's affective trajectories (8.2.7); and exploring the affective trajectories of students during learning tasks focusing on affective transition in collaborative, and problem based learning pedagogical frameworks (8.2.8). These contributions are presented and discussed in detail in the following sections. In table 8.1, a mapping of the research objectives to the relevant contributions and literature review sections is presented to enable the reader a holistic view of this research process.

Table 8.1 Research objectives met.

No	Research Objectives	Objectives Met
1	Examine the nature, and structural elements of emotion.	Literature review section 2.6
2	Investigate the machine learning and affect modelling approaches used by modern AC systems.	Literature review sections 2.5 and 2.7
3	Study the role and influence of emotion in the learning process.	Literature review sections 2.8, 2.9 and 2.11
4	Introduce a framework for utilizing the AT theory to AC.	Contribution 8.2.2
5	Demonstrate the applicability of the AT hypothesis in an educational context.	Contribution 8.2.1
6	Extend on the AT hypothesis by demonstrating the role of individual differences in the construction of emotional processes.	Contribution 8.2.1
7	Present an accurate and interpretable adaptive fuzzy logic classification system.	Contribution 8.2.3
8	Propose and test a computational model of emotion which is the combination of the AV and AT hypothesis models.	Contribution 8.2.4
9	Extend and optimize the fuzzy classification model in order to model the AV-AT.	Contribution 8.2.3
10	Investigate the transitions between affective states during collaborative and activity led learning tasks.	Contribution 8.2.8

11	Exploit the advantages of the FCM methodology to provide a tool for emotion modelling.	Contribution 8.2.7
12	Propose a novel survey design to elicit affect information in various contexts.	Contribution 8.2.5
13	Suggest safe and simple ways to develop individualized models of emotion.	Contribution 8.2.6

8.2.1 Extending on the AT hypothesis

This research was based on Kirkland's work (Kirkland 2012) and achieved to extend their context free AT framework. The application of the AT theory in a specific context was evaluated by providing evidence of this theory's ability to model emotions in an educational context. The correlation results obtained from the statistical analysis, revealed the strong relations between a set of educationally oriented emotions, and the basic AT elements; namely current state, prediction, and evaluation of the experienced outcome. These relations were also demonstrated by the ability of simple classification systems to map values of the basic AT elements to values of the eight selected emotions with a reasonable accuracy. Consequently the research findings supported with evidence that the AT hypothesis is applicable in a specific context such as education.

Moreover, this research explored individual differences in the construction of emotion, under the AT scope. It was argued that an individual combines the basic affective elements of their affective trajectory through time, in a highly personalised way, in order to provide a label, to describe their affective state. This hypothesis was supported with the use of an adaptive mechanism to create personalised models of the AT theory. The adaptive models were specifically designed to take into account, and magnify individual differences. The importance of individual differences in the construction of emotion processes was demonstrated by the massively improved performance observed in the classification results provided by the adaptive models, compared to the corresponding non-adaptive models, for the same number of fuzzy sets. Summarizing on the research findings, the author proposed and constructed a more personalised, and contextualized emotion modelling theory thus extending on the original AT hypothesis.

8.2.2 Introducing a framework for applying the AT theory to Affective Computing

This research introduced the AT theory to Affective Computing domain for the first time. This was achieved by utilizing an adaptive fuzzy computational technique to model AT hypothesis, and by proposing a basic AC architecture, and a framework for utilizing the AT theory to monitor student's affective trajectories during learning tasks. It is argued that, in contrast to other appraisal emotion theories and complex models, the AT provides a more straightforward, and applicable way of modelling emotion. Due to this simplicity, the AT could provide a powerful tool in the hands of AC practitioners.

8.2.3 The fuzzy technique for fuzzy set and fuzzy rule extraction, and adaptation.

The fuzzy computational technique developed for extracting knowledge from data (section 5.4), was a considerable improvement to the adaptive online fuzzy inference system (AOFIS) which relied upon (Doctor 2005). This can be attributed to a number of design choices, and modifications made in many parts of the computational mechanism, such as the fuzzy set and fuzzy rule extraction, and the adaptation method. The suggested adaptation approach demonstrated better classification performance for a small number of fuzzy sets, compared to the original AOFIS technique. This improvement translates to a better trade-off between accuracy and interpretability, a very important aspect for applications where interpretability of the extracted knowledge, is a crucial factor. Secondly, the modifications made in the construction of the fuzzy sets, and the fuzzy system's inference procedure, allowed for the optimization of the technique through a genetic algorithm, which is another important choice contributing to its performance.

8.2.4 The AV-AT computational model of emotion

In this Thesis a novel emotion representation is presented, the AV-AT model. This new representation was tested through online and offline experiments, and the results discussed in sections 6.5 and 6.7 illustrated that the AV-AT model was more effective in differentiating between the labels we choose to describe our affective state, when compared to the popular Arousal Valence (AV) representation (Russell 2003), or the Affective Trajectories hypothesis (Kirkland, 2012). These findings support the potential usefulness of the model in the hands of AC researches in order to use sets of emotions, which describe better their user's affective state, when compared to other approaches. As shown in chapter 2, AC researchers are restricted by their choice of emotion representation. For example, if they use basic emotion models such as Ekman's Big Six, those emotions may not be relevant to the context of the application. If they use an arousal valence representation, they would be bounded to choose emotions that are easily separable in AV space, thus resulting in sets of emotions, which are not reflective of the entire spectrum of the user's affective state. On the contrary, the AV-AT model offers more flexibility in the choice of target emotions by harnessing the benefits of a two-stage, and 3D emotion representation. Furthermore, a framework for utilizing the AV-AT model in AC applications was presented by implementing a personalised learning system. The limitations of the AV-AT framework were identified, and structural modifications were suggested, in order to develop a benchmark AC architecture, utilizing the AV-AT, towards promoting the users' wellbeing in different application fields such as affective driving and affective gaming.

8.2.5 A novel design for an online survey exploring affect relations

A novel survey design for inducing user emotion, and eliciting affect information was created. This design extended on the previous experimental design introduced by Kirkland et al. (Kirkland 2012) for modelling the AT hypothesis, due to its user-centered scenario structure. This design enables the investigation and modelling of the underlying affective relations of constructivist models of emotions (like the AT or the AV-AT), in specific contexts. It is argued that, the scenario-based survey design induces stronger emotion responses to the participants, compared to the context free sentences of Kirkland et al.. Describing real life situations, that take place in real settings, enhances the efforts of participants to visualise themselves in the scenario, thus enabling them to provide more accurate affect related values and linguistic labels, to describe their affective state. This survey design can be used in order to model and explore affect relations, in contexts different from education, such as driving or gaming, by simply altering the scenarios described, to match the new context.

8.2.6 Offline adaptation process

The data obtained from both online surveys were utilized in a unique way in the proposed methodologies. After using the general population of each survey to train the corresponding models, the responses provided by a specific participant were utilized as desired changes to the pre-trained system's predicted values to modelled input states. This offline adaptation process allowed for the personalization of the extracted computational models. Moreover, the importance of this process was highlighted by the massively improved classification performance of the constructed fuzzy systems, before their deployment in real time. This offline adaptation process can be used as a preliminary step for other AC systems, which utilize different ML adaptation techniques, to model affect related information. This process would facilitate the creation of more user-tailored systems, especially in cases where online adaptation is challenging. For instance, it is simpler and safer to provide an already personalised computational model of emotion for a driver by collecting user-specific data from qualitative interaction (e.g. an online survey), rather than perform the necessary changes to a generic model, while they are driving the car.

8.2.7 A novel hierarchical fuzzy methodology for monitoring student's affective trajectories

A novel hierarchical fuzzy methodology was developed. This methodology consists of a genetically optimized adaptive fuzzy system and an FCM, to model and monitor the student's affective trajectories through time. The presented computational methodology includes an adaptive fuzzy system responsible to incorporate low-level information concerning the basic elements of a student's affective trajectory, and an FCM, which models high-level information of the affective transitions a student experiences during learning tasks. To the best of the author's knowledge, utilizing affective transition information to predict the student's affective state is a novel approach, which has not been applied before in real time, or in a specific context, like education. Previous experiments conducted by Lin et al. did not apply this information as a means to recognize their user's affective state, instead their FCM based model was a tool to run simulation scenarios (Lin 2013). Moreover, the model developed by Metallinou et al. was not suitable for practical implementation in a specific context. This is due to the fact that the team used a context free database, containing interactions among actors, to train their system, and utilized as inputs to the developed system, both previous and future observations (Metallinou 2012). In addition, compared to the AT and AV-AT emotion modelling frameworks presented in chapters 5 and 6, the suggested computational methodology showed improved performance in recognizing the user's affective state. At the same time, the proposed computational methodology demonstrates an enhanced potential for emotion recognition and modelling, since it is able to easily extend its structure, in order to incorporate other factors that contribute in the creation of the student's affective state, such as the teacher's affective state. This ability is attributed to the underlying FCM structure, which as shown in chapter 3, is a computational methodology able to include new concepts in its design.

8.2.8 Affective trajectories of students during collaborative learning tasks.

By using statistical tools to analyze the data collected from the online and offline experiments, this research offered an additional insight on the student’s affective state during learning tasks. It was demonstrated that certain education related emotions correlate strongly with specific aspects of a student's affective trajectory through time. For example, the experimental results revealed the close connection of "flow" with the prediction element, thus demonstrating the paramount importance of nurturing positive expectations in the classroom, in order for the students to feel interested and engaged in the learning activity. Additionally, the author investigated the affective transitions of students occurring during collaborative and activity led learning tasks, in the context of PBL and ALL. Statistical analysis results yielded that certain affective transitions occurred above, or below chance levels. The most prominent affective transitions were the ones between states that share common structural elements, such as positive or negative valence (e.g. flow to excitement, or boredom to frustration). The majority of the experimental results were in line with the findings of other research teams, despite the fact that these teams investigated affective transitions of students in different educational contexts, such as virtual environments, or interaction with intelligent tutoring systems (Baker 2007, D’Mello 2007).

8.3 Limitations

The research that led to the creation of this Thesis was conducted to support the emotion modelling and recognition goals of AC systems. This research had to overcome barriers, which related to the complex nature of emotion, and the ambiguity of affect related data. The limitations pertaining to this research are discussed below.

- A limitation is posed by the structure of the proposed computational emotion models. All frameworks and implementations of personalised learning systems described in these series of studies, relied on capturing basic affective elements, in the beginning and end points of learning activities, so as to provide values for the target emotions. However, emotions are short-lived episodes, which could potentially change many times during the course of a single activity, like a presentation or a discussion. The proposed systems might have provided accurate estimates during the start and end points of the activity, yet they did not account for the changes of the student's affective state occurring during a single activity. Nevertheless, the start and end points of an activity provide a good estimate of the student's affective trajectory during a learning session, while at the same time, they are suitable points in time for delivering feedback to the student. For example, it is more suitable for a tutor to support a student before or after the completion of their presentation, rather than while they are presenting. The feedback provided to the student may include a visual representation of achievement, a motivational tip, a learning related complement, or other supporting actions.

- The automation of the process relies on the ability of the system to unobtrusively capture basic cognitive and affective information, to enable the system to calculate estimates of the basic elements. As outlined in section 6.8, previous research demonstrated that arousal and valence elements can be extracted from physiological sensors. These sensors become less and less obtrusive as the technology advances, as a result they can have a minimal annoyance to the student's efforts. However, prediction and evaluation of the outcome elements are cognitive and appraisal related elements, which are very difficult to extract automatically. Nonetheless, observations during the experimental tutorial sessions led to the conclusion that students are happy to offer their predictions and evaluations on the educational process, and in addition, these elements are closely related to the user's psychological profile, previous experiences in similar courses, and mood of the day. However, these claims were based on debriefing a small number of participants, and despite having a logical base, at this point they cannot be generalised.
- Providing accurate estimates for a vague notion like emotion, or even for more basic affective elements, such as arousal and valence, is a very challenging task. In addition, the notions of the emotions under investigation, or the meaning of affective elements like arousal and valence are discipline specific, and therefore they pose challenges for a non-specialist, or a non-native English speaker to grasp immediately. This fact was visible on the participants' provided values, especially in the data obtained from the online surveys. There is an inherent difficulty in collecting affect related data from humans, which results in datasets containing a considerable amount of noise and outlier artefacts. This aspect is not unique to the approaches presented in this Thesis, but it is present in all AC research. Fuzzy Logic based ML techniques were chosen to account

for this challenge, since they are able to deal with the uncertainties concerning emotion and human data collection.

- Optimally a very large dataset is needed in order to test and provide supporting evidence in favour of new emotional representations. Compared to Kirkland’s studies where 40 and 31 individuals participated in two studies respectively, this research aimed for a larger population. A total of 80 participants completed the first survey, 89 participants completed the second survey, and 21 of them also took part in two tutorial sessions. Despite the population being relatively large, the author believes that an even larger dataset would be able to provide more compelling evidence towards a more objective modelling of the basic elements.

8.4 Future Research Directions

There are several future research directions, which are interesting to discuss. These directions arise from the strengths and the limitations of the research findings and they are presented as follows.

- The AV-AT model of emotion is a versatile model, which could provide a useful tool for performing sentiment analysis during the interaction of individuals or groups of people with social networks. Additionally, despite the fact that the tutorial sessions provided a measure of the method's performance, and useful ideas about its practical implementation, greater insight in the underlying emotion theory can be achieved by applying this method to the vast social network data. Monitoring the affective associations that millions of users make, concerning their predictions about the future, their evaluations of certain outcomes, and the emotion words they choose to describe their affective state, could reveal hidden affect relations and patterns, to facilitate the understanding of human emotion. This can be achieved through employing sentiment analysis and natural language processing tools, in order to capture and analyze posts, status updates, and other affect related text made available by social media users. In order to exploit fully the benefits of the AV-AT's emotion modelling method in social network sentiment analysis, the necessary infrastructures (i.e. data centers, cloud infrastructures etc.) should be able to process, analyze, and store big data. This type of large-scale sentiment analysis could be beneficial in the development of e-learning platforms and systems, or in the design of applications from different fields where the user's affect is used as a factor in order to provide more focused feedback, and user specific services.

- As pointed out in section 2.1, the student's affective state is influenced by a large number of socio-environmental factors. By exploiting the advantages of the FCM methodology, the method presented in this Thesis is able to easily expand to incorporate these factors in its design. Factors such as the teachers' affective state, the time of day, educational or personal achievements, the ratio of playtime against study time, overall group or class affective state, environmental factors etc. can be added into the model to improve its performance. A combination of expert opinion, along with the observation of students performing learning tasks can provide the necessary data in order to expand the FCM subsystem. This data can be obtained using a multitude of sources, such as RSS feeds, physiological sensors, and with the use of observational audiovisual equipment. For example, video cameras could be responsible for monitoring the students, during collaborative learning sessions. Post analysis of the video recording should be able to offer the information needed to explore the relations between the concepts under investigation, and train the corresponding computational models. Expert opinion could be taken into account in the same manner, as we did in our research for the affective transitions information, in order to provide values of FCM weights, which reflect the relation of each of the factors with the student's affective state.
- In Kazemzadeh et al.'s work the researchers used two different emotion representations in order to create a lexicon between different emotion vocabularies. Towards this purpose, the researchers utilized an arousal valence dominance representation of emotion, to map emotion words from different vocabularies to emotion space. They utilized type-2 FL to represent the meaning of emotion words in that space, and through applying similarity measures, they translated from one vocabulary to another (Kazemzadeh 2013). The AV-AT model proved its potential at differentiating between emotions and providing an effective mapping of their meaning in the corresponding emotion space. As a result, the AV-AT can be used in conjunction with the computational approach proposed by Kazemzadeh et al. as an emotion representation tool towards translating between different dictionaries.
- From a computational perspective, an expansion of the fuzzy technique to incorporate type-2 Fuzzy Logic is a promising way towards improving

classification accuracy of the developed systems. The notions under investigation in this research, and the data provided by the participants comprised of a high percentage of uncertainty and noise, which could potentially be better represented by type-2 fuzzy sets. Previous research has demonstrated that systems based on type-2 fuzzy logic sets are able to better handle noise and model uncertainty, than the corresponding systems, which utilize type-1 fuzzy sets (Wu 2006, Hagras 2004, Wu 2012). By designing a new survey where the participants have the ability to provide an interval of values, instead of a single value, to describe the basic affective elements or the targeted emotion labels, would allow additional degrees of freedom to the participants for expressing their affective state. This kind of training data could be used to construct type-2 fuzzy sets, and extract the corresponding fuzzy rules to describe the underlying affect relations. This shall enable the constructed computational model to exploit the advantages of type-2 fuzzy sets to better model opinions from different individuals, and the intra and interpersonal uncertainties related to human emotion (Wu 2012, Mendel 2010).

- Exploring a way to model and automatically extract the predictions and expectations of students towards upcoming learning activities would be a very interesting and challenging direction. This would allow the full automation of the presented emotion methodology, without distracting the student for explicitly providing values of the prediction element. In order to achieve this, some of the observations made during the experimental tutorial sessions of this research should be quantified. For example, a survey or practical tutorial experimental setting can be utilized, in which the participants before commencing, would be asked to provide information about their background knowledge, performance in similar subjects, some psychological profile characteristics, and other related information. The data provided could be analyzed to identify the correlations between these factors, and the predictions the participants made during the experimental session. In addition, emphasis should be given in the relation between the mood of the participant during the experimental sessions with the predictions they provide. Such a relation has already been observed in the experiments conducted for the purposes of this research. More specifically, participants were more likely to make positive predictions when in a positive valenced mood and vice versa. As discussed in detail in section 6.8, valence correlates strongly with changes in human physiology, including changes in skin temperature (McFarland 1985), and heart rate (Rainville 2006). Therefore, modern tools such as the Autosense or Empatica E3 and E4 devices could be used to capture and analyse the corresponding physiological signals. These signals along with the collected user specific information (background knowledge, performance in similar subjects, psychological profile characteristics etc.) could provide the inputs for a classification system to calculate estimates of the user's predictions.

- As mentioned in chapter 6, there is no obvious reason why any of these affect modelling approaches cannot be applied in contexts different to education, given the necessary context specific modifications are applied. Neither the extended AT, nor the AV-AT, or the affective transitions models are explicitly inclusive of the educational context. Especially in challenging application fields such as medicine, the presented approaches could prove very useful at modelling the user's affective state (Karyotis 2016). Details for realizing this vision were provided in section 6.8, where the author discussed the modifications needed so that the AV-AT model can be applied in a gaming, or a driving application.

Appendix A- Online Survey 1 material

This appendix provides the experimental materials used during Online Survey 1, which was conducted to explore and model the personalised and contextualized AT hypothesis described in Chapter 5. The survey was designed and completed with the use of the online survey tool QuestionPro that participants accessed online from their personal computers. Prior to completing the survey, the participants received electronic copies of instructions, and they were asked to provide their informed consent. All participants were volunteers and no compensation was given for their time. The survey was scenario based. A scenario is defined as a short realistic story describing an education related situation, in which the participants were asked to imagine themselves as the main heroes. The instructions provided to the participants described in detail the overall process for completing the survey, and included definitions for all emotions and basic affective elements.

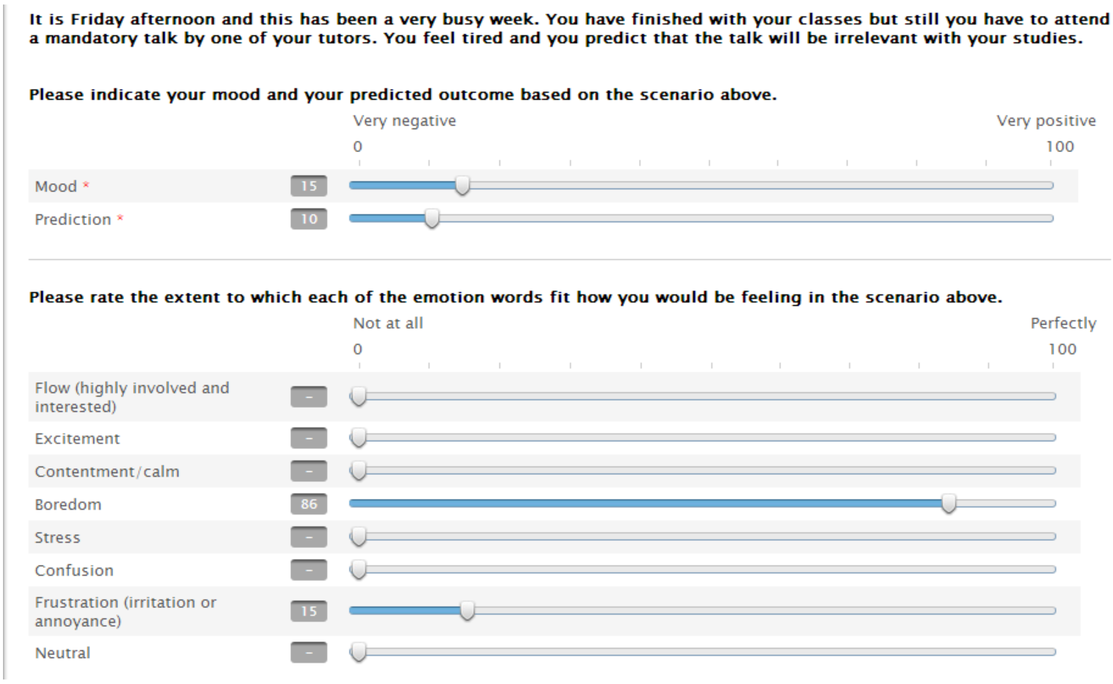
In this Appendix we provide copies of:

- The instructions provided to the participants.
- The consent documentation of the experiment.

Online Survey 1 Instructions to participants

During this session, you will be presented with different scenarios. **It is important that you try and imagine yourself in the scenario.** In every scenario there are two parts. In the first part you will read the beginning of a story where your mood (how "good" or "bad" you feel) and your prediction will be described. Then you must try to picture yourself in the story. Using the sliders provided rate your mood and prediction. The sliders range from 0 (representing a very negative mood or prediction) to 100 (very positive mood or prediction). You will then be asked to choose from a list of emotions and rate the extent to which each emotion fits how you would be feeling in the scenario. Use the sliders to rate the emotions you selected, the sliders range from 0 (not at all) to 100 (perfectly).

For example:



It is Friday afternoon and this has been a very busy week. You have finished with your classes but still you have to attend a mandatory talk by one of your tutors. You feel tired and you predict that the talk will be irrelevant with your studies.

Please indicate your mood and your predicted outcome based on the scenario above.

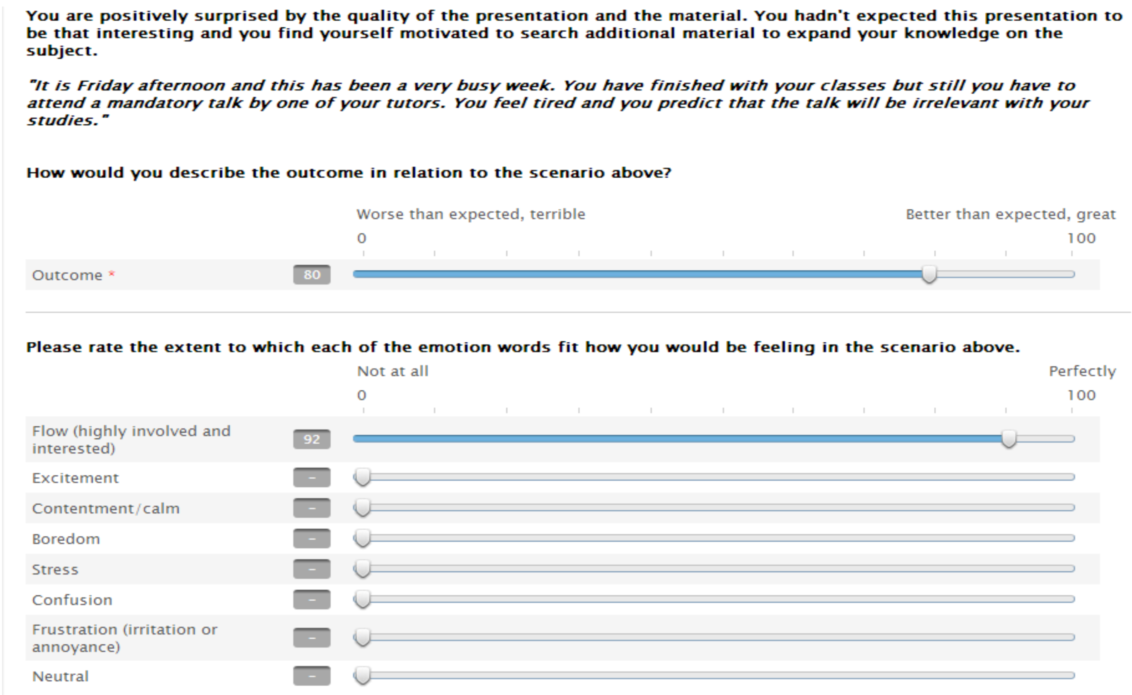
		Very negative 0 — Very positive 100
Mood *	15	
Prediction *	10	

Please rate the extent to which each of the emotion words fit how you would be feeling in the scenario above.

		Not at all 0 — Perfectly 100
Flow (highly involved and interested)	–	
Excitement	–	
Contentment/calm	–	
Boredom	86	
Stress	–	
Confusion	–	
Frustration (irritation or annoyance)	15	
Neutral	–	

Here the participant believes that the scenario describes a bad mood (he is tired and he doesn't want to attend this seminar) and a negative prediction (he believes that the subject is going to be irrelevant with his studies). So he chooses 15 (negative mood) and 10 (negative prediction) for the first part and then he chooses 86 for boredom and 15 for frustration because he believes that boredom is very related to his emotional state in the scenario while frustration has also a week relation with the story.

In the second part you will be presented with the outcome of the scenario. This time you will have to rate the outcome of the story, compared to the prediction you made in the first part. Again use the slider to choose your rating from 0 (worse than expected) to 100 (better than expected). To help you recall the scenario, it is re-shown in italics below. Finally you will be asked once more to choose from a list of emotions and rate the extent to which each emotion fits how you would be feeling now. Again use the sliders to rate the emotions you selected, the sliders range from 0 (not at all) to 100 (perfectly).For example:


You are positively surprised by the quality of the presentation and the material. You hadn't expected this presentation to be that interesting and you find yourself motivated to search additional material to expand your knowledge on the subject.

"It is Friday afternoon and this has been a very busy week. You have finished with your classes but still you have to attend a mandatory talk by one of your tutors. You feel tired and you predict that the talk will be irrelevant with your studies."

How would you describe the outcome in relation to the scenario above?

Worse than expected, terrible — Better than expected, great

0 — 100

Outcome * 80

Please rate the extent to which each of the emotion words fit how you would be feeling in the scenario above.

Not at all — Perfectly

0 — 100

Flow (highly involved and interested) 92

Excitement –

Contentment/calm –

Boredom –

Stress –

Confusion –

Frustration (irritation or annoyance) –

Neutral –

In this case the participant considers that the outcome is better than he has expected so he chooses 80 in the first scale, and he strongly believes that the emotion described is flow so he chooses 92 for flow.

The emotions you will be asked to choose from are:

Flow: You feel highly involved and interested in performing a certain task, you are fully immersed in a feeling of energized focus, full involvement and enjoyment in the process of the activity you are performing.

Excitement: A feeling of high arousal where you feel eager enthusiastic and interested.

Contentment/calm: A feeling of mild satisfaction, piece of mind.

Boredom: You are feeling impatient or fatigued from lack of interest, you don't feel engaged in the activity and you have trouble concentrating.

Stress: A feeling of mental tension where you feel very worried or anxious.

Confusion: You have a lack of understanding and an inability to act or decide.

Frustration: A feeling of irritation or annoyance also related to anger and disappointment.

Neutral: Neither feeling good or bad, active or passive.

*** When asked you can enter as many emotions as you like to describe the emotion state in the scenario.**

Online Survey 1 Consent Form

Survey: AT Survey

Dear participant,

You are invited to participate in our survey "Affective Trajectories". In this survey, you will be asked to complete a set of questions about educational related emotions. It will take approximately 25 minutes to complete the questionnaire.

Your participation in this study is completely voluntary. There are no foreseeable risks associated with this project. However, if you feel uncomfortable answering any questions, you can withdraw from the survey at any point. It is very important for us to learn your opinions. Your survey responses will be strictly confidential.

If you have questions at any time about the survey or the procedures, you may contact Mr. Charalampos Karyotis by email at the email address karyotic@uni.coventry.ac.uk.

Thank you very much for your time and support. Please start with the survey now by clicking on the Continue button after ticking the Agree box below. At first you will be presented with the necessary information about how to answer the questions and then with the survey itself.

☐ I Agree

Appendix B- Online Survey 2 material

This appendix provides the experimental materials used during Online Survey 2, which was conducted in order for the new AV-AT model of emotion described in Chapter 6, to be modelled and explored. In this Appendix, we provide copies of:

- The instructions provided to the participants.
- The consent documentation of the experiment.

Online Survey 2 Instructions to participants

During this session, you will be presented with different scenarios. It is important that you try and imagine yourself as taking part in the described situation. In every story there are two parts. In the first part you will read the beginning of a story where your emotion state will be described. Then you must try to picture yourself in the story and using the sliders provided rate your prediction, your valence and your arousal. You will then be asked to choose from a list of eight emotions and rate the extent to which each emotion fits how you would be feeling in the scenario. In the second part you will be presented with the outcome of the scenario. This time you will have to rate the outcome of the story, compared to the prediction you made in the first part and as before also provide ratings for your valence and arousal levels. To help you recall the scenario, it is re-shown in italics below. Finally, you will be asked once more to choose from a list of emotions and rate the extent to which each emotion fits how you would be feeling now. Again, use the sliders to rate the emotions you selected.

The basic elements you will be asked to rate are:

Prediction: your evaluation of the predicted outcome presented in the first part of the story, ranging from very negative (0) to very positive (100).

Valence: how negative or positive you feel, ranging from unpleasant (0) to pleasant (100).

Arousal: your level of activation, how passive or active you feel, ranging from deactivated, low arousal (0) to activated, high arousal (100).

Outcome: your evaluation of the outcome of the story presented in the second part of the in respect to your prediction in the first, ranging from worse than expected, terrible (0) to better than expected, great (100).

The emotions you will be asked to choose from are:

Flow: you feel highly involved and interested in performing a certain task, you are fully immersed in a feeling of energized focus, full involvement and enjoyment in the process of the activity you are performing.

Excitement: a feeling of high arousal where you feel eager enthusiastic and interested.

Contentment/Calm: a feeling of mild satisfaction, piece of mind.

Boredom: you are feeling impatient or fatigued from lack of interest, you don't feel engaged in the activity and you have trouble concentrating.

Stress: a feeling of mental tension where you feel very worried or anxious.

Confusion: you have a lack of understanding and an inability to act or decide.

Frustration: a feeling of irritation or annoyance also related to anger and disappointment.

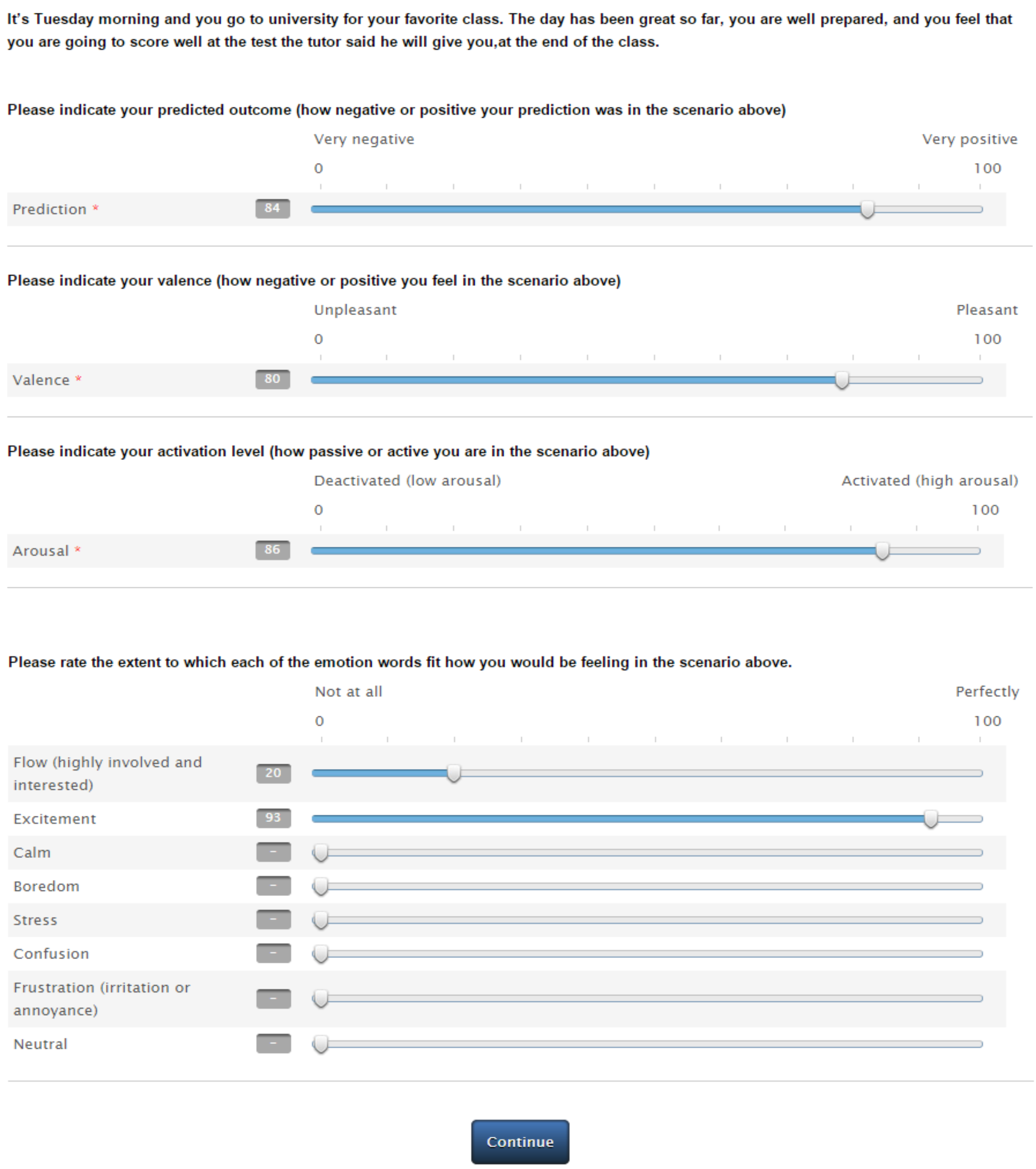
Neutral: neither feeling good or bad, active or passive.

You can rate the extend to which each emotion fits how you would be feeling in every part of the scenario from not at all (0) to perfectly (100). You can choose as many emotions as you like. If you believe that the emotion word isn't represented in the scenario you can leave the slider in the original position.

.

Below we present as an example the responses of a participant in both parts of a scenario:

First part:



It's Tuesday morning and you go to university for your favorite class. The day has been great so far, you are well prepared, and you feel that you are going to score well at the test the tutor said he will give you,at the end of the class.

Please indicate your predicted outcome (how negative or positive your prediction was in the scenario above)

Very negative 0 — Very positive 100

Prediction * 84

Please indicate your valence (how negative or positive you feel in the scenario above)

Unpleasant 0 — Pleasant 100

Valence * 80

Please indicate your activation level (how passive or active you are in the scenario above)

Deactivated (low arousal) 0 — Activated (high arousal) 100

Arousal * 86

Please rate the extent to which each of the emotion words fit how you would be feeling in the scenario above.

Not at all 0 — Perfectly 100

Flow (highly involved and interested) 20

Excitement 93

Calm –

Boredom –

Stress –

Confusion –

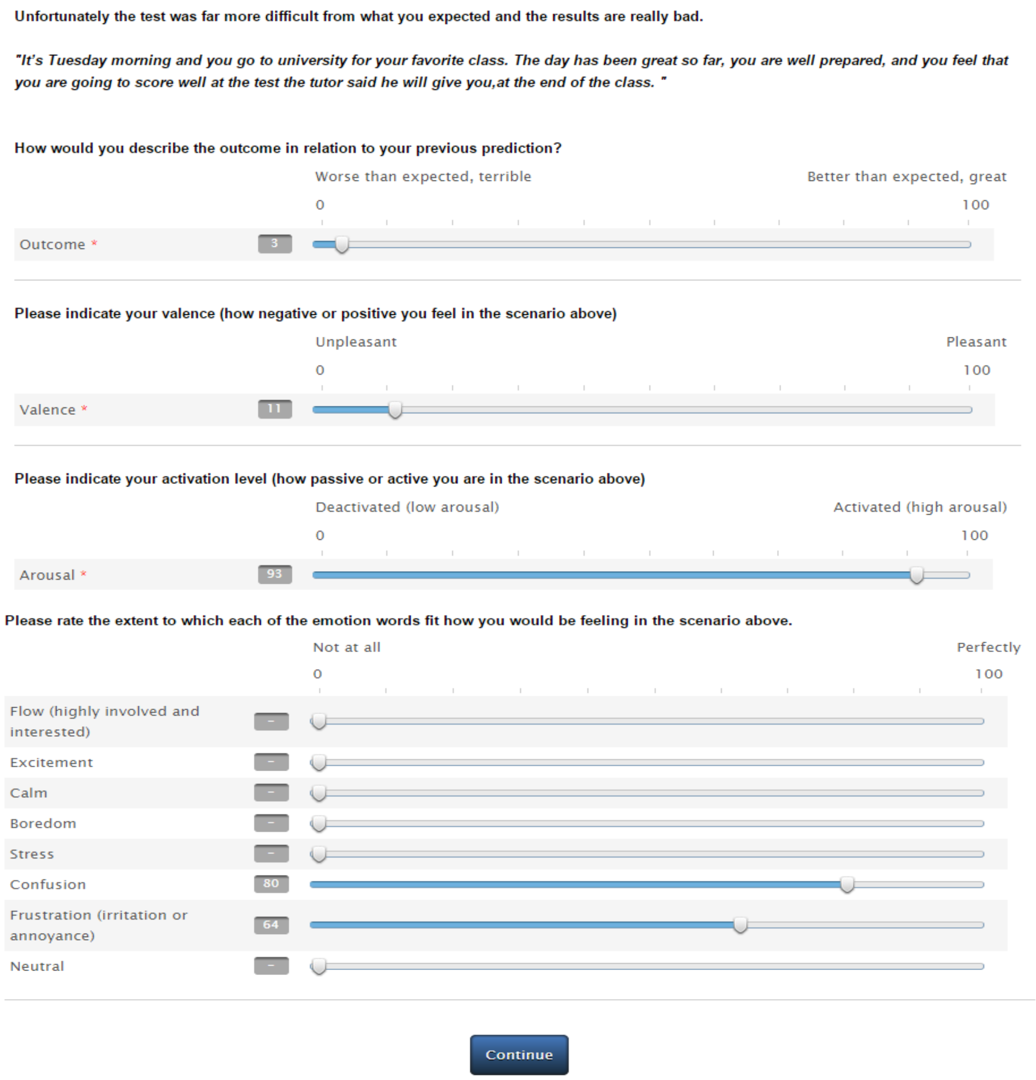
Frustration (irritation or annoyance) –

Neutral –

Continue

In this case, the participant after reading the scenario and imagining himself in the situation described, they make a positive prediction (he feels he is going to score well), positive valence (the day has been great, he is well prepared), and that he will be activated and anxious to take the test. So he chooses 84 for prediction (positive prediction), 80 for valence (positive valence, pleasant), and 86 for arousal (activated, high arousal). After scoring these elements he chooses 93 for excitement and 20 for flow because he believes that excitement is much related to his emotion state in the scenario while flow has also a week relation with the story.

Second part:



Unfortunately the test was far more difficult from what you expected and the results are really bad.

"It's Tuesday morning and you go to university for your favorite class. The day has been great so far, you are well prepared, and you feel that you are going to score well at the test the tutor said he will give you,at the end of the class. "

How would you describe the outcome in relation to your previous prediction?

Worse than expected, terrible — Better than expected, great

0 — 100

Outcome * 3

Please indicate your valence (how negative or positive you feel in the scenario above)

Unpleasant — Pleasant

0 — 100

Valence * 11

Please indicate your activation level (how passive or active you are in the scenario above)

Deactivated (low arousal) — Activated (high arousal)

0 — 100

Arousal * 93

Please rate the extent to which each of the emotion words fit how you would be feeling in the scenario above.

Not at all — Perfectly

0 — 100

Flow (highly involved and interested)	–
Excitement	–
Calm	–
Boredom	–
Stress	–
Confusion	80
Frustration (irritation or annoyance)	64
Neutral	–

Continue

In this case the participant considers that the outcome is far worse than what he had expected so he chooses 3 in the Outcome scale (worse than expected terrible). He feels bad so he rates valence with 11 (unpleasant), and is very alert so he provides a value of 93 for arousal (activated, high arousal). He strongly believes that confusion describes very well his state in this scenario, so he chooses 80 for confusion. He also feels disappointed and angry with his performance and provides a rating of 64 for frustration.

Online Survey 2 Consent Form

AFFECT MODELLING

Dear participant,

You are invited to participate in our survey concerning "Affect Modelling". In this survey, you will be asked to complete a set of questions about emotions related to education. It will take approximately 30 minutes to complete the questionnaire. Your participation in this study is completely voluntary. There are no foreseeable risks associated with this project. However, if you feel uncomfortable answering any questions, you can withdraw from the survey at any point. It is very important for us to learn your opinions. Your survey responses will be strictly confidential. If you have questions at any time about the survey or the procedures, you may contact Mr. Charalampos Karyotis by email at the email address karyotic@uni.coventry.ac.uk .Thank you very much for your time and support. Please start with the survey now by clicking on the Continue button after ticking the Agree box below. At first you will be presented with the necessary information about how to answer the questions and then with the survey itself.

☐ **I Agree**

Appendix C- Tutorial session 1

This appendix provides the experimental materials used during practical tutorial 1, which was conducted in order to evaluate the AV-AT model of emotion described in Chapter 6, and collect affective transition data during collaborative learning tasks. We utilized the data obtained to evaluate and optimize the AV-AT approach and explore the affective transitions of students in PBL. In this Appendix, we provide:

- The instructions provided to the participants.
- The consent documentation of the experiment.
- An overview of the first tutorial.
- The learning material used to conduct this tutorial session.

The learning material includes:.

- An introductory presentation on Fuzzy Logic.
- A discussion on Fuzzy Logic.
- A Class game.
- A Quiz.
- A second presentation on Fuzzy Logic.
- An online tool for constructing fuzzy systems.
- A group project.
- A presentation exercise.

Tutorial 1 Instructions to participants

During this two-session tutorial on Fuzzy Logic you will be prompted by the system at different points in time to provide estimates concerning elements describing your emotion and cognitive state. Using the dialog boxes displayed by the system, please provide ratings concerning the following:

prediction: your evaluation of the predicted outcome concerning an upcoming activity, ranging from very negative (0) to very positive (100).
valence: how negative or positive you feel, ranging from unpleasant (0) to pleasant (100).
arousal: your level of activation, how passive or active you feel, ranging from deactivated, low arousal (0) to activated, high arousal (100).
outcome: your evaluation of the outcome of the activity in which you just participated ranging from worse than expected, terrible (0) to better than expected, great (100).

After scoring on the basic elements the system will produce an output which will include values of eight emotions. Namely:

Flow: you feel highly involved and interested in performing a certain task, you are fully immersed in a feeling of energized focus, full involvement and enjoyment in the process of the activity you are performing.
Excitement: a feeling of high arousal where you feel eager enthusiastic and interested.
Contentment/Calm: a feeling of mild satisfaction, piece of mind.
Boredom: you are feeling impatient or fatigued from lack of interest, you don't feel engaged in the activity and you have trouble concentrating.
Stress: a feeling of mental tension where you feel very worried or anxious.
Confusion: you have a lack of understanding and an inability to act or decide.
Frustration: a feeling of irritation or annoyance also related to anger and disappointment.
Neutral: neither feeling good or bad, active or passive.

Each emotion will be given a value from the system ranging from 0-100 which represents the extent to which each of the emotion words describe your affective state at that point of time ((0) not at all, (100) perfectly). If you are not happy with the system's results you are free to provide your own values by utilizing the corresponding dialog boxes displayed at your screen. In any case, it is important to provide honest answers. Commence by signing the corresponding consent forms. It is important to note that it is required from you to provide honest answers and that you are free to leave at any time in case you feel any discomfort.

Tutorial 1 Consent form

In order to take part in the experiment please read carefully and sign the statements below.

There are no foreseeable risks associated with these experiments and data will be anonymised and kept secure in a password- protected laptop.

If you require further information about the experiment or want to be informed about the results when they are published, please email Karyotis Charalampos at: karyotic@uni.coventry.ac.uk

I agree to participate in this experiment and understand that I am entitled to refuse an experimenter's request and am free to leave at any time.

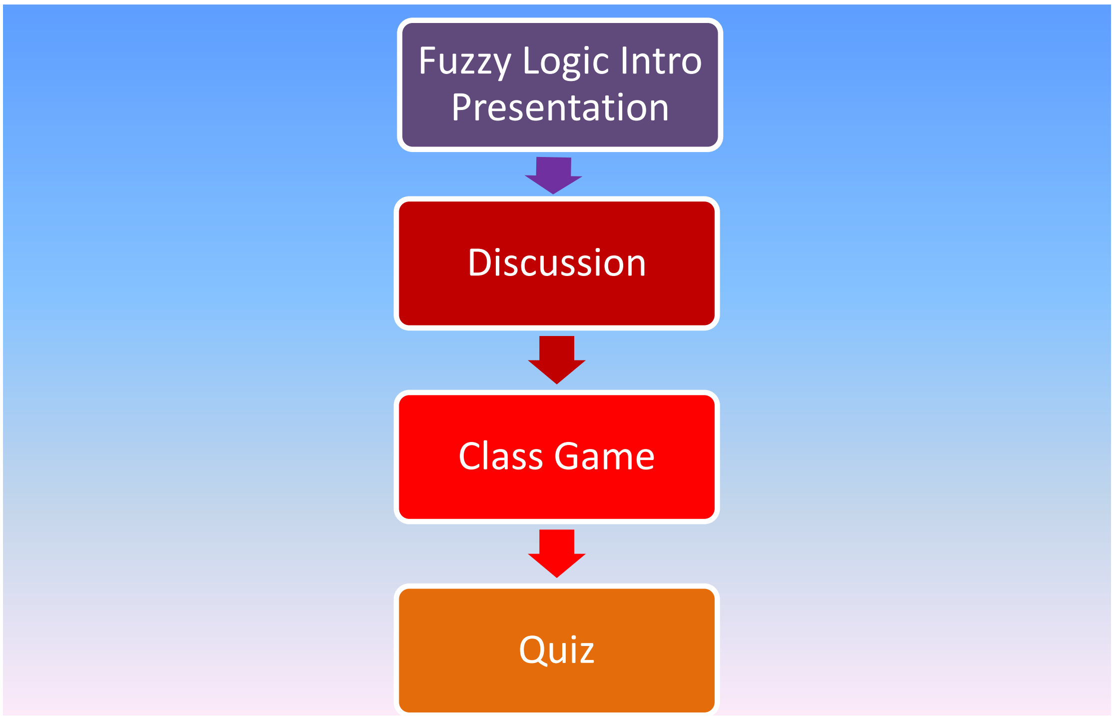
Signed: ______________________________

Full Name: ____________________________

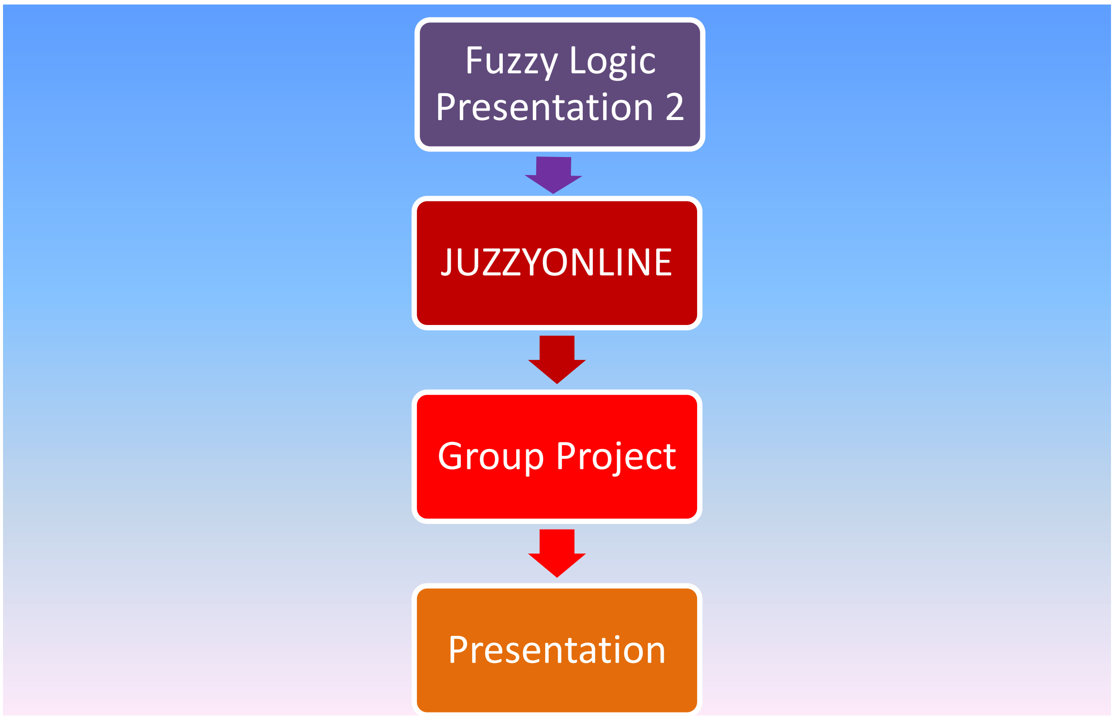
Date: _______________________________

Tutorial 1 Structure

Session 1



Session 2



Session 1-Lecture

Basic Concepts

FUZZY LOGIC INTRODUCTION I

Logic

Like many other things, it all started with the ancient Greeks, who first formalized logic.

Aristotle is credited with claiming that statements cannot both be true in the same sense at the same time.

A thing either is or it is not.

Logic

Hmmm…. Consider the following:

- The Epimenides paradox "All the Cretans are liars". (Epimenides is a Cretan).
- Suppose John is around 1.8 m tall and we take tall to mean six feet or taller. If John is 1 cm under 1.8 m, then John is not tall. If we were to increase John's height by 2 cm , then we would consider John tall.

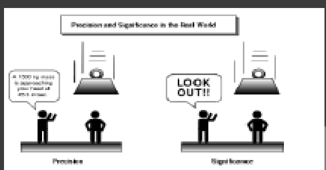
Precision

John's height example demonstrates also something else:

The problem doesn't lie in the precision of the height measurement. Actually, the more precisely we know the height, the more difficult it is for us to accept the sharp, arbitrary classification. It's probably that our concept of "tall" is inherently fuzzy.

Precision

There is a trade off between significance and precision something that humans have been managing for a very long time. Nothing can demonstrate this better than the following picture…..



Uncertainty

Before the 20th century, science was considered to be devoid of uncertainty. The scientific view at the time is summarized by Scottish physicist and mathematician William Thomson (better known as Lord Kelvin)

"I often say that when you can measure what you are speaking about, and express it in numbers, you know something about it; but when you cannot measure it, when you cannot express it in numbers, your knowledge is of a meager and unsatisfactory kind".

Uncertainty

Latter uncertainty became firmly established as a part of science.

In 1871, Austrian physicist Ludwig Boltzmann introduced what became known as statistical thermodynamics.

In 1926 Werner Heisenberg formulated the principle of uncertainty.

"So far as the laws of mathematics refer to reality, they are not certain. And so far as they are certain, they do not refer to reality."
Albert Einstein in Geometry & Experience

Fuzzy Logic

Fuzzy logic was developed by Lotfi A. Zadeh in the 1960s in order to provide mathematical rules and functions which permitted natural language queries and uncertainty handling.

Fuzzy logic is based on the idea that all things can be described in degrees. Temperature, height, speed, distance all come on a sliding scale. The motor is running really hot. Tom is a very tall guy.

Fuzzy Logic

Fuzzy logic is a set of mathematical principles for knowledge representation based on fuzzy sets / degrees of membership.

Unlike two-valued Boolean logic, fuzzy logic is multi-valued. It deals with degrees of membership and degrees of truth. Instead of just black and white, it employs the spectrum of colors, accepting that things can be partly true and partly false at the same time.

Real Life Fuzzy Concepts

In life we sometimes must accept shades of truth, or grades of truth. In formal logic and in electronics we deal with things that have only two truth values, zero (0 or FALSE) and one (1 or TRUE). However, let's consider the possibility of partial truth. If John is six feet tall, then the statement "John is tall" might have a truth value of .9.

Another way of stating this might be to say "Pat is a member of the set of tall people with a membership grade of 0.9."

Real Life Fuzzy Concepts

The concept of grades of truth or grades of membership in sets is something that many of us actually use in making decisions in our life. We choose a place to live or a career to follow not because of yes or no factors.

Rather, we tend to think in terms of the truth value of statements like "This place is a good place to live." or "This career is one for which I am well suited".

Fuzzy Logic and Probability

Fuzzy Logic is considered to be one of the methods suitable for modeling uncertainty. Nevertheless, one major criticism of fuzzy logic theory is the argument that Fuzzy Logic can be subsumed by probability theory.

Both theories, while having certain aspects such as dealing with uncertainty in common, nevertheless cannot be reasoned to be identical or being contained one within the other. In fact both theories are not competitive or even exclusive but in fact complementary as argued by Zadeh.

Fuzzy Logic and Probability

Consider the example of a scuba tank containing breathable air for 1 hour of diving when filled.

If we say "There is a 50% chance that the tank was filled during the last maintenance", it means that the likelihood of the tank being empty or filled is equal.

If a degree of truth is 50%, i.e. 0.5 (in fuzzy logic degree of membership terms) that the scuba tanks is filled, it means that the scuba tank is half-filled.

Fuzzy Logic and Probability

While both theories have analogies, the goal in specification of information both theories pursue is completely different.

The fundamental goal of probability theory is the definition of the likelihood of occurrence of an event or condition.

Fuzzy Logic on the other hand does not focus on the likelihood of occurrence of an event or condition, but on the degree of truth of this event or condition.

Fuzzy Sets

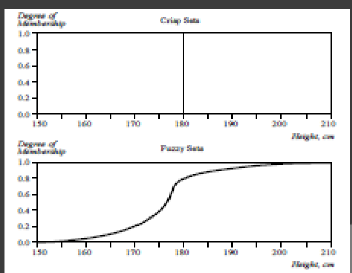
Fuzzy logic starts with the concept of a fuzzy set. A fuzzy set is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership. In contrast to a crisp set where an element can either belong (degree of membership=1) to the set or not belong to the set(degree of membership=0).

Fuzzy Sets

The classical example in fuzzy sets is tall men.

Name	Height, cm	Degree of Membership	
		Crisp	*Fuzzy*
Chris	208	1	1.00
Mark	205	1	1.00
John	198	1	0.98
Tom	181	1	0.82
David	179	0	0.78
Mike	172	0	0.24
Bob	167	0	0.15
Steven	158	0	0.06
Bill	155	0	0.01
Peter	152	0	0.00

Fuzzy Sets



Membership Function

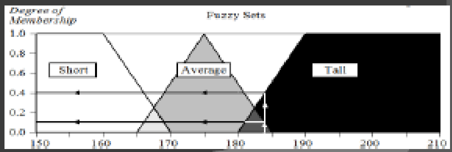
In the fuzzy theory, a fuzzy set A is defined by a function μ(x) called the membership function. Where:

- μ(x) =1 if x is totally in A.
- μ(x)=0 if x is not in A.
- 0<μ(x)<1 if x is partly in A.

This degree, a value between 0 and 1, represents the degree of membership, also called membership value, of element x in set A.

Membership Function

Men's heights consists of three fuzzy sets: short, average and tall men. A man who is 184 cm tall is a member of the average men set with a degree of membership of 0.1, and at the same time, he is also a member of the tall men set with a degree of 0.4.



Operations on Fuzzy sets

As in crisp sets we can define operations in fuzzy sets as well.

Lets examine three very commonly used operators:

- Complement
- Intersection
- Union

Complement

Crisp Sets: Who does not belong to the set?

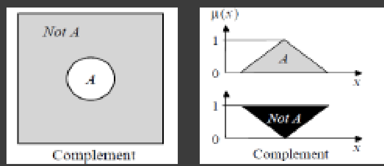
Fuzzy Sets: How much do elements not belong to the set?

The complement of a set is an opposite of this set. For example, if we have the set of tall men, its complement is the set of NOT tall men.

If A is the fuzzy set, its complement can be found as follows

$$\mu_{\neg A}(x) = 1 - \mu_A(x)$$

Complement



Intersection

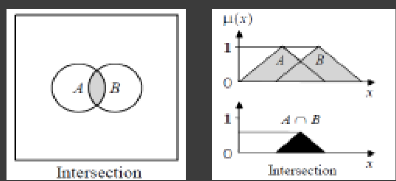
Crisp Sets: Which element belongs to both sets?

Fuzzy Sets: How much of the element is in both sets?

As an example for crisp sets, the intersection of the set of tall men and the set of fat men is the area where these sets overlap. In fuzzy sets, an element may partly belong to both sets with different memberships. A fuzzy intersection is the lower membership in both sets of each element. The fuzzy intersection of two fuzzy sets A and B is:

$$\mu_{A \cap B}(x) = min\,[\mu_A(x), \mu_B(x)] = \mu_A(x) \cap \mu_B(x),$$

Intersection



Union

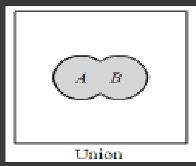
Crisp Sets: Which element belongs to either set?

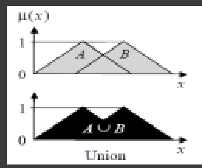
Fuzzy Sets: How much of the element is in either set?

The union of two crisp sets consists of every element that falls into either set. For example, the union of tall men and fat men contains all men who are tall OR fat. In fuzzy sets, the union is the reverse of the intersection. That is, the union is the largest membership value of the element in either set. The fuzzy operation for forming the union of two fuzzy sets A and B on universe X can be given as:

$$\mu_{A \cup B}(x) = max\,[\mu_A(x), \mu_B(x)] = \mu_A(x) \cup \mu_B(x)$$

Union





Linguistic Variables

At the root of fuzzy set theory lies the idea of linguistic variables.

- A linguistic variable is a fuzzy variable.
- For example, the statement "John is tall" implies that the linguistic variable *John takes* the linguistic value tall.

Fuzzy Rules

In fuzzy expert systems, linguistic variables are used in fuzzy rules.

A fuzzy rule can be defined as a conditional statement in the form:

IF x is A THEN y is B where x and y are linguistic variables; and A and B are linguistic values determined by fuzzy sets on the universe of discourses X and Y, respectively.

Fuzzy Rules

For example

IF speed is fast THEN stopping distance is long.

A rule can also contain multiple antecedents(IF part)

IF speed is fast and the tyres are bad THEN stopping distance is very long.

IF speed is fast or the tyres are bad THEN stopping distance is long.

It can also contain multiple consequents (THEN part)

IF speed is fast and the tyres are bad THEN stopping distance is long and danger is high.

Session1-Discussion

Below are some known quotes from some very famous people. Firstly, choose any one that you like. Try to argue in favor or against your favorite quote to your group and explain how your chosen quote is related to fuzzy logic.

"Fuzzy theory is wrong, wrong, and pernicious. What we need is more logical thinking, not less. The danger of fuzzy logic is that it will encourage the sort of imprecise thinking that has brought us so much trouble. Fuzzy logic is the cocaine of science."
William Kahan

"Fuzzification is a kind of scientific permissiveness. It tends to result in socially appealing slogans unaccompanied by the discipline of hard scientific work and patient observation."
Rudolf Kalman

"As complexity increases, precise statements lose meaning and meaningful statements lose precision."
Lofti Zadeh

"Precision is not truth."
Henri Matiss

"Sometimes the more measurable drives out the most important."
René Dubos

"Vagueness is no more to be done away with in the world of logic than friction in mechanics."
Charles Sanders Peirce

"I believe that nothing is unconditionally true, and hence I am opposed to every statement of positive truth and every man who makes it."
H. L. Mencken

Session1-Class Game

Discuss with the rest of the Class and write down how many hours a day you spend on your computer filling the table below.

Name	Hours
John	8
Peter	6
Charlie	0
Kim	1
Sasha	7
Robert	1
Maya	7

Can you define and draw some fuzzy sets to represent the amount of time spent by people on their computers?

It is logical to assume that a person, who spends many hours using his computer, is also familiar with new technologies. As a result, a system responsible for predicting the familiarity of a person with new technologies based on the hours he spends on his computer could contain the following rule.

If Time spent is long then the person is very familiar with technology.

Are the hours we spend on our computers related to anything else? Can you express these relations with the help of fuzzy rules?

Session1- Quiz

Short Exercises on Fuzzy Logic

a)

i. Explain the difference between a classical crisp set and a fuzzy set

ii. What is a membership function of a fuzzy set?

iii. Can a fuzzy membership be True and False at the same time?

iv. What is a fuzzy variable?

b) Consider the following real variables from everyday life:

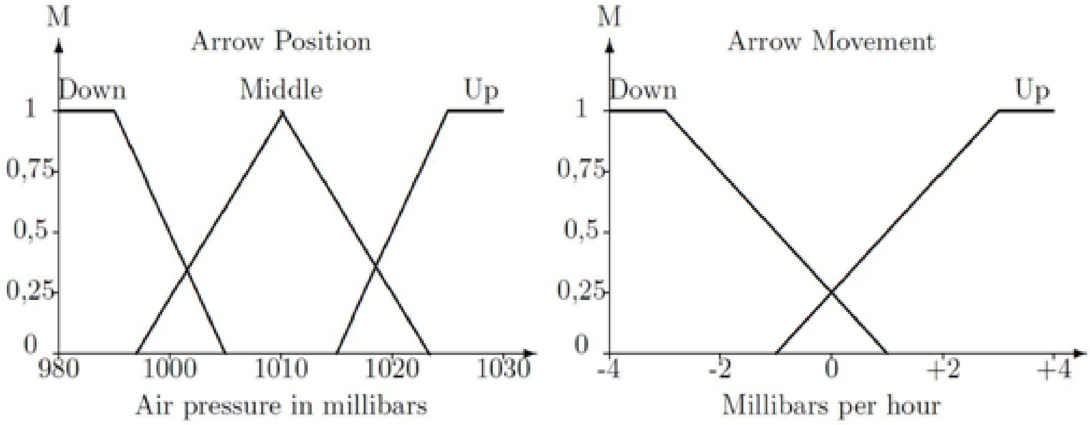
- Income measured in £UK.
- Speed measured in meters per second.
- A TV show measured in how much you are interested watching it.
- A meal measured in how much you like to eat it.
- A traffic light measured in what color is on.

i. In each case, suggest a fuzzy variable corresponding to these real variables.
ii. For which of these five variables is the use of a fuzzy variable not necessary and why?

c) Consider the following fuzzy expert system for weather forecast:

Rule	Condition	Action	Confidence
R1:	IF *arrow is down*	THEN *clouds*	$M = 0.8$
R2:	IF *arrow is in the middle* AND *moving down*	THEN *clouds*	$M = 0.6$
R3:	IF *arrow is in the middle* AND *moving up*	THEN *sunny*	$M = 0.6$
R4:	IF *arrow is up*	THEN *sunny*	$M = 0.8$

The following two plots represent the membership functions of two fuzzy variables describing the position of the arrow of barometer (left) and the direction of its movement (right):



The air pressure is measured in millibars, and the speed of its change in millibars per hour. Answer the following questions:

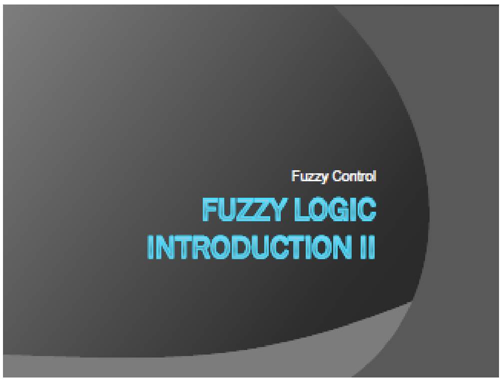
i. How much is the arrow Down, Up or in the Middle if it indicates that the pressure is 1020 millibars? Use membership functions on the graphs.

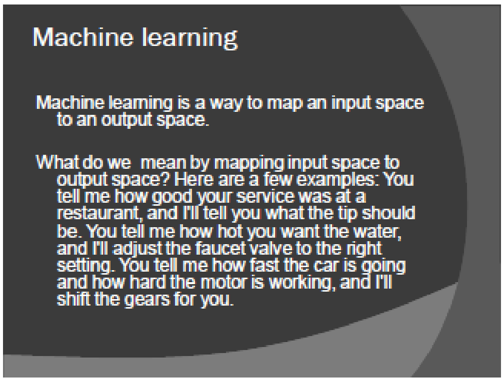
ii. How much is the arrow moving Down or Up if the pressure changes -2 millibars every hour?

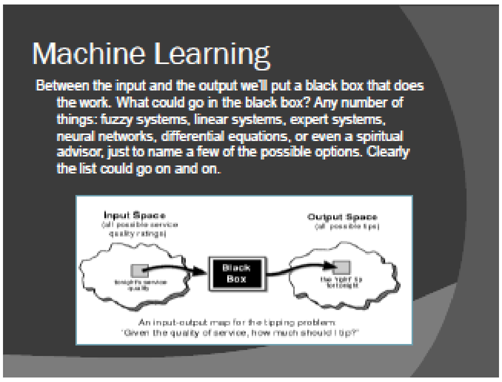
iii. Using the membership values found above and confidence of the rules in the table calculate the degree of cloudy (use the min or product operation to combine membership values of rule antecedent part).

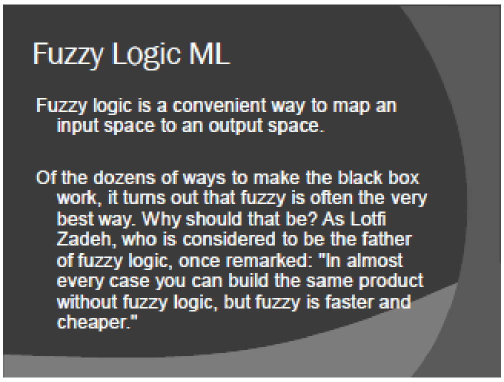
d) Name three strengths and three weaknesses of fuzzy expert systems.

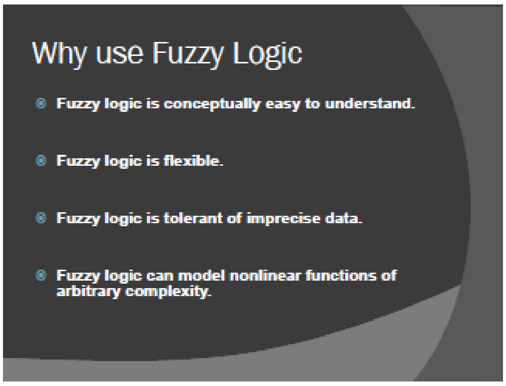
Session2-Lecture

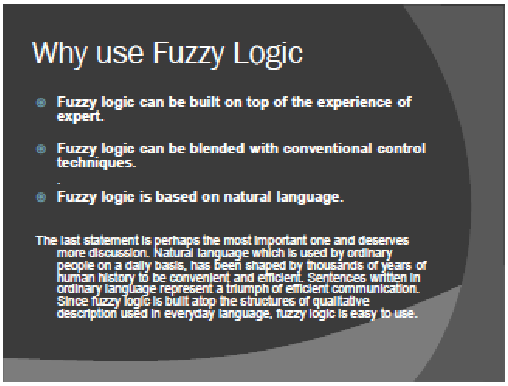












Mandani fuzzy system

In order to understand the fuzzy approach as a machine learning technique. Let's take a look at a simple fuzzy system responsible for predicting the risk of a project given the number of people working on it and the available funding.

This system will use the most commonly used fuzzy technique called Mamdani method.

How does a mandani fuzzy system works???

The Mamdani-style fuzzy inference process is performed in four steps:

- Fuzzification of the input variables
- Rule inference
- Aggregation of the rule outputs
- Defuzzification.

How does a mandani fuzzy system works???

Our problem is a simple two-input one-output problem that includes three rules:

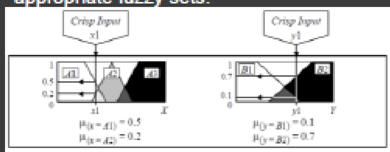
Rule: 1
IF x is A3 THEN z is C1
IF project funding is adequate OR y is B1 OR project staffing is small THEN risk is low

Rule: 2
IF x is A2 AND y is B2 THEN z is C2
IF project funding is marginal AND project staffing is large
THEN risk is normal

Rule: 3
IF x is A1 THEN z is C3
IF project funding is inadequate THEN risk is high

Step 1:Fuzzification

The first step is to take the crisp inputs, x1 and y1 (project funding and project staffing), and determine the degree to which these inputs belong to each of the appropriate fuzzy sets.



Step 2 Rule inference

- The second step is to take the fuzzified inputs, μ(x=A1) = 0.5, μ(x=A2) = 0.2, μ(y=B1) = 0.1 and μ(y=B2) = 0.7, and apply them to the antecedents of the fuzzy rules.
- If a given fuzzy rule has multiple antecedents, the fuzzy operator (AND or OR) is used to obtain a single number that represents the result of the antecedent evaluation.
- This number (the truth value) is then applied to the consequent membership function.

Step 2 Rule inference

To evaluate the disjunction of the rule antecedents, we use the OR **fuzzy operation. Typically, fuzzy expert systems make use of the classical fuzzy operation union:**

$$\mu_{A \cup B}(x) = max\ [\mu_A(x), \mu_B(x)]$$

Similarly, in order to evaluate the conjunction of the rule antecedents, we apply the **AND fuzzy operation intersection:**

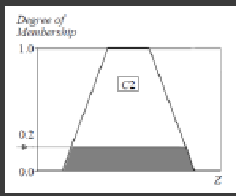
$$\mu_{A \cap B}(x) = min\ [\mu_A(x), \mu_B(x)]$$

Step 2 Rule inference

- The result of the antecedent evaluation can be applied to the membership function of the consequent.
- The most common method of correlating the rule consequent with the truth value of the rule antecedent is to cut the consequent membership function at the level of the antecedent truth. This method is called **clipping**.
- Since the top of the membership function is sliced, the clipped fuzzy set loses some information. However, clipping is still often preferred because it involves less complex and faster mathematics, and generates an aggregated output surface that is easier to defuzzify.

Step 2 Rule inference

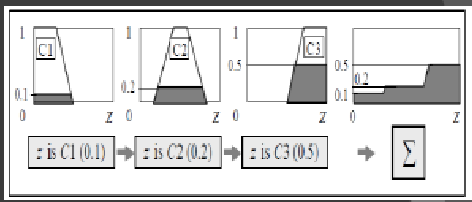
For example for rule 2…



Step 3: Aggregation of Rule Outputs

- Aggregation is the process of unification of the outputs of all rules. We take the membership functions of all rule consequents previously clipped or scaled and combine them into a single output fuzzy set.
- The input of the aggregation process is the list of clipped or scaled consequent membership functions, and the output is one fuzzy set over each output variable.
- Note that aggregation is the union of the total clipped area over the output fuzzy sets which is equivalent to applying the max operation.
- So if two fired rules have the same consequent fuzzy set which is clipped or scaled at two different levels respectively, then the max of the two levels will be used to define the clipped area for the given consequent MF.

Step 3: Aggregation of Rule Outputs



Step 4: Defuzzification

- The last step in the fuzzy inference process is defuzzification.
- Fuzziness helps us to evaluate the rules, but the final output of a fuzzy system has to be a crisp number.
- The input for the defuzzification process is the aggregate output fuzzy set and the output is a single number.

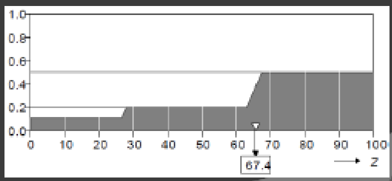
Step 4: Defuzzification

There are several defuzzification methods, but probably the most popular one is the centroid technique. It finds the point where a vertical line would slice the aggregate set into two equal masses. Mathematically this centre of gravity (COG) can be expressed as:

$$COG[C(w)] = \frac{\sum_{i=1}^{q} w_i C(w_i)}{\sum_{i=1}^{q} C(w_i)}$$

Step 4: Defuzzification

$$COG = \frac{(0+10+20)\times 0.1+(30+40+50+60)\times 0.2+(70+80+90+100)\times 0.5}{0.1+0.1+0.1+0.2+0.2+0.2+0.2+0.5+0.5+0.5+0.5} = 67.4$$



Decisions Decisions

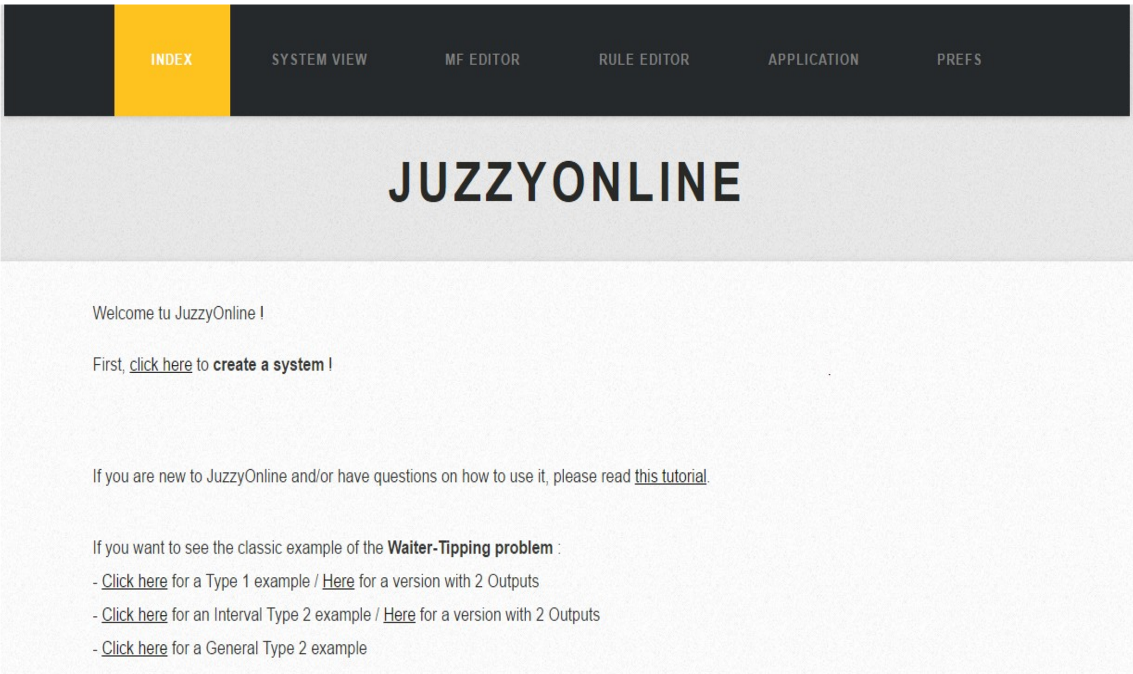
This simple example is used to demonstrate some principles and basic elements of a fuzzy logic system.

In reality in order to design a fuzzy system you have to make a lot of decisions in almost every part of the system. (define appropriate inputs, define input-output MF's, choose defuzzification method etc.)

Where are the Fuzzy Systems? - What are They Doing Now?

- Shifting gears in automatic transmissions in cars
- Focusing your camera and camcorder
- Running the cruise controls on many cars
- Running subways in Japan
- Controlling dishwashers and washing machines
- Simulating army movements in Lord of the rings movies.
- and many, many more!

Session2-Juzzy-Online



Session2-Group Project-Presentation

Work with your team and think of a problem in your everyday life where machine learning can be applied. After deciding on the problem, try to design a simple fuzzy logic system to model it and provide a solution. This involves choosing the appropriate inputs, creating the necessary membership functions to describe your inputs and your outputs and designing the necessary fuzzy rule base which will be used to map your inputs to your outputs.

Firstly create your design on paper and later try to implement the same system with Matlab's fuzzy logic tool box.

Create a short Power Point presentation to demonstrate your system to the class, explaining the design choices you made in the different parts of the system (4-5 slides).

Appendix D- Tutorial session 2

This appendix provides the experimental materials used during practical tutorial 2, which was conducted in order to evaluate the AV-AT model presented in chapter 6 and the FFE and FFA configurations of our final system, described in Chapter 7. The data collected in this tutorial was also used to explore the affective transitions of students inPBL. In this Appendix, we provide:

- The instructions provided to the participants.
- The consent documentation of the experiment.
- An overview of the second tutorial.
- The learning material used to conduct this tutorial session.

This material includes:.

- An introductory presentation on Machine Learning.
- A video presentation.
- A discussion.
- A Quiz.
- A presentation on Neural Networks.
- Tutorial on Matlab's NN toolbox.
- A demonstrative NN example.
- A presentation exercise.

Tutorial 2 Instructions to participants

During this two-session tutorial on Machine Learning you will be prompted by the system at different points in time to provide estimates concerning elements describing your emotion and cognitive state. Using the dialog boxes displayed by the system please provide ratings concerning the following:

prediction: your evaluation of the predicted outcome concerning an upcoming activity, ranging from very negative (0) to very positive (100).
valence: how negative or positive you feel, ranging from unpleasant (0) to pleasant (100).
arousal: your level of activation, how passive or active you feel, ranging from deactivated, low arousal (0) to activated, high arousal (100).
outcome: your evaluation of the outcome of the activity in which you just participated ranging from worse than expected, terrible (0) to better than expected, great (100).

After scoring on the basic elements the system will display a dialog box asking you to provide a value ranging from 0-100 which represents the extent to which each of the emotion words provided below describes your affective state at that point of time ((0) not at all, (100) perfectly). Namely the emotions you will be asked to choose from are:

Flow: you feel highly involved and interested in performing a certain task; you are fully immersed in a feeling of energized focus, full involvement and enjoyment in the process of the activity you are performing.
Excitement: a feeling of high arousal where you feel eager enthusiastic and interested.
Contentment/Calm: a feeling of mild satisfaction, piece of mind.
Boredom: you are feeling impatient or fatigued from lack of interest, you don't feel engaged in the activity and you have trouble concentrating.
Stress: a feeling of mental tension where you feel very worried or anxious.
Confusion: you have a lack of understanding and an inability to act or decide.
Frustration: a feeling of irritation or annoyance also related to anger and disappointment.
Neutral: neither feeling good or bad, active or passive.

Commence by signing the corresponding consent form. It is important to note that it is required from you to provide honest answers and that you are free to leave at any time in case you feel any discomfort.

Tutorial 2 Consent form

In order to take part in the experiment please read carefully and sign the statements below.

There are no foreseeable risks associated with these experiments and data will be anonymised and kept secure in a password- protected laptop.

If you require further information about the experiment or want to be informed about the results when they are published, please email Karyotis Charalampos at: karyotic@uni.coventry.ac.uk

I agree to participate in this experiment and understand that I am entitled to refuse an experimenter's request and am free to leave at any time.

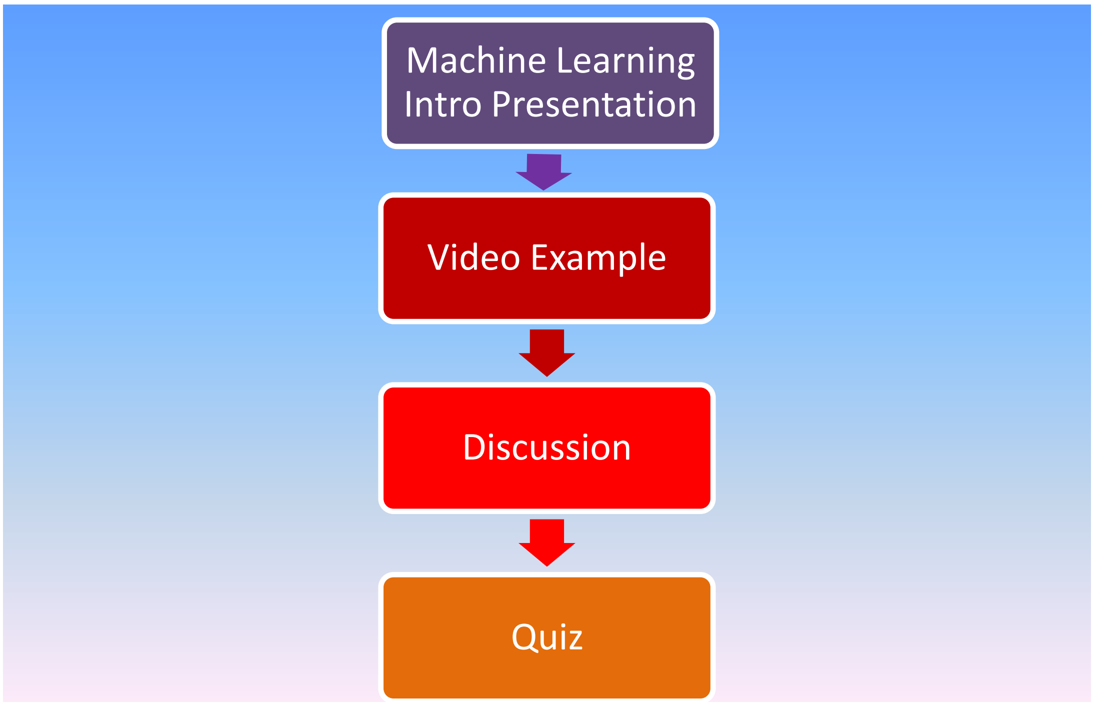
Signed: ________________________________

Full Name: ______________________________

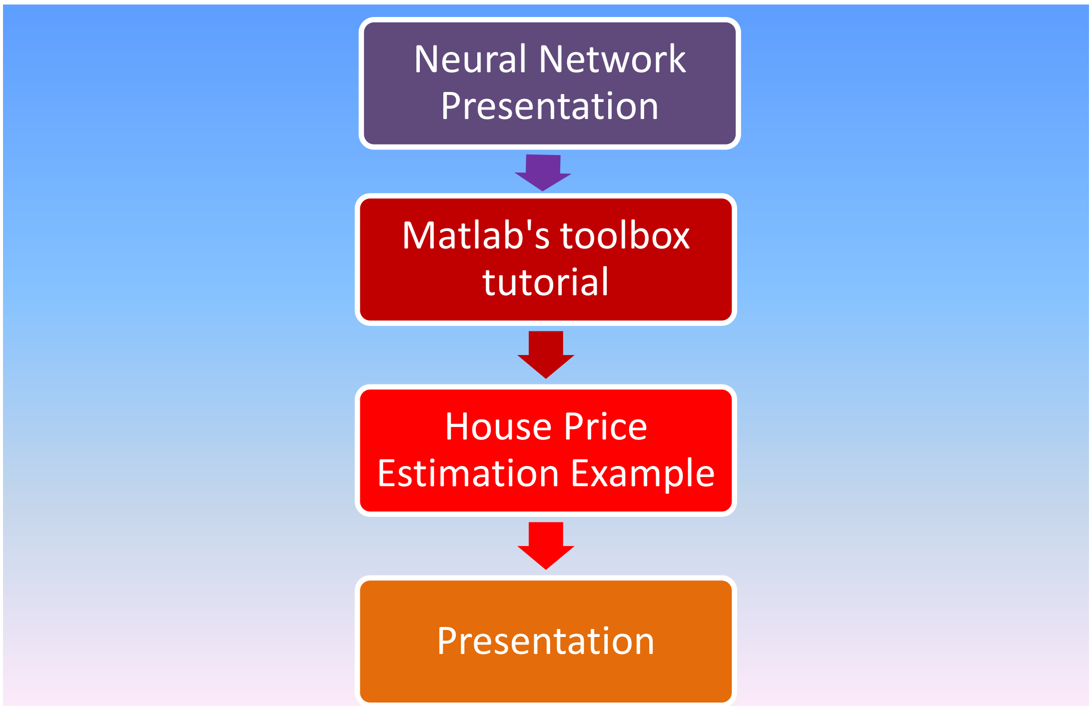
Date: _________________________________

Tutorial 2 Structure

Session 1



Session 2



Session1-Lecture (Chang 2011)

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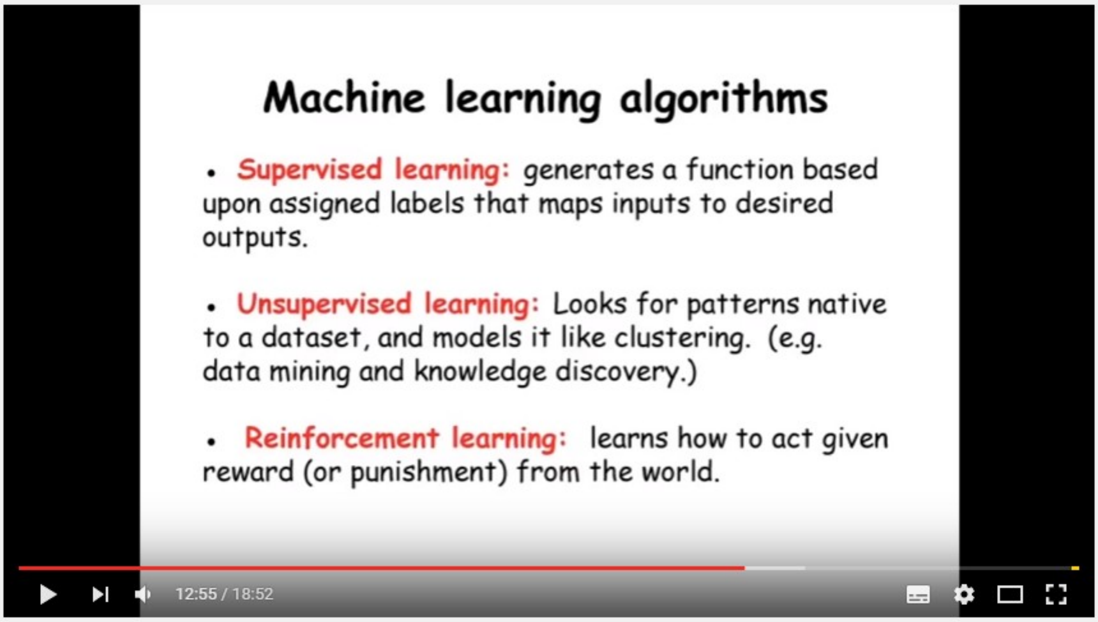
Session1-Video example



Artificial Intelligence: Machine Learning Introduction

Session1-Discussion

Researchers and Computer scientists in order to create new and efficient machine learning techniques have copied theories and principals from other disciplines.

Examples of the above are very known machine learning and optimization approaches such as genetic algorithms, neural networks, reinforcement learning etc.

Discuss and try to discover which principals have the researchers taken in to account in order to create these machine learning techniques.

Hints:

- **Genetic algorithms follow the principal of evolution.**
- **Neural networks mimics the way our brain works.**
- **How does your dog learn to do new tricks or avoid chewing the couch?**

Imagine yourselves as new and promising computer scientists and try to think of another principal from any other scientific discipline, which could be potentially used in order to build a new machine-learning algorithm.

Session1-Quiz

Machine Learning - Quiz 1

Question 1

A computer program is said to learn from experience E with respect to some task T and some performance measure P if its performance on T, as measured by P, improves with experience E. Suppose we feed a learning algorithm a lot of historical credit application data, and have it learn to predict which applications are good credit and which are not good credit. In this setting, what is T?

(a) None of these.

(b) The probability of it correctly predicting a future date's weather.

(c) The process of the algorithm examining a large amount of historical weather data.

(d) The credit prediction task.

Question 2

Suppose you are working on credit prediction, and you would like to predict whether a new application is to be approved for credit. You want to use a learning algorithm for this. Would you treat this as a classification or a regression problem?

(a) Classification.

(b) Regression.

Question 3

Suppose you are working on stock market prediction, Typically tens of millions of shares of Yahoo stock are traded (i.e., bought/sold) each day. You would like to predict the number of Yahoo shares that will be traded tomorrow. Would you treat this as a classification or a regression problem?

(a) Classification.

(b) Regression.

Question 4

Some of the problems below are best addressed using a supervised learning algorithm, and the others with an unsupervised learning algorithm. Which of the following would you apply supervised learning to? (Select all that apply.) In each case, assume some appropriate dataset is available for your algorithm to learn from.

(a) Have a computer examine an audio clip of a piece of music, and classify whether or not there are vocals (i.e., a human voice singing) in that audio clip, or if it is a clip of only musical instruments (and no vocals).

(b) Given data on how 1000 medical patients respond to an experimental drug (such as effectiveness of the treatment, side effects, etc.), discover whether there are different categories or "types" of patients in terms of how they respond to the drug, and if so what these categories are.

(c) Take a collection of 1000 essays written on the US Economy, and find a way to automatically group these essays into a small number of groups of essays that are somehow "similar" or "related".

(d) In farming, given data on crop yields over the last 50 years, learn to predict next year's crop yields.

Question 5

Which of these is a reasonable definition of machine learning?

(a) Machine learning is the field of allowing robots to act intelligently.

(b) Machine learning is the field of study that gives computers the ability to learn without being explicitly programmed.

(c) Machine learning means from labelled data.

(d) Machine learning is the science of programming computers.

Session2-Lecture (Andras 2011)

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Session2-Matlab's NN toolbox tutorial

Session2-House Price Estimation example

House Price Estimation

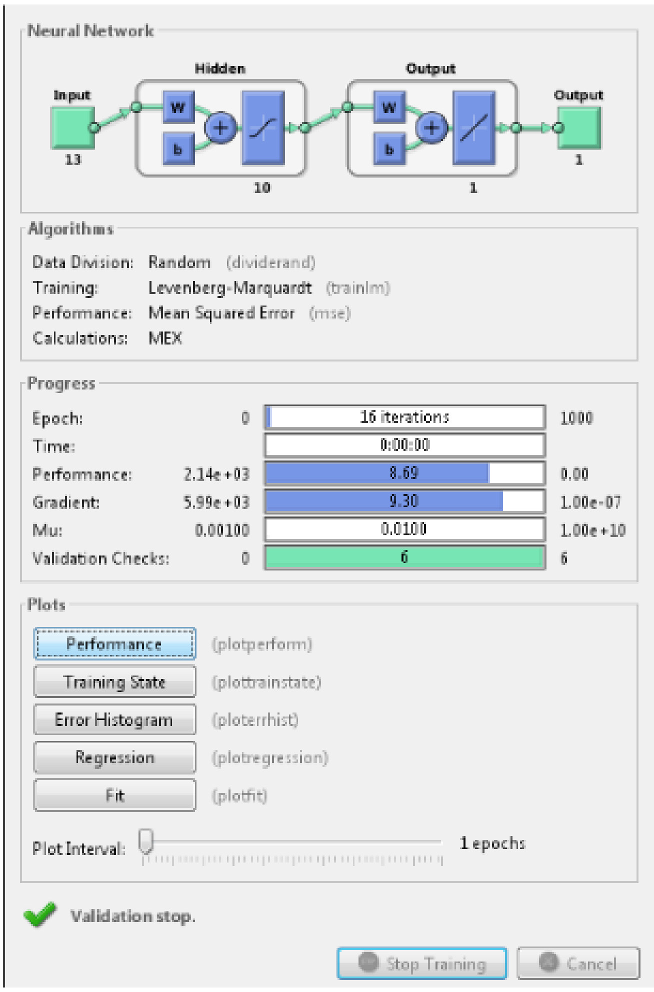
This example illustrates how a function fitting neural network can estimate median house prices for a neighborhood based on neighborhood demographics.

The Problem: Estimate House Values

In this example we attempt to build a neural network that can estimate the median price of a home in a neighborhood described by thirteen demographic attributes:

```
 1. Per capita crime rate per town
 2. Proportion of residential land zoned for lots over 25,000 sq. ft.
 3. proportion of non-retail business acres per town
 4. 1 if tract bounds Charles river, 0 otherwise
 5. Nitric oxides concentration (parts per 10 million)
 6. Average number of rooms per dwelling
 7. Proportion of owner-occupied units built prior to 1940
 8. Weighted distances to five Boston employment centres
 9. Index of accessibility to radial highways
10. Full-value property-tax rate per $10,000
11. Pupil-teacher ratio by town
12. 1000(Bk - 0.63)^2
13. Percent lower status of the population
```

This is an example of a fitting problem, where inputs are matched up to associated target outputs, and we would like to create a neural network which not only estimates the known targets given known inputs, but can generalize to accurately estimate outputs for inputs that were not used to design the solution.



Session2-Presentation

At the previous tutorial we have introduced fuzzy logic while in this session we have made a brief presentation on artificial neural networks. Search the web with your team and try to make a short presentation (5-6 slides) presenting the advantages and disadvantages of those two techniques. If you had to resolve a problem by applying a machine learning technique where would you prefer to use fuzzy logic and where your choice would be neural networks?

Appendix E-Experts

In this Appendix, we provide the questionnaire given to a group of three experts in order to train FCM1, which is the FCM configuration relying upon the opinion of experts (chapter 7). FCM1 was utilised in combination with the fuzzy adaptive rule base system used to model the AV-AT model of emotion (referred to as "Fuzzy" in chapter 7) in order to construct the FFE configuration of our final system.

For the purposes of our research project please provide a linguistic label to describe the relation existing between two emotion labels describing a student's emotional state at two consecutive points in time. Please indicate the direction and strength of each of these relations by utilizing the following labels. {Negative very strong, negative strong, negative medium, negative weak, zero or not related, positive weak, positive medium, positive strong, positive very strong} .

For example: a student which is in flow and engaged in time t it is possible to remain in flow so this relation can be described in the table as positive strong in the corresponding cell of the matrix.

	Emotions time t+1							
Emotions time t	**Flow**	**Excitement**	**Calm**	**Boredom**	**Stress**	**Confusion**	**Frustration**	**Neutral**
Flow								
Excitement								
Calm								
Boredom								
Stress								
Confusion								
Frustration								
Neutral								

FCM1 weight matrix.

0,5	0,416667	0,166667	-0,33333	-0,08333	0,166667	-0,5	-0,25
0,416667	0,5	0,083333	-0,33333	0,083333	-0,16667	-0,25	-0,16667
0,416667	0,083333	0,416667	0,166667	-0,41667	-0,33333	-0,41667	0,166667
-0,41667	-0,5	-0,08333	0,5	0,166667	0,166667	0,416667	0,166667
-0,25	-0,08333	-0,33333	-0,16667	0,333333	0,416667	0,333333	-0,33333
0	-0,33333	-0,33333	0	0,333333	0,416667	0,416667	-0,16667
-0,5	-0,41667	-0,25	0,25	0,416667	0,083333	0,5	-0,08333
0	0	0,333333	0,166667	-0,16667	0,083333	-0,33333	0,5

References

Akinci, H.M., Yesil, E. (2013) 'Emotion Modelling Using Fuzzy Cognitive Maps'. *IEEE 14th International Symposium on Computational Intelligence and Informatics (CINTI),* held 19-21 Nov. 2013 in Budapest, 49-55

AlZoubi, O., Calvo, R.A., and Stevens, R.H. (2009) 'Classification of EEG for Emotion Recognition: An Adaptive Approach'. in Nicholson, A., Li, X. (eds.) *AI 2009: Advances in Artificial Intelligence. Lecture Notes in Computer Science* 5866, 52-61

Amer, M., Jetter, A.J., and Daim, T.U. (2013) 'Scenario planning for the national wind energy sector through Fuzzy Cognitive Maps'. in *Proceedings of PICMET'13*, 'Technology Management in the IT-Driven Services'. held 28 July – 1 Aug. 2013 in San Jose CA, 2153-2162

Andras, P. (2011) An Introduction to Artificial Neural Networks [lecture notes] available from <https://www.staff.ncl.ac.uk/peter.andras/annintro.ppt> [10 July 2016]

Antonacopoulou, E. P., and Gabriel, Y. (2001) 'Emotion, learning and organizational change: Towards an integration of psychoanalytic and other perspectives'. *Journal of Organizational Change Management* 14(5), 435-451.

Arnold, M.B. (1960) *Emotion and Personality*. New York: Columbia University Press.

Ashwin, T.S., Jose, J., Raghu, G., and Reddy, G.R.M. (2015) 'An E-Learning System with Multifacial Emotion Recognition Using Supervised Machine Learning'. in Choppella, V., Kinshuk, S.I., *Proceedings of IEEE 7th International Conference on Technology for Education (T4E)*. held 10-12 Dec. 2015 in Warangal, India. CPS, 23-26

Ayesh, A., and Blewitt, W. (2015) 'Models for computational emotions from psychological theories using type I fuzzy logic'. *Cognitive Computation* 7(3), 285-308

Bachorowski, J., and Owren, M.J., (2001) 'Not all Laughs are Alike: Voiced but not Unvoiced Laughter Readily Elicits Positive Affect'. *Psychological Science* 12 (3), 252–257

Baker, R.S., D'Mello, S.K., Rodrigo, M.M.T., and Graesser, A.C. (2010) 'Better to be frustrated than bored: The incidence, persistence, and impact of learners' cognitive–affective states during interactions with three different computer-based learning environments'. *International Journal of Human-Computer Studies* 68(4), 223-241

Baker R.S.J.D., Rodrigo, Ma, M.T., Xolocotzin U.E. (2007) 'The dynamics of affective transitions in simulation problem-solving environments'. in *Affective Computing and Intelligent Interaction. Proceedings of Second International Conference, ACII'.* held 12-14 Sept. 2007 in Lisbon, Portugal. ed. by Paiva, A.C.R., Prada, R., Picard, R.W., Heidelberg: Springer, 666-677

Baker, R., Corbett, A., Koedinger, K., and Wagner, A. (2004) ‘Off-task behavior in the cognitive tutor classroom: When students game the system’. in Dykstra-Erickson, E., Manfred, T. (eds.) *Proceedings of ACM Computer Human Interaction Conference on Human Factors in Computing Systems.* held 24-29 April 2004 in Vienna, Austria. 383-390

Banda, N., Engelbrecht, A., and Robinson, P. (2015) ‘Continuous emotion recognition using a particle swarm optimized NARX neural network’. *In IEEE International Conference on Affective Computing and Intelligent Interaction (ACII)*. held 21-24 Sept.2015 in Xi'an, China, 380-386

Barrett, L.F., Mesquita, B., and Gendron, M. (2011) ‘Context in emotion perception’. *Current Directions in Psychological Science*, 20(5), 286-290.

Barrows, H.S. (1996) ‘Problem-based learning in medicine and beyond: A brief overview’. *New Directions for Teaching and Learning* 68 (3), 3-12

Bashashati, A., Fatourechi, M., Ward, R.K., and Birch, G.E. (2007) ‘A Survey of Signal Processing Algorithms in Brain Computer Interfaces Based on Electrical Brain Signals’. *Journal of Neural Engineering* 4 (2), 32-57

Baumeister, R.F., Bratslavsky, E., and Vohs, K.D. (2001) 'Bad is stronger than good'. *Review of General Psychology* 5(4), 323–370

Becker Asano, C. (2013) ‘WASABI for affect simulation in human-computer interaction: Architecture description and example applications’. in *Proceedings of 1st Workshop on Emotion Representation and Modelling in Human-Computer-Interaction-Systems (ERM4HCI) in conjunction with the International Conference on Multimodal Interaction (ICMI)*. Held 9-13 Dec. 2013 in Sydney, Australia. Heidelberg: Springer

Becker, C., Kopp, S., Wachsmuth, I. (2004) ‘Simulating the Emotion Dynamics of a Multimodal Conversational Agent’. in *Affective Dialogue Systems. Lecture notes in Computer Science* 3068. Springer, 154–165

Benarde, M.A. (1973) *Our Precarious Habitat: An Integrated Approach to Understanding Man’s effect on his Environment.* 2nd edn W. W. Norton & Company

Bernardo, D., Hagras, H., and Tsang, E. (2013) ‘A Genetic Type-2 Fuzzy Logic Based System for Financial Applications Modelling and Prediction. *IEEE International Conference on Fuzzy Systems (FUZZ)*, held 7-10 July 2013 in Hyderabad, India., 1-8

Bhavsar, H., and Ganatra, A. (2012) ‘A Comparative Study of Training Algorithms for Supervised Machine Learning’. *International Journal of Soft Computing and Engineering (IJSCE) 2*(4), 2231-2307

Bian, D., Wade, J., Swanson, A., Warren, Z., and Sarkar, N. (2015) ‘Physiology-based Affect Recognition during Driving in Virtual Environment for Autism Intervention’. in *Proceedings of the 2nd International Conference on Physiological Computing Systems*. held 11-13 Feb. 2015 in Angers, France. 137-145

Biederman, I. (1987) ‘Recognition-by-components: A theory of human image understanding’. *Psychological Review* 94 (2), 115–147

Birdwhistle, R. (1970) Kinesics and Context: Essays on Body Motion and Communication. University of Pennsylvania Press

Bogomolov, A., Lepri, B., Ferron, M., Pianesi, F., and Pentland, A.S. (2014) ‘Pervasive Stress Recognition for Sustainable Living’. in *IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops).* held 24-28 March 2014 in Budapest, Hungary. 345-350

Boole, G. (1854) *An Investigation of the Laws of Thought: on which are founded the Mathematical Theories of Logic and Probabilities*. Dover Publications.

Bors, A. G., and Pitas, I. (1996) 'Median radial basis function neural network'. IEEE *Transactions on Neural Networks* 7(6), 1351-1364

Boud, D., and Walker, D. (1993) 'Barriers to reflection on experience'. *Using experience for learning*, 73-86.

Bower, G. (1981) ‘Mood and Memory’. *American Psychologist* 36 (2), 129-148

Bradley, M.M., and Lang, P.J. (1999) ‘*Affective Norms for English Words (ANEW): Instruction Manual and Affective Ratings*’. Technical Report C1, The Center for Research in Psychophysiology, University of Florida

Bradley, M.M., and Lang, P.J. (2007) ‘*Affective Norms for English Text (ANET): Affective Ratings of Text and Instruction Manual*’. Technical Report No. D-1, University of Florida

Broekens, J. (2015) ‘Emotion Engines for Games in Practice: Two Case Studies using Gamygdala’. In *IEEE International Conference on Affective Computing and Intelligent Interaction (ACII).* held 21-24 Sept.2015 in Xi’an, Chia. 790-791

Buche, C., Chevaillier, P., Nédélec, A., Parenthoën, M., and Tisseau, J. (2010) ‘Fuzzy Cognitive Maps for the Simulation of Individual Adaptive Behaviors’. *Computer Animation and Virtual Worlds* 21(6), 573-587

Bui, T., Heylen, D., Poel, M., and Nijholt, A. (2002) ‘Parlee: An Adaptive Plan Based Event Appraisal Model of Emotions’. in *KI 2002: Advances in Artificial Intelligence. Lecture Notes in Computer Science* 2479, 129-143

Cacioppo, J.T. (2003) ‘Introduction: Emotion and Health’. In *Handbook of Affective Sciences*. ed. by Davidson, R.J., Sherer, K.R., and Goldsmith H.H., New York: Oxford University Press, 1047-1052

Cakmak, O., Kazemzadeh, A., Yildirim, S., and Narayanan, S. (2012) ‘Using Interval Type-2 Fuzzy Logic to Analyze Turkish Emotion Words’. In *IEEE Signal & Information*

Processing Association Annual Summit and Conference (APSIPA ASC), 2012 Asia-Pacific, held 3-6 Dec. 2012 in Hollywood CA. 1-4.

Calvo, R.A., and D'Mello, S. (2010) 'Affect Detection: An Interdisciplinary Review of Models, Methods, and their Applications'. *IEEE Transactions on Affective Computing* 1(1), 18-37

Cambria, E., Mazzocco, T., and Hussain, A. (2013) 'Application of Multi-dimensional Scaling and Artificial Neural Networks for Biologically Inspired Opinion Mining'. *Biologically Inspired Cognitive Architectures* 4, 41-53

Caridakis, G., Karpouzis, K., and Kollias, S. (2008) 'User and Context Adaptive Neural Networks for Emotion Recognition'*. Neurocomputing* 71(13), 2553-2562

Carson, D., Gilmore, A., Perry, C., and Gronhaug, K. (2001) *Qualitative Marketing Research*. London: Sage.

Carvalho, J.P. (2013) 'On the Semantics and the Use of Fuzzy Cognitive Maps and Dynamic Cognitive Maps in Social Sciences'. *Fuzzy Sets and Systems* 214, 6-19.

Cassady, J.C., and Johnson, R.E. (2002) 'Cognitive test anxiety and academic performance'. *Contemporary Educational* Psychology 27(2), 270-295

Chang, Y.F., (2011) 'An Overview of Machine Learning'. [lecture notes] <disp.ee.ntu.edu.tw/class/An%20Overview%20of%20Machine%20Learning.pptx> [10 July 2016]

Chen, J., Hu, B., Xu, L., Moore, P., and Su, Y. (2015) 'Feature-level Fusion of Multimodal Physiological Signals for Emotion Recognition'. In *IEEE International Conference on Bioinformatics and Biomedicine (BIBM*). held 9-12 Nov. 2015 in Washington DC. 395-399

Chovil, N. (1991) 'Discourse-Oriented Facial Displays in Conversation' *Research on Language and Social Interaction* 25 (1-4), 163-194

Cichosz, J., and Slot, K. (2007) 'Emotion Recognition in Speech Signal using Emotion-Extracting Binary Decision Trees'. in Paiva, A., Prada, R., Picard, R. W. (eds.) *Proceedings of Affective Computing and Intelligent Interaction: Second International Conference ACII 2007*. held 12-15 Sept 2007 in Lisbon, Portugal

Cohen, I., Sebe, N., Garg, A., Lew, M.S., and Huang, T.S. (2002) 'Facial Expression Recognition from Video Sequences. In *Proceedings of IEEE International Conference on Multimedia and Expo (ICME'02)* 2, 121-124

Colquitt, J.A., LePine, J.A., and Noe, R.A. (2000) 'Toward an Integrative Theory of Training Motivation: A Meta-analytic Path Analysis of 20 Years of Research'. *Journal of Applied Psychology* 85 (5), 678-707

Cooke, G., Lewis, P., Glendinning, I., (2014) 'Evaluating Postgraduate Students' Perceptions of Activity Led Learning: Findings from a Longitudinal Study'. in *42nd Annual Conference of European Society for Engineering Education (SEFI 2014)*, at University of Birmingham, Birmingham, UK

Cook, D.J., Augusto J.C., Jakkula V.R. (2009) 'Ambient Intelligence: Technologies, Applications and Opportunities'. *Pervasive and Mobile Computing* 5(4), 277-298

Cozolino, L. (2006) *The neuroscience of human relationships: Attachment and the developing social brain*. New York, London: W. W. Norton & Company.

Craig, S., Graesser, A., Sullins, J., and Gholson, B. (2004) 'Affect and Learning: An Exploratory Look into the Role of Affect in Learning'. *Journal of Educational Media*, 29 (3), 241-250

Csikszentmihalyi, M. (1990) Flow: the Psychology of Optimal Experience. New York: Harper Row

Cunningham W.A., and Zelazo, P.D. (2010) 'The Development of Iterative Reprocessing: Implications for Affect and its Regulation'. in *Developmental Cognitive Social Neuroscience.* ed. by Zelazo, P.D., Chandler, M., and Crone, E., New York, NY: Psychology Press, 81-98

Cunningham, W.A., Dunfield, K.A., and Stillman, P.E. (2013) 'Emotional States from Affective Dynamics'. *Emotion Review* 5 (4), 344-355

Damasio, A. (1994) *Descartes' Error.* New York, NY: Avon Books

Darwin, C. (1965) *The Expression of the Emotions in Man and Animals.* Chicago, IL: University of Chicago Press, 526

Dawson, M.E., Schell, A.M., and Filion, D.L. (2007) 'The Electrodermal System'. in *Handbook of Psychophysiology*. ed. by Cacioppo, J.T., Tassinary, L.G., Berntson, G.. Cambridge: Cambridge University Press

Dernoncourt, F. (2011) 'La Logique Floue : entre raisonnement humain et intelligence artificielle' [online] available from <http://francky.me/doc/FCS2-Report%20-%20La%20Logique%20Floue%2020110204a.pdf> [10 July 2016]

Dias, J., Mascarenhas, S., and Paiva, A. (2014) 'Fatima Modular: Towards an Agent Architecture with a Generic Appraisal Framework," in *Emotion Modelling, Lecture Notes in Computer Science*. ed by Bosse, T., Broekens J., Dias, J., and Van der Zwaan, J. Switzerland: Springer, 8750, 44–56

D'Mello, S., Taylor, R.S., and Graesser, A. (2007) 'Monitoring Affective Trajectories during Complex Learning'. In McNamara, D.S., and Trafton, J.G. (eds.), *Proceedings of the 29th Annual Meeting of the Cognitive Science Societ.* Austin TX: Cognitive Science Society, 203-208

D'Mello, S.K., Craig, S.D., Gholson, B., Franklin, S., Picard, R., and Graesser, A.C. (2005) ‘Integrating Affect Sensors in an Intelligent Tutoring System’. in *Affective Interactions: The Computer in the Affective Loop Workshop at 2005 International Conference on Intelligent User Interfaces*. New York: AMC Press, 7-13

D'Mello, S.K., Craig, S.D., Sullins, J. and Graesser, A.C. (2006) ‘Predicting Affective States Expressed through an Emote-Aloud Procedure from AutoTutor's Mixed-Initiative Dialogue’. International Journal of Artificial Intelligence in Education. 16(1), 3-28

D’Mello, S.K., & Kory, J. (2012) ‘Consistent but Modest: A Meta-Analysis on Unimodal and Multimodal Affect Detection Accuracies from 30 Studies’. in Morency L.P., Bohus, D., Aghajan, H., Nijholt, A., Cassell, J., and Epps, J. (eds.). *Proceedings of the 14th ACM International Conference on Multimodal Interaction*, 31-38

D'Mello, S.K., and Graesser, A. (2012) ‘AutoTutor and Affective AutoTutor: Learning by Talking with Cognitively and Emotionally Intelligent Computers that Talk Back’. ACM Transactions on Interactive Intelligent Systems (TiiS), 2(4), 23.

D’Mello, S.K., Olney, A., Williams, C., and Hays, P. (2012) ‘Gaze Tutor: A Gaze-Reactive Intelligent Tutoring System’. *International Journal of Human-Computer Studies*, 70(5), 377-398

D’Mello, S.K., and Calvo, R.A. (2013) ‘Beyond the Basic Emotions: What Should Affective Computing Compute?’. in S. Brewster, Bødker, S., and Mackay, W. (eds.) In *Extended Abstracts on the ACM SIGCHI Conference on Human Factors in Computing Systems (CHI 2013),* 2287-2294

Doctor, F. (2015) Introduction to Fuzzy Logic and Software Tools Partial Solutions [lecture notes] module M28COM Evolutionary and Fuzzy Systems, 05 June 1015, Coventry: Coventry University

Doctor, F., Syue, C.H., Liu, Y. X., Shieh, J.S., and Iqbal, R (2016) ‘Type-2 Fuzzy Sets Applied to Multivariable Self-Organizing Fuzzy Logic Controllers for Regulating Anesthesia’ *Applied Soft Computing*, 38, 872-889

Doctor, F., Hagras, H., and Callaghan, V. (2005) ‘A Fuzzy Embedded Agent-Based Approach for Realizing Ambient Intelligence in Intelligent Inhabited Environments’. *IEE Transactions on Systems, Man and Cybernatics- Part A: Systems and Humans*, 35(1), 55-56

Dictionary.com ‘emotion’ in Dictionary.com Unabridged. [online] Source location: Random House, Inc. <http://www.dictionary.com/browse/emotion> Available from: http://www.dictionary.com/. [July 8, 2016]

Ducatel, K., Bogdanowicz, M., Scapolo, F., Leijten, J. and Burgelman, J.C., (2001) ‘Scenarios for Ambient Intelligence in 2010’*. Office for Official Publications of the European Communities*

Dyrek, F. (2009) Theory of knowledge:" There can be no knowledge without emotion… until we have felt the force of the knowledge, it is not ours"(adapted from Arnold Bennett). Munich: GRIN Verlag

Ekman, P. (1992) 'An Argument for Basic Emotions'. *Cognition & Emotion* 6(3-4), 169–200

Ekman, P., and Friesen, W.V. (2003) *Unmasking the Face. A Guide to Recognising Emotions from Facial Expressions*. Los Altos, CA: Malor Books

Ekman, P. (1999) Basic emotions. In The *Handbook of Cognition and Emotion*. ed. by Dalgleish, T., and Power, T. New York.: John Wiley & Sons, 45-60

Elbeltagi, E., Hegazy, T., and Grierson, D. (2005) 'Comparison Among Five Evolutionary-based Optimization Algorithms'. *Advanced Engineering Informatics* 19(1), 43-53

El-Nasr, M.S., Yen, J., and Ioerger, T.R. (2000) 'Flame—Fuzzy Logic Adaptive Model of Emotions'. Autonomous *Agents and Multi-agent Systems* 3(3), 219-257

Eyben, F., Wöllmer, M., Poitschke, T., Schuller, B., Blaschke, C., Färber, B., and Nguyen-Thien, N. (2010) 'Emotion on the Road—Necessity, Acceptance, and Feasibility of Affective Computing in the Car'. in *Advances in Human-Computer Interaction* [online] ed. By Karpouzis, K., Article ID 263593, available from <http://www.hindawi.com/journals/ahci/2010/263593/cta/> [8 July 2016]

Field, A. (2013) *Discovering statistics using IBM SPSS Statistics: and sex and drugs and rock 'n' roll 4th edn.* London: Sage ISBN 9781446249178.

Fink, G.A. (2014) *Markov Models for Pattern Recognition: From Theory to Applications.* 2nd edn. London: Springer Science & Business Media.

Fisher, R. A. (1922) 'On the interpretation of chi square from contingency tables, and the calculation of P'. *Journal of the Royal Statistical Society* 85, 87–94

Frijda, N. H. (1986) *The Emotions.* New York: Cambridge University Press.

Froelich, W., Papageorgiou, E.I., Samarinas, M., and Skriapas, K. (2012) 'Application of Evolutionary Fuzzy Cognitive Maps to the Long-term Prediction of Prostate Cancer'. *Applied Soft Computing*, 12(12), 3810-3817

Fung, C. K., Kwong, C. K., Chan, K. Y., and Jiang, H. (2014) 'A guided search genetic algorithm using mined rules for optimal affective product design'. *Engineering Optimization* 46(8), 1094-1108

Gendron, M., and Barrett, L.F. (2009) 'Reconstructing the Past: A Century of Ideas about Emotion in Psychology'. *Emotion Review* 1(4), 316–339

Georgiou, D.A., and Botsios, S.D. (2008) Learning Style Recognition: A Three Layers Fuzzy Cognitive Map Schema'. in IEEE International Conference on Fuzzy Systems, 2008 (FUZZ-IEEE 2008) in conjunction with IEEE World Congress on Computational Intelligence. held 1-6 June 2008 in Honk Kong. 2202-2207

Glendinning, I., and Michalska, A. (2012) ‘ALL for Masters: Exploring Effective Delivery of Activity Led Learning for Taught Postgraduate Students’. *International Conference on Innovation, Practice and Research in Engineering Education (EE2012).* held 18-20 September 2012 at Coventry University, UK

Gilleade, K., Dix, A., and Allanson, J. (2005) ‘Affective Videogames and Modes of Affective Gaming: Assist me, Challenge me, Emote me’. In *Proeedings of Digital Games Research Association (DiGRA) Conference*. *‘Changing Views- Worlds in Play’.* held in 16- 20 June 2005, in Vancouver, Canada

Given, L. M. (2008) *The Sage encyclopedia of qualitative research methods*. Los Angeles, CA: Sage Publications. ISBN 1-4129-4163-6.

Goleman, D. (1995) *Emotional Intelligence.* New York: Bantam Books

Gordon, E. (2000) *Integrative neuroscience: Bringing together biological, psychological and clinical models of the human brain*. Singapore: Harwood Academic Publishers.

Gray, J.A. (1982) *The Neuropsychology of Anxiety.* Oxford: Oxford University Press.

Graesser, A.C., Chipman, P., Haynes, B.C., and Olney, A. (2005) ‘AutoTutor: An Intelligent Tutoring System with Mixed-Initiative Dialogue’. *IEEE Transactions on Education* 48(4), 612-618

Graesser, A.C., McDaniel, B., Chipman, P., Witherspoon, A., D’Mello, S.K., and Gholson, B. (2006) ‘Detection of Emotions during Learning with AutoTutor’. in Son, R. (ed.), *Proceedings of the 28th Annual Meeting of the Cognitive Science Society*. Mahwah, NJ: Erlbaum, 285-290

Gratch, J., and Marsella, S. (2004) ‘A Domain-Independent Framework for Modelling Emotion’. *Cognitive Systems Research* 5(4), 269–306

Gratch, J., and Marsella, S. (2005) ‘Evaluating a Computational Model of Emotion’. *Autonomous Agents and Multi-Agent Systems* 11(1), 23–43

Groumpos, P.P., and Stylios, C.D. (2000) ‘Modelling Supervisory Control Systems using Fuzzy Cognitive Maps’. *Chaos, Solitons & Fractals* 11(1), 329-336

Gurney, K. (1997) An introduction to neural networks. London: UCL press

Hamari, J., Shernoff, D. J., Rowe, E., Coller, B., Asbell-Clarke, J., and Edwards, T. (2016) ‘Challenging Games Help Students Learn: An Empirical Study on Engagement, Flow and Immersion in Game-Based Learning’. *Computers in Human Behavior* 54, 170-179

Han, J., and Kamber, M. (2011) *Data Mining Concepts and Techniques.* 3rd edn. Waltham, MA: Morgan Kaufman, Elsevier

Hatfield, E., Cacioppo, J.T., and Rapson, R.L. (1994) *Emotional Contagion*. New York: Cambridge University Press

Hendel-Giller, R., Hollenbach, C., Marshall, D., Oughton, K., Pickhorn, T., and Schilling, M. (2011) *The neuroscience of learning: A new paradigm for corporate education*. St. Louis, Missouri (USA): The Maritz Institute.

Homenda, W., Jastrzebska, A., and Pedrycz, W. (2014) ‘Modelling Time Series with Fuzzy Cognitive Maps’. In 2014 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), 2055-2062

Hudson, L., and Ozanne, J. (1988) 'Alternative Ways of Seeking Knowledge in Consumer Research'. *Journal of Consumer Research* 14(4), 508–521

Hyndman, R.J., and Koehler, A.B. (2006) 'Another look at measures of forecast accuracy'. *International Journal of Forecasting* 22(4), 679-688

James, W. (1884) ‘What is an emotion?’. *Mind* 34, 188–205

James, W. (1890) *The principles of psychology*. (vol. 1). New York, NY: Holt

James. L., and Nahl, D. (2000) *Road Rage and Agressive Driving.* Amherst, NY: Prometheus Books

Johnson, D.W., and Johnson, R.T. (1974) ‘Instructional Goal Structure: Cooperative, Competitive or Individualistic’. *Review of Educational Research* 44(2), 213–240

Iqbal, R., Doctor, F., Romero, M. and James, A. (2013) ‘Activity-led learning approach and group performance analysis using fuzzy rule-based classification model’. In IEEE international Conference on Computer Supported Cooperative Work in Design (CSCWD). held 27-29 June 2013, in Whistler, BC. IEEE, 599-606

Izard, C.E. (1971) *The Face of Emotion.* New York: Appleton-CenturyCrofts.

Jayne, C. (2015) Machine Learning Quiz 1 [lecture notes] module M24COM Machine Learning, Coventry: Coventry University. [10 October 2014]

Kang, C.C., Chuang, Y.J., Tung, K.C., Chao, C.C., Tang, C.Y., Peng, S.C., and Wong, D.S.H. (2011) 'A genetic algorithm-based boolean delay model of intracellular signal transduction in inflammation'. *BMC bioinformatics* 12(1), S17

Kar, R., Chakraborty, A., Konar, A., and Janarthanan, R. (2013) ‘Emotion Recognition System by Gesture Analysis using Fuzzy Sets’. in *Swarm, Evolutionary, and Memetic Computing, Lecture Notes in Computer Science*. ed. by Panigrahi B. K.,Suganthan, P.N., Das, S., and Dash, S.S..Springer International Publishing, vol.8298, 354-363

Karyotis, C., Doctor, F., Iqbal, R., James, A., and Chang, V. (2017) 'A fuzzy computational model of emotion for cloud based sentiment analysis'. *Journal of Information Sciences*. In press. http://dx.doi.org/10.1016/j.ins.2017.02.004

Karyotis, C., Doctor, F., Iqbal, R., and James, A. (2016) ' An Intelligent Framework for Emotion Aware E-Health Care Support Systems'. in IEEE Symposium Series on Computational Intelligence for Human-like Intelligence. held 6-9 December 2016 in Athens, Greece. IEEE

Karyotis, C., Doctor, F., Iqbal, R., James, A., and Chang, V. (2016).' A Fuzzy Modelling Approach of Emotion for Affective Computing Systems'. in, The 1st International Conference on Internet of Things and Big Data, Special Session, Recent Advancements in Internet of Things, Big Data and Security (RAIBS). held 23-25 April 2016, Rome, IT

Karyotis, C., Doctor, F., Iqbal, R., and James, A. (2015) 'An Intelligent Framework for Monitoring Students Affective Trajectories Using Adaptive Fuzzy Systems'. in IEEE International Conference on Fuzzy Systems. held 2-5 August 2015 in Istanbul, Turkey. IEEE, 1-8

Kazemzadeh, A., Lee, S., and Narayanan, S. (2013) 'Fuzzy Logic Models for the Meaning of Emotion Words'. *IEEE Computational Intelligence Magazine* 8(2), 34-49

Khalili, Z., and Moradi, M.H. (2008) 'Emotion Detection using Brain and Peripheral Signals'. In 2008 *Cairo International Biomedical Engineering Conference (CIBEC). IEEE,* 1-4

King, J.A., Rosal, M.C., Ma, Y., Reed, G., Kelly, T., Stanek III, E.J., and Ockene, I.S. (2000) 'Sequence and Seasonal Effects of Salivary Cortisol'. *Behavioral Medicine* 26(2), 67–73

Kirkland, T., and Cunningham, W.A (2012) 'Mapping Emotions Through Time: How Affective Trajectories Inform the Language of Emotion'. *Emotion* 12(2), 268–282

Kityama, S., Markus, H., Kityama, S. (1999) 'Is there a Universal Need for Positive Self-regard?'. *Psychological Review* 106(4), 766–794

Kolb, D., Lublin, S., Spoth, J., and Baker, R. (1986) 'Strategic management development: using experiential learning theory to assess and develop managerial competencies'. *Journal of Management Development* 5(3), 13-24

Komulainen, E., Meskanen, K., Lipsanen, J., Marko Lahti, J., Jylhä, P., Melartin, T., Wichers, M., Isometsä, E., Ekelund, J. (2014) 'The Effect of Personality on Daily Life Emotional Processes' PLoS ONE [online] 9(10), available from <http://journals.plos.org/plosone/article?id=10.1371/journal.pone.0110907> [8 July 2019]

Kort B., Reilly, R. and Picard R. (2001a) 'An Affective Model of Interplay between Emotions and Learning: Reengineering Educational Pedagogy—Building a Learning

Companion'. In *Proceedings of the IEEE International Conference on Advanced Learning Technology: Issues, Achievements and Challenges*. Held 6-8 August 2001 in Madison, WI. IEEE, 43–48.

Kort B., Reilly, R. and Picard, R.W. (2001b) 'External Representation of Learning Process and Domain Knowledge: Affective State as a Determinate of its Structure and Function'. in: Proceedings of the Workshop in Artificial Intelligence in Education (AIED). held 19-21 may 2001 in San Antonio, TX. IEEE, 64–69

Kosko, B. (1986) 'Fuzzy Cognitive Maps'. *International Journal of Man-Machine Studies* 24(1), 65-75

Kotsiantis, S.B., Zaharakis, I., and Pintelas, P. (2007) 'Supervised Machine Learning: A review of Classification Techniques'. in *Proceedings of the 2007 Conference on Emerging Artificial Intelligence Applications in Computer Engineering: Real Word AI Systems with Applications in eHealth, HCI, Information Retrieval and Pervasive Technologies*. Amsterdam: IOS Press, 3-24

Kowalczuk, Z., and Czubenko, M. (2016) 'Computational Approaches to Modelling Artificial Emotion–An Overview of the Proposed Solutions'. *Frontiers in Robotics and Artificial Intelligence [online]* 3(21). available from <http://journal.frontiersin.org/article/10.3389/frobt.2016.00021/full> [10 July 2016]

Kring, A.M., Gordon, A.H. (1998) 'Sex Differences in Emotion: Expression, Experience, and Physiology'. *Journal of Personality and Social Psychology* 74(3), 686-703.

Lang, P.J., Bradley, M.M., and Cuthbert, B.N. (2008) '*International Affective Picture System (IAPS): Affective Ratings of Pictures and Instruction Manual*'. Technical Report A-8. The Center for the Study of Emotion and Attention, University of Florida

Lazarus, R.S. (1991) 'Progress on a Cognitive-Motivational-Relational Theory of Emotion'. *American Psychologist* 46(8), 819-834

Lazzerini, B., and Mkrtchyan, L. (2010) 'Risk Analysis using Extended Fuzzy Cognitive Maps'. *In 2010 International Conference on Intelligent Computing and Cognitive Informatics (ICICCI).* held 22-23 June 2010 in Kuala Lumpur Malaysia. IEEE, 179-182

LeDoux, J. E. (2000) 'Emotion circuits in the brain'. *Annual Review of Neuroscience* 23, 155-184

Lee, C.K., Yoo, S.K., Park, Y.J., Kim, N.H., Jeong, K.S., and Lee, B. (2006) 'Using Neural Network to Recognize Human Emotions from Heart Rate Variability and Skin Resistance'. In IEEE *27th Annual International Conference of the Engineering in Medicine and Biology Society (IEEE-EMBS).* held 1-4 September 2005 in Shanghai, China. IEEE, 5523-5525

Lee, C.M., Narayanan, S., and Pieraccini, R. (2001) 'Recognition of Negative Emotions from the Speech Signal. In *IEEE Workshop on Automatic Speech Recognition and*

Understanding (ASRU). held 9-13 December 2001 in Madonna di Campiglio, Italy. IEEE, 240-243

Lee, C.C., Mower, E., Busso, C., Lee, S., and Narayanan, S. (2011) 'Emotion Recognition using a Hierarchical Binary Decision Tree Approach'. *Speech Communication* 53(9), 1162-1171

Leu, F.Y., Liu, J.C., Hsu, Y.T., and Huang, Y.L. (2014) 'The Simulation of an Emotional Robot Implemented with Fuzzy Logic'. *Soft Computing* 18(9), 1729-1743

Levenson, R.W. (1988) 'Emotion and the Autonomic Nervous System: A Prospectus for Research on Autonomic Specificity'. In *Social Psychophysiology and Emotion: Theory and Clinical Applications.* ed. by Wagner, H. L. Oxford, England: John Wiley & Sons, 17–42

Lewis, P., and Glendinning, I. (2014) 'Evaluating Postgraduate Students' Perceptions of Activity Led Learning: Findings from a Longitudinal Study'. in 42nd Annual Conference of European Society for Engineering Education (SEFI 2014). held 15-19 September 2014 at University of Birmingham, UK

Li, Q., Yang, Z., Liu, S., Dai, Z. and Liu, Y. (2015) 'The Study of Emotion Recognition from Physiological Signals'. In 7th International Conference on Advanced Computational Intelligence (ICACI). Held 27-29 march 2015 in Wuyi,China. IEEE, 378-382

Lin, J., Miao, C., and Shen, Z. (2012) 'A FCM Based Approach for Emotion Prediction in Educational Game'. In 7th International Conference on Computing and Convergence Technology (ICCCT), 2012 IEEE, 980-986

Lin, J., Shen, Z., and Ailiya, C.M. (2013) 'An Affective Model for Inter-generational Social Games'. *International Journal of Information Technology* 19(2)

Lindquist, K.A. (2013) 'Emotions Emerge from More Basic Psychological Ingredients: A Modern Psychological Constructionist Model'. *Emotion Review* 5(4), 356-368

Lisetti, C.L., Yasavur, U., de Leon, C., Amini, R., Visser, U. and Rishe, N. (2012) 'Building an On-Demand Avatar-Based Health Intervention for Behavior Change'. In Youngblood G.M., and McCarthy, P.M. (ed.) *Proceedings of the Twenty-Fifth International Florida Artificial Intelligence Research Society Conference*. held 23-25 May 2012 at Marco Island, Florida, USA. AAAI Press,175-180

Lokannavar, S., Lahane, P., Gangurde, A., and Chidre, P. (2015) 'Emotion recognition using EEG Signals'. *Emotion*, 4(5), 54-56

Lomas, T. (2016) 'Towards a Positive Cross-cultural Lexicography: Enriching our Emotional Landscape through 216 'Untranslatable' Words pertaining to Well-being'. *The Journal of Positive Psychology* 5(11), 546-558

Lotte, F., Congedo, M., Le´cuyer, A., Lamarche, F., and Arnaldi, B. (2007) 'A Review of Classification Algorithms for EEG-Based Brain- Computer Interfaces'. *Journal of Neural Engineering* 4(2), R1

Mandryk, R. L., and Atkins, M. S. (2007) 'A Fuzzy Physiological Approach for Continuously Modelling Emotion during Interaction with Play Technologies'. *International Journal of Human-Computer Studies* 65(4), 329-347

Marinier, R., and Laird, J. (2008) 'Emotion-driven Reinforcement Learning'. Cognitive Science 32(1), 115– 120.

Marinier, R.P., Laird, J.E., and Lewis, R.L. (2009) 'A Computational Unification of Cognitive Behavior and Emotion'. *Cognitive Systems Research* 10(1), 48-69

Markinos, A., Papageorgiou, E., Stylios, C., and Gemtos, T. (2007) 'Introducing Fuzzy Cognitive Maps for Decision Making in Precision Agriculture'. In *Precision agriculture* 7, ed. by Stafford J. V. Wageningen Academic Publishers, 223-231

Marsella, S., Gratch, J., and Petta, P. (2010) 'Computational Models of Emotion'. in *A Blueprint for Affective Computing-A Sourcebook and Manual*. ed. by Scherer, K. R., Bänziger, T., and Roesch, E. Oxford: Oxford University Press, 21-46

Matiko, J.W., Beeby, S.P., and Tudor, J. (2014) 'Fuzzy Logic Based Emotion Classification'. In *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP*). held 4-9 May in Florence Italy. IEEE, 4389-4393

Mayer, J.D., Caruso, D., and Salovey, P. (1999) 'Emotional Intelligence meets Traditional Standards for an Intelligence'. *Intelligence* 27, 267-298.

McDougall, W. (1926) *An Introduction to Social Psychology.* Boston: Luce & Co.

McFarland, R.A. (1985) 'Relationship of Skin Temperature Changes to the Emotions Accompanying Music'. *Biofeedback and Self-regulation* 10(3), 255–267

McQuiggan, S.W., Robison. J.L., and Lester, J.C. (2010) 'Affective Transitions in Narrative-Centered Learning Environments'. *Educational Technology & Society* 13 (1), 40–53

Mehrabian, A. (1995) 'Framework for a Comprehensive Description and Measurement of Emotional States'. *Genetic, Social, and General Psychology Monographs* 121(3), 339-361

Metallinou, A., Wöllmer, M., Katsamanis, A., Eyben, F., Schuller, B., and Narayanan, S. (2012) 'Context-sensitive Learning for Enhanced Audiovisual Emotion Classification'. *IEEE Transactions on Affective Computing* 3(2), 184-198

Molins-Ruano, P., Sevilla, C., Santini, S., Haya, P. A., Rodríguez, P., and Sacha, G. M. (2014) 'Designing Videogames to Improve Students' Motivation'. *Computers in Human Behavior* 31, 571-579

Mora-Torres, M., Laureano-Cruces, A. L., Gamboa-Rodríguez, F., Ramírez-Rodríguez, J., and Sánchez-Guerrero, L. (2013) 'An Affective-Motivational Interface for a Pedagogical Agent'. *International Journal of Intelligence Science* 4(1), 17-23

More, W.S., Woodruff, J.D., and Gottschalk, W. (1974) *Emotions and adult learning*. Farnborough: Saxon House.

Moridis, C.N., and Economides, A.A. (2008) 'Toward computer-aided affective learning systems: a literature review'. *Journal of Educational Computing Research* 39(4), 313-337

Morse, G. (2006) 'Decisions and desire'. *Harvard Business Review* 84(1), 42

Mowrer, O.H. (1960) *Learning Theory and Behavior*. New York: Wiley.

Murugappan, M. (2011) 'Human Emotion Classification Using Wavelet Transform and KNN'. In Proceedings of the 2011 International Conference on Pattern Analysis and Intelligent Robotics (ICPAIR). held 28-29 June 2011 in Putrajaya, Malaysia. IEEE, 148-153

Nagamachi, M. (1995) 'Kansei Engineering: A New Ergonomic Consumer-oriented Technology for Product Development'. *International Journal of industrial ergonomics* 15(1), 3-11

Nanty, A., and Gelin, R. (2013) 'Fuzzy Controlled PAD Emotional State of a NAO Robot'. In *2013 Conference on Technologies and Applications of Artificial Intelligence (TAAI)*. held 6-8 December 2013 in Taipei, Taiwan. IEEE, 90-96

Nasoz, F., Lisetti, C., and Vasilakos A. (2010) 'Affectively Intelligent and Adaptive Car Interfaces'. *Information Sciences* 180 (20), 3817–3836

Newell, A. (1990) *Unified Theories of Cognition.* Cambridge, MA: Harvard University Press

Nicolai, A., and Choi, A. (2015) 'Facial Emotion Recognition Using Fuzzy Systems'. In *2015 IEEE International Conference on Systems, Man, and Cybernetics (SMC).* held 9-12 October 2015 in Kowloon, Hong Kong IEEE, 2216-2221

Oatley, K., and Johnson-Laird, P.N. (1987) 'Towards a Cognitive Theory of Emotions'. *Cognition & Emotion* 1, 29-50

Orero, J.O., and Rifqi, M. (2014) 'Design of a Fuzzy Affective Agent Based on Typicality Degrees of Physiological Signals'. In *Information Processing and Management of Uncertainty in Knowledge-Based Systems* of the series Communications in Computer and Information Science, (CCIS vol. 443), Springer International Publishing, 304-313

Ortony, A., and Turner, T.J. (1990) 'What's Basic about Basic Emotions?'. *Psychological Review* 97(3), 315–331

Ortony, A., Clore, G., and Collins, A. (1988) *The Cognitive Structure of Emotions*. Cambridge, MA: Cambridge University Press.

Osgood, C.E., and Tzeng, O.C.S. (eds.) (1990) *Language, Meaning, and Culture: The Selected Papers of C.E. Osgood*. New York: Praeger Publishers

Oyane, N.M.F., Bjelland, I., Pallesen, S., Holsten, F., Bjorvatn, B., (2008) 'Seasonality is Associated with Anxiety and Depression: the Hordaland Health Study'. *Journal of Affective Disorders* 105(1), 147–155

Pan, Y., Shen, P., and Shen, L. (2012) 'Speech Emotion Recognition Using Support Vector Machine'. *International Journal of Smart Home*, *6*(2), 101-108

Panksepp, J. (1982) 'Toward a General Psychobiological Theory of Emotions'. *The Behavioral and Brain Sciences* 5(3), 407-467

Papageorgiou, E.I. (ed.) (2013) *Fuzzy Cognitive Maps for Applied Sciences and Engineering: From Fundamentals to Extensions and Learning Algorithms*. (vol. 54) of the series Intelligent Systems Reference Library Berlin: Springer Science & Business Media.

Papageorgiou, E.I. (2013). 'Review Study on Fuzzy Cognitive Maps and Their Applications During the Last Decade'. In *Business Process Management* (vol. 444) of the series Studies in Computational Intelligence. ed. by Glykas, M., Berlin: Springer, 281-298

Papageorgiou, E.I., and Salmeron, J.L. (2014) Methods and Algorithms for Fuzzy Cognitive Map-based Modelling. In *Fuzzy Cognitive Maps for Applied Sciences and Engineering* (vol. 54) of the series Intelligent Systems Reference Library. Berlin: Springer, 1-28

Papakostas, G.A., and Koulouriotis, D.E. (2010) 'Classifying Patterns using Fuzzy Cognitive Maps. In *Fuzzy Cognitive Maps* (vol. 247) of the series Studies in Fuzziness and Soft Computing. Ed. by Glykas, M., Berlin: Springer, 291-306

Pardos, Z.A., Baker, R.S., San Pedro, M.O., Gowda, S.M., and Gowda, S. M. (2013) ' Affective states and state tests: Investigating how affect throughout the school year predicts end of year learning outcomes'. In Proceedings of the Third International Conference on Learning Analytics and Knowledge (LAK '13). held 8-12 April in Leuven, Belgium. ACM, 117-124

Pearson, K. (1900) 'On the criterion that a given system of deviations from the probable in the case of a correlated system of variables is such that it can be reasonably supposed to have arisen from random sampling'. *Philosophical Magazine* 50(5), 157–175

Pekrun, R. (1992) 'The Impact of Emotions on Learning and Achievement: Towards a Theory of Cognitive/Motivational Mediators'. *Applied Psychology* 41(4), 359-376

Pham, P., and Wang, J. (2015) ‘Attentive Learner: Improving Mobile MOOC Learning via Implicit Heart Rate Tracking’. In Artificial Intelligence in Education (vol. 9112) of the series Lecture Notes in Computer Science. ed. by Conati, C., Heffernan, N., Mitrovic, A., and Verdejo M.F. Berlin: Springer, 367-376

Piaget, J. (1981) *Intelligence and affectivity*. Annual Reviews, CA

Picard, R. W., Papert, S., Bender, W., Blumberg, B., Breazeal, C., Cavallo, D., Machover, T. Resnick, M. Roy D. and Strohecker C. (2004) 'Affective learning—a manifesto'. *BT Technology Journal* 22(4), 253-269.

Picard, R. (1995) *Affective computing Technical Report no. 321.* Cambridge: MIT Media Laboratory

Picard, R. (1997) *Affective Computing*. Cambridge, MA: MIT Press

Plutchik, R. (1980) *Emotion: A Psychoevolutionary Synthesis*. New York: Harper and Row

Popescu, M.C., Balas, V.E., Perescu-Popescu, L., and Mastorakis, N. (2009) 'Multilayer Perceptron and neural networks'. *WSEAS Transactions on Circuits and Systems* 8(7), 579-588

Potkonjak, V., Gardner, M., Callaghan, V., Mattila, P., Guetl, C., Petrović, V.M., and Jovanović, K. (2016) ‘Virtual Laboratories for Education in Science, Technology, and Engineering: A Review’. *Computers & Education* 95, 309-327.

Qoussini, A.E.M., Jusoh, B., and Yah, Y. (2014) ‘A Review on Personalization and Agents Technology in Mobile Learning’. In *2014 International Conference on Intelligent Environments (IE).* Held 30 June- 4 July 2014 in Shanghai, China. IEEE, 260-264

Quan, C., and Ren, F., (2016) ‘Weighted High-order Hidden Markov Models for Compound Emotions Recognition in Text’. I*nformation Sciences* 329, 581-596

Ram, R., Palo, H.K., Mohanty, M.N., and Suresh, L.P. (2016) ‘Design of FIS-based Model for Emotional Speech Recognition’. In *Proceedings of the International Conference on Soft Computing Systems* (vol. 397) of the series Advances in Intelligent Systems and Computing. ed. by L. Padma Suresh, L.P., and Panigrahi, B.K., Springer India, 77-88

Rank, S., and Petta, P. (2005) ‘Appraisal for a Character-based Story-World’. in *Intelligent Virtual Agents, (vol. 3661) of Lecture Notes in Computer Science*. ed. by Panayiotopoulos, T., Gratch, J., Aylett, R., Ballin, D., Olivier, P., and Rist T., Berlin: Springer, 495–496

Rainville, P., Bechara, A., Naqvi, N., and Damasio, A.R. (2006) ‘Basic Emotions are Associated with Distinct Patterns of Cardiorespiratory Activity’. *International Journal of Psychophysiology* 61(1), 5–18

Rank, S., and Petta, P. (2007) ‘From ActAffAct to BehBehBeh: Increasing Affective Detail in a Story-World’. in *Virtual Storytelling. Using Virtual Reality Technologies for Storytelling, (vol. 4871) of Lecture Notes in Computer Science*. ed. by Cavazza, M., and Donikian, S. Berlin: Springer, 206–209

Reisenzein, R. (2009) ‘Emotional Experience in the Computational Belief-Desire Theory of Emotion’. *Emotion Review* 1(3), 214-222

Ren, F., and Quan, C. (2012) ‘Linguistic-based Emotion Analysis and Recognition for Measuring Consumer Satisfaction: An Application of Affective Computing’*. Information Technology and Management* 13(4), 321-332

Rieger, S.A., Muraleedharan, R., and Ramachandran, R.P. (2014) ‘Speech Based Emotion Recognition using Spectral Feature Extraction and an Ensemble of kNN Classifiers’. in *9th International Symposium on Chinese Spoken Language Processing (ISCSLP)*. held 12-14 September 2014 in Singapore. IEEE, 589-593

Rish, I. (2001) ‘An Empirical Study of the Naive Bayes Classifier’. in *IJCAI 2001 Workshop on Empirical Methods in Artificial Intelligence* 3 (22), 41-46, IBM New York

Rousseau, D. (1996) ‘Personality in Computer Characters’. In *Proceedings of the AAAI Workshop on Entertainment and AI / A-Life.* held in Portland, Oregon. AAAI Press, 38–43

Russell, J.A. (1980) ‘A Circumplex Model of Affect’. *Journal of Personality and Social Psychology* 39(6), 1161–1178

Russell, A., Bachorowski, J.A., and Fernandez-Dols, J.M. (2003) ‘Facial and Vocal Expressions of Emotion’. *Annual Review of Psychology* 54(1), 329-349

Russell, J.A. (2003) ‘Core Affect and the Psychological Construction of Emotion’. *Psychological Review* 110(1),145–172

Sabourin, J.L., and Lester, J.C. (2014) ‘Affect and Engagement in Game-Based Learning Environments’. *IEEE Transactions on Affective Computing* 5(1), 45-56

Salmeron, J.L. (2010) ‘Modelling Grey Uncertainty with Fuzzy Grey Cognitive Maps’. *Expert Systems with Applications* 37(12), 7581-7588

Salmeron, J.L. (2012) ‘Fuzzy Cognitive Maps for Artificial Emotions Forecasting’. *Applied Soft Computing* 12(12), 3704-3710

Salmeron, J.L., and Lopez, C. (2012) ‘Forecasting Risk Impact on ERP Maintenance with Augmented Fuzzy Cognitive Maps’. *IEEE Transactions on Software Engineering* 38(2), 439-452

Scherer, K.R. (2001) ‘Appraisal Considered as a Process of Multilevel Sequential Checking’. In *Appraisal Processes in Emotion: Theory, Methods, Research*. ed. by Scherer, K.R., Schorr, A., and Johnstone T. Oxford: Oxford University Press, 92-120

Scherer, K. R., Bänziger, T., and Roesch, E. (2010). *A Blueprint for Affective Computing: A Sourcebook and Manual*. New York, NY: Oxford University Press.

Schmidt, L.A., Fox, N.A., Rubin, K.H., Sternberg, E.M., Gold, P.W., Smith, C.C., and Schulkin, J. (1997) 'Behavioral and Neuroendocrine Responses in Shy Children'. *Developmental Psychobiology* 30(2), 127–140

Schulkin, J., Gold, P.W., McEwen, B.S., (1998) 'Induction of Corticotropin-releasing Hormone Gene Expression by Gluco-corticoids: Implication for Understanding the States of Fear and Anxiety and Allostatic Load'. *Psychoneuroendocrinology* 23(3), 219–243

Sebe, N., Lew, M.S., Cohen, I., Garg, A., and Huang, T.S. (2002) 'Emotion Recognition using a Cauchy Naive Bayes Classifier'. in *Proceedings of the 16th International Conference on Pattern Recognition.* Held 11-15 August 2002 in Quebec, Canada. IEEE, 17-20

Sharma, R., Pavlovic, V.I., and Huang, T.S. (1998) 'Toward Multimodal Human-Computer Interface'. in *Proceedings of the IEEE* 86(5), 853-869

Shelton, J.B., and Smith, R.F. (1998) 'Problem-based Learning in Analytical Science Undergraduate Teaching'. *Research in Science and Technological Education* 16 (1), 19-29

Shen, L., Wang, M., and Shen, R. (2009) 'Affective e-Learning: Using" Emotional" Data to Improve Learning in Pervasive Learning Environment'. *Educational Technology & Society* 12(2), 176-189

Shen, L., Xie, B., and Shen, R. (2014) 'Enhancing User Experience in Mobile Learning by Affective Interaction'. in *2014 International Conference on Intelligent Environments (IE)*. Held 30 June- 4 July in Shanghai, China. IEEE, 297-301

Sikka, K., Dhall, A., and Bartlett, M. (2015) 'Exemplar Hidden Markov Models for Classification of Facial Expressions in Videos'. in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW).* held 7-12 June in Boston, MA. IEEE*,* 18-25

Sokolova, M.V., Fernández-Caballero, A., López, M.T., Martínez-Rodrigo, A., Zangróniz, R., and Pastor, J.M. (2015) 'A Distributed Architecture for Multimodal Emotion Identification'. In *Trends in Practical Applications of Agents, Multi-Agent Systems and Sustainability* (vol. 372) of the series Advances in Intelligent Systems and Computing. ed. by Bajo, J., Hernández, J.Z., Mathieu, P., Campbell,A., Fernández-Caballero, A., Moreno, M.N., Julián, V., Alonso-Betanzos, A., Jiménez-López, M.D., and Botti, V. Springer International Publishing, 125-132

Song, S., Zhong, X., Li, H., Du, J., and Nie, F. (2014) 'Smart Classroom: From Conceptualization to Construction'. In *2014 International Conference on Intelligent Environments (IE)*. held 30 June- 4 July in Shangai, China. IEEE, 330-332

Stein, N.L. and Levine, L.J. (1991) ‘Making Sense out of Emotion’. in *Memories, thoughts, and emotions: essays in honor of George Mandler.* ed. by Kessen, W., Ortony, A., and Kraik, F. Hillsdale, NJ: Erlbaum, 295–322

Stevenson, R.A., and James, T.W. (2008) ‘Affective Auditory Stimuli: Characterization of the International Affective Digitized Sounds (IADS) by Discrete Emotional Categories’. *Behavior Research Methods* 40(1), 315-321

Student, D. (2013) Artificial Intelligence: Machine Learning Introduction [video] available from https://www.youtube.com/watch?v=-rMMTv7XLYw [10 July 2016]

The Maths Works (2016) House Price Estimation [online] available from http://uk.mathworks.com/help/nnet/examples/house-price-estimation.html [10 July 2016]

The Maths Works (2016) The Neural Network Toolbox 7.0 [online] available from <http://uk.mathworks.com/videos/getting-started-with-neural-network-toolbox-68794.html> [10 July 2016]

Tian, F., Gao, P., Li, L., Zhang, W., Liang, H., Qian, Y., and Zhao, R. (2014) ‘Recognizing and Regulating e-learners’ Emotions Based on Interactive Chinese Texts in e-Learning Systems’. *Knowledge-Based Systems* 55, 148-164

Tolman, E.C. (1948) ‘Cognitive Maps in Rats and Men’. *Psychological Review* 55(4), 189-208

Tomkins, S.S. (1984) ‘Affect theory’. in *Approaches to emotion*. ed. by Scherer, K.R., and Ekman, P. Hillsdale, NJ: Erlbaum, 163-195

Tsai, J.L., Louie, J.Y., Chen, E.E., and Uchida, Y. (2007) ‘Learning What Feelings to Desire: Socialization of Ideal Affect through Children's Storybooks’. *Personality and Social Psychology Bulletin*, 33(1), 17-30

Tseng, K.C., Lin, B.S., Han, C.M., and Wang, P.S. (2013) ‘Emotion Recognition of EEG Underlying Favourite Music by Support Vector Machine’. In *2013 International Conference on Orange Technologies (ICOT)*. held 12-16 March 2013 in Tainan, Taiwan. IEEE, 155-158

Turing, A. M. (1950) ‘Computing Machinery and Intelligence’. *Mind* 59(236), 433-460

Van Cauter, E. (1989) ‘Physiology and Pathology of Circadian Rhythms’. in Recent *Advances in Endocrinology and Metabolism*. ed. by Edwards C.R.W., and Lincoln D.W. Edinburgh, UK: Churchill Livingstone, 109–134

Vijayan, A.E., Sen, D., and Sudheer, A.P. (2015). ‘EEG-based Emotion Recognition using Statistical Measures and Auto-Regressive Modelling’. In *2015 IEEE International Conference on Computational Intelligence & Communication Technology (CICT).* held 13-14 February 2015 in Ghaziabad, India. IEE, 587-591

Virtual Labs [Online] Available from <http://cse22-iiith.vlabs.ac.in/exp4/index.html > [13 January 2017]

Wagner, C. (2013) 'Juzzy – A Java based Toolkit for Type-2 Fuzzy Logic', in Proceedings of the IEEE 2013 Symposium on Advances in Type-2 Fuzzy Logic Systems (T2FUZZ) , held 16-19 April 2013 in Singapore, IEEE, 45-52

Wagner, C. and Pierfitte, M. (2013) Juzzy Online [online] available from <http://ritweb.cloudapp.net:8080/JuzzyOnline/> [28 June 2016]

Walk, R.D., and Walters, K.L. (1988) Perception of the Smile and Other Emotions of the Body and Face at Different Distances. In Bulletin of the Psychonomic Society 26, 510–510

Walker, B.R., Best, R., Noon, J.P., Watt, G.C., Webb, D.J., (1997) 'Seasonal Variation in Glucocorticoid Activity in Healthy Men'. *Journal of Clinical Endocrinology and Metabolism* 82(12), 4015–4019

Watson, J. B. (1930) *Behaviorism.* Chicago: University of Chicago Press.

Weiner, B., and Graham, S. (1984) 'An Attributional Approach to Emotional Development'. in *Emotions, Cognition, and Behavior*. ed. by Izard, C.E., Kagan, J., and Zajonc, R.B., New York: Cambridge University Press, 167-191

Wells-Parker, E., Ceminsky, J, Hallberg, V., Snow, R.W., Dunaway, G., Guiling, S., Williams, M., and Anderson, B. (2002) 'An Exploratory Study of the Relationship between Road Rage and Crash Experience in a Representative Sample of US Drivers'. *Accident Analysis and Prevention* 34(3), 271–278

Wester, S., Vogel, D., Pressly, P., and Heesacker, M. (2002) 'Sex Differences in Emotion: A Critical Review of the Literature and Implications for Counseling Psychology'. *The Counseling Psychologist* 30(4), 630-652

Whissell,C.M., (1989) 'The Dictionary of Affect in Language'. in *Emotion: Theory, Research and Experience. The Measurement of Emotions (vol.4)*. ed. by Plutchik, R., and Kellerman, H. Academic Press, 113-131

Whitaker, C.W.A. (2002) Aristotle's De Interpretatione: Contradiction and Dialectic. Oxford University Press

Wiggins, J.B., Boyer, K.E., Baikadi, A., Ezen-Can, A., Grafsgaard, J.F., Ha, E.Y., and Wiebe, E.N. (2015) 'JavaTutor: An Intelligent Tutoring System that Adapts to Cognitive and Affective States During Computer Programming'. in *Proceedings of the 46th ACM Technical Symposium on Computer Science Education (SIGCSE 2015).* held 5-8 March 2015 in Kansas City, Missuri. New York, NY: ACM, 599-599

Wilkerson, L. (1996) 'Tutors and Small Groups in Problem-Based Learning: Lessons from the Literature." in *Bringing Problem-Based Learning to Higher Education: Theory* *and Practice*. ed. by Wilkerson, L., and Gijselaers, W.H. San Francisco: Jossey-Bass, 23-32

Wilkins, M.F., Boddy, L., Morris, C.W., and Jonker, R.R. (1999) 'Identification of phytoplankton from flow cytometry data by using radial basis function neural networks'. *Applied and Environmental Microbiology* 65(10), 4404-4410

Wilson-Medhurst, S., Dunn, I., White, P., Farmer, R., and Lawson, D. (2008) ‘Developing Activity Led Learning in the Faculty of Engineering and Computing at Coventry University through a Continuous Improvement Change Process’. In *Proceedings of Research Symposium on Problem Based Learning in Engineering and Science Education*. held 30 June- 1 July 2008 in Aalborg, Denmark

Wilson-Medhurst, S. (2008) ‘Towards Sustainable Activity Led Learning, Innovations in Teaching Learning and Assessment’. In EE2008: Innovation, Good Practice and Research in Engineering Education. The Higher Education Academy Engineering Subject Centre. Loughborough: Loughborough University

Wirz-Justice, A. (2005) ‘Chronobiological Strategies for Unmet Needs in the Treatment of Depression’. *Medicographia* 27 (3), 223–227

Wu, D. (2012a) ‘Fuzzy Sets and Systems in Building Closed-loop Affective Computing Systems for Human-Computer Interaction: Advances and New Research Directions’. In IEEE International Congress on Fuzzy Systems. held 10-15 June 2012 in Brisbane, Australia. IEEE, 1-8

Wu, D. Courtney,C.G., Lance,B.J., Narayanan,S.S., Dawson, M.E., Oie, K.S., Parsons, T.D. (2012b) ‘Optimal Arousal Identification and Classification for Affective Computing Using Physiological Signals: Virtual Reality Stroop Task’. *IEEE Transactions on Affective Computing* 1(2), 109–118

Wu, D. (2013) ‘Affective Computing and Fuzzy Logic Overview and Outlook’. submitted to IEEE Transactions on Fuzzy Systems.

Yerkes, R., and Dodson, J. (1908) ‘The Relation of Strength of Stimulus to Rapidity of Habit-Formation’. *Journal of Comparative Neurology and Psychology* 18(5), 459-482

Yu, S. N., and Chen, S. F. (2015) 'Emotion state identification based on heart rate variability and genetic algorithm'. In Engineering in Medicine and Biology Society (EMBC), 37th Annual International Conference of the IEEE, 538-541.

Zadeh, L.A. (1965) ‘Fuzzy sets’. *Information and Control* 8(3), 338-353

Zeidner, M. (1998*) Test anxiety: The state of the art*. New York: Plenum

Zeng, Z., Pantic, M., Roisman, G.I., and Huang, T.S. (2009) ‘A Survey of Affect Recognition Methods: Audio, Visual, and Spontaneous Expressions’. IEEE Transactions on Pattern Analysis and Machine Intelligence, 31(1), 39-58

Zheng W.L., and Lu, B.L. (2015) 'Investigating Critical Frequency Bands and Channels for EEG-based Emotion Recognition with Deep Neural Networks'. IEEE Transactions on Autonomous Mental Development, 7(3), 162-175

Zull, J. (2002) *The art of changing the brain.* Sterling, VA: Stylus Publishing.