

Adaptive Intelligent Personalised Learning (AIPL) Environment

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PhD Thesis

The University of Hull

Schools of Arts and New Media

A Thesis submitted to the University of Hull for the degree of Doctor of Philosophy

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## ***Acknowledgement***

During the writing of this Thesis the author has received help, guidance, support and inspiration from a variety of people (especially my family).

I would like to say a thank you to all the people behind the screen for this making Thesis possible, especially my supervisor (Dr Darren Mundy) for guiding and supporting; study and dyslexia support, without any one help this Thesis would not be possible and thank you so much. I am also grateful to the University of Hull, for allowing me to study for a PhD and the time allocated to me (you are inspirational place to work at).

A very special thanks to my supervisor, Darren Mundy, who has greatly improved this Thesis by being an inspiring and supportive supervisor. Finally I would like to thank all my friends and family for support and encouragement thorough out the work with this Thesis.

## ***Declaration***

The author declares that all the materials presented for examination is my own work and has not been written for, in whole or in part by any other person. The author declares that Chapters 1, 2, 3, 4, 5, 6, and 7 are completely derived from work carried out throughout the time spent at the University Of Hull.

## ***Abstract***

As individuals the ideal learning scenario would be a learning environment tailored just for how we like to learn, personalised to our requirements. This has previously been almost inconceivable given the complexities of learning, the constraints within the environments in which we teach, and the need for global repositories of knowledge to facilitate this process. Whilst it is still not necessarily achievable in its full sense this research project represents a path towards this ideal.

In this Thesis, findings from research into the development of a model (the Adaptive Intelligent Personalised Learning (AIPL)), the creation of a prototype implementation of a system designed around this model (the AIPL environment) and the construction of a suite of intelligent algorithms (Personalised Adaptive Filtering System (PAFS)) for personalised learning are presented and evaluated. A mixed methods approach is used in the evaluation of the AIPL environment. The AIPL model is built on the premise of an ideal system being one which does not just consider the individual but also considers groupings of likeminded individuals and their power to influence learner choice. The results show that: (1) There is a positive correlation for using group-learning-paradigms. (2) Using personalisation as a learning aid can help to facilitate individual learning and encourage learning on-line. (3) Using learning styles as a way of identifying and categorising the individuals can improve their on-line learning experience. (4) Using Adaptive Information Retrieval techniques linked to group-learning-paradigms can reduce and improve the problem of mis-matching. A number of approaches for further work to extend and expand upon the work presented are highlighted at the end of the Thesis.

## ***Abbreviations***

|          |  |
|----------|--|
| (aDeNu)  | Adaptive Dynamic online Educational system based on User Modelling |
| (AES-CS) | Adaptive Educational System based on Cognitive Styles              |
| (AEH)    | Adaptive Educational Hypermedia                                    |
| (AH)     | Adaptive Hypermedia  |
| (AHA)    | Adaptive Hypermedia Architecture                                   |
| (AHES)   | Adaptive Hypermedia Educational Systems                            |
| (AHS)    | Adaptive Hypermedia System   |
| (AIR)    | Adaptive Information Retrieval                                     |
| (AHR)    | Adaptive Hypermedia Retrieval                                      |
| (AIPL)   | Adaptive Intelligence Personalised Learning                        |
| (APA)    | American Psychological Association                                 |
| (ACER)   | Australian Council for Educational Research                        |
| (BGP-MS) | Belief, Goal and Plan Maintenance System                           |
| (CC&SB)  | Collaborative Categorization and Semantic Bridging                 |
| (CG)     | Categorising of Groups   |
| (CP)     | Contextual Profile   |
| (CF)     | Collaborative Filtering  |
| (CBT)    | Computer Based Training  |
| (CSCL)   | Computer-Supported Collaborative Learning                          |
| (COI)    | Community of Inquiry   |
| (CMS)    | Content Management System  |
| (DP)     | Device Profile   |
| (DCMI)   | Dublin Core Metadata Initiative                                    |
| (DBL)    | Dynamic Background Library   |
| (EHELP)  | EnHanced ELearning Repository                                      |
| (ET)     | Electronic Textbooks   |
| (xHTML)  | eXtensible HyperText Markup Language                               |
| (XML)    | eXtensible Markup Language   |
| (ELES)   | ELearning EcoSystem  |
| (XAIDA)  | eXperimental Advanced Instructional Design Associate               |
| (E-ACM)  | Extended Abstract Categorization Map                               |
| (GUMS)   | General User Modelling System                                      |

|           |   |
|-----------|---|
| (GTE)     | Generic Tutoring Environment  |
| (HCI)     | Human Computer Interaction  |
| (HMA)     | Hierarchy Matching Algorithm  |
| (IEEE)    | Institute of Electrical and Electronics Engineers                       |
| (ILE)     | Intelligent Learning Environment  |
| (ITS)     | Intelligent Tutoring Systems  |
| (INSPIRE) | INtelligent System for Personalized Instruction in a Remote Environment |
| (ILASH)   | Incorporating Learning Strategies in Hypermedia                         |
| (KBMT)    | Knowledge-Base Machine Translation                                      |
| (KRS)     | Knowledge Representation System   |
| (LMS)     | Learning Management Systems   |
| (LOM)     | Learning Object Metadata  |
| (LO)      | Learning Objects  |
| (LP)      | Learning Profile  |
| (LPQ)     | Learning Process Questionnaires   |
| (LS)      | Learning Styles   |
| (LSQ)     | Learning Style Questionnaires   |
| (Moodle)  | Modular Object-Oriented Dynamic Learning Environment                    |
| (MOT)     | My Online Teacher   |
| (MOT 2.0) | My Online Teacher 2.0   |
| (NSMA)    | Non-Semantic Matching Algorithm   |
| (OPAL)    | OPen Adaptive Learning  |
| (OKBC)    | Open Knowledge Base Connectivity  |
| (PAFS)    | Personalised Adaptive Filtering System                                  |
| (PCMES)   | Personalised Continuing Medical Education Solution                      |
| (PLE)     | Personalised Learning Environments                                      |
| (PRS)     | Personalised Recommender System   |
| (RDF)     | Resource Description Framework  |
| (RSS)     | Rich Site Summary or Really Simple Syndication                          |
| (RAID)    | Reusable, Accessible, Interoperable, and Durable                        |
| (SBA)     | Semantic Bridging Algorithm   |
| (SCORM)   | Sharable Content Object Reference Model                                 |
| (SLP)     | Self-learning profiles  |
| (SLAOS)   | Social Layers of Adaptation and their Operators                         |

|          |                                    |
|----------|------------------------------------|
| (UM)     | User Modelling                     |
| (UMT)    | User Modelling Tools               |
| (UPE)    | User Profile Evolution             |
| (VLE)    | Virtual Learning Environments      |
| (Web-IT) | Web Intelligent Trainer            |
| (OWL)    | Web Ontology Language              |
| (OWL-S)  | Web Ontology Language for Services |
| (WSMO)   | Web Service Modelling Ontology     |

# Chapter 1: Introduction

## 1.1 Background

“Tell me and I’ll forget; show me and I may remember; involve me and I’ll understand”

Chinese Proverb

The process of learning can be recognised as individualistic, complex and sometimes chaotic. This learning process begins within the womb and doesn’t stop until the day we die. Throughout our lives our learning approach continually evolves as our experiences in learning mould and shape our future experiences. In addition, the context of a particular learning experience may have an influence on the way we approach developing our understanding (Scribber 1999).

Learners preferentially take in and process information in different ways to enable them to learn a given domain topic area; this can be achieved through application of the brain, senses and physical movement. The application of these items can be realised through seeing, hearing, reflecting, acting, reasoning, intuition, analysing and visualizing. An individual will apply these items in different ways dependent on circumstance and their own individual approach to learning. These approaches to learning can be determined to be different learning styles. According to Heord (2002), learning styles are referred to as an individual’s preference of processing material; in other words, each of us may have different styles, with different characteristics, of acquiring and using information when learning. Felder et al., (2005) suggests that learning styles are characteristics of cognitive, psychological, and affective behaviours that serve as indicators as to how learners perceive, interact, and respond to the learning environment. Whilst each individual may have a different learning style, it is possible, through generic learning styles, to group and categorise learner approaches (Gomes et al., 2007)<sup>1</sup>.

Differences in the ways individuals learn create problems for the tutor. Learning is not a one size fits all approach. For example, given a student called Fred and a student called

---

<sup>1</sup> It is noted that there is criticism of this approach. A critical response to learning styles is contained within Section 2.1.4.



Wilma and a lecture on website authoring. Wilma may learn more effectively through the lecturer verbally instructing her on how to create a website whilst Fred may be different and learn most effectively through working through a specified laboratory worksheet. As evidenced in research (Robotham, 1999; Zhenhui, 1996; Osborn et al., 2003) sometimes mismatches occur between the learning styles of the majority of students in a class and the teaching style of the professor; in these circumstances the students may become bored and inattentive in class, do poorly in tests, and get discouraged about the course or the lecturer, so it is important to aim to make learning materials as appropriate to the learner as possible.

To overcome these problems, domain experts strive for a balance of instructional methods. If a balance is achieved, then students will be taught partly in a manner they prefer, which leads to an increased comfort level and willingness, to learn (Felder, 1995). However, Felder et al., (2005) indicates that sometimes a balance cannot be achieved and diversity is a key issue. This problem of providing diverse content for equally diverse learner groups is extremely difficult to achieve and unlikely to meet with success all of the time. However, advanced intelligent systems (Brusilovsky et al., 1996; Soller, 2001; Xu et al., 2006; Laurillard 2008 and Jeremić et al., 2009) supporting the learning process have been making in-roads towards overcoming this issue. The concept of a Personalised Learning Environment (PLE) is now starting to come to fruition. According to the United Kingdom's Department for Education, PLE's provide an adaptive educational approach that is individual, interesting and tailored to learners' needs and requirements (DfES Publications, 2004).

There are currently multiple examples of PLE that are being used within institutions. The literature review of this Thesis outlines a range of these examples. In general though, many of these examples suffer from all, or a number of the following issues.

- Lack of use of Semantic Web meta-data as formal descriptors for learning objects (Nilsson et al., 2001; Guzman et al., 2005; Jeffery et al., 2007).
- Multiple different standards for contextual representation (Huang et al., 2003; Dietze et al., 2007; Gašević et al., 2007).
- Lack of integration into a Virtual Learning Environment (VLE) (Chen et al., 2001;

Sampson et al., 2002; Maguire et al., 2006).

- Problems with techniques used to match learning objects to individual learning styles (Krichen, 2006; Milosevic et al., 2007; Sampson et al., 2002).
- Flexibility in relation to the banks of learning objects that can be used i.e. do they provide access to large repositories of learning objects such as those found on the web or simply to Learning Objects associated with a module (Safran et al., 2006).

The work presented in this Thesis focuses on presenting a solution to a number of the issues outlined above through the development of a framework and tool for personalised learning.

## **1.2 Motivation**

The introduction section focused on one of the major problems of learning, the fact that generally the learning content is not personalised to the learner's needs. To do this in a physical environment we can introduce the concept of one-to-one teaching support for students with the teacher providing customised learning materials to match the student's needs. Obviously, this is not a realistic idea in the physical form due to limitations of cost, time and the requirement for the teacher to gain experience of the learner's mechanisms for learning in different contexts.

In a virtual environment researchers have demonstrated that tailored approaches to learning are achievable. Whilst present VLE's can be adapted they haven't been specifically constructed to encompass personalised learning approaches. According to Treviranus et al., (2006), a personalised learning environment should provide adaptable and accessible features to users' requirements. Safran et al., (2006) agrees with Treviranus et al., (2006) and suggests that PLE's can be developed (whether from an existing VLE or specific Personalised learning environment solution) to act like a bridge between the learner and learning object repositories. Safran, Treviranus and Dolog et al (2006) argue that PLE's have the potential to be learner centric and be designed around the student's academic needs.

The author's literature review found approaches to matching learning content to learners still have significant limitations. Therefore the motivation behind this study is to address these problems through the theoretical modelling and practical development of a tailored approach to the personalisation of learning.

### ***1.3 Research Question, Aim and Objectives, Hypotheses***

From the introduction section (and explained in greater depth in Chapters 2 and 3) it shows that by using technology we can get closer to personalised learning experiences, where the needs of the user are individually considered in decisions made on content to deliver. However, there are still problems most ostensibly with the matching of users to learning materials.

In relation to this problem area, the past five years has seen a significant growth in socially oriented web applications designed around embracing community annotation and recommendation e.g. social networking sites such as Facebook and social sharing sites such as YouTube. This growth is often associated with the term 'Web 2.0' (Di Nucci, 1999) popularised by Tim O'Reilly and Media Live in 2007 (O'Reilly 2007), also known as the 'participatory web' (Decrem, 2006). Aspects of this growth are already impacting on the field of e-learning (see Section 2.2.2 e-learning 2.0) and in the personalisation of learning materials. However, systems designed to take advantage of this advancement are still at a relatively early stage (and certainly were at the outset of this PhD work). Therefore the focus of this PhD is on the following question:

Can the underlying principle of web 2.0, that of the 'participatory web', be used as the basis for a model to provide more intelligent personalisation of learning content to users?

In essence, this will explore whether an intelligent environment which incorporates the ideas of social and community grouping can be developed to aid in the personalisation of learning materials to the learner.

This question can be broken down into the objectives listed below:

- Provide a critical overview of the current research trends within the areas of e-learning most closely linked to this Thesis, those of: adaptive learning, personalised learning and learner pathway organisation.
- Utilise the knowledge of the identified current issues in order to develop a new approach to resolving the research problem.
- Design a model based on the concepts of personalised adaptive filtering to facilitate the construction of individual PLE's.
- Implement a prototype of the proposed model cataloguing significant design and implementation challenges faced.
- Evaluate the new approach using sets of learners across learning contexts. Critically evaluate project success/failure and approaches taken.

Critically examining the literature there is an apparent lack of emphasis on treating individuals as members of groups of learners with the same learning approaches. The author believes that group categorisation can make a difference to the learning process, in particular, encouraging group annotation and rating of learning objects (in essence utilising the power of collective intelligence) could make a difference to learning object recommendation. Therefore the author presents the following two hypotheses to be evaluated within the Thesis which link directly to the research question.

- Grouping individuals based on their learning approaches and enabling the development of collective intelligence and the rating of learning resources will lower the proportion of materials perceived to be mismatched by the individual.
- Ensuring separation of collective intelligence on a group by group basis rather than on a community basis will impact positively on lower instances of mismatched materials e.g. Group A might rate an object as 1 (low) and Group B might rate an object as 10 (high). An amalgamated rating would not emphasise the objects importance or unimportance to members of either group.

## ***1.4 Methodology and Methods***

This research project will commence with a detailed literature review around the fields of e-learning with a particular focus on personalised learning approaches. This approach will

help to identify issues within the field of personalised learning from which further research paths can be pursued, such as: the investigation of pedagogical frameworks for personalised learning; an analysis of intelligent personalisation systems; and examination of approaches to matching between the learner and the learning materials.

The challenges associated with designing a new novel solution to personalised learning will involve: overcoming the limitations of current systems; the development of a theoretical model that incorporates the principles of collaborative grouping and learning-based-paradigms; the introduction of an Adaptive Information Retrieval filtering mechanism to aid in the reduction of mismatching; and an empirical study through the use of a test bed to support the hypothetical model.

The author will adopt an empirical approach, involving the creation of an experimental test bed focused on evaluating the model through practice. The experimental solution will focus on providing small test groups with contextual learning scenarios, which will be used in a personalised learning environment. The author will adopt an approach that will involve the use of: interviewing, observations and questionnaires to retrieve results from the testing. These results will be then used to create an evaluation and summative conclusion.

### ***1.5 Research Contributions***

This Thesis, through the analysis, design, creation and evaluation of a model for personalised learning, provides contributions both theoretically and practically to the field of e-learning.

In theoretical terms, the Thesis:

- Provides an incremental enhancement to an existing framework for personalised learning through the addition of concepts of learner groups and a group rating system linked to learning styles.
- A new personalised learning model that supports collaborative grouping and the concept of Collective Intelligence.
- Details a three stage evolutionary algorithm approach to match learning objects to learners needs based on learning styles and group categorisation.
- Presents a new pedagogical learning model, to support the amalgamation of

learning styles on-line.

- Provides contributions to e-learning literature in the area of personalised learning environments (Costello and Mundy, 2009a) (Costello and Mundy, 2009b).

In practical terms, the Thesis:

- Provides a solution for personalised learning with the development of a personalised learning environment.
- Details the evaluation of this environment linked into specific learning scenarios.
- Provides a novel approach to categorising individuals into grouping through the use of a complex rule base.
- Uses Adaptive Information Retrieval techniques as a way of filtering learning materials based upon collaborative grouping and learning-based-paradigms.

## ***1.6 Thesis Outline***

**Chapter 1:** Has presented an introduction into the Thesis, the underlying research question, objectives, motivation, and methodology.

**Chapter 2:** This chapter provides an evaluation of approaches to the personalisation of learning. The literature covered includes learning theories, traditional learning, e-learning and personalised learning.

**Chapter 3:** The requirements for and approaches to personalising the learner experience are covered in this chapter. The focus is on the research problem and current research methods attempting to solve this issue.

**Chapter 4:** A novel approach to learner personalisation: A pedagogical preference learning approach designed around the learner.

**Chapter 5:** A Personalised Adaptive Filtering System – Describes the innovative way of applying Adaptive Information Retrieval techniques to personalised learning.

**Chapter 6:** Experimentation - Providing statistical data to support the hypothesis within this Thesis.

**Chapter 7:** Critical Evaluation of Success - Providing arguments to support the hypothesis and the final view on how effective the new learner-centric pedagogical learning environment was within the real-world.

## Chapter 2 Learning a Personalised Approach

This chapter provides a critical introduction to learning, e-learning, e-learning 2.0, User Modelling and most relevant to this Thesis the area of personalised learning. The chapter starts with an introduction to learning and how people learn. It follows this with a brief examination of e-learning, e-learning 2.0, User Modelling and the opportunities in e-learning for facilitating learners' needs. Finally, the chapter critically analyses the approaches to personalised learning developed by other researchers in the area.

### 2.1 Learning

A simple definition of learning as posed by Cambridge (2004) is “*the process of getting knowledge or a new skill*”. Learning refers to the orientation of problem solving, decision making, and using embedded real-life tasks and activities to enable the learner to think, communicate, and build upon prior knowledge and experience (Schmidt 2005). Learning takes place with respect to content and context; you learn something somewhere (Edelson, 2001).

Teaching, according to Bereiter et al., (1989), Laster (2004) and Grabinger et al., (1995), provides the learner with the opportunity to develop a firm conceptual base for the content of coherent knowledge structures. Building on this base the learner will develop effective ways of synthesizing, processing and transforming knowledge.

As outlined in Section 1.1 (background), learners have individual approaches to how they learn. There are many different types of learning theories that can be used to describe these approaches. The following sections analyse the following four learning theories thought to be of most direct relevance to this Thesis:

- Social Learning Theory
- Experiential Learning
- Cognitive Behavioural Theory
- Learning Styles/Strategies



### 2.1.1 Social Learning Theory

According to Bandura (1969) social learning theory reflects on how one person learns through the use of actions, feelings, and thoughts, after observing a learning experience. Ormrod (1999) suggests that social learning theory explains learning in terms of a continuous reciprocal interaction between cognitive, behavioural, and environmental influences. Ormrod (1999) indicates that social learning theory provides a model to describe how learners' often learn most effectively from observing other people.

Stahl et al., (2006) and Jones (2010) indicate that they have applied social learning theory in Computer-Supported Collaborative Learning (CSCL), to encourage students to learn together in small groups via the use of interactive software; allowing students to learn by expressing their questions; pursuing lines of inquiry together; teaching each other; and seeing how others are learning. Social learning theory in accordance with Stahl et al., (2006) and Jones (2010) could provide potential for providing learner personalisation within electronic collaborative environments.

This theory was considered within this Thesis to support: group activities, classification of group' s dependant on behaviour, challenges & interest (Stahl et al., 2006) and group problem solving (Ormrod 1999). The model presented in this Thesis encompasses elements of individuals learning through the learning experiences of others by enabling the capture of individual and group responses to learning content. However, this does not happen through observation, it happens through an individual reflective process, so individuals are essentially making decisions on learning content based on the experiences of others.

### 2.1.2 Experiential Learning

David Kolb in 1985 provided a cyclical model for experiential learning within the field of adult learning. There are four levels to the Kolb model, which characterize the learning process: concrete experience, reflective observation, abstract conceptualisation, and active experimentation.

- **Concrete experience:** stresses that there needs to be an obvious relationship between the learner, knowledge gained and practical experience.

- **Reflective observation:** focuses on learners developing through watching others or developing observations about one's own experience that can be used to analyse the effect of what works and what does not, what was learned about the situation.
- **Abstract conceptualization:** uses theories to explain observations, concepts, principles, and/or generalised learning concepts. These concepts might include patterns, rules, methods, or the beliefs of the domain expert.
- **Active experimentation:** refers to taking on the general learning concept from the abstract conceptualisation section, to demonstrate practically how that principle works within other areas.

Kindley, (2002) and Beard et al., (2007) suggest that the application of experiential learning theory within the context of computer based learning can be supported through literature across multiple fields such as social and cognitive psychology and philosophy. Kindley (2002) and Goodyear (2005) suggest that applying experiential learning theory to computer based learning focuses the domain expert on building exercises and tasks to suit the four different levels of the learning process.

Using the recommendations of (Kolb D., 1985; Kindley 2002; Goodyear 2005; and Beard et al., 2007) the pedagogical model developed within Chapter 4, will adhere to Kolb's cyclical model for identifying individual learner preferences to enable course-content to be matched to the individual, thus, hopefully improving individual performance and learning experiences while studying online.

McLoughlin et al., (2002), indicates that encompassing the ideas of experiential learning in approaches to content production and delivery can provide the individual with a multitude of learner choices that can be tailored to their personalised learning classification. Dabbagh (2005) suggests that individual learning emphasizes on the systematic interaction between pedagogical theories and learning technologies. Having a design based on pedagogical theory allows for the development of more personalised learning experiences. This is an important point which guides in Chapter 4, the development of a pedagogical model to support learner personalization.

### **2.1.3 Cognitive Behaviorist theories**

There have been a variety of key researchers in the field of cognitive and behaviourist

theory, for example: John B. Watson; Edwin R. Guthrie; and F. B Skinner. According to Hearst (2006), John B. Watson, was the founder of behaviourism, in which his research led to techniques used in animal laboratory's to understand behaviour being mapped to and applied to the analysis of the behaviour of human beings. The goal of behaviourism within psychology was to predict and control behaviour, not to analyze consciousness into its elements or to study vague "functions" or processes like perception, imagery, and volition (Hearst, 2006).

Clark (2005) suggests that Edwin R. Guthrie Jr believed in the contiguity explanation of learning through the notion of the `principle of association`: if two events appear close together, in time or space, then they will become associated with each other. Hilgard (2006) indicates that Guthrie's theory was associated with the three laws of association, which are: the laws of similarity, contrast, and contiguity.

“Many animals are four-footed, so the child easily learns to group a cat, a dog, and a cow as animals through their similarities” (Hilgard, 2006).

According to Skinner (1985), behaviourism theories are directly associated with the positivist and operationalist views belonging to methodology and philosophical sciences within the field of human behaviour. *“The Behaviourism theories were directly linked into: how a person remembers when tied into the learning experience (complex thinking and problem solving)”* (Skinner, 1985).

Skinner's (1985) theory focuses on attempts to provide behavioural explanations for a range of cognitive phenomena (learning is a function of change in behaviour).

There are a variety of other Cognitive and Behaviourist theories that can be applied to an educational setting, for example, Gestalt Cognitive learning theory. According to Cooper (2005), the Gestalt Cognitive learning theory originated from three main researchers: Werthimer, Kohler, and Koffa who did their early work in Germany. Gestalt Cognitive learning theory proposes that learning consists of the grasping of a structural whole and not just a mechanistic response to a stimulus. According to Torrans et al., (1999), the Gestalt Cognitive learning theory is not so much concerned with what the learner learns; it is how the learner learns and the environment in which the learner learns within.

De Freitas et al. (2006) indicates that cognitive behaviourist theories can be used to represent how informal and formal learning can support and reinforce one's learning abilities in order to accelerate their learning process, by incorporating activities that stimulate cognitive and motivation skills. One of the theories associated with cognitive behaviourist theories is that of Riding-Cognitive Style Analysis, which can be used to identify and determine the individual's preferred learning style/trait (Riding et al., 1997; Peterson et al., 2003; Karagiannidis et al., 2004). The Riding-Cognitive Style Analysis was considered within this Thesis because it has the potential to support not just the individual, but also provide a way for the domain expert to map learning context to a variety of different situations like collaborative learning approaches. De Freitas et al., (2006) suggest that applying the theory to a collaborative learning approach allows the individuals to engage either in a self-directed, visually or interactive way.

“A recognition of the strengths and weaknesses of one's own style naturally leads to the formation of strategies (coping behaviour)” (Riding et al., 1997 p.10)

Taking the principles of Gestalt Cognitive learning theory it is thought that this could provide support for a model within this Thesis which considers an individual as a whole (with respect to learning styles, context and needs) and the online environment which they learn through equally as more than just individual learning objects (considering the wider experience of groups of learners in the environment).

#### **2.1.4 Learning Styles/strategies**

Learning Styles (LS) are characterised as individual approaches to learning, for example, an individual may learn through seeing visual objects, hearing an oration, reflecting on past experiences and through practical problem solving. Felder et al. suggest that individuals have preferred approaches to learning. According to Felder et al., (1998), using a learning-style model can enable domain experts to classify individual students in relation to their learning approaches.

Different researchers like White (2004) and Learnactivity (2002), suggest that learning styles can be identified by the following; perceptual modality (how learners take in and perceive information), information processing, and personality patterns. Researchers like

Kurt Lewin, Jean Piaget, David Kolb, Paul Sinclair, Benjamin Bloom, Phil Race, and Peter Honey & Alan Mumford, and many more all noted that identification of learning styles may lead to an influence on learner progression. Learning styles emphasise the fact that individuals perceive and process information in a variety of different ways this also implies that how much individuals learn can depend on whether the educational experience is geared towards their particular style of learning. Learning styles can have beneficial influences within the educational system that can affect students' curriculum, assessments, and how particular modules are taught (Funderstanding 2001). It is these primary conceptual thoughts that could improve the students' learning experience if the domain expert considers the range of learning styles presented to them within a group of students. According to Koper et al., (2004) and Marshall et al., (2005) the results from the categorisation process enable course content to be either more explanatory or more structured towards a majority of learner' s needs. According to Karagiannidis et al., (2004), Canavan (2004) and Kanninen (2009) learning styles are used within computer based learning to enhance teaching by accommodating the students' learning preferences. Canavan (2004) suggests that the integration of learning styles, within computer based learning can enable course content, exercises, discussions, and tasks to be developed to facilitate a variety of learner' s needs and abilities. This Thesis uses learning style categorisation as a mechanism to enable personalisation of learning content delivered to individual users and as a mechanism to group learners together. This grouping within the learning model presented within Chapter 4 facilitates more targeted feedback from users who share common learning approaches. However, the concept of learning styles being used within education is a two-sided-dagger, in which some researchers indicate say it is a positive thing; while others say they do not assist the individual at all and can just lead to confusion. According to Julie Henry (an educational correspondent) in a 2007 Sunday Telegraph article, Baroness Greenfield (a prominent female neuroscientist) stated that

*“the method of classifying pupils on the basis of "learning styles" is a waste of valuable time and resources”*

and that of

*"The rationale for employing VAK (Visual, Auditory and Kinaesthetic) learning styles appears to be weak. After more than 30 years of educational research in to learning styles there is no independent evidence that VAK, or indeed any other learning style inventory, has any direct educational benefits”* (Henry 2007).

In 1990, Eisenstadt et al., had suggested the notion of 'Neophytes' in learning, which translates to novice/beginner. Eisenstadt et al., (1990) suggested within their research that for some people, learning was difficult to grasp, and it was too hard to adjust to a learning experience even though attempts may be made to simplify and support them. The research concluded several issues why this might be:

*“It could be because of the learning activity was tricky and required lots of practices: Alternatively, it might be the case that novices are never provided with (or at least never acquire) a clear model, which leads them astray”* (Eisenstadt et al., 1990).

The research conducted by Eisenstadt et al., (1990) indicates that no matter what features applied by the domain expert to assist some individuals, the learner might still find it difficult and even if the materials are personalised in some way to them they may still have difficulty learning.

*“Much study has been addressed to learning styles but still the field over the subject is not clear. Many controversies rise from the fact that there are so many different learning styles. Each style deals with a different aspect on learning but there isn't a style which incorporates all”* (Kanninen 2009).

However, according to Sadler-Smith (1996) the use of learning styles within education provides a vital tool to assist the individual and improve their learning experience by enabling the course content to be designed in accordance to how they learn. Learning styles can be used to allow the student to facilitate their acquisition of knowledge, skills or attitudes through study or experience in accordance to their preference learning style. Karagiannidis et al., (2004), Canavan (2004) and Kanninen (2009) agree with Sadler-Smith's views that using learning styles can have beneficial influences within the educational system. From the author's perspective; learning styles do provide a building block for which the domain expert has some knowledge on how that individual will function when processing new skills and concepts. However, caution will be adhered with respect to learning styles within this Thesis especially in light of the research findings from Eisenstadt et al., (1990).

## **2.2 E-learning**

As identified in Section 2.1.4, traditional non-computer based approaches to the personalisation of learning materials (based on learning styles) have involved domain experts in the production of multiple resources to enable a best fit to individual learners. In such a scenario either the learner, or the domain expert, needs to have knowledge of the learners approach to learning. The use of technology can assist in the profiling of the learner and the retrieval of resources which best fit their individual learning styles. Therefore this section focuses on e-learning, moving through to the new wave of learning technologies based on the power of the social web, e-learning 2.0.

According to Stojanovic et al., (2001), Nichols (2003) and Alsultanny (2006), e-learning is an efficient, effective way of providing a just-in-time learning approach by offering a dynamically changing technological environment that aims to replace old-fashioned time-place content learning.

*“E-learning is part of the biggest change in the way our species conducts training since the invention of the chalkboard or perhaps the alphabet. The development of computers and electronic communications has removed barriers of space and time. We can obtain and deliver knowledge anytime anywhere”*  
(Welshe et al., 2003)

E-learning is essentially comprised of three main features: web-based infrastructures/technologies; pedagogical learning theories; and standards, which include SCORM and LOM.

### **2.2.1 E-learning environments and issues**

Many e-learning frameworks try to provide mechanisms that encourage the learning experience to be more pleasurable and are designed around the concept of the student as the focus. According to Treviranus et al., (2006), e-learning frameworks are technology applications that are adaptable and accessible to end user requirements. Many educational institutions across the United Kingdom have focused on bringing e-learning to the individual user, by the use of several different commercial on-line educational mediums, the most pertinent of which to this research are outlined below.

In 1997, the company Blackboard was formed as an educational consultancy, and merged with CourseInfo LLC in 1998, producing shortly after their first commercial Learning Management System (LMS). Over a short amount of time Blackboard acquired through merger new organisations and new technologies leading to a merger in 2005 with Web CT a leading MS used in Higher and Further Education at the time. Following this merger Blackboard emerged as the leading LMS in the market.

Another prominent e-learning package that is used throughout the United Kingdom is called Modular Object-Oriented Dynamic Learning Environment (Moodle). According to Dougiamas et al., (2001) Moodle is open source software, offering course management for learning resources. It also integrates communication tools, supports timed quizzes, manages assignment submissions etc.

More recent developments have seen the platform SAKAI gain footholds in the learning management sector. SAKAI is a rich functional tool, developed as an open source system, incorporating learning standards based materials using the SCORM standard (for more information concerning SCORM, please see Chapter 3) and offering similar functionality to Blackboard and Moodle (Falmer et al., 2005).

Xu et al., (2003) and Dalsgaard (2006) indicate that not all LMS's are the same; however, they do have similarities and attributes which belong only to them. LMS are used to organise and manage e-learning courses including the management of students' details, discussion forums, file sharing, management of assignments, etc... LMS's use a variety of different tools to run and manage e-learning courses (Xu et al., 2003). In addition to the LMS which are integrated into a large number of educational institutions, individuals have experimented with the use of more semantically oriented system designs.

According to Siemens (2004) traditional LMS focus directly on features, facilities and tools as a centre point instead of a personalised approach that would allow more control to the end-users, instructors, and learners. As indicated by Siemens "*while LMS are useful for certain learning functions, advanced thinking skills and activities (i.e. the more learning mimics real life) require a move away from one-tool-does-it-all, and move towards picking tools for the required task - based on learner (not designer/organization) needs*" (Siemens 2004).



Dalsgaard (2006) and Hernández-Leo et al., (2006) do agree with Siemens (2004) about the current limitations associated with traditional LMS and expand further by saying that traditional LMS do not take into consideration the new direction of research trends by incorporating social and community approaches that “*emphasizes on self-governed learning activities*” (Dalsgaard 2006).

According to Sclater (2008) students are increasingly using Web 2.0 oriented platform features to assist within their learning experience, and only resorting back to LMS for details relating to their current educational tasks. Sclater (2008) suggests that

“there are various questions at this time for faculty and university information technology staff who believe in the benefits of e-learning and need to decide whether their LMS remains an appropriate medium in which to facilitate it”.

He then goes onto to ask the following questions:

*“Can we bring some of the social networking facilities that students find so appealing inside the institution?”*

*Should we use tools hosted elsewhere on the internet by others?*

*Should we simply allow learners to select appropriate tools for themselves?”*

(Sclater 2008, P2)

Sclater (2008) indicates that LMS are not effectively used by institutions because they are only being used as storage and a delivery medium. This is echoed by many other researchers’ e.g. (Godwin-Jones 2002; Govindasamy 2004; and Harman et al., 2007).

According to Šimić et al., (2004) there are currently attempts being made to improve current LMS through the incorporation of improved methods of metadata collection for content or context, and search or retrieval of learning materials, based on meta tags. Incorporating semantic web technologies into current LMS designs will enable a relationship to be matched between existing materials found within the local repository of learning materials or externally sourced learning content. This attempt to overcome the common problem of ‘*one-tool-does-it-all*’ associated with LMS as indicated by Siemens (2004).

Semantic Web annotation according to Uren et al., (2006) and Pahl et al., (2009) provides a way of enhancing specific retrieval of materials related to an individual and also brings improved interoperability to the LMS. Uren et al., indicates that:

*“these benefits, however, come at the cost of increased authoring effort. We have, therefore, argued that integrated systems are needed which support users in dealing with the documents, the ontologies and the annotations that link documents to ontologies within familiar document authoring environments”*  
(Uren et al., 2006).

Denaux et al., (2005) and Dagger et al., (2007) indicate that another approach that researchers are taking to overcome some of the issues identified by (Siemens and Šimić 2004; and Uren et al., 2006) is the use of another form of Semantic Web technology called Web Ontology Language (OWL). Koper (2006) indicates that the application of OWL to LMS, can aid in the development and identification of learning patterns and authoring. According to Pahl et al., (2009) these future trends of LMS should be able to achieve: adaptability and reasoning belonging to the individuals through the identification of user traits and behaviour patterns (i.e. User Modelling).

### **2.2.2 E-Learning 2.0**

The concept of Web 2.0 was popularised by O’ Reilly and MediaLive International in 2004, but had roots in literature prior to this point (Madden et al., 2006). O’ Reilly defines the term in a seminal piece ‘What is Web 2.0. Design Patterns and Business Models for the Next Generation of Software’ (O’Reilly, 2005; 2007) capturing seven key principles about what is encompassed by the term ‘Web 2.0’. What can be seen as the core principles across other individuals (Hagemann et al., 2008; Lee et al., 2008; Wijaya et al., 2008; Weber et al., 2007; and Multisilta 2008) attempting to define Web 2.0 are the principles of: ‘Web as platform’ and ‘harnessing collective intelligence’.

The ‘Web as platform’ principle simply outlines the shift over the past five to seven years of previously desktop based application functionality to web based services. In addition, the growth of web based services which allow for the collection of shared resources e.g. Flickr and YouTube. This principle removes issues previously existing with the interoperability of applications across platform as now applications run via the web browser which is cross

platform compatible.

According to O' Reilly, "*Hyper linking is the foundation of the web. As users add new content and new sites, it is bound in to the structure of the web by other users discovering the content and linking to it*" (O' Reilly 2007). Therefore capturing the essence of how users navigate the web and their impressions of web content through mechanisms such as tagging, page rating, and collaborative sharing, can aid users in identifying resources to meet their specific needs.

According to Anderson (2008) Web 2.0 is more than just a web platform it is a service that offers more than just sharing content, tagging, wikis, blogs, and social networking. Web 2.0 is an easy way for people to publish self-generated materials like music, videos and photos.

Also coined alongside Web 2.0 is the term e-learning 2.0, which according to Ghali et al., (2009), Safran et al., (2007), and Ullrich et al.,(2008), refers to on-line learning environments that incorporate the idea of the Social Web making use of technologies such as collaborative authoring tools, rating tools, social identification (e.g. bookmarking) and annotation. According to Hamburg et al., (2008) e-learning 2.0 uses web-based tools to create new forms of learning materials (e.g. blogs, video sharing repositories, social networking spaces etc...) and to provide different ways of delivering learning materials. Hamburg et al., (2008) and Ullrich et al., (2008) suggest that incorporating social web concepts into on-line environments can assist with collaborative learning through the use of formal learning; the creation and construction of content; and the receiving and giving of feedback through discussion groups.

According to Safran et al., (2007) and Ullrich et al., (2008), e-learning 2.0 can be categorised or identified within two particular themes, these are: Technology and Social Networking. These link in to the Web 2.0 themes of 'web as platform' and 'harnessing collective intelligence'.

- **Technology:** According to Safran et al., (2007) and Ullrich et al., (2008) the use of technology within e-learning 2.0 can provide support for a variety of key educational features: Wiki-blogs, pod-casts, RSS (Rich Site Summary or Really Simple Syndication), and e-portfolios.

- **Social Networking:** According to Safran et al., (2007), Chatti et al., (2007) and Ghali et al., (2009) social interaction plays an important part within e-learning 2.0 because it allows students to interact, share ideas, communicate (e-mail, chat, video conference), and use forum's to discuss problems. According to Hamburg et al., (2008) collaborative learning may provide a useful perspective on learning, knowledge creation and management from a social networking perspective. There are a variety of e-learning 2.0 environments that can be found within literature; however, several will be discussed.

The first example to look at is a European project financed under the European e- learning Initiative called the SMEs Improving E-Learning Practices (SIMPEL) project, which was introduced in 2008 by Hamburg et al., The SIMPEL project focused on analyzing, understanding and suggesting mechanisms –“*to involve SMEs and e-learning experts in a community of practice to share knowledge and to develop participative training strategies based on elearning 2.0*”. One particular aspect of the project focused on the use of Moodle to provide a way of using blogs to distribute and share information on services or products. According to Hamburg et al., (2008) the use of SIMPEL, provided a way of blending knowledge, communication and learning. It also through identification of scenarios provided mechanisms through which educators could establish ways in which to best integrate e-learning 2.0 technologies into their educational practice. Hamburg et al., (2008) suggests that by understanding the right mix of approaches and technologies then “*e-competences*” can be achieved.

Like the Hamburg et al., (2008) approach Ghali et al., (2009) tries to blend a variety of approaches to achieve “*e-competences*” through the use of an e-learning 2.0 system called MOT 2.0 (My Online Teacher 2.0), which is an adaptive authoring and delivery system. According to Ghali et al., (2009) MOT 2.0 focuses on: content recommendation; adaptation of the authoring environment; and it allows students to contribute in the development process of course content. This approach to learning means that learning content is created and distributed in a very different manner. Rather than being of a linear approach based around the lecturer and the desired syllabus, it can incorporate the learner through every possible step of introducing course work, exercises, and tasks.

Alevizou et al., (2010) has similar views to (Hamburg et al., 2008; Ghali et al., 2009) about the use of the new generation of e-learning 2.0 technologies to facilitate collaborative learning. Alevizou et al., (2010) introduces a specialised web-site called CLOUD, which is used for sharing resources, and ideas on learning and teaching. Cloudmark was designed according to Alevizou et al., (2010) to facilitate and focus primarily on social networking within online learning by investigating practices of socialisation; sharing and editing content within, wikis and social media. Cloudmark uses collective intelligence, as a way of analysing how humans can potentially share, collaborate, produce and reproduce knowledge. Alevizou et al., (2010) indicate that Cloudmark attempts to solve issues concerning: mobilization of resources; sharing resources between learners; and meditating social relations.

It is clear to see that this new generation of e-learning 2.0 is focused on applying some form of collaborative community learning through the use of collective intelligence (Hamburg et al., 2008; Ghali et al., 2009; Alevizou et al., 2010; Safran et al., 2007; Ullrich et al., 2008).

According to Safran et al., (2007) the use of e-learning 2.0 within on-line learning will become more frequent and also lead to the incorporation of collaboratively created content in traditional learning environments. Hamburg et al., (2008) and Ghali et al., (2009) have similar thoughts to Safran et al., (2007) about the future trends which they suggest should focus on incorporating the social web into on-line learning environments to allow other students to assist each other, share ideas, and make on-line learning more community focused. However, as Chatti et al., (2007) questions, within modern society will busy learners adopt this approach of having a collaborative community? Hamburg et al., (2008) does indicate that future trends must try to overcome other issues like:

- “Lack of immediate context of applying the learning for example by incorporating new learning in a personal knowledge schema or portfolio;
- Lack of time and lack of access to sufficient bandwidth to ensure high quality training, especially user-friendly tools and quality content;
- The attitude of managers– they often have not enough knowledge or are not convinced of the effectiveness of e-learning. Instead they put their trust in classroom-based training. Many of them prefer “learning from peers” Hamburg et

al., (2008)

The work contained within this Thesis sits within the scope of systems designed as E-Learning 2.0 systems due to a focus on encompassing the principles of collaborative & community based learning, the integration of group-learning-paradigms; and the intelligent matching and tailoring of the system to meet the learner's needs. This new approach to e-learning will replace the traditional Virtual Learning Environment (VLE), that is often cumbersome and expensive - and which tends to be structured around courses, timetables, testing, and often driven by the needs of the institution rather than those of the individual learner. These new ideas and concepts have the potential to act as a way of offering a personalised tailored approach to: exchange and reuse of learning objects; tailored learning activities; and matching content to individual preferences. Computer based research towards the personalisation of learning experiences has been undertaken since the 1970's. The next few sections will introduce early forms of achieving this through User Modelling, and stereotyping, moving on in the final section of this chapter to outline research in personalized learning.

### ***2.3 User Modelling***

When users interact with a computer, they provide a great deal of information about themselves. Even when they are not physically at a computer, users continuously radiate data, by walking, speaking, moving their eyes, and gesturing. User Modelling enables architectures to be built to interpret this type of information and personalise learning experiences taking into account individual behaviours, habits, and knowledge.

User Modelling is an approach embedded in Human Computer Interaction (HCI) design to enable designers to understand how people use their soft/web-ware. A user model is a mechanism through which a user can be described and analysed in relation to their use of a particular piece of soft/web ware. The approach enables designers to overcome problems linked to user perceptions reducing opportunities for error and improving the time taken by users to understand designed interfaces.

The design of modern systems is increasingly user-centered, with users now often involved from the planning stages of web development. Early user involvement can help prevent

serious mistakes in web systems. Benefits of a user-centered approach like: User Modelling are mainly related to time and cost savings during development, completeness of system functionality, repair effort saving, as well as user satisfaction.

User Modelling is usually traced back to the late 1970' s (Razmerita et al., 2008; Kobsa et al., 1994), in which a lot of work was done in this area of research relating to how application systems were developed, and how different types of information was collected from different users. According to Kobsa (2001) there were a number of developments in the 1980 s, which pushed the barriers of User Modelling with the introduction of the General User Modelling System (GUMS) that was designed by Tim Finin in 1986. This allowed developers to use simple hierarchies and facts stated in the Prolog programming language, to describe scenarios and introduce rules and reasoning to shape understanding. Kobsa (2001) indicated that new approaches were developed in the mid nineties, which advanced the field further with the development of:

- User Modelling Tools (UMT): According to Tasso et al., (1999) UMT was introduced in 1994 to represent the user interests with regards to good traits and bad traits of the system and co-occurrence relationships among them. UMT was used to seek assumptions belonging to systems before various resolution strategies were applied.
- The Belief, Goal and Plan Maintenance System (BGP-MS): According to Kobsa et al., (1995) the BGP-MS User Modelling system was used to adapt personalised traits of the users relating to: previous knowledge, beliefs, and goals.

Applications which integrate User Modelling capabilities require software tools to enable the capture of assumptions about users based on their use of the application, mechanisms to store and represent these assumptions, intelligence to go beyond the assumptions and make suggestions in new contexts and provide methods of re-evaluating assumptions when the user makes inconsistent choices (Kobsa et al., 2005).

A number of systems have been constructed to use User Modelling to personalise user experiences these are critiqued below.

In 1994, Brusilovsky introduced an Intelligent Learning Environment (ILE) which adapted

to individual student behaviour. The ILE was built around the design concepts of Intelligent Tutoring Systems (ITS), which capture personal features belonging to the individual and extract relevant details like: personal factors (e.g. interests/hobbies), cognitive styles, learning strategies and personal knowledge. The ILE used recommendations belonging to the tutor to extract and suggest the best teaching approach (problem or example) for individual students. Once the student had made a decision this was recorded in the environment to assist with the correct delivery method that the learner preferred. The problems associated with this particular model, was the time it takes for the environment to learn and adjust to a variety of learning situations and actions belonging to the individual; a complexity in integrating different features of the learner into every module; and irregularities caused by enabling the individual to modify their own profile. However, according to Brusilovsky using an ILE to identify how an individual learns did assist with and improved the learning experience on-line for those students using the ILE.

According to Orwant (1995) the designer of the DOPPELGÄNGER User Modelling system is based on a two part approach. The first part is used to enable data to be gathered about user's traits. The second part carries out analytical responses to enable the application to make changes related to assumptions made about user interests. DOPPELGÄNGER enables the retrieval of specific community traits (utilising aspects of collective intelligence) to fill in gaps belonging to the individual to enable a task to be carried out. The DOPPELGÄNGER user model according to the designer was based upon a system design only incorporating some aspects of a pragmatic pedagogical approach. These aspects pivoted upon knowing particular interests of the individual user. The system design did not take into consideration the reduction of learning materials delivered to the user through advanced searching functionality. However, a collaborative community approach was used based on an examination of the time taken by other users in reviewing/using learning materials. This information was used to filter out inappropriate or irrelevant materials. This approach did not always provide or predict an accurate picture of how long each individual user may spend on particular tasks or activities.

Berendt in 2007 uses User Modelling through the use of data mining to interpret and extract interests, behaviours and patterns, belonging to individual users to assist with the delivery of learning content. In addition, the system designed by Berendt used this information to group users (e.g. users with low IT literacy or users with limited language



comprehension) and collect and share rating and tagging information from these user groups about particular learning resources. According to Berendt (2007) there is evidence to support this approach; however, further research is needed in the field of: semantics, data mining, pedagogy, system design, and finally privacy. The application of further research into these areas will enable further improvements to be made, through the identification and use of elements of a user model to match the needs of individual users in specific learning scenarios.

Bringing the research up to date from 1990's to 2010, User Modelling has been applied to a variety of areas belonging to e-learning, and in particular one area of interest to this Thesis is Adaptive Hypermedia Educational Systems (AHES). According to Martin et al., (2008) and Neji (2009), AHES are systems which utilise user models to adapt particular learning environments to the specific needs of individuals. According to Martins et al., (2008) User Modelling within adaptive hypermedia involves using perturbation. This method considers that the knowledge and the student aptitudes are a perturbation of the specialist knowledge and not a subset of his/her knowledge before adapting the system needs.

There are a number of modern computer based systems that include aspects of User Modelling to adapt or try to understand user's behaviour, learning abilities, and even psychological profiles these are:

- Adaptive Hypermedia Educational Systems Martin et al., (2008) and Neji (2009)
- EU4ALL, Douce et al., (2009)
- User Profile Evolution (UPE), Neji (2009)
- Adaptive Dynamic online Educational system based on User Modelling (aDeNu)

Neji (2009) suggests that using User Modelling within on-line educational contexts will enable e-learning to provide more accurate information retrieval based on the profiling of behavioural, psychological and emotional states of individual users. According to Douce et al., (2009) using User Modelling within VLE's can provide a way of incorporating pedagogical profiles to design more personalised approaches. Santos et al., (2009) has the same ideas as Douce et al., (2009) but also indicates that using User Modelling within e-

learning can help bring personalisation through the use of social sharing including the development and integration of communities.

Boticario et al., (2007) and Martins et al., (2008) suggest educational systems that use User Modelling as a way of identifying and extracting user traits have been successful in a variety of institutions. However, there is a need for a generic model that can offer the same success from trials belonging to small scale institutions which can be imported more readily into mainstream environments. According to Martins et al., (2008) other areas of User Modelling must be researched further to deal with: interoperability issues caused by systems using different standards e.g. a mixture of eXtensible Markup Language (XML), Resource Description Framework (RDF), Sharable Content Object Reference Model (SCORM), Learning Object Metadata (LOM), Web Ontology Language (OWL), WiseOwl; appropriate use of pedagogical theories and learning styles in personalisation systems; presentation and navigation of learning materials within e-learning environments (Sosnovsky et al., 2008); and the development of adaptable courseware to support a variety of individual learning needs (Boticario et al., 2007).

The analysis of existing work in relation to User Modelling plays a fundamental role in supporting the development of the ideas presented in this Thesis in developing the Adaptive Intelligent Personalised Learning (AIPL) environment. According to Schiaffino et al., (2008) these new approaches to personalisation will enable the future development of VLE, which support and provide provision for more accessible and personalised learning content and structures. It is these recommendations from Schiaffino et al., (2008) that present ideas towards the development of a new novel approach based on User Modelling to provide an environment tailored around the 'Learner'.

Schiaffino et al., (2008) suggests that these particular approaches can be categorised into personalised learning. According to Miliband personalised learning refers to a system in, which *"careful attention is paid to their individual learning styles, motivations and needs; there is rigorous use of pupil target setting linked to high quality formative assessment and marking"* (Miliband 2004). The next section will expand on the notion of personalised learning, and how it directly relates to this Thesis.

## ***2.4 Personalised Learning***

Personalised learning enables individual preferences to be applied to the learning environment according to end user needs. Each end user may require a different approach to learning in particular contexts. According to DO-IT (2003) and Alkhasawneh et al., (2007), learning preferences refer to how students and end users respond to the learning environment. This flexibility in modification of the learning approach to the individual learner can be achieved through the use of web-based technologies (Sakagami et al., 1997).

According to De Meo et al., (2007), in addition to the learning preferences of the student, it is also important that the domain expert be aware of their own learning techniques to assist and support the individual learners. At the moment e-learning is an important field of research where different methodologies and pedagogical approaches often co-exist. According to Harun (2001), there is a wide range of factors that can either motivate or discourage the individual learner. These factors centre primarily on the learning materials themselves (quantity, quality, diversity etc...) and the e-learning environment (tools, accessibility etc...).

Personalised learning environments are allowing learning to be tailored to an individual's need. Skills and knowledge can be developed faster and when needed through 'just-in-time' learning. According to Harun (2001), Laurillard (1993) and Kabassi et al., (2004) the advancement of PLE's have provided the opportunity for learner's to have on-line and motivational support from professional domain experts. People learn best when they can learn what they need at the moment they need it. This can allow them to immediately apply their newly gained knowledge, which can improve performance. More importantly, immediate application cements the knowledge gained and makes it far more likely that the knowledge will be retained. According to Laurillard (1993), to assist the individual learner on-line within a personalised learning environment the system can model their process of learning to create an environment where learners engage in learning conversations and activities. Liber et al., (2004) indicates that to achieve a personalised learning experience on-line, domain experts must manage the complexity of the learning activities, by using different methods.

Personalised learning will be used within this Thesis to enable the learning environment to

support the individual through matching the needs of the individual and filtering out any redundant learning materials. As mentioned by Laurillard (1993) and Liber et al.,(2004) adopting a Personalised Learning Approach will enable the individual to achieve a personalised learning experience on-line through managing the complexity of the learning activities, by using a variety of learning methods.

#### **2.4.1 Research in Personalised Learning – An Overview**

PLE's are developed to incorporate a variety of approaches that take into account different ways of learning. These different approaches comprise a variety of techniques: knowledge representation; cognitive learning styles; adaptation to the learner needs; search; and retrieval techniques.

Personalised learning encapsulates pedagogical approaches that adjust to individual learning preferences. Frameworks for personalised learning provide learners with the opportunity to support different goals and learning needs. Bruen (2002) suggests that PLE's are versatile in supporting educational components, which are closely associated with course contexts.

Conlan et al., (2002) introduced a pedagogical learning environment (OPAL) that uses Kolb/McCarthy's learning style models to categorise learners into continuums (e.g. abstract/concrete and active/reflective). The pedagogical learning cycle is categorised as the following:

- Innovative learning - concrete/reflective in which the learner prefers to be shown the practical application of new material.
- Analytic learners abstract/reflective in which the learner is being presented with a well-documented sequential ordered approach to the materials.
- Commonsense learner - abstract/active in which the learner uses guided activities to keep them up to date with the learning materials and contents.

The OPAL model according to Moura (2006) would enable the delivery of content that was personalised to the learner's cognitive preferences. However, the OPAL model has not

been transformed into a practical framework for learning delivery. According to Koper et al., (2004), the development of learning design models can support strategies to consider specific existing learning processes based upon different pedagogical models. Rosmalen et al., (2006) suggests that a PLE can provide extensive mechanisms to improve learner performance.

There are a number of different approaches for achieving personalised learning experiences, the most pertinent of which to this Thesis research are outlined below. In 1999, Dietinger et al., proposed the Dynamic Background Library (DBL) which uses an intelligent algorithm built around the concepts of keyword relevance and user profiles to filter large knowledge bases for data relevant to what the user wishes to learn about. According to García-Barrios et al., (2004) the EHELP (EnHanced ELearning Repository) environment that uses the DBL has provided the learner with the flexibility of reducing large amounts of unwanted materials and improving the learner's performance. However, literature surrounding the EHELP environment has demonstrated a few limitations with the model, these are: the environment only retrieves partial search results from a knowledge base; manual intervention in the search function is required; complexity in use and lack of usability design (García-Barrios et al., 2004; and Mödritscher et al., 2005).

Hauren (2001) described a Personalised Continuing Medical Education Solution (PCMES) which focused on providing individually relevant learning materials based on expertise, interest and need. The algorithm at the heart of this solution needed to match personal attributes to the knowledge base to retrieve just in time materials. PCMES provided a learning environment that could handle real time response to a medical database, which would bring back learning materials that were appropriately associated with the academic level of the learner. The PCMES environment had several benefits, according to Hauren (2001), these were: delivery of low cost learning; up to date repositories and the provision of on-line support for students. Hauren (2001) indicated that the major limitation of the PCMES model was the complexity of the environment and the amount of staff training and staff time required in its usage.

In 2002, Conlan et al and Bruen created two similar online environments that were called OPen Adaptive Learning (OPAL) and Adaptive Hypermedia System (AHS), which were

specifically designed to make learning content more tailored to the individual. Bruen (2002) indicated that the AHS e-learning environment did not provide the flexibility to reach large audiences with a single body of content, and did not cater for the majority of individuals while studying on-line. The AHS tried to match the student's prior knowledge to existing preferences to facilitate personalised learning.

The Web Intelligent Trainer (Web-IT) according to Kabassi et al., (2004) provided a protected environment for novice users who can work on modules, as they would normally do, while the system silently reasons about their actions and offers adaptive tutoring to their situation. The Web-IT environment used an intelligent trainer algorithm to reason with the learner by suggesting or prompting appropriate learning paths to enable the novice to have a more personalised learning experience. The Web-IT environment was based on the 'relevance principle' theory by Sperber and Wilson (1986), which refers to how individuals only remember knowledge that is relevant to them. Kabassi et al., (2004) indicates that the Web-IT environment needs more empirical research with regards to the intelligent trainer. The empirical search needs to focus on analysis of the domain and technical experts to understand how tutors react to different age groups and learning experiences.

With the advancement of on-line technologies in 2006, Rosmalen et al introduced the aLFanet framework, which was used to match a multitude of pedagogical templates, to the learner in terms of providing a variety of different learning tasks. The environment analyses the learner progress throughout the learning process and suggests the appropriate learning path to take. The intelligent tutor/agents interpret the individual preferences, and take courses of action to support their needs. The design of the aLFanet environment presents some issues, according to Rosmalen et al., (2006) these were: the incapability of interoperability between different standards and pedagogical learning approaches and questions over the complexity with regards to taking more advantage of modern internet technologies.

Most recently De Meo et al., (2007) proposed the X-Learn system, which is a multi-agent system for adapting e-learning based on user preferences, history, expertise and requirements. According to Liu et al., (2007), there are a variety of problems associated with the X-Learn system: compatibility issues with software; media functionality (sounds, videos etc...); and how students needed special training in how to use the e-learning

environment. However, in addition to the limitations of the X-Learn environment, the research demonstrated that when it did work the environment provided real time streaming, on-line tutor support, and resource management.

Thyagarajan et al., (2007) introduces a new two-tier e-learning environment called eLearner that supports the learner by using adaptive algorithms to improve the performance of the learner this is measured through reduced browsing time of learning objects. The eLearner environment focuses on the adaptive course content that matches learning characteristics and interoperability across platforms. The e-learning environment that Thyagarajen et al., (2007) suggest covers different aspects, from learning materials standards; interoperability issues; and making use of on-line technologies; however, very little qualitative and quantitative research was found to support the framework within the academic world.

Zia et al., (1999) indicate that most Intelligent Tutoring Systems (ITS) works by focuses directly on the domain topic that the student wishes to learn. ITS according to Zia et al., (1999), uses questioning techniques to extract how the session is going and by doing this can update its teaching strategies.

*“An intelligent tutor takes Computer Based Training (CBT) and customizes it to the needs of each individual student, just like a real human tutor would do”* (Zia et al., 1999)

Intelligent Tutoring Systems are used to facilitate problem solving skills, learning habits, abstract reasoning, and verbal skills within on-line learning. Rau et al., (2009) agrees with Zia et al., (1999) about Intelligent Tutoring Systems providing a way of facilitating learning; however, Rau et al., (2009) version does not ask or prompt the user for questions instead it used correct and incorrect solution paths to adjust the context. If an error does reoccur the system will

*“produce feedback messages to enable the student reconsider their answer by either reminding them of a previously-introduced principle or by providing them with an explanation of their error”* (Rau et al., 2009).

Ghali et al., (2010) introduces an adaptive Web 2.0 e-learning tool called My Online

Teacher (MOT), which was developed to support a variety of features and facilities like: collaborative authoring; group-learning-paradigm; social annotation (group rating, feedback, etc...); adaptive hypermedia recommendation facility (which provides learning context based on other people previous reading materials).

*“The aim behind including collaborative authoring and social annotation within MOT 2.0 is to define improved adaptive materials based on communities of practice”* (Ghali et al., 2010)

Ghali et al., (2010) indicated that some of the features provided by MOT 2.0 such as grouping, subscriptions, communications, recommendations, accessing other people’s material were useful and assisted with their learning experience.

According to De Bra et al., in 2003 an Adaptive Hypermedia Architecture (AHA) was developed to support on-line course development via the use of user guidance; *‘conditional (extra) explanations; and conditional link hiding`* (De Bra et al., 2003). Adaptive systems try to anticipate the needs and desires of the user. Any knowledge that the Adaptive Hypermedia Architecture (AHA) has belonging to learner is based on previous actions. The system may simply monitor what a user is doing or it may ask questions to enable the architecture to adapt to his or her needs.

In 1998, Brusilovsky et al., suggested a system called InterBook, which represents educational material as a set of Electronic Textbooks (ET). Brusilovsky et al., (1998) indicate that InterBook is a Web-based education facility that accommodates the users by supporting: different backgrounds; prior knowledge of the subject and learning goals; and user adaptively guidance through course materials. Brusilovsky (2007) indicates that future trends of e-learning will focus on Adaptive Hypermedia, which will involve using hypermedia and User Modelling together to assist with personalisation.

*“Adaptive hypermedia systems (AHS) offer an alternative to the traditional ‘one-size-fits-all’ hypermedia and Web systems by adapting to the goals, interests, and knowledge of individual users as they are represented in the individual user models”* (Brusilovsky 2007).

Brusilovsky (2007) indicates that to achieve Adaptive Hypermedia Systems (AHS) link generation and link annotation will have to be developed, which at is currently being



investigated through the use of: ALICE an electronic textbook about the Java programming language; ELM-ART a Web-based systems with adaptive navigation support; ISIS-Tutor: non-adaptive, adaptive annotation, and a combination of both adaptive hiding and annotation; and finally the work done by De Bra AHA!.

Klašnja-Milićević et al., (2010) has indicated that to improve the effectiveness of e-learning is to incorporate personalized learning. This can be achieved by using Adaptive e-learning system that incorporates a variety of different learning strategies and technologies to predict and recommend the preferred learning material. This can be achieved by recommending and adapting the appearance of hyperlinks or simply by recommending actions and resources.

#### **2.4.2 Issues with Personalised Learning Environments**

Researchers like Kabassi et al., (2004), Dixon (2007) and Juhary (2005), have indicated that PLE' s fail in delivering on-line learning because, on-line domain experts have not taken into consideration the students' capabilities with respect to computer literacy. Rosmalen et al.,(2006) and Chieu, (2007) agree with the same concepts that students with very little computer related skills can find it difficult to learn in personalised e-learning environments due to the complexity of the components required to personalise systems to their needs.

Researchers like Dixon (2007) and Juhary (2005) have indicated similar views to Kabassi et al., (2004), and have argued that it would be difficult to design course context and structure to facilitate student' s needs with very little ICT skills. In order to deliver course content, activities and services, specific research is required in the area of instructional design; learner centric'ness; a wide range of functionalities; and domain experts to support and guide the learning cycle. According to Liber et al., (2004) and Santos et al., (2006), the problems with these approaches are the complexity of managing individual environments to compensate the needs of the learners.

However, according to Dixon (2007) and Juhary (2005), to compensate for the individual learning experience a more effective learning process must be designed and implemented. This would involve direct interaction at the design stage amongst the learners and the domain experts, which would enable a balance to be developed; however, this identifies

areas of support and time, which sometimes the domain expert does not have. According to De Meo et al., (2007), to effectively improve the problems identified by Dixon (2007) and Juhary (2005), different web-based technologies and standards must be used for on-line materials.

Thyagarajan et al., (2007) and Chieu (2007) indicate that the components for adapting to individual needs can be everyday technology, but the problem is associated with how the learning materials are structured, as it is not feasible to describe all the conditions that are required for determining which part of on-line materials is appropriate for different learner's needs. According to Chieu (2007) and Meccawy et al., (2007), learning environments must be flexible enough to support platform dependences, which can lead different institutions to use learning materials from other on-line sources.

In addition Juhary (2005) suggests that an important factor that needs to be solved within PLE's is how to identify suitable learning theories, this would effectively enable a whole new learning experience to be developed and supported by the environments.

To achieve, features like that of Intelligent Tutoring Systems (ITS), AHA, or even AdeLE, the use of User Modelling is required. User Modelling utilizes the knowledge from the individual to assist or guide where every possible within the learning environment. User Modelling varies within on-line learning due to their task or complexity. The basic form of User Modelling takes into consideration aspects of the individual; however complex User Modelling can facilitate system adaptations like: filtering requests; representation of user interests; representation of knowledge.

This Thesis, will hope to address some of the issues associated with Personalised Learning, by using User Modelling to develop a new filtering approach; adjusting the learning content and materials to support the user's interests; and finally incorporating grouping to create a positive learning experience.

## ***2.5 Summary***

This chapter guides the reader through the necessary steps required to enable a comprehensive guide to be developed on personalising learning. The first initial step was to identify what aspects can affect the learning process of the individual; this involved researching different learning theories. Secondly, the chapter focused on e-learning and more recent advancements related to e-learning 2.0, coupling technologies power with the influence of the social web. Finally, the chapter presents a critical overview of research related to user modelling, stereotyping and personalised learning systems.

Chapter 3 presents a more detailed analysis of the elements required in the development of a personalised learning environment; those of the development of a semantic knowledge base and a fundamental approach to matching learners with materials.

## **Chapter 3: Requirements for and approaches to personalising the learner experience**

On-line learning communities provide participative models for the creation, management and exchange of networked community resources to facilitate individual learner needs. Researcher's like Coman., (2002), Mühlhäuser., (2003), Cristea., (2005), Treviranus et al., (2006), Juhary (2007) and Thyagarajan et al., (2007) have shown that there is a greater need for environments to be designed around the student's requirements (learner-centric) and to provide additional facilities to exploit the learner's full potential. Academic literature based around learner-centricity has indicated that certain features have already improved learning on-line, with improvements in the interoperability of learning materials (Britian et al., 2006) and the development of innovative pedagogical learning approaches (Boticario et al., 2003; and Cagiltay et al., 2006). However, there are still problems to be solved.

The analysis of literature related to personalised learning in Chapter 2 effectively results in three substantial problem areas. The first problem area is the representation of learning materials within learning repositories. The second problem area is how the learner is profiled and the final problem area is matching the learner to the learning materials. This chapter deals with each of these different problem areas individually.

Sections 3.1 and 3.2 discuss the semantic representation of learning materials outlining technologies such as the semantic web, OWL, RDF, LOM and SCORM. Section 3.3 discusses technologies for profiling individual learners including their limitations. Finally, Section 3.4 describes technologies used for matching individual learners to learning materials.

### ***3.1 Semantic Web***

#### **3.1.1 Introduction**

The Semantic Web is an integrated mesh of web data that is used to link up information/data that we use every day. The Semantic Web provides an efficient way of

representing a common framework that allows data to be shared and represented within the World Wide Web. The Semantic Web enables data to be integrated and combined to allow re-usability within applications, communities, and organisations. According to the W3C (2007), the Semantic Web can be categorised into two specific identifiable areas: common formats of data used for integration and combination; and recording how the data relates to the real world object.

The concept of the Semantic Web was devised by Tim Berners-Lee to improve, extend and standardise data that is stored within HTML documents (Berners-Lee et al., 2002). The problem with the majority of data on the Web is that, it is stored in a contextual form that is difficult to use on a large scale because there is no one standard for publishing data in such a way as it can be easily processed by anyone (Palmer, 2001).

### 3.1.2 Technology

There are several technologies that are available for constructing Semantic Web data. According to Dumbill (2002) and Matthews (2005), eXtensible HyperText Markup Language (xHTML), OWL, RDF, Meta-data and XML can be used to create a translational data model. The translational data model must support a variety of syntax to facilitate structured information for a machine to understand and process. Table 1 introduces some of the technologies that can be used to create semantic mark-up of learning objects.

|       |  |
|-------|--|
| xHTML | XHTML forms the foundation of web content. Semantic information can be embedded within XHTML using meta-data as recommended by (Dumbill 2000 and Kesteren 2007). The 'class' attribute has been used in the past to facilitate mark-up of learning objects (Dumbill 2000 and Kesteren 2007). However, the problem with XHTML is that it is not a specific structure for learning object representation and cannot be used in an interoperable way to record significant amounts of data about individual objects (Downes, 2001). |
|-------|--|

|     |  |
|-----|--|
| XML | <p>Garro et al., in 2002 introduces XML as “<i>a language for representing and exchanging data over the Internet. XML embodies both representation capabilities, typical of HTML, and data management features</i>” (Garro et al., 2002, P3).</p> <p>McGreal et al., (2001), Polsani (2003) and Garro et al., (2010) indicate that XML is ideal for achieving representation of learning materials because it provides a way of dealing separately with content, structure and appearance, to semantically mark up objects.</p> <p>Garro et al., (2002) indicates that XML provides an efficient and effective way of representing and classify learning objects like: “<i>documents, slides, simulations, role plays, questionnaires, pre- recorded lessons, classroom lessons</i>) and their relationships with respect to their objective, topic, used media, etc... (i.e. LOM) (Garro et al., 2002, P2).</p> |
| RDF | <p>RDF provides a way for describing web resources. Devedžić (2004) suggests that RDF provides the necessary way of representing details belonging to a web resource through the use of tools that use common syntax. According to Heery (1998), RDF syntax is based on a data model that enables properties to be described in a descriptive structure.</p> <p>RDF aims to build a web of overlapping metadata vocabularies to create a market for data merging, aggregation, annotation and filtering services. McGreal et al., (2001), Finland (2004) and Farrell et al., (2004) suggest that RDF can be used to semantically represent learning objects on-line.</p>   |

|  |   |
|--|---|
| OWL  | <p>According to Antoniou et al., (2009) OWL is aimed at being the “<i>standardised and broadly accepted ontology language of the Semantic Web</i>” (Antoniou et al 2009, P1). Bateman et al., (2006) suggests that OWL is built upon RDF and RDF Schema to a large extent, to provide a knowledge representation to allow for more intelligent searching and retrieval over other resources.</p> <p>According to Horrock et al., (2003) OWL is primarily designed to represent information about categories of objects and how objects are interrelated. Parsia et al., (2004) and Bouquet et al., (2005) agrees with Horrock et al., (2003) but expands further on the notion by indicating that OWL uses XML Schema, to represent, build and maintain learning objects found within repositories.</p> |
| LOM  | <p>According to Bateman et al., 2006, LOM “is the most widely used specification for learning object metadata”. LOM is taxonomy of terms and descriptors, which are constrained by a preset vocabulary. LOM is used to annotate learning objects within the repository to provide a standard for describing learning objects. According to Bateman et al., (2006) LOM can be used within adaptive and personalised learning to provide a way of annotating learning objects. LOM is further explained in Chapter 5.</p>   |
| The Dublin Core Metadata Initiative (DCMI) | <p>The DCMI is an open organisation engaged in the development of interoperable metadata standards used within on-line learning. Xu et al., (2007)* suggests that the DCMI is used to describe data belonging to the “<i>content, format or attributes of a data record or information resource</i>” (Xu et al., 2007, P2). The Dublin Core standard provides a way of describing, sharing, finding, retrieving and managing data.</p> <p>Xu et al., 2007, indicates that the Dublin Core Metadata standard can be used to represent on-line materials within a variety of domains, like those found in medical and educational institutions. For more information about the Dublin core Metadata standard, please see Chapter 5.</p>   |

Table 1: Technologies used for constructing Semantic Web Data

### ***3.2 Related Issues***

The Semantic Web can be exploited within e-learning to provide a platform for implementing different learning materials and objects. The Semantic Web can facilitate e-learning, personalised or adaptive learning environments by introducing descriptive annotations that can be closely mapped to the learning profiles or specific learning needs as shown by Sancho et al., (2005) and Cerri (2002).

Markellou et al., (2004) and Dieng-kuntz (2007) indicate that the quality and coherence of the material cannot be guaranteed when representing learning materials in a repository. Brusilovsky et al., (2007) agrees with Markellou et al., (2004) and Dieng-Kuntz (2007) about the lack of high quality resources found within repositories; as stated within the Open Corpus Adaptive Educational Hypermedia project.

Brusilovsky et al., (2007) indicates there are more issues than just the lack of high quality learning materials like: resources may change without notice; standards are not backward compatible enough within the changing technologies; and there are major interoperability issues between a variety of VLE' s. Research from Cristea (2004) has indicated that there is a lack of support for and problems with keeping the systems up-to-date when newer versions of Semantic Web standards have been released.

According to Dicheva et al., (2004) and Nordeng et al., (2005) navigational issues, cognitive overload and standard intractability are still issues associated with the Semantic Web within e-learning.

### ***3.3 Learning Materials Standards***

Learning Materials standards are used throughout adaptive, personalised and e- learning environments. The motivation behind the use of learning materials standards is to primarily overcome issues of interoperability between on-line learning systems; and the idea of reusing learning materials. Learning materials standards provide the domain expert with tools to: describe the characteristics of learning resources; index the learning materials according to specification; and facilitate more precise retrieval according to learning context.



According to Verbert et al., (2004), there are a number of learning materials standards that are being developed and implemented to support on-line learning, these include: LOM and SCORM. The following sections will discuss LO (3.3.1), LOM (3.3.2) and SCORM (3.3.3) in greater detail.

### **3.3.1 Learning Objects (LO)**

According to Bannan-Ritland et al., (2000) and Friesen (2004) learning objects can be regarded as an educational resource, which use metadata to enable more precise search and retrieval from learning repositories. *“Learning objects describes any digital resource that can be reused to support learning”* (Wiley, p. 20). The IEEE itself implies that learning objects can include *“multimedia content, instructional content, instructional software and software tools [and] in a wider sense...learning objectives, persons, organizations, or events”* (IEEE, 2001).

Learning objects make it easy and convenient for educational course designers to assemble instructional materials, which are well-defined and structured to support different pedagogical models. Bannan-Ritland et al., (2000) indicates that separating content and context within the learning process provides some benefit to the designer by providing greater flexibility of reusing learning objects. Friesen (2004) suggests that to gain the full potential of learning objects within an education environment, they need to be labeled, and described in ways that make learning objects simpler to integrate and support. According to Friesen (2004), learning objects have the potential to benefit the learner if the learning environment has the capability of using different pedagogical learning approaches in their retrieval.

Learning objects are used within this Thesis to represent course content belonging to:

- 1) How to wire a plug, which will be used to test the initial retrieval findings belonging to the Adaptive Intelligence Personalised Learning (AIPL) environment.
- 2) A full Java module will be used to examine and compare results from the initial findings and also from another VLE called Moodle.

The learning objects will enable the domain expert to develop course content to suit the required learning outcomes of the module (e.g. how to wire a plug and how to program in Java).

### **3.3.2 Learning Object Metadata**

The LOM data model specifies which aspects of a learning object should be described and what vocabularies may be used for these descriptions; it also defines how this data model can be amended through additions or constraints. Barker (2005) indicates that resources can be tailored to suit the specialised needs of an on-line community. Course designers and publishers may use the LOM standard along with other specifications to mark-up learning resources with a description of the learning object. LOM is a multi-part standard that specifies a conceptual data schema that defines the structure of a metadata instance for a learning object. Data schema are used to create meta-data instances for learning objects, which can be used by a learning technology system to manage, locate, evaluate or exchange learning objects.

The purpose of LOM is to facilitate search, evaluation, acquisition, and use of learning objects, for instance by learners or instructors. LOM facilitates the sharing and exchange of learning objects by enabling the development of categories and inventories while taking into account the diversity of lingual contexts in which the learning objects and their metadata are reused. By specifying a common conceptual data schema, this ensures that bindings of LOM have a high degree of semantic interoperability.

The core of this Thesis focuses on facilitating the matching of learners to learning objects. In this context, LOM is of interest and can be used as a useful mechanism to represent learning materials. For more detail about LOM, IEEE-SA (2002) provides an excellent resource. LOM will be used within this Thesis to represent the learning objects, which can be found within Chapter 5. LOM will assist the domain expert in labeling activities, and classifying the activity.

### **3.3.3 Shareable Courseware Object Reference Model**

SCORM can be described as an architecture for developing web-based instructional

materials in a way that will allow a global e-learning community to use. It also lets users create their own units of instruction by mixing and matching individual content objects. The overall framework of SCORM describes a model for structuring and aggregating content, along with a run-time environment for presenting the materials to end users via a web browser.

SCORM is a set of specifications for developing, packaging, and delivering high-quality education and training content/materials, whenever and wherever they are needed. SCORM provides strict guidelines for designing course materials with the use of the terminology Reusable, Accessible, Interoperable, and Durable (RAID) in the creation and implementation of learning objects. According to Jones (2002) and Henriques et al., (2004), RAID can be explained as the following:

- Reusable: Easily modified and used by different development tools and platforms.
- Accessible: Can be searched and made available as needed by both learners and content developers.
- Interoperable: Operate across a wide variety of hardware, operating systems and web browsers.
- Durable: Do not require significant modifications with new versions of system software.

SCORM standards provide facilities for: search, identification and content retrieval within a repository. This way, it is easier for learners to identify, retrieve, and incorporate valuable content from different sources. SCORM constitutes an important first step towards freeing learning content objects from individual implementations. It is intended to provide the technical means for content objects to be easily shared across multiple learning delivery environments; however, this does not solve all of the technical challenges that must be overcome to create robust instructional objects.

The main purpose of this Thesis is to provide a way of matching the learners to learning materials. In this context, of learning objects SCORM can be seen as an area of interest which provides as way of providing a descriptive framework to annotate on-line learning materials. For more detail about SCORM the Advanced Distributed Learning Initiative (2010) provides an excellent resource.

### **3.3.4 Limitations of SCORM and LOM based repositories**

There have been many investigators that have discussed the limitations to the SCORM model. Engel Brecht (2003) points out that the SCORM model has several issues associated with it, these are: reusability issues, metadata representations and security concerns over code malware. Wirski et al., (2004) agrees with (Engelbreht 2003) that reusability issues brought about by a lack of interoperability between learning objects from one repository to another is a significant problem with SCORM based systems. According to Nakabayashi et al., (2007) some of the interoperability issues have been solved dependent on learning activities (same learning content), and adaptive functionality of the repository. Nakabayashi et al., (2007) suggests that other problems do exist and these are: usability of learning objects, adaptation of learning activities, and time concerned for the domain expert to develop these approaches.

Suthers (2001) suggests that the LOM metadata model lacks the metadata representations for the domain expert to describe learning objects and additional issues like interactivity. Further analysis of Qin et al, 2002, also indicates that LOM like SCORM suffers from interoperability issues. Cebeci et al., (2005) indicates that issues associated with the representation of learning objects, which Suther (2001) and Qin et al., (2002) had indicated, have now been solved through greater standardisation of practice. However, Cebeci et al., (2005) points out that there are now more prominent issues like too much flexibility, accessibility and interoperability that must be solved.

Karampiperis et al., (2005) indicate that SCORM, and LOM have similar problems, that they are incapable of providing a solid format for reusing learning objects between repositories. SCORM and LOM have limiting abilities with cross platform repositories (interoperability), and shared learning activities (interactivity).

According to Hatala et al., (2004) researchers have been trying to standardise learning object metadata by using emergent specifications towards learning objects. Najjar et al., (2006) suggests learning objects that are represented by metadata must be flexible and diversifiable to enable the learner to search through a repository to find specific content that meets expectations. According to Najjar et al., (2006) to overcome these limitations learning objects must be rich with descriptive details that enable search mechanisms to scan

through and retrieve appropriately relevant materials.

### **3.3.5 Summary of learning object standards**

Learning object standards are used to allow learning objects to be represented by a descriptive metadata model that enables sharing among distributed repositories. Due to the vision of the Semantic Web, a large body of research regarding learning materials standards has been well documented in literature through the use of descriptive models like, SCORM, LOM, OWL, RDF, etc... (Bannan-Ritland et al., 2000; Friesen 2004). Finding ways in which the models can interoperate and bridge between repository instances can facilitate improved functionalities including digital libraries (Decker et al., 2000; Lu et al., 2004 and Sure et al., 2005), e-learning (Sancho et al., 2005), information sharing, search, retrieval, and transformation.

Another problem is in creating a matching balance between search and retrieval of desired learning materials for the learner. Basically, learners need to perform content retrieval by interacting with: search engines or LMS including queries that have to be resolved based on knowledge descriptions. To enable content retrieval across distributed contexts, appropriate matching techniques are required to determine a semantic mapping between learning object descriptions defined using different standards (Knight et al., 1994; Chaudri et al., 1998; Noy et al., 2001; Yao et al., 2007).

### ***3.4 Profiling***

It is clear that from Chapter Two, profiling through the aid of User Modelling is extensively used (Dietinger et al., 1999; Boticario et al., 2007; Martins et al., 2008 and Neji 2009) in a variety of educational settings to filter large knowledge repositories of data. Neji (2009) suggests that using User Modelling within on-line educational contexts will enable e-learning to provide more accurate information retrieval based on the profiling of behavioural, psychological and emotional states of individual users.

### 3.4.1 Profiling the individual

Profiling is used to compare or identify a subject's behaviour or the behaviour of others in similar circumstances. The key to good profiling is in deriving what background information can be extracted and by identifying certain patterns of the individual. There are many different types of profiling, which stem from DNA profiling to profiles that assist with learning. There are several different types of profiles that can be used within learning, these are:

- Learning Profile (LP): According to Hummel et al., (2003) LP's enable psychologists to retrieve specific learning habits, and issues of the individual to enable the teacher and the student to better understand their own learning habits. Hummel et al., (2003) indicate that there are a number of issues to contend with when using LP's, within an on-line learning environment these are: roaming profiles; ever changing learning styles of the individuals; and the transfer of retrieving LP values from server to client. Boticario et al., (2006) indicated that LP's require the following improvement: integration of authoring tools and more documentation explaining how to implement different adaptive scenarios.
- Contextual Profile (CP): Safran et al., (2006) indicate that CP stores raw information about terminologies, concepts and context related to a course and course materials. CP's enable the system to access basic information from the learner/domain expert. According to Safran et al., (2006) the CP, must be flexible within the design to compensate for metadata storage. Strang et al., (2002) indicates that using CP's within on-line environments provide insufficient ways of describing complex contextual data structures.
- Device Profile (DP): De Meo et al., (2007) indicate that a DP stores some characteristic aspects of individuals, such as the types of medium (e.g. video, audio, etc.), or the software that the student uses. Boticario et al., (2006) suggests that there are often problems of usability and accessibility in relation to different devices. DP's help to at least indicate where problems may occur.
- Self-learning profiles (SLP): According to Manuel et al., (2001) SLP are used within the fields of context extraction and evaluation of course materials. According to Shih et al., (2005) SLP are capable of identifying learner needs and adjusting the learning environment accordingly. The SLP can adapt the profiles to fit a variety of different learning situations, and prompt the user in the right direction.

Each of the profiles mentioned provide the opportunity to assist the individual within a learning environment by helping to adjust the environment based on the profiled needs of the user. Much of the research has demonstrated that profiles can assist within the environment; however, consideration must be taken when dealing with raw information, learners details, interoperability, and data exchange so that problems don't arise when the learners uses them.

### **3.4.2 Profiling and categorising the individual**

Profiles have been applied and adapted to many different environments to facilitate and reduce information overload by taking into consideration user interests, themes, pedagogical learning theories, and software sharing. The profiles enable students to adjust learning environments according to how they learn and filter the repository for appropriate learning objects. According to Subramaniam (2006), profiles can capture and store information about users' personal data (e.g. name, contact address, etc.), relations (i.e. with their classmates and teachers), performance (i.e. their learning progress), and specific learning needs. According to Hummel et al., (2003), Zahedi (2003), Sinha et al., (2004), Tzouveli et al., (2005) and Subramaniam (2006), using profiles has enabled environments to adapt to groups' with similar interests, skills, projects, location and personalised settings. This presents the opportunity for the individual to experience a more specific group surrounding and better correlation between group/collaborative environments. De Meo et al., (2007) agrees with the research of Hummel et al., (2003) and Kabassi et al., (2004) that using profiles in on-line learning can enable e-learning environments to adapt to the specific needs of the individual. However, a profile can offer more than just the personality traits of the individual.

Research conducted by Bloedom et al., (1996) incorporates weight-based algorithms to facilitate learning experience by exploiting key terminologies within the user profile, which can be applied to the filtering mechanisms to reduce information overload. Bloedom et al., (1996) indicates that user profiles can be adapted for the World Wide Web and academic use by incorporating weight-based algorithms that interrogate key terminologies in the learner profile and the retrieval of relevant web-based documents for comparison purposes. The comparison takes place by using a weight-based algorithm that exploits the evidence

and compares the relativity, thus providing a mechanism for the user to filter out the unnecessary retrieval of documents.

The idea of using learning profiles that can quickly adapt to the individual has been incorporated into the design of AIPL, which can be found within Chapter 4 and also Chapter 5 PAFS. Learning profiles are used to store a detailed description of how an individual prefers to learn and also what behaviours they have. Over time ones own learning style adjusts according to experiences gained, and within AIPL, the learning profile will prompt the individual to carry out their learning style questionnaire again every 2-3 months to ensure that individuals have correct matching patterns, for more information on the learning profile please see Chapter 5 (PAFS). Machine learning of changes over time of student learning style could be a place for further research.

Categorisation within learning profiles can enable greater flexibility when designing course contents with the pedagogical approach that creates a correlation between the learning experience and the learner. Kolb et al., (1999) suggests that experimental learning helps to define flexible learning experiences at a more comprehensible level that encourages guidance, support, and facilities to aid learners. Heery et al., (2000) expand on educational learning profiles by incorporating a relationship between the Semantic Web specifications and the data elements that are used to describe documentation within heterogeneous environments and communities. These profiles enable different communities to access learning profiles to retrieve knowledge through specific repositories to facilitate mechanisms for file sharing, peer-to-peer sharing and documentation. According to Aroyo et al., (2006) when applying learning profiles to e-learning environments research has discovered that using this particular technique has unearthed issues surrounding adaptability.

According to Simon et al., (2002) learning profiles have been applied to adaptive e-learning frameworks to facilitate and maintain personalised learning. Adaptive environments provide access to all kinds of educational resources. Simon et al., (2002) suggests that the LP can be trained to facilitate a fully electronic educational service that enables a tutoring system to assist the learner when encountering problems. The LP can be fully integrated into a web-based adaptive environment, which automatically registers learning details, and a personal record of achievements. To achieve the LP, matching



ontologies of additional academic services are required to incorporate various types of educational services that model the learner's previous knowledge; this enables the LP to describe the capabilities of the student.

Simon et al., (2002) indicates that matching ontologies must be used to provide educational resources that correlate to the most used LP and to additional repositories with the use of mainstream Semantic Web technologies. According to Simon et al., (2002) and Thalmann et al., (2007), a learner profile can be used to assist the learner experience by adjusting the requirements to fit the need of the current learning situation; however, other researchers King et al., (2005), Stash et al., (2006), and White et al., (2006) indicate that matching the learner needs involves a mixture of techniques and theories to provide a more efficient and effective way of improving the learning experience.

### **3.4.3 Stereotyping and categorising the individual**

Another type of profiling found within Computer Science is that of the work from Elaine Rich, which introduced a type of individual/group classification called stereotypes. Stereotypes are based on modelling groups of users who share common interests or characteristics, which can be extracted to form clusters of group-paradigms.

According to Rich (1979) the use of stereotypes, can be achieved by using a small set of words (simple self description) to enable a system to adapt to individual needs. Rich (1979) suggests that to treat users as individuals stereotyping can be used to identify distinct personalities and goals, which will provide a useful mechanism for building models of individual users on the basis of a small amount of information.

Elaine Rich in 1979 suggests that *“there are many theories about why people use stereotypes, but one of the most certain explanations is that people use stereotypes as a means for dealing with the fact that the world is far more complex than they can deal with without some form of simplification and categorization”* (Rich 1979, P3) .

According to Melia et al., (2009) and Brusilovsky et al., (2010) the use of stereotyping within on-line learning enables a system to adapt to a variety of individual needs like retrieving relevant information; knowledge of a subject, and learning style.

As stated by Brusilovsky et al., *“to create and maintain an up-to-date user model, an adaptive system collects data for the user model from various sources that may include*

*implicitly observing user interaction and explicitly requesting direct input from the user” (Brusilovsky et al., 2010, P1).*

Stereotyping is used to help the system to simplify the world it is based on by analysing the individual characteristics of a person. Once stereotyping has been carried out and analysed the next step is to cluster all possible users into several groups depending on the initial design. All users belonging to the same stereotype will be treated in the same way by the adaptation mechanisms.

There are many researchers within literature that use stereotyping to categorise the individual, for example: Brusilovsky in 2001 caters for the individual by using an e-learning environment that adapts to their learners goals by using the knowledge level, background, interests, preferences, stereotypes, cognitive preferences, and finally learning styles of users. Frias-Martinez et al., (2007) used stereotyping to determine the behaviour and personal perceptions of users within a personalised web-based application; and Melia et al., in 2009, used adaptive courseware to suit a variety of individual needs by using: knowledge of a subject, and learning styles.

According to Bartolini et al., (2009) and Rich (2009) stereotyping is very similar to Collaborative Filtering (CF), in the fact that they are both used to search and retrieve items belonging to particular criteria. Bartolini et al., (2009) suggests that CF exploits similarities in user behaviour before recommending search and retrieval patterns. Drachsler et al., (2009) indicates that both CF and stereotyping can be used together to reduce information over-load and reduce unwanted assumptions about individuals and groups.

Within this Thesis the author has focused on using CF in conjunction with profiling to reduce unwanted assumptions of the individual with the aid of learning styles. This particular type of profiling can be seen as having similar traits to stereotyping that was introduced by Elaine Rich back in the late 1970's. For more information about the CF and profiling, used within this Thesis please see Chapter 5 Personalised Adaptive Filtering System (PAFS).

### **3.4.4 Issues**

There are a number of key problem areas associated with profiling techniques, which vary dependant on the task or function they are meant to perform. According to Tzouveli et al., (2005), extracting data, preferences or user history can be an extensive task, which requires a range of computer skills and knowledge. Subramaniam (2006) agrees with Tzouveli et al., (2005) about the development and instructional design of the extraction process for using profiles and indicates that if the profiles are not correctly designed around the students/learners' needs, then a lack of competency can create conflicts with the personal learning of the individual.

Subramaniam (2006) indicates that the instructional design stage of the profile must work, to ensure that instructional balance between the profiles and the students' needs is implemented successfully. According to Ensminger et al., (2004) and Williams (2004), using profiles to match students' needs within an environment requires further research. De Haan et al., (2003) indicates that using a variety of methods and tools to assist with guidance while selecting different types of profiles could provide a more blended suitable learning experience. Williams (2004) has the same thoughts as De Haan et al., (2003) by indicating that using procedural and strategic knowledge in the development of a learner profile can create a more effective learning experience.

### **3.5 Matching**

A large amount of learning material is created and delivered on-line every day. This has made it increasingly difficult for individuals to control and effectively manage their own learning process. On-line educators are finding it very difficult to adapt to the requirements of individual learners in virtual environments. In comparison traditional teaching can be adaptive with teachers adapting to learner needs when lecturing, tutoring, and guiding them through the learning process. However, whether traditional or on-line, true personalisation of experience is a difficult concept to realise. Educators are now striving for ways to match learners' requirements to content through technology to create an efficient and effective way to improve their learning experience.

### ***3.5.1 Approaches to matching***

The matching process involves systems in programmatically determining the suitability of learning resources for individual learners. This process can be achieved in many different ways. This section outlines research in this area and highlights the limitations of current approaches.

Knight et al., (1994) proposed a Knowledge-Base Machine Translation (KBMT) engine that uses matching to facilitate search and retrieval of word-based text to assist the learner with language translation. The Hierarchy Matching Algorithm (HMA) used a multi word strategy that tried to search for multiple meanings of the same word (Homophones) to reduce assumptions made within the search process. According to Knight et al (1994) the HMA had a 96% accuracy rate when retrieving learning objects from a knowledge base repository. However, because of the nature of the approach chosen by (Knight et al., 1994), it still required the intervention of the domain expert and learner to validate retrieval of search, and content that was brought back.

In 1998, Chaudri et al created a Knowledge Representation System (KRS) that uses the Open Knowledge Base Connectivity (OKBC) API to provide an interrogation mechanism that would enable the learner/domain expert to make assumptions and control the behaviour response of the KRS algorithm when retrieving specific search patterns. Chaudri et al., (1998) indicated that the KRS algorithm provided an effective way of using semantic matching mechanisms to assist the domain/learner with keyword searches. Literature surrounding the KRS algorithm indicates that depending on the complexity and severity of the search it could bring back a null search, at which point the assistance of the domain expert/learner would be required to intervene and adjust the search accordingly.

Noy et al., (2001) introduces the PROMPT algorithm, which uses a form of OKBC mechanism to enable the domain experts/learners to perform any-keyword search. This particular approach provided the domain expert with the opportunity to search by using linguistic similarity i.e. matching words/relations. According to Noy et al., (2001) this matching algorithm approach had a 74% success rate when being used by users for knowledge acquisition/retrieval.

In 2004, Li et al suggest an e-commerce algorithm that matches the request of the user to a

variety of internet based advertisements. The algorithm interrogates a query from the user then through the use software agents/bots conducts web-based crawls to retrieve desired search results. The prototype algorithm relies on the use of metadata, however, in addition to the algorithm the user has to have knowledge of special characters and phrases, which enable the user to create more specificity in the search. Li et al., (2004) indicate that using matching algorithms was complex; however, if simplified at the user front end it has the potential to produce successful results.

Hull et al., 2006, describes a framework that uses matching algorithms to facilitate user requests, by using semantic descriptors for particular topics. The framework that Hull et al., (2006) suggest enables the matching algorithm to scan through the metadata that represents the topic area and bring back only appropriate materials to the search of the user/learner. The approach that Hull et al., (2006) had taken indicates that only domain experts with knowledge of Web Ontology Language for Services (OWL-S) and Web Service Modeling Ontology (WSMO) could use this feature.

Yao et al., (2007) argues that keyword searches, and page ranking are inadequate when large repositories are searched, which involve individuals manually going through the results brought back one at a time. Yao et al., (2007) indicates that the typical Knowledge Retrieval system as seen in Figure 1 involves three major steps, these are:

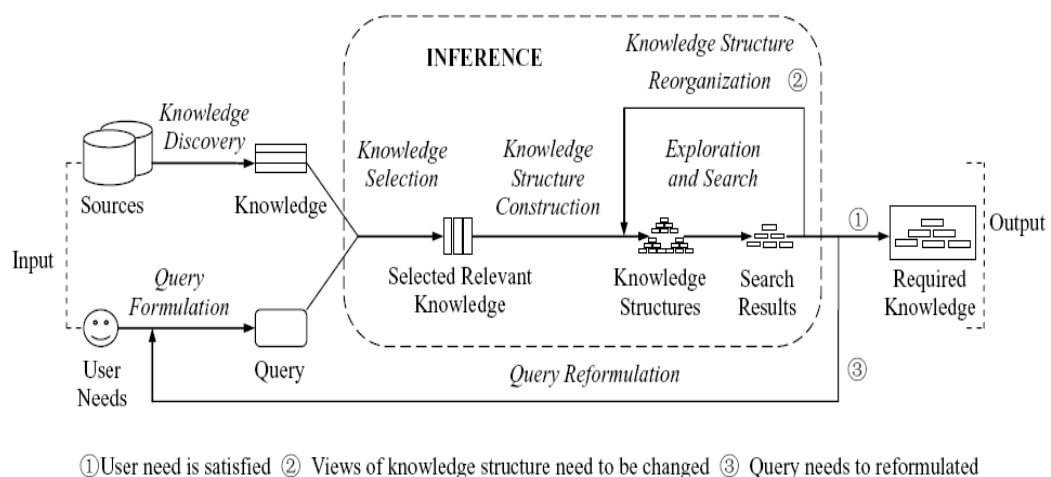


Figure 1: Yao et al., (2007) Typical KR System

- 1) Meeting the learners needs when conducting searches
- 2) Understanding the structures through which searches are conducted
- 3) Modifying search criteria

To overcome the limitations of knowledge base retrieval according to Yao et al., (2007) researchers must include some of the following approaches: collective family trees; hierarchical data representation; intelligent knowledge selection; and knowledge based structures to reduce information retrieval. The model that Yao et al., 2007 proposed was only a theoretical concept that could be applied to support a new model.

In 2006, Eze et al suggested a framework for Personalising Multimedia Learning Resources that uses profile matching to enable the learner to view learning materials. According to Eze et al., (2006) the e-learning framework uses a profile matching mechanism that utilises the learner preference to retrieve learning materials. Eze et al., (2006) indicates that the framework was used as a driving force to enable the development of a personalised one-to-one learner experience. For more information see Figure 2.

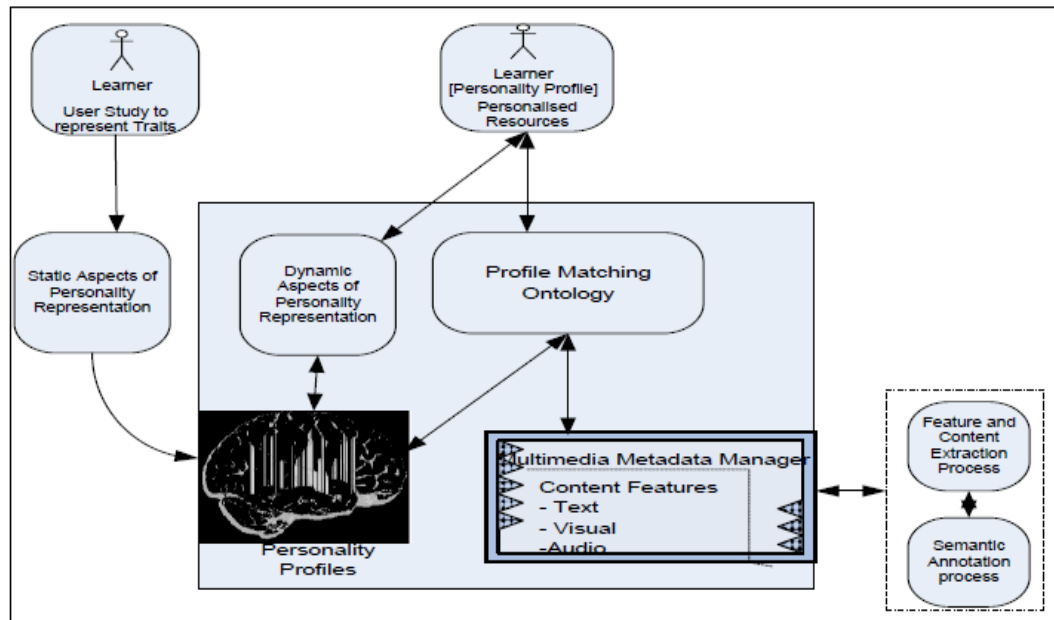


Figure 2: Frameworks for Personalised Multimedia Learning Resources (Eze et al., 2006)

Eze et al., (2006) indicated that there was one major design flaw within the e-learning model, which was all about providing a personalised learning resource for effective learning, but this did not provide an adequate approach for providing media resources towards the learner's traits.

The research that was carried out by Eze et al., (2006) indicated that there were three possible areas of improvement these were:

- 1) To the personality component for domain profiling of the learner
- 2) In using semantic metadata to represent multimedia of specific context using XML and RDF.
- 3) In the development of the matching algorithm.

Hummel et al., (2007) suggested a personalised adaptive model that focused on producing a Personalised Recommender System (PRS). The model that Hummel et al., (2007) had suggested focused on sequencing learning activities (the creation of a Learning Path), CF, and ratings. The PRS model uses several different types of mechanism to enable matching to take place between the learner and the learning materials. The first technique that Hummel et al., 2007, used was an information-based approach that uses learning technology standards, metadata and the Semantic Web to mark up the learning materials. The second technique that Hummel et al., 2007 suggested was the use a social-based approach that was designed and implemented using: data mining, social software and CF. Hummel et al., (2007) indicates that their design approach has several limitations associated with it, these are:

- Limited metadata mark up of learning materials using RDF/XML
- The course management software was only capable of running a limited amount of learning activities.
- Limitation of research focusing on stigmergy approach of allowing individual to form their own groups instead of assistance from the domain expert.

Hummel et al., (2007) indicated that future trends will or should be addressed towards using users as a centrepiece.

Mencke et al., (2007) introduces an e-learning framework —Learning Environmentl that enables technology to enhance the performance and the effectiveness of on-line learning mediums. The framework uses a combination of web-based technologies and software agents to provide a mechanism to improve: pedagogic diversity, learning activities, interoperability between different frameworks; and functionality improvement. According to Mencke et al., (2007) there are several issues concerned with this particular framework these are: dynamic design of the e-learning framework; complexity and how the components react while being using within an on-line environment; data and knowledge acquisition.

In 2008, Wang introduced an e-learning framework called IDEAL, which was used to acquire knowledge about the learner by interrogating their previous learning experiences. This interrogation was achieved by using a rule base that provided the e-learning environment with a mechanism to group learners according to relevance, browsing habits, and statistics. Wang (2008) suggested that the IDEAL e-learning framework was a success in providing a potential way of improving performance; however, failed to take into consideration the student's individual needs (how the individual learns according to their own styles; pedagogical learning approaches; and learning states).

### **3.5.2 Issues**

This section focuses on the issues that have been identified within Section 3.5. The research in this section has focused on approaches to matching individuals to learning materials thus personalising their learning experience.

Eze et al., (2006), Mencke et al., (2007) and Wang (2008) suggest that there are several issues concerned with e-learning frameworks, these are:

- They do not provide a dynamic approach that is learner centric.
- They are not generally matched to a flexible pedagogical learning model.
- All present different approaches to matching the learner to the learning materials, there is no one 'golden bullet' approach to matching.

Eze et al., (2006), Hull et al., (2006), and Hummel et al., (2007) indicate that there are issues associated with using semantic metadata to represent multimedia. According to Hull et al., (2006) the use of semantic metadata, would provide algorithms with the opportunity to scan, interrogate and retrieve specific learning materials in accordance with a personalised approach.

Researchers like Knight et al., (1994) and Chaudri et al., (1998) believe that the use of keyword searches still need the intervention of the domain expert and learner to validate retrieval of search, and content. Li et al., (2004), Hull et al., (2006) and Liu et al., (2010) indicate that using matching algorithms is complex and that depending on the complexity and severity of the search could bring back a null search.



However, there are indicators in Section 3.5, that learning environments using intelligent matching approaches to link students to learning resources can provide an effective learning experience. Intelligent matching will be used within this Thesis to enable matching to take place between the individual and the learning materials, for more information regarding the matching approaches used within this Thesis please see Chapter 5, PAFS.

### ***3.6 Summary***

This chapter has focused on presenting key elements of any framework to personalise a learning experience for individuals. The key elements are the use of semantic technology to represent learning objects, a mechanism for understanding user requirements and a method of matching user requirements to the search and retrieval of items from an on-line repository.

Sections 3.1, 3.2 and 3.3 indicate that any learning objects used on-line must be in some way semantically marked up, to enable effective information retrieval even if the semantic mark up is based on something other than current educational standards. LOM compliance provides at least a standard to work to in marking up the learning objects in knowledge bases even if this compliance is thought to be fraught with interoperability problems (Engelbrecht 2003; Wirski et al., 2004).

Section 3.4 provided information about other research projects in the field of profiling users. Again, this is a very complex area with a multitude of different approaches for developing user profiles everything from learning styles through learner personalities to learner progress.

The last Section 3.5 focused on providing an explanation of current approaches to matching user profiles to knowledge base materials. Again clearly there is a large amount of work currently taking place into this area but there is no single solution which provides a panacea for all.

The next Chapter will build on the issues presented in this Chapter to develop a framework for personalised learning which encompasses elements of the three areas outlined above, but concentrates in specific on providing unique contributions with relation to matching users with learning content.

## **Chapter 4: Virtual Learning Environment & Pedagogical Approach**

This chapter focuses on the development of a pedagogical model to support the personalisation of a learning environment for users. Chapters Two and Three have outlined existing research in the area of personalised learning, providing a detailed investigation of producing, searching, intelligently matching, and retrieving semantically annotated learning materials. These Chapters indicate that there are still limitations to existing research in the field. Of interest within this Chapter is the need to continue the investigation of the application of pedagogical models to support the personalisation process.

### ***4.1 Findings Brought Forward From Literature Review***

In this section, the author provides support for the framework presented in 4.3 providing the linkage between current research issues and the research of the author. In designing and developing a framework for personalised learning there are many issues in all of the three areas (4.1.1 semantic knowledge representation, 4.1.2 learner profiling and 4.1.3 matching) that have been identified from the previous chapters.

#### **4.1.1 Semantic Knowledge Representation**

The literature review from Chapter 3 indicates that semantic knowledge based searches must be used when designing a framework for personalisation, this presents a challenge from perspectives such as:

- How do we mark up the data? Which standard(s) do we use?
- Who marks up the data? Will they mark up the data? Can we trust their mark-up?
- Can we automatically generate meta-data for learning resources? If we can, then how accurate is the meta-data?
- What do we do with all the non-semantic data?
- Are there performance issues involved in searching semantic learning materials or does semantic data availability improve search and retrieval performance?

There continues to be a great amount of work (e.g. Soto et al., 2005; Andrews et al., 2009; Jeremic et al., 2009; Zhuhadar et al., 2009, Reynolds et al., 2010, Brut et al., 2011 etc...) focused on semantic representation of learning materials suggesting that this is still a large and complex issue.

### **4.1.2 Learner Profiling**

Profiling the individual is a significant challenge. At this present moment in time as detailed in the previous chapter, different approaches to profiling individuals and combinations of approaches are still being evaluated. Again, there are many challenges to this aspect, for example:

- Which profiling mechanisms work? Do they scale? Are they applicable across cultures and nationalities?
- What else do we need to consider in relation to profile?
- Do profiles change over time and how can we build this flexibility into a tool?
- Can profiles be used in personalising learning experiences?

### **4.1.3 Matching**

Finally, we have the complex problem of matching profiles to the semantic knowledge base whatever the basis of the profile, or the nature of the data. There are usability issues inherent with some of the more complex matching mechanisms; however, if the interface is simplified we can improve the nature of the online learning experience for users. Very few of the current matching mechanisms make use of social structures and social rating systems coupled with learner profiles and semantic learning object retrieval. The author suggests group based mechanisms which enable learners to use and develop collaborative intelligent community learning structures, can make a difference in better enabling learner selection of learning resources (Ghali et al., 2009; Safran et al., 2007; and Ullrich et al., 2008). In addition, this kind of solution may help to improve the issue identified by (Hull et al., 2006) in meeting learner needs more effectively in searching. Such group based mechanisms and support for the development of collaborative intelligence are presently absent from many personalisation frameworks such as those defined by Gutierrez et al., (2004), Hummel et al., (2007), Wang (2008), Ghali et al., (2009), and Hamburg et al.,

(2008).

This Thesis will build upon the framework presented by Eze et al., (2007) for the following reasons:

- Eze et al.'s framework was developed within the University of Hull therefore there continues to be support for its further development.
- The research carried out by Eze et al., (2007) led to the practical development of a tool to semantically annotate multimedia resources but did not lead to the full development of a system to support the theoretical model. Therefore at this moment in time there has been no evaluation of the model in practice.
- This work expands upon the originally defined framework and integrates aspects of collective and collaborative intelligence to support the personalisation process. This is implemented through an Adaptive Information Retrieval (AIR) feature, see Chapter 5 PAFS.
- The work of Eze et al. represented progress towards support for the development of a personalised learning environment, which was relevant to the focus of the Thesis at the outset of the research.

In addition to building on the Eze et al., (2007) framework, the work within this Thesis also considers the impact of issues presented by: Knight et al., (1994), Chaudri et al., (1998), Yao et al., (2007), Mencke (2007), and Alevizou et al., (2010) as presented in Chapter's Two and Three. This includes issues related to the use of collaborative community based learning; however, the community concept within this Thesis will be used to develop collective intelligence relevant to individual learning resources for different classifications of learners.

The following Section 4.2 provides support for the development of a pedagogical model to support the personalisation process. Following this, in Section 4.3, a framework for developing a personalised learning solution is presented. In the final section, limitations of the framework are proposed prior to its development and testing.

## ***4.2 A Pedagogical Approach***

Chapter 2 focused on outlining learning theories, because learners should be matched to learning materials based on their approaches to learning. This is supported through Smith's (2000) suggestion that the individual learning experience can be categorised into

pedagogical approaches to aid individual needs. Smith et al., (1998) also suggests that using pedagogical approaches like learning styles and learning theories enables the student to learn effectively and efficiently. Power et al., (2005), Santos et al., (2003) and Cristea (2005) suggest that by applying pedagogical learning approaches to learning environments can provide an opportunity to better match the students needs to learning techniques and theories designed around the learner. According to Smith (2000), learner-centric approaches provide enhancements and personalisation to learning, which support a multitude of individual learning needs. Pedagogical learning approaches are associated with learning strategies, theories, traditional teaching methods, and what educational researchers indicate are the best possible ways for students to learn within a personalised learning environment.

Researchers Carthey (1993), Calder (2002), and White (2004) indicate that by using direct correspondence to the learning experience via the usage of learning styles and theories, it is possible to aid the individual within the generic learning situation. One particular e-learning environment that uses learning styles is that of Adaptive Educational Hypermedia (AEH) systems. According to Cristea (2004) the Adaptive Educational Hypermedia system was created by Brusilovsky (2001) to cater for the needs of each individual student by adapting to their learning styles. According to Kalaydjiev et al., (2002) and also a recent study carried out by Brown et al., (2007) regarding AEH environments they had noticed that personalisation could not always be possible due to many variables regarding learning styles, learning materials in general, course development, and finally the choice of test subjects. Brown et al., (2007) suggests that clarification of the learning style must be freely available to make sure that the correct tests can be re-evaluated at a later time.

Another personalised e-learning model that was considered with the idea of adapting to individual needs was the LAOS model, which according to Cristea et al., (2003) was designed to incorporate and to facilitate the needs of: flexibility, expressivity, reusability, non-redundancy, co-operation, inter-operability, and finally standardisation. According to Cristea et al., (2003) incorporating the different categories within an on-line learning environment can provide feedback patterns, which will lead to the enrichment of learning materials, in accordance with the adaptability of and pedagogical differences between course materials. The main concept of LAOS is to define either: stereotypes, or groups of users within an on-line environment. However, according to Muntean et al., (2007) the

new QoE-LAOS e-learning environment, was developed to overcome issues of performance-aware adaptation, that were found within the first model. As indicated by Muntean et al.,

*“The QoE extension to LAOS allows for the description of performance-related content features, definition of delivery and display environment characteristics, and performance-based content adaptation rules”* (Muntean et al., 2007).

According to Muntean et al., (2007) the extension to LAOS still has some issues belonging to adaptation of course-content, in terms of what to deliver dependant on behavioural traits of the individual whether it is static or multimedia learning materials. Another e-learning framework that uses learning styles is that of the work produced by Melia et al., (2009) which uses adaptive courseware to move away from the traditional standard of one size - fits all, and instead looks to personalisation through the use of adapting courseware to suit a variety of individual needs by using: knowledge of a subject, and learning style. It provides this functionality through a courseware validation approach which builds on the approaches suggested in AEH and LAOS. The CAVIAR system presented by (Melia et al., 2009) provides the course-creator with the chance to use any learning styles that they feel fits the individual, through the use of learner stereotypes in terms of goals and presumed knowledge. According to Melia et al., (2009) this allows the course creator to define learner groupings in terms of their learning goals and assumed initial knowledge prior to starting the course-ware. However, the design approach by Melia et al., 2009, within the CAVIAR system would have provided the author with the following limitations:

- CAVIAR focuses primarily on courseware construction, providing a model to validate courseware requirements against elements such as *“the incorrect sequencing of learning resources, an instructional design being applied incorrectly, or an inconsistency in the adaptive course-ware structure”* (Melia et al., 2009). This focuses on material prior to delivery.
- The complexity issues associated with mark-up metadata belonging to on-line objects to fit the variety of different learning styles. CAVIAR can aid pre-delivery in resolving incorrect matching.

Researchers like Carthey (1993), Calder (2002), Cristea et al., (2003), White (2004),

Muntean et al., (2007), Melia et al., (2009), and Chen et al., (2010) have all tried to solve a variety of adaptive and personalised e-learning issues, by incorporating different techniques like: stereotyping, grouping, goal orientation, pedagogical approaches, and knowledge acquisition. One particular approach of interest to this Thesis was that of Eze et al., (2007), which matches course context to the individual, through the use of pedagogy. Eze's in 2007 introduced the idea of using learner profiles, semantics, and a matching ontology to assist with information retrieval. Research from Zouaq et al., (2007) supported the use of the idea of using pedagogical approaches like (Brusilovsky 2001; Kalaydjiev et al., 2002; Cristea et al., 2003\*; Brown et al., 2007; Muntean et al., 2007; and Eze et al., 2007) especially for the design of learning materials. Khan et al., in 2007 introduced the CAPEODL model that used pedagogical approaches to assist the individuals on-line through the use of learning styles. The pedagogical approaches taken by Khan et al., (2007) and Eze et al., (2007), was reinforced by (Coffield, 2004; Calder 2002; Miller 2004; Atherton 2005) who all indicated that if you used learning styles would ensure a better given set of resources specific to a particular learning style. It was important to this Thesis to use pedagogical approaches to ensure that learners were placed first, within the educational life cycle, and thus enabling the research from Eze et al., (2007), Zouaq et al., (2007), Khan et al., (2007), Brown et al., (2007), and Muntean et al., (2007) to fit into place. The supportive claims by (Coffield, 2004; Calder 2002; Miller 2004; Atherton 2005) ensured that the use of pedagogy within education and particularly that of learning styles can benefit the learner were established.

The use of: stereotyping, CF, collective intelligence, terms of goals and presumed knowledge could have been used as indicated by (Cristea et al., 2003; Cristea 2004; Brusilovsky 2001; Melia et al., 2009), however, this would not have resulted in a substantial contribution to literature. The recommendations made within this Thesis, would still fit in to the ideas of Melia et al., (2009) about trying to rid the world of a one size fits all approach to teaching. According to Miller (2004), there is no such thing as a 'wrong' way to introduce pedagogical learning theories to groups of learners.

#### **4.2.1 The Pedagogical Model**

The pedagogical model presented within Figure 3 is directly derived from research literature, which can be found within Chapter 2 and Chapter 4. Riding et al., (1997)

suggest that by amalgamating several learning styles we can support performance by providing a way for multiple variations of learning activity to be written. The research conducted by Lowe et al., (1994) identified consistencies between two different learning style models for example, the reflective observation stage from Kolb can be linked to reflective learning category from Honey and Mumford can be used within on-line learning.

Papanikolaou et al., (2001) indicated that they used the extended version of Honey and Mumford learning model within their INSPIRE model to enable them to probe the general behavioural tendencies of learners while studying on-line. This approach belonging to Papanikolaou et al., (2001) was also used by Stash et al., (2004); however, within their model they do not offer learners the opportunity to conduct the Learning Style Questionnaires (LPQ`s) online, whereas the personalised environment presented within this Thesis does.

In addition to the variation of the pedagogical model being used by Stash et al., (2004) the approach here within this Thesis does focus directly on asking each individual learner how they prefer to learn to assist with profiling and matching, which can be found within Chapter 5, Section PAFS. Schippers et al., (2005) pedagogical approach solely focused on two critical aspects, which were to use 'reflecting on experience' belonging to the Honey and Mumford learning model to investigate team reflective activities. Studying the differences between the pedagogical approaches taken by Papanikolaou et al., (2001), Stash et al., (2004) and Schippers et al., (2005), the authors pedagogical approach has an extra dimension, 'activities', which is focused on the development of activities matched to different learning models enabling course materials to be descriptively marked-up in multiple learning styles.

The pedagogical model used within this Thesis will build upon the work carried out by: Schippers et al., (2005) in using more than one particular aspect of a learning model i.e. both the Honey & Mumford and Kolb learning models will be used to assist in individual and group categorisation; Papanikolaou et al.,' (2001) and Stash et al.,' (2004) work will be expanded to incorporate aspects of asking how the individual prefers to learn, and also what general learning behavioural traits can be identified from the individuals.

The pedagogical model presented in Figure 3 works by bridging between the theoretical aspects of learning (from abstract conceptualisation) to the practical application of knowledge (to concrete experience). The gap is bridged through gaining a detailed



understanding of the learner from an amalgamation of two learning style models and using those learning style models to facilitate the search for matched activities, thus personalising the pedagogical model to the learner. In short, the model presented in Figure 3 contains three key concepts, a learning cycle (from conceptualisation through to concrete experience), learning activities and an amalgamated learning style model. These three concepts are further described in Sections 4.2.2, 4.2.3 and 4.2.4.

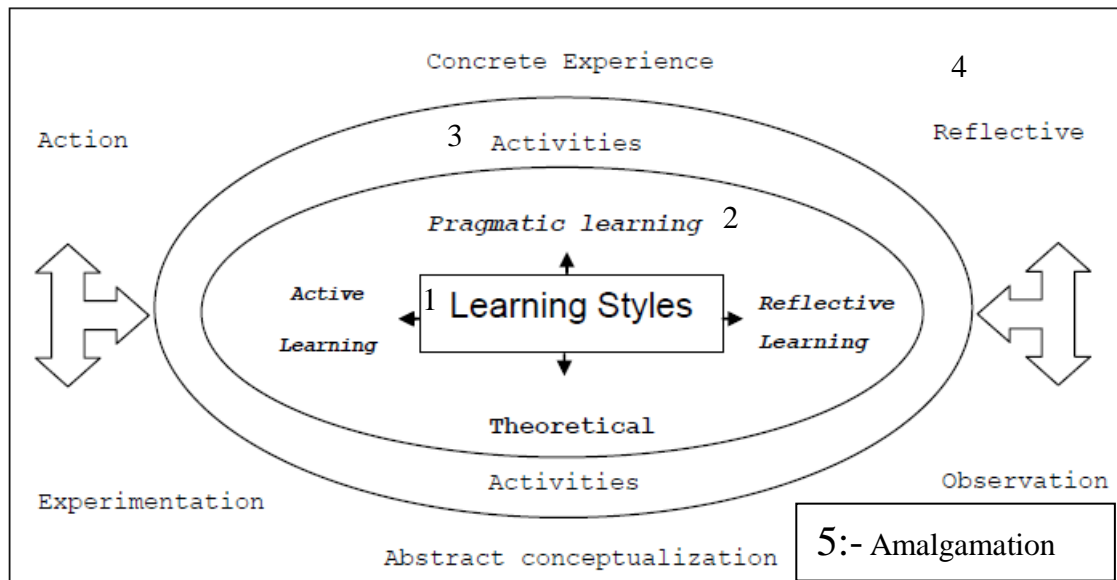


Figure 3: Pedagogical Model (Original)

The Pedagogical Model, illustrated within Figure 3, is divided into 5 categories, these are:

- 1) As defined in section 2.1.4, Learning Styles (LS) are used by academics to help identify how a particular individual might learn. Identifying how an individual learns enables academics to adjust course materials tailored towards their needs. This approach enables the individuals to react differently within the learning process, by creating interesting exercises that challenges and supports particular learning style/s (Castillo et al., 2004; and Moenikia et al., 2010). According to Stash et al., (2004), Schippers et al., (2005), Manochehr (2006), Brown et al., (2006), Chapman 2009, and Moenikia et al., (2010) LS's have been effectively used within e-learning to identify and support individuals through their learning process. This wealth of literature has shown that by incorporating LS's into e-learning environment can provide: customisation of learning materials (Costello et al., 2009\*); tailored learning paths (Gutierrez et al., 2004); and adaptation (Costello et al., 2009; Stash et al., 2004);

- 2) The first learning style being used within the Pedagogical Model is that of, Honey & Mumford. The Honey & Mumford learning style model enables the academic to identify and highlight an individual's learning characteristics and preferences (Honey & Mumford 2006; and Schippers et al., 2005). Once this information has been extracted the tutor can adjust his/her learning materials to equip the student with learning opportunities which match the way they prefer to learn (Honey & Mumford 2006).

The Honey & Mumford LS model has been extensively used throughout e-learning (Stash et al., 2004; Chapman 2009), and according to Šimonova et al., (2011) it can result in a wealth of diverse learning material being developed or collected together to ensure a more tailored individual experience.

According to researchers like Kabassi et al., (2004), Dixon (2007), and Juhary (2005) it would be difficult to design course content and structure to facilitate student's needs without incorporating activities. In order to deliver course content, activities are developed and weaved into the initial design of the curriculum; this provides academic(s) with an opportunity to create materials that are learner centric (Decker et al., 2000; Lu et al., 2004 and Sure et al., 2005).

- 3) The Second learning style to be used within the Pedagogical Model is that of Kolb's. Kolb's Model enables academics to identify how an individual might perceive and process new information including course materials such as exercises or video tutorials. According to Kolb (1985) identifying the individual learning style enables the lecturer to have a greater understanding of how a learner will behave towards the learning process. Kolb et al., (1999) suggests that by using this particular approach, it will help to define a flexible learning experience at a more comprehensible level that encourages guidance, support, and facilities to aid learners.

Kindley, (2002) and Beard et al., (2007) suggests that by applying experiential learning theory to on-line learning environments can enable the domain expert to build tailored specific exercises and tasks to suit the needs of the individual within the learning process. This approach enables the AIPL model to identify and adapt

the learning content to suit the needs of the individuals, while they are studying on-line.

- 4) According to Riding et al., (1997), Schippers et al., (2005), and Phan (2006), amalgamating learning styles within the education process enables the academic to identify a variety of learning behaviours and traits belonging to the individual, enabling the learning resources created or collected to be more supportive of their needs, thus helping to improve their engagement and enjoyment with the exercise(s). Enabling the amalgamation of the learning styles together, will enable the model to adjust to a variety of student needs within the categorisation process. This approach will enable learning materials to be tailored across a wider spectrum of learning needs (linking sound to text based instruction; incorporating videos to enable students to reflect upon tasks).
- 5) As indicated by Lowe et al., (1994); Stash et al., (2004), Castillo et al., (2004) and Cassidy 2004; Castillo et al., 2004; Schippers et al., 2005; Phan 2006; Manochehr 2006; and Moenikia et al., 2010) the use of multiple learning styles is to identify and design learning materials in accordance with: individual learning preferences; interaction with the learning materials; and how the individual perceives the learning content. This approach enables a tailored learning approach for students who need different learning materials to stimulate them.

#### **4.2.2 An amalgamated learning style model**

The review of existing systems found within 3.5.1 Approaches to matching shows that by providing a way for the individual to select learning resources has assisted with improving the learning experience. In many cases adaptation to learning styles has taken a singular learning model approach by providing learner's with different presentations of learning activities linked to appropriate learning style classifications.

According to Stash et al., (2004), Castillo et al., (2004) and Moenikia et al., (2010), by providing the learner with the ability to select a variety of learning styles customised to their own learning traits, we can provide a more holistic approach, thus enabling the learners to use a multitude of learning activities based on one or two different learning

styles to better facilitate the learning process. However, Stash et al., (2004) suggests from their research, learners do not know their own learning style and it can be difficult for them to select the right one. Manochehr (2006) and Moenikia et al., (2010) agree with Stash et al., (2004) about how some learners don't know their own learning styles, and it is important for the domain expert to facilitate student understanding of applicable learning styles. According to Manochehr (2006) and Stash et al., (2004) it is important to create flexibility within the on-line environment. It is important that the domain expert is aware of how the learner obtains his or her skills and how they will use them to access learning materials to assist with their progress. Riding et al., (1997), Stash et al., (2004), Schippers et al., (2005), Manochehr (2006) and Moenikia et al., (2010) suggest that to overcome issues mentioned it is easier for the domain expert to select a variety of learning styles, which the individual can use while studying on-line. According to Riding et al., (1997) through using a singular learning style within a learning environment we can either provide a negative/positive learning experience in accordance to the design relating directly to the learning activities. However, Riding et al., (1997) suggest that by amalgamating several learning styles we can support performance by providing a way for multiple variations of learning activity to be generated, modified, or appropriated, thus enabling the students ability to interpret materials in accordance to how they learn as an individual.

Stash et al., (2004) indicates that using a multitude / amalgamation of learning styles within a learning environment enables the learner to inspect the current learning style model and change it according to the student's perception. According to Stash et al., (2004), the following learning styles were used to create an amalgamation within the AHA & MOT learning environments: Honey & Mumford's learning model and Holist vs. Serialist style (cognitive learning theories).

However, other researchers like Schippers et al., (2005), have provided evidence to support different multi-dimensional use of learning styles within the learning environment by using the Kolb learning model and the Honey & Mumford learning model. Schippers et al., (2005), provides a close examination into the Kolb and Honey & Mumford learning models, and indicates that certain aspects of the two learning styles can be closely mapped together. According to Riding et al., (1997) and Phan (2006), by amalgamating learning styles we can improve academic performance through the adaptation of learning materials. The study that Schippers et al., 2005, conducted solely focused on two critical aspects,

which were reflective observation from Kolb's (1985) learning model, and the reflective learning styles from Honey and Mumford (1995)' s learning model.

Research conducted by Lowe et al., (1994) identified a consistency between the reflective observation from Kolb and reflective learning that Honey and Mumford uses. Lowe et al., (1994) suggested that learners, who were placed within the concrete experience category within the Kolb 1984 learning model, were less likely to be an educational match for reflective learning by Honey and Mumford. Further research indicated that active experimentation from Kolb's learning model bears a close resemblance to Honey and Mumford' s active learners. However, their research did indicate that Honey and Mumford' s learning styles (reflective, active and analytical) bare a close relationship to reflective observation from the Kolb 1984 learning style model. According to Cassidy (2004), the Honey and Mumford's learning model has close similarity with Kolb's experiential learning model. The similarities refer to the descriptive nature of the Learning style questionnaires and the measurements that are used to identify the learners.

The model presented in Figure 3 outlines an amalgamation of two learning style models, that of Honey and Mumford (Honey et al., 2006) and that of Kolb (Kolb et al., 2004; Chapman 2009)., these have been used within this Thesis to provide a pedagogical learning layer for the Adaptive Intelligent Personalised Learning model. This particular approach was used because of the recommendation from literature (Lowe et al., 1994; Cassidy 2004; Castillo et al., 2004; Schippers et al., 2005; Phan 2006; Manochehr 2006; and Moenikia et al., 2010) about the use of multiple learning styles to provide a way for the domain expert to design learning materials in accordance with: individual learning preferences; interaction with the learning materials; and how the individual perceives the learning content. Manochehr (2006) believes that the use of learning styles within on-line learning provides the individual with a good predictor on how he/she might prefer to learn. Moenikia et al., (2010) indicates that the domain expert can help and assist individuals by designing learning materials in accordance to learning preference, which leads to improved learning.

*“Therefore, it is better to make the content of electronic learning include activities appropriate for various learning styles so that learners can choose suitable activities based on their preferred style” (Moenikia et al., 2010)*

The Honey & Mumford learning style approach has been applied either partially or completely to a variety of e-learning environments like those of: AHA & MOT (Cristea et al., 2003); INtelligent System for Personalized Instruction in a Remote Environment (INSPIRE), (Keenoy et al., 2004), which provided literature with successful evidence. However, according to Brown et al., (2006) other alternative approaches have been used within e-learning like the AES-CS by Triantafillou et al., (2002) that uses cognitive styles; or that of ILASH by Bajraktarevic et al., (2003), which used summarising and questioning to match learning materials to individuals. Another e-learning system that does not focus on the Honey & Mumford learning style approach is that of iWeaver, which used kinaesthetic styles to associate the individual with learning materials and finally CS-383 Carver et al., (1999) that uses reflective styles to adapt the individual to the learning context.

Researchers like Triantafillou et al., (2002), Cristea et al., (2003), Bajraktarevic et al., (2003), Brown et al., (2006), Phan 2006, and Moenikia et al., (2010) have all used learning styles before within literature. These approaches have enabled e-learning platforms to create and adjust their own settings to accommodate a students preferred learning traits. However, these approaches have previously been based on the use and integration of a single learning style. The problem with the integration of a singular learning style is that this only provides one set of data for an individual and this data may not provide a completely clear picture as to what learning resources may be most suitable for the learner. The solution demonstrated in this Thesis focuses on the bringing together of multiple learning styles in order to create greater clarity over an individuals preferred learning processes. Literature surrounding these learning styles has identified that ‘Honey & Mumford’ & Kolb’s could be blended together. Blending these two learning styles together helps to enable four things:

Dealing with the ‘Concept Drift’ see Chapter 5, Section 5.2.3.2 for an explanation;

Providing an environment that is capable of not just adapting to one learning style but blending them together to create an environment that would support group-based-learning, for more information on group-based-learning, please see 4.3.1 Discussion of models used within AIPL.

Creating an environment that is more tailored and personalised towards the individuals, through supporting the community within sharing ratings, and personal views.

Retrieving academic materials that are directly relevant to the individual, instead of shifting through exercises that were tailored to support their preferred learning traits.

This section has covered the use and integration of learning models in systems designed to personalise and adapt courseware delivery for individual users. Building on the recommendation of researchers' like (Stern et al., 1999; Magoulas 2003; Stash et al., 2004; and Schippers et al., 2005) it is recognised that models such as those provided by Honey & Mumford (Honey et al., 2006) or Kolb (Kolb et al., 2004; Chapman 2009) can be used to assist with building more personalised learning solutions. The amalgamated learning style model presented in Section 4.2.1 should improve the flexibility of pedagogical approaches being used within on-line learning. The next section will look at how important it is to create a balance between learning activities and different learning theories.

### **4.2.3 Learning Activities**

Learning activities play an important part in creating a grounded theoretical approach that brings together different learning theories within the pedagogical model. Learning activities are used to provide educational materials that facilitate not just the curriculum but how the learner might be stimulated within an educational experience. Learning activities play an important role within the AIPL model in providing the learner with the necessary requirements for the completion of the programme.

The AIPL model presented within this Thesis should make it possible to map contextual learning materials to the personal learning strategy of the individuals' needs and requirements. The model is aimed at reducing mismatching between individuals/groups and the learning materials. This is achieved by gathering knowledge about individuals in a knowledge based system and using filtering techniques to reduce the number of learning activities retrieved that are not suited to the learner' s specification. According to Biggs (2003) learning activities must provide the learners with the opportunity to use a multitude of skills to ensure that they achieve appropriate learning outcomes associated to the learning that they are involved in. Applying learning activities to the AIPL environment in accordance with Biggs will support the learner, by providing materials, resources and strategies to evidence how learning has taken place.

According to O' Brien (1981) when applying learning activities to an educational environment, they are used as a process to facilitate the learning process. In relation to AIPL, students will be presented with a number of learning activities related to single tasks giving the learner more direct control over their own learning experience.

The AIPL model will use social collaboration and collaborative annotation mechanisms (for more information see Chapter 5) associated with learning activities, to link directly into the pedagogical model and provide a way for the retrieval and recommendation of specific learning activities.

#### **4.2.4 The Learning Cycle**

The cycle incorporated into the model is based on the concept of experiential learning moving from conceptualisation through to gaining concrete experience of a learning task or vice versa. According to Atherton (2005), the concept of experiential learning explores the learning cycle pattern of the learner by incorporating: experience, reflection, conceptualisation and action. It is recognised that a learner may choose to only develop concrete experience without obtaining any element of abstract conceptualisation and vice versa. However, the process should be supported for a learner to move through learning activities from conceptualisation, through to experience, or from experience through to conceptualisation.

In the model, the cycle is important in recognising that there is often space between gaining a practical understanding of a problem and gaining knowledge of the underlying concepts. It suggests that learning activities need to be developed to support all elements of the continuum, in whichever direction the learner decides to go. It also suggests that a match can be made between learner profiles based on the amalgamation of learning styles, and activities to support knowledge acquisition again across the continuum. In a clearer explanation, this suggests that whilst a learner may prefer to learn through practical activity (as identified by their learning style), this practical activity can be designed to either aid in: learning the conceptual knowledge; obtaining concrete experience; or in gaining other elements across the continuum.



### ***4.3 Adaptive Intelligent Personalised Learning (AIPL)***

Taking the above sections into account, the related research detailed in Chapters 2 & 3, and the focus of this Thesis, the author set about designing a model for the intelligent adaptation of a VLE to learner requirements (personalisation). To enable the whole implementation of the AIPL environment the following aspects were required:

- Pedagogical approaches: Dabbagh (2005) indicates that individual learning emphasizes on the systematic interaction between pedagogical theories and learning technologies (McLoughlin et al., 2002) (see Section 2.1.8).
- Educational learning materials standards: According to (Decker et al., 2000; Lu et al., 2004 and Sure et al., 2005) learning materials standards can provide for interoperability and bridge between repositories for information sharing, search, and retrieval (see Section 3.3.5).
- Profiling and categorising the individual: Hummel et al., (2003) and Boticario et al., (2006) indicate that by profiling the individual we can influence the learning process, enabling the environment to understand how the individual can learn most effectively (see Section 3.4.1).
- Matching: Understanding individuals needs can result in clearer identification of resources which match those needs from the resources available to the learner (Bunderson et al., 2000; Souto et al., 2002; Luckin 2008). This matching process can play a significant part in the personalisation of learning experiences to learners.
- Grouping: Profiling the individuals according to Hummel et al. (2003), Zahedi (2003), Sinha et al., (2004), Tzouveli et al. (2005) and Subramaniam (2006) provides the e-learning environment with a way of grouping students with the same learning traits and habits together, to assist within the learning cycle and in the recommendation of learning materials (see Section 3.4.2).

In addition to the above, two other important factors require consideration: educational balance and mis-matching.

- Educational Balance: According to Stash et al., (2006); Svensson et al., (2007); and De Meo et al., (2007), research communities are trying to create educational balance on-line by building systems around the learner (the development of learner-

centric learning environments) to enable a more specific learning experience (see Sections 3.4 to 3.4.2).

- Mis-matching: King et al., (2005); White et al., (2006); Stash et al., (2006) suggest that often mis-matching can occur between learners and delivered educational resources. This can be as a result of elements such as: limitations with regards to profile construction; poorly designed learning resources; lack of consideration of a range of learning styles; limitations with regards to learner devices and instructional tools; and inappropriate delivery of resources to match learner needs (see Section 2.1.9).

The next section of this Thesis focuses on a discussion of the underlying influences (other learner personalisation models) relating to the development of the AIPL model.

#### **4.3.1 Discussion of models used within AIPL**

This particular section critically examines several relevant e-learning models, to provide support for the creation of the AIPL model (see Section 4.3.2). Each model, within this section will be discussed and explained with regards to how it has influenced the AIPL model. There are several important models (Community of Inquiry; Simplified representation for the ELearning EcoSystem (ELES); and the Reference model for mobile social software for learning) aimed at providing personalisation by incorporating aspects of community knowledge capture and collective intelligence. These models focus on: describing the individual; monitoring behaviour/relationship/interaction or extracting information belonging to the individual before fitting them into a community or group. These models extract and derive information based upon a learner's personal preferences, which are then used to control the flow between users and other entities within a social group-learning-paradigm.

The Community of Inquiry (COI) model according to Anderson (2005) facilitates the capture of learner experiences and uses these learner experiences to guide other learners in their selection of learning resources. The model encourages individuals using the system to construct personal meaning around individual learning resources and present their thoughts about resources to communities of other users. User groups are collected together on the basis of commonalities drawn from an evaluation of personality and emotional traits. However, according to Campbell et al., (2005) this particular model may-not provide

opportunities for some individuals to fit into communities due to how grouping is performed by the model. Campbell et al., (2005) indicates that using personality and emotional traits to form communities could actually cause constraints. Ling (2007) expands further on the limitations of the model and indicates these could arise because of: capability differences of learners; participation opportunities for learners; and language fluency.

The ELES model takes the fundamentals of organic eco-systems and attempts to encapsulate these ideas in a community based learning model. This model sees communities of learners, teachers and learning material developers as existing as part of an organic whole. With each fundamental part (and elements within each part e.g. learner communities) having a role to play in knowledge acquisition, and transfer around the system. As indicated by Chang et al., (2005) in order for the ELES to be successful it is up to each individual or group to find their niche before environmental conditions are met and adapted to. However, the research carried out by Dong et al., (2009) has overcome the issues belonging to Chang et al., (2005) by implementing a new model based on ELES called the Cloud Computer Infrastructure. This new model uses learning styles, learning preferences, and cognitive levels to initialize groups of learners and establish and overcome group discrepancies. According to Dong et al., (2009) the main feature of the Cloud Computer Infrastructure was implemented to efficiently utilise resources within the e-learning ecosystem.

The model presented within this Thesis, the AIPL model, enables grouping to be performed through the use of learning styles, to avoid issues of behaviour and emotional group-learning-paradigms indicated by Campbell et al., (2005), Chang et al., (2005), and Ling (2007). Learners will be placed into a learning-group-paradigm based not on capability, nor that of self-finding, rather, with how that individual likes to learn. As indicated by Dong et al in 2009, with their Cloud Computer Infrastructure, the use of the group-learning-paradigm can assist the individual or community within their learning experience. Shute (2009) agrees with the similar idea of Dong et al. (2009) by indicating that by knowing more about the individual either through the use of: what the student knows, believes, and can do, can improve learning experiences. Even though Shute's (2009) model was directly focused on stealth assessment, it provided the AIPL model with reassurance that taking a personalised approach based on socially constructed grouping can

assist within the learning experience.

As stated in the previous paragraphs the AIPL model has originated from a variety of different e-learning models; however, the Community of Inquiry model by (see Figure 4) has been the main inspiration for AIPL.

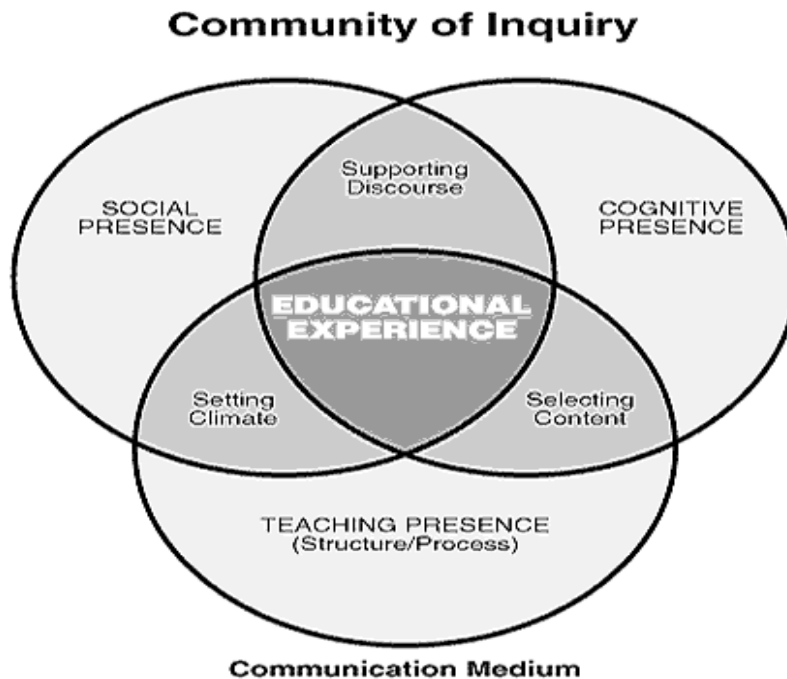


Figure 4: Community of Inquiry Model (Anderson, 2005)

The next section will focus on an explanation of the AIPL model, indicating elements of influence from pre-existing models.

#### 4.3.2 AIPL model

The AIPL Model (see Figure 5) used within this Thesis has been inspired by the Community of Inquiry model by Anderson (2005) and the simplified representation for the e-learning eco-system (ELES) by Chang et al., (2005).

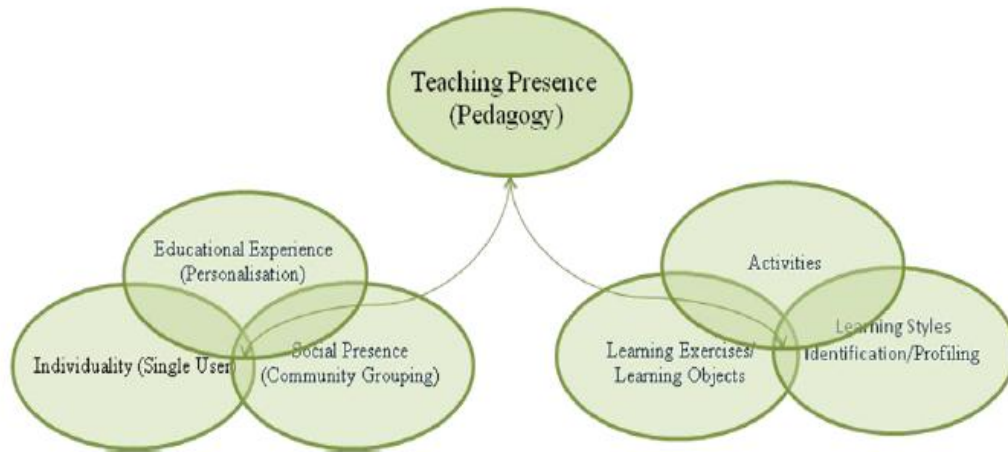


Figure 5: Model of AIPL (Original)

The AIPL model presented within this Thesis can be divided into four main areas:

### **Teaching Presence (Pedagogical Approach)**

*“Teaching Presence is the design, facilitation, and direction of cognitive and social processes for the purpose of realizing personally meaningful and educationally worthwhile learning outcomes”* (Anderson 2005). The AIPL model uses Teaching Presence as a way of designing pedagogical approaches to facilitate the educational experience either from the learner working within a community or individually.

### **Activities**

These are used within the model to provide different views about objects, based on personal preferences (Learning Styles Identification & Profiling). Learning objects can be used to create relations between activities with personal preferences like: activities of their peers; structured learning activities (singular/collaborative); to support learning anything, anywhere, anytime. The relations and activities were used in accordance with the research and recommendations from De Jong et al. (2008), and Shute (2009). Shute (2009) suggests that to optimise the learning experience, you need to engage the learner in an activity that challenges them self-consciously. De Jong et al., (2008) suggest that the use of rich media within learning contexts can improve the experience for the learners. Relations (profiling) and activities (learning exercises) act as a bridge to match individual/groups to learning objects within the repository.

### **Educational Experience, Individuality and Social Presence (Community-grouping)**

According to Garrison et al., (2000) the educational experience belonging to the Community of Inquiry model is used to incorporate teachers and students as centre points within their educational process. This particular aspect belonging to Garrison et al. (2000) will play a central role in the AIPL model because it will allow personalisation to be considered in relation to: learning styles and preferred pedagogical learning approach; learning traits; or behavioural traits.

According to Chang et al., (2005) and De Jong et al., (2008) in their models individuality is used to hold information about user' s traits, properties and common interests. Within AIPL the same concepts belonging to real world and individuality are applied to that of De Jong et al., (2008). According to Garrison et al., (2000) and Anderson (2005) social presence is used to aid the ability of learners to project themselves through the use of commitment and participation to achieve a further development of higher-order thinking skills and collaborative work.

The next section will focus on the system design of the AIPL model, in which further explanation of the model and its application will be discussed (see Sections 4.3.2 to 4.3.4). A system design representation of the AIPL environment can be found in Figure 6.

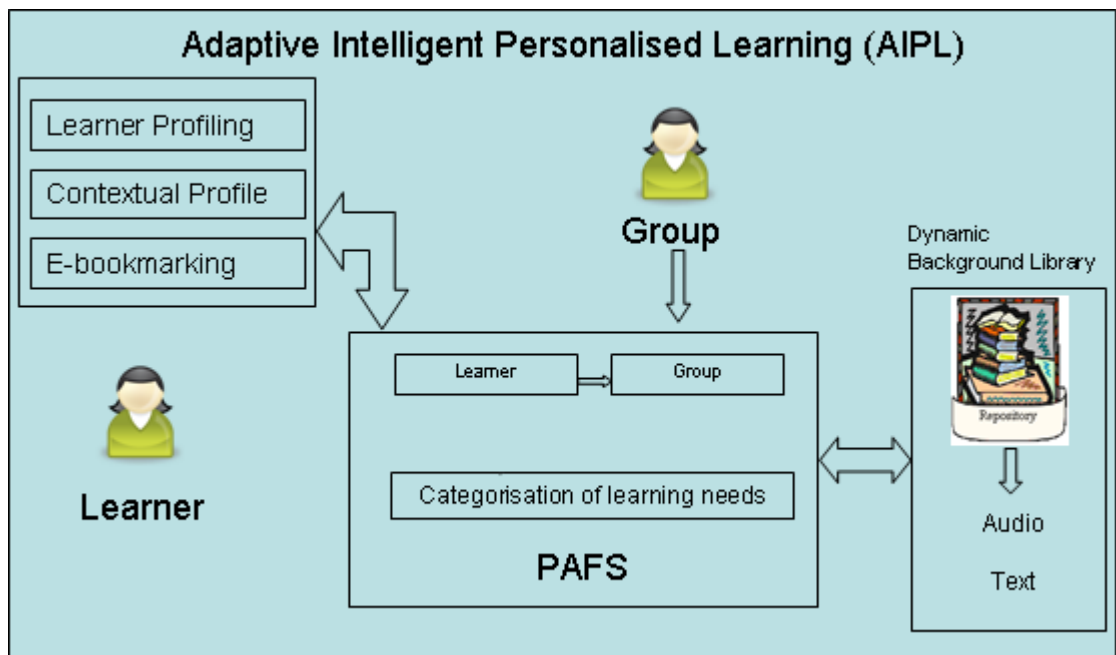


Figure 6: System Design of AIPL (Original)

For clarity, Section 4.2 the Pedagogical Model was required to provide a foundation layer for the AIPL model to be built upon.

#### Discussion about group-learning-paradigm as applied in AIPL

Looking at the group-learning-paradigm (Group) that is found within AIPL this can be compared to the work of (Spector et al., 2003). Spector et al., (2003) suggests that early instructional models encapsulating the group-learning-paradigm were used to support functions such as the annotation of learning materials and representations of knowledge (e.g. concept mapping). These particular features enabled researchers to design the following frameworks - Generic Tutoring Environment (GTE), Modelisation par Objects Types (MOT), and eXperimental Advanced Instructional Design Associate (XAIDA). These early systems were used to create relationships by determining how and when to provide the combination of materials to the learners within a sequenced approach to the topic area.

Students learn better through the group-learning-paradigm when they are categorised into similar learning traits or preferences (Spector et al., 2003 & Benbunan-Fich et al., 2006). Benbunan-Fich et al., (2006) indicate that the use of the group-learning-paradigm within on-line learning environments enable learner's to discover what needs to be learned by interacting with course content. However, according to Benbunan-Fich et al., (2006) some

researchers believe that this approach is more effective than the traditional instruction-based programmes. Benbunan-Fich et al., (2006) recommends the use of group categorisation processes to share resources; and finds that explaining to others clarifies one's own understanding.

Cristea et al., (2010) uses the group-learning-paradigm within the Social Layers of Adaptation and their Operators (SLAOS) Framework. According to Cristea et al., (2010) the use of the group-learning-paradigm enables resources to be represented through metadata, which can be categorised by: ratings, feedback, etc. The rating and feedback mechanism within the SLAOS framework enables users to use CF by calculating and working out the average rating belonging to the learning materials.

*“A specific advantage in e-learning 2.0 is the fact that the collective knowledge of other users can be exploited: the user is not a singular entity anymore, and other users can help him (or her)”* (Cristea et al., 2010).

The SLAOS Framework can be used within three particular areas, these are: (1) working on a project of the same topic; (2) finding peer-reviews based on what other learners have used; (3) suggesting specific items for the learner to read within a specific learning context.

The group-learning-paradigm found within this Thesis, builds upon the work carried out by Spector et al., (2003), Benbunan-Fich et al., (2006), and finally by Cristea et al., (2010), through:

- grouping learners with common learning style themes;
- matching learning materials to or across these themes
- collecting community rating data related to individual learning materials (in the context of learning style themes);
- and using peer-reviews belonging to learning objects to assist with retrieval (in the context of learning style themes).

### **Description of the AIPL model**

The system design of AIPL can be categorised into three sections:



- 1) The Learner Profile including individual learner profile, contextual profile, and E-bookmarking
- 2) The Personalised Adaptive Filtering System (PAFS)
- 3) A Dynamic Background library

### **4.3.3 The Learner Profile including: the individual learner profile; contextual profile and E-bookmarking**

#### **4.3.3.1 Learner Profile**

We can think of the learner profile in AIPL as an object which represents the requirements of the learner. The object provides input to the adaptive filter to match individuals with learning materials. Looking at the research detailed in Chapter 3 Learner Profiles have been applied and adapted to suit many different educational needs, for example, in the reduction of information overload. There are many different approaches to the generation of a learner profile focusing on a range of different values, everything from personality traits of the user, through academic profile, to learning styles. Learner profiling in the context of this Thesis will be specifically focused on representing the user preferences on how they prefer to learn through the aid of an amalgamation of learning styles, please see Section 4.2.1 The Pedagogical Model.

The Learner Profile that is used within this Thesis will enable the learning process cycle to compensate for the personalised learning trait of the learner in question. The Learner Profile focuses on specific indicators of approaches students have to learning, which are retrieved by using learning styles within a pedagogical learning framework (for more information see Section 4.2.1 The Pedagogical Model). The Learner Profile with the assistance of a filtering mechanism, see Chapter 5 PAFS, attempts to realistically categorise the student learning style.

The Learner Profile acts as a bridge to extract evidence about the learner through the use of specific evaluation mechanisms, for example, in the case of learning styles through a professional LPQ. In the case above, the questionnaires that are used to identify the individual's learning style can be found in Appendix 1 LPQ. Once the Learner Profile has recorded the results from the questionnaire, the results can be used to facilitate learner

needs and requirements in the learning environment.

Each element of the learner profile is treated separately; a learners profile may be composed of multiple elements, some with conflicting values. The job of the adaptive filtering system is to represent to the learner the impact of their particular approaches to learning (and other learner profile information) on the set of results retrieved, and to recommend appropriate learning materials to match elements of their learner profile. The detailed explanation of how this impacts on CF and recommendation is contained within Chapter 5.

#### **4.3.3.2 Contextual Profile**

The contextual profile used within this Thesis plays an important part within AIPL, because it allows the individual to store raw information about the learning content like: concepts, dates, terminologies, leading researchers, and descriptions. This was based on similar ideas to User Modelling and on the research conducted by (Kobsa et al., 1995; Martin et al., 2008 and Neji 2009) in enabling the contextual profile to take into consideration: user needs and traits.

The contextual profile enables the architecture to interrogate external sources when retrieving specific learning materials (Kabassi et al., 2004; Safran et al., 2006). The profile within AIPL will have similar attributes that Kabassi et al., (2004) and Safran et al., (2006) have indicated including the following: the CP will use raw information about concepts, learning context, and terminologies that are associated with on-line course materials. The data can be stored in numerical or textual form dependent on the item stored.

#### **4.3.3.3 E-Bookmarking**

Social bookmarking is a technique used to offer the individual the opportunity to store, manage, and organise learning resources. Bookmarking provides necessary methods for enabling the individual user to record URLs, which can then be retrieved at any time. According to Hotho et al., (2006), social bookmarking provides the opportunity for people to share and copy resources from other users, and label them with one's own notation. Most

social bookmark services, according to Damianos et al., (2006), encourage the user to organise their bookmarks with informal notation instead of the traditional browser-based system of folders. Social bookmarking enables people to view bookmarks associated with a chosen topic area, and include information about the number of users who have bookmarked them. Koivunen et al., (2001) suggest that social bookmarking enables users to share their thoughts and specific details concerning the web pages.

Traditionally, social bookmarking has been applied to the World Wide Web and the individual user via browsers such as Internet Explorer, Netscape, or Mozilla Firefox. According to Golder et al., (2005) and Damianos et al., (2006), these social bookmarking facilities provide the individual with an information retrieval technique that groups together key features and specifications. However, researchers like Dell (2003), Safran et al., (2007) and Dobrzanski et al., (2007) are applying bookmarking to e-learning to provide facilities to record and store learning materials from the repository. According to Dell (2003), this gives students the opportunity to search for and retrieve learning materials. E-bookmarking will be used in AIPL to store and categories learning materials belonging to an individual/community. This will be discussed in more detail in Chapter 5.

#### **4.3.4 Personalised Adaptive Filtering System (PAFS)**

The Personalised Adaptive Filtering System plays an important central role in AIPL. PAFS responsibility is in matching materials to the learner profile through computational algorithms (Hull et al., 2006; Hummel et al., 2007). PAFS also integrates the concepts of collaborative community learning to enable learners to gain recommendations on learning materials retrieved, which can be related to e-learning 2.0 literature (Hummel et al., 2007; etc.; Chatti et al., 2007; Hamburg et al., 2008; Ullrich et al., 2008; Ghali et al., 2009 and Cristea et al., 2010). PAFS takes the input of the learner profile into its computational algorithms then interrogates the learning repository to find materials that correspond. Once materials have been found they are then displayed to the user. At its most simple PAFS undertakes keyword searches of the repository and brings back learning objects related to the keyword search (Chaudri et al., 1998; Noy et al., 2001; Li et al., 2004). At its most complex PAFS uses the learner profile to filter and sort materials retrieved in accordance with community grouping and rating (Yao et al., 2007; Hummel et al., 2007; Cristea et al., 2010).

## **Discussion about the different types of Information Retrieval that PAFS could use**

The content of any e-learning environment needs e-courses (Jones 2002), and resources (Burgos et al., 2006). Although course materials and resources cannot be changed by the learner, the domain expert can build a variety of learning materials fitting different: learning traits (Spector et al., 2003; Benbunan-Fich et al., 2006); learning styles (Smith's 2000); pedagogical learning approaches and theories (Santos et al., 2003; Power et al., 2005; Cristea 2005).

Within any adaptive or personalised e-learning framework, either if it is traditionally or e-learning 2.0 based, the course content can be adapted to assist the learners by using a variety of techniques (Tang et al., 2005) like: Adaptive Information Retrieval; Adaptive Hypermedia; CF; Community Collaborative Filtering; and the Group-Learning-Paradigm.

### **Adaptive Information Retrieval**

According to Tang et al., (2005) and Burgos et al., (2006) adaptive information retrieval, works by retrieving information that is relevant to the user request. Neji (2009) suggests that current AIR systems do not take into consideration of: evolution of Human behaviour; lack of psychological aspects; and finally emotional aspects that can be stored within the user profile to assist with information retrieval.

Tang et al., (2005) suggests that by using AIR techniques, educational resources can be tagged and rated based upon: relevancy, technicality, and usability. One of the adaptive Information Retrieval techniques that have been adopted within PAFS allows individuals to use keyword searches (Chu et al., 2011) to filter out resources that are held within a dynamic background library. The second feature belonging to PAFS is based upon the recommendation of: (Tang et al., 2005; Burgos et al., 2006; Yao et al., 2007; Neji 2009), which allows the learner/s to give feedback (ratings) towards the learning materials, in which the community could share the recommended choices.

However, in addition to using ratings data belonging to a particular group or community, the AIPL model enables individuals to use external references belonging to the course-

context. In 2002, Brusilovsky et al., introduced a framework called the KnowledgeTree that uses Adaptive Information Retrieval as a way of allowing the learners to search for relevant learning materials based upon learning styles, and their own preferences, while at the same time using Adaptive Hypermedia (AH) to suggest course-content. Voorhees (2008) indicates that a higher ranking reflects the system's idea of which documents are likely to be relevant to the topic. This approach enables the individual to receive the most updated response belonging to a learner's goal. However, Voorhees (2008) does indicate that future trends of AIR could be the use of Adaptive Hypermedia, which will incorporate features of Adaptive Information Retrieval. Casamayor et al., (2009) suggests that as long as learners are placed within the right category or with his or her own group then retrieval and sharing of materials can assist within learning on-line.

### **Adaptive Hypermedia**

According to Tang et al., (2005) Adaptive Hypermedia has been studied extensively within literature. Adaptive Hypermedia Retrieval (AHR) works by examining the contents of learning resources that have been used by the individual, to derive and extract important features belonging to: behaviour; learning traits; interests; knowledge states. Brusilovsky et al., (2002) and Brusilovsky (2002) indicates that the use of Adaptive Hypermedia technologies within on-line learning will provide further adaptation and personalisation for an individual. One particular e-learning framework that uses Adaptive Hypermedia is KnowledgeTree, introduced by Brusilovsky et al., in 2002. KnowledgeTree offers adaptive navigation support like: adaptive annotation, sorting, and direct guidance, which enables individual learners to select the most relevant items within the repository. Graf (2006) indicates that there are variety of frameworks like: The Extended Abstract Categorization Map (E-ACM) (Graf 2006); Personalised Access to Local Information and services for tOurists PALIO system (Zarikas et al., 2001); AAHS; and finally the work of Cristea et al., (2010) and Ghali et al., (2009) with the concepts of (AHA & MOT 2.0), that employs adaptive hypermedia to enable personalisation to reduce information overload.

### **Summary of discussion**

PAFS is designed to incorporate Adaptive Information Retrieval techniques: to encourage guidance and to facilitate the learner through the use of community-based filtering within

educational or academic institutions (Martin et al., 2008; Martin et al., 2008\*; Voorhees 2008; Neji 2009). However, the design concept for PAFS came from a variety of ideas and concepts like: User Modelling; Matching; Filtering; and literature surrounding e-learning 2.0 systems. According to Graf (2006) and Brusilovsky et al., 2008, Adaptive Hypermedia and Adaptive Information Retrieval can be used independently or amalgamated together as long as the individual is placed within the right community or group.

Additional research from (Orwant 1995; Yao et al., 2007; Martin et al., 2008; Voorhees 2008; Brusilovsky et al., 2008; Neji 2009; and Douce et al., 2009) provided theoretical concepts and issues that were applied to the PAFS architecture like CF involving rating, tagging, e-bookmarking, and keyword searching. Tang et al., (2005), Graf (2006), and Brusilovsky et al., (2008), have all identified that the use of Adaptive Information Retrieval can achieve similar results to that of Adaptive Hypermedia environments.

#### **4.3.5 Dynamic Background Library**

The centralized knowledge repository of AIPL uses standard taxonomies to consolidate information into one place allowing knowledge to be searched and retrieved with greater efficiency and accuracy.

The learner has access to teaching materials, peer-reviewed papers (Coman, 2002) and other resources. The learning materials used within the repository of knowledge comply with the LOM standard. This identifies certain key aspects: interoperability, accessibility and reusability of web-based learning content (Hadjivassiliou et al., 2002). Additional e-learning materials are required to assist and help the learner in the rapid growth of knowledge. Using a dynamic repository alongside the existing VLE would support the retrieval of learning objects from outside the course content via the internet. According to Mödritscher et al., (2005) using a Dynamic Background Library can make the learning experience more personalised.

In AIPL, a dynamic library resource is used to facilitate learning on-line by enabling website addresses and ratings to be stored in conjunction with already produced static materials in the repository such as sound, graphics, and videos. PAFS interrogates the Dynamic Background Library for materials relevant to individual users and in this context the

dynamic background library simply acts as a knowledge repository.

#### ***4.4 Challenges of the AIPL Model***

There are a number of challenges which can lead to limitations of the model provided above.

- The knowledge base – it is clear from existing research that providing a semantic knowledge repository which contains consistent and validated learning materials is a difficult task. In relation to this, storage of meta-data linked to learning styles and other learner profile aspects is not automatically built into the SCORM and LOM standards.
- The AIPL model depends on an assumption that learner profiles, however, they are constructed can be used in order to determine learner's pathways and associated learning materials. This assumption whilst backed up by some researchers can be questioned once we start constructing the learner profile in relation to particular learning styles or other elements.
- Finally, linked to the above the learner profile needs to be flexible, in that it has been shown through research that individuals over time develop different learner approaches and indeed learner approaches to tasks may be different dependent on the learning task, for example, we may adopt a mechanism for learning to drive and another mechanism for learning the highway code. So the learner profile has to be adaptable dependent on context.

#### ***4.5 Summary of Chapter***

This Chapter has presented material related to the development of a model to support the personalisation of a learning environment for users. This has involved the development of an amalgamated pedagogical learning model linked to a personalisation model (AIPL). The roots of these two models in academic literature are also described. Following the presentation of these models a system design has been developed and this has also been outlined above.

## **Chapter 5 A Personalised Adaptive Filtering System (PAFS)**

This chapter describes one of the major contributions of this Thesis, PAFS. It does this through initially presenting the motivation for the development of PAFS (Section 5.1). It then moves on to detail the challenges and complexities associated with PAFS (Section 5.2). This is followed by a general overview of the PAFS (Section 5.3), and finally the summary of the chapter (Section 5.4).

### ***5.1 Inspiration***

The majority of the inspiration for PAFS comes directly from research work already detailed in this Thesis. However, this section will indicate the main inspiration behind each of the three functions of PAFS starting with the keyword search facility, moving on to the semantic meta-data contextual search function, and ending with the motivation behind the collaborative categorisation and recommendation function.

As indicated in Chapter 3 there are a number of systems including the Knowledge-Base Machine Translation (KBMT) system, proposed by Knight et al. In 1994, which use simple keyword searches to determine matches between learning materials and learners? Simple keyword search algorithms suffer from performance problems particularly when the size of the learning repository is large. In relation to the standard keyword search function, a number of different algorithms have been evaluated and assessed in relation to how they would work in a PAFS context. These algorithms are detailed in Section 5.3.

The semantic meta-data contextual search function builds on work related to search engine retrieval, and spider bots in relation to filtering materials marked up using LOM or SCORM and semantic meta-data. This approach lies in determining matches between indicated search parameters (from the learning profile and contextual profile) and the marked up content.

Finally, the collaborative categorisation and recommendation function draws on research such as that by (Deeb, 2007, Bajraktarevic et al., 2003, and Becks et al., 2003). Deeb in 2007 communicates ideas about using communities of learners to rate particular learning



materials in order to enable learners to determine the most appropriate learning path. Deeb's ideas focus on evaluations of learning objects derived from whole group responses similar to recommender systems such as that used by eBay. Bajraktarevic et al., (2003) indicates that by using rating, and navigation aids to create a correlation between the learner and the materials, this enables other learners to share knowledge and personal views. The concepts and ideas presented within Bajraktarevic et al., (2003) can be classed as the new generation of e-learning 2.0 like that of (Safran et al., 2007; Chatti et al., 2007; Ullrich et al., 2008; and Ghali et al., 2009). Researchers like Safran et al., (2007), Chatti et al., (2007) and that of Ghali et al., (2009), indicate that by using on-line communities, social grouping or group-learning-paradigms, we can assist the individual learner when retrieving learning materials.

Finally, according to Tzouveli et al., (2005) and Subramaniam (2006), using profiles of groups of learners has enabled environments to adapt to: similar group habits, interests, skills, projects, location and personalised settings. So in relation to this final function the inspiration is in creating a collaborative mechanism for rating and recommending objects based on the grouping of learners linked to elements such as learning styles. So for example, an individual can see recommendations about learning objects from individuals with related learning profiles, rather than just seeing a whole group view which may, or may not be appropriate. The recommendation of learning objects (linked to separate groups of learners) can be achieved using two methods these are: AIR, and AHR (the use of learning paths). According to Tang et al., (2005) and Burgos et al., (2006) adaptive information filtering, works by retrieving information that is only relevant, and categorized to the user request. Ghali et al., (2009) and Cristea et al., (2010) suggests that Adaptive Hypermedia Retrieval using learning paths, works by examining the contents of the page, it derives and extracts important features associated with: behaviour; learning traits; interests; and knowledge state.

These can be used to assist other individuals while retrieving learning materials. For more information concerning Adaptive Information Retrieval and Adaptive Hypermedia, please see Chapter 4, Section 4.3.2 Personalised Adaptive Filtering System 'PAFS'.

Tang et al., (2005) suggest that the use of any of the two techniques, Adaptive Information Retrieval or Adaptive Hypermedia Retrieval can assist the individual/group

when retrieving learning materials based upon a particular learning style, learning traits, or grouping category.

## ***5.2 Design Challenges***

This section details particular design challenges linked to the development of an algorithm (or series of algorithms), PAFS, that can be used to match learner profiles to learning content. The challenges faced relate to the following:

- How do we represent learning styles on-line?
- How can the learner profile be represented and interrogated?
- How can we group? What do groups consist of? How can we make best use of the power of the group?
- Homogenous versus collections of representations
- Dealing with ratings and group lifecycles

### **5.2.1 Representation of Learning Styles in Semantic Data**

Challenges related to semantic representation have been outlined in earlier chapters. Issues such as the lack of semantically marked up resources, different standards used, and issues regarding the keyword association of different authors are clear barriers to the successful implementation of any personalisation system that requires semantic data. Of particular importance to PAFS is the problem of how do we represent learning styles in semantic data.

Stojanovic et al., (2001) indicate that profiles and learning materials can be represented by using semantic metadata; however, the domain expert must fully understand the different metadata schemas, and the vocabulary associated with them before their application. Stojanovic et al., (2001) indicate that there are a variety of web-based technologies that can be used to represent profiles, these are: XML, RDF and WiseOwl, for more information about these different web-based technologies please refer to Chapter 3 (Section 3.1.2 technologies).

Cristea (2004) agrees with (Stojanovic et al., 2001) about applying semantic knowledge representation to learning materials, via the use of XML-based languages. Cristea

(2004) indicates that using semantic technologies provides researchers with tools to represent data via high level representation such as logic, rules, and IF-Then-Else statements.

According to Cristea (2004), semantic knowledge representation must take into account some of the following aspects: flexibility, expressivity, reusability, non-redundancy, cooperation, inter-operability, and standardisation. Applying semantic knowledge for the representation of materials can support and assist a variety of educational resources. Koper et al., (2004) agrees with Cristea (2004), about applying semantic knowledge to learning materials and educational systems by using descriptive elements and attributes, for personalising educational resources. Koper et al., (2004) indicates that xHTML can be used as a tool to represent linkage between learning object and particular learning styles.

Other researchers like Cristea (2004), Dumbill (2000) and Kesteren (2007) all indicate that you can use XML, and xHTML, as a way of representing specific design concepts within learning materials. For example Dumbill (2000) and Kesteren (2007) indicate that within xHTML you can use the class tag as a way of representing additional information belonging to learning materials.

Research has shown that learning objects can be semantically tagged in accordance to different types of learning styles. Researchers like Cristea (2004), Dumbill (2000) and Kesteren (2007) have provided an insight into how to mark-up specific values relating to learning styles identification within learning objects. User Modelling has played an important part in representing the user profile, by accommodating their learning styles; learning preferences; behavioural traits; interests and knowledge. Researchers like (Kobsa et al., 1995; Tasso et al., 1999; Martin et al., 2008; Douce et al., 2009; and Neji 2009) have used User Modelling to represent the individual learning preference. Koper et al., (2004) indicates that Learning Object Models, or databases can hold learning style data about individuals this can then be transformed into a semantic representation which can be compared against learning object data.

### 5.2.1.1 The solutions to representing Learning Styles in Semantic Data

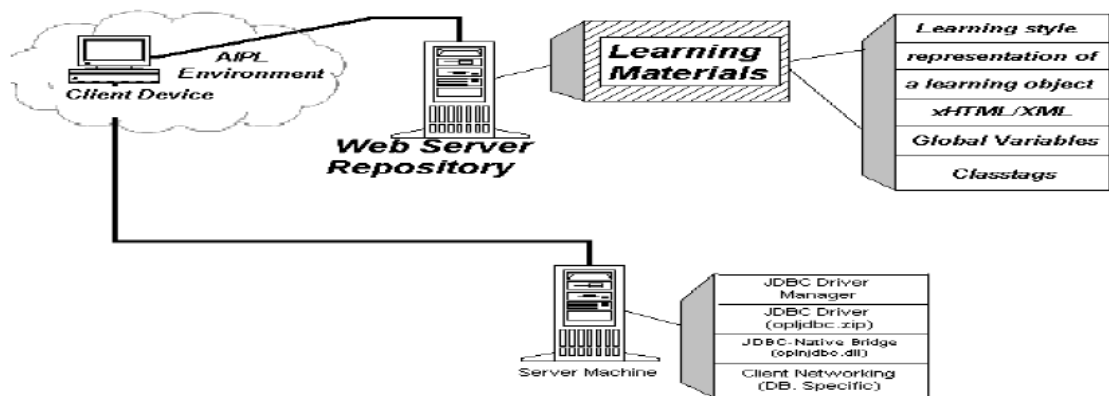


Figure 7: Solution to representing learning styles on-line

To overcome some of the issues of flexibility and reusability within the AIPL model, learning materials are held on a Web Server. The web server enables the author to place learning content on-line to be shared across different academic institutions and provide facilities for web-crawlers and spider bots to search and retrieve. To achieve this approach each learning object online will be represented using LOM as an industry standard.

As mentioned early on in Chapter 2, and that of Section 5.2.1 User Modelling does play an important role within the representation of the learner profile. According to Froschl (2005) without any information about the user then the adaptive system is not able to adapt. By using the recommendation of Froschl (2005), Santos et al., (2009) and Douce et al., (2009) the learning style will be represented in semantic data online, using XHTML/XML coupled with the LOM standard to provide a way for spider bots/or search filtering mechanism to interrogate and compare additional data structures/tags for more details.

In Section 3.1.2.5 Waldo (2005), provided a XML structure that allows the author to place additional details to represent a learning object, see Figure 8.

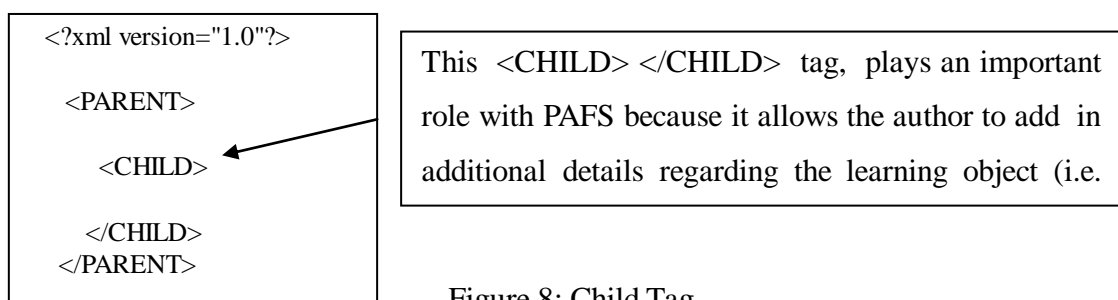


Figure 8: Child Tag

Also in Section 3.1.2.1 Dumbill (2000) and Kesteren (2007) suggest that xHTML as a Semantic Web standard can allow data to be extracted by a machine from a document intended for consumption. The layout that Dumbill (2000) and Kesteren (2007) Suggested can be seen in Figure 9.

```
<P>
  <SPAN CLASS= "learning Object" ID= "LO identification" >
    <SPAN CLASS= " " > </SPAN>,
    <SPAN CLASS= " "> </SPAN>
  </SPAN>
</P>
```

*Figure 9: Span Class*

Using global variables and class tags as a way of providing specific details regarding the learning object will provide a way for PAFS to extract tags from the learning objects and compare these tags against the semantic representations of the learner profiles. For a graphical representation of this solution see Figure 12.

## **5.2.2 Representation of the Learner Profile & the Learner Profile Lifecycle**

The following subsections address these issues respectively. According to Dolog et al., (2005) learning profiles have a variety of key challenges associated with them ranging from: representing learner profiles (5.2.2.1); accessing the learner profile (5.2.2.2); integration of how to process heterogeneous profiles (5.2.2.3) and in addition to the above research, the profile life-cycle (5.2.2.4). How PAFS deals with these problems is indicated below.

### **5.2.2.1 Representing learner profile**

Dolog et al., (2003) indicates that the representation of the learner profile can be depicted in a variety of ways ranging from: interests, experience, learning preferences, disabilities, and knowledge. It is however, important that the learner profile depicts and represents the correct category it was designed for. The Dolog et al., 2003, learning profile example was

based upon learner information, which contained the following items: content type, identification, competency, goal, accessibility, activities, affiliation, interests, relationships and security issues.

However, other researchers like Mainemelis et al., (2002) indicate that learner profiles can be used to represent: learner traits, learning theories and learning styles. Sampson et al., (2002) and Sampson et al., (2002)\* like Mainemelis et al., (2002) uses the following features to represent the necessary aspects for representing the learner profile: authentication, requirements, preferences, interests, and goals.

To represent the learner profile on-line, according to Dolog et al., (2003), web based technologies are required. This is due to accessibility restrictions, security, and querying capabilities. Kobsa et al., (1995), Tassco et al., (1999), Aroyo et al., (2006) and Martin et al., (2008) indicate that the learner profile must be able to represent a variety of learning traits, to enable a tailored learning experience to be generated.

#### **5.2.2.1.1 Solutions to representing the learner's profile**

To overcome the issues of how to represent the learner profiles with the AIPL environment the author used similar ideas of that from (Dolog et al., 2003; and Mainemelis et al., 2002) about using learning styles as a way of categorising how some one learns. Enabling the learner's profiles to be categorised by learner styles provided the author with a way of representing what factors should be placed into the profile.

The learner profiles within AIPL will require the following factors: course ID, student ID, access rights, learning style identification, and group type.

The learner profile within AIPL has the following data structure properties to enable the learner profile to work effectively when being interrogated by the Personalised Adaptive Filtering System.

|            |              |           |           |     |            |     |           |     |             |     |
|------------|--------------|-----------|-----------|-----|------------|-----|-----------|-----|-------------|-----|
| Student ID | Access Right | Course ID | LT        | LTV | LT         | LTV | LT        | LTV | LT          | LTV |
| 3100034    | Y/N          | 3002      | Pragmatic | 11  | Analytical | 8   | Reflector | 4   | Theoretical | 12  |

Continued:

|                     |     |                        |     |                            |     |                        |     |            |
|---------------------|-----|------------------------|-----|----------------------------|-----|------------------------|-----|------------|
| LT                  | LTV | LT                     | LTV | LT                         | LTV | LT                     | LTV | Group type |
| Concrete experience | 2   | Reflective observation | 4   | Abstract conceptualization | 1   | Active experimentation | 5   |            |

*Figure 10: Learner's Profile*

The example in Figure 10 is original and used within the AIPL model. The learner profile will be stored using a database management system, which will hold the personal values and traits of the individual.

### **5.2.2.2 Accessing the learner profile**

According to Dolog et al., (2005) accessing the learner profile, a system must be able to deal with issues like: interoperability; exchangeability of data, and data mappings between system variables. According to Aroyo et al., (2006) learning profiles have limited interoperability between one system to another, thus creating barriers when trying to accomplish tasks.

Aroyo et al., (2006) and Sampson et al.,(2002) suggest that learning profiles should be designed through the use of adaptive web technologies to enable different architectures to be used, these are: adaptive web-based systems, adaptive hypermedia systems, and adaptive task-based systems. However, to represent different learning profiles via a multitude of different architectures, the internal variables must be able to be directly mapped in accordance with the technology being used. Aroyo et al., (2006) indicates that data mapping between system variables can be tedious and manually intensive.

#### **5.2.2.2.1 Solution to Accessing the learner profile**

As stated in Section 4.1.3 this Thesis builds upon the e-Learning framework presented by Eze et al. (2006) see Figure 11. This web based framework aligns with the recommendations of (Aroyo et al., 2006; Dolog et al., 2005; and Sampson et al., 2002) to use web-based architectures to facilitate on-line learning. It also enables the exploitation of

learning styles as a mechanism of identifying how the learner prefers to learn, as supported by Calder (2002), Brusilovsky et al., (2003), Coffield, (2004), Dolog et al.,(2004), Miller (2004), Atherton (2005), Wang et al., (2008)\*, Martins et al., (2008)\*, and Alves et al.,(2008).

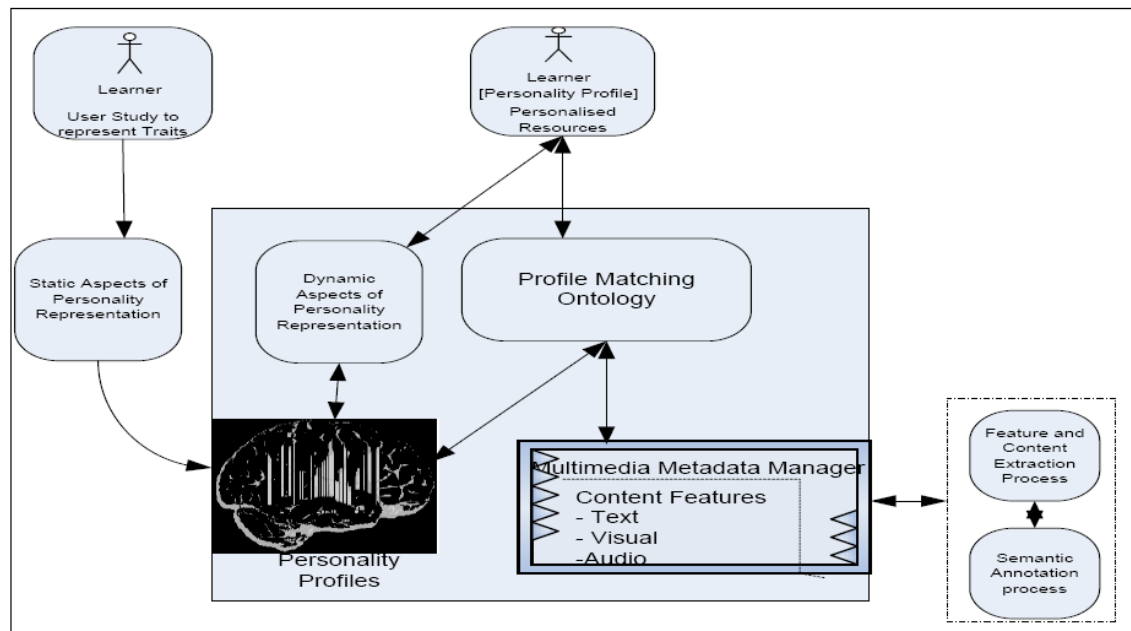


Figure 11: Eze e-learning Framework

Eze et al., (2006) indicated that there was one major design flaw within their e-learning framework, which was the lack of provision of an adequate personalised approach for providing media resources to match the learner traits.

The research that was carried out by Eze et al., (2006) indicated that there were three possible areas of improvement these were: the development of a personality component for the domain profiling of a learner; the use of semantic metadata to represent multimedia of specific context using XML and RDF; and finally the algorithm to match learner to learning resource.

The changes to the e-learning Framework from Eze et al., (2006) enabled the development of AIPL to be created, for example: a new improved pedagogical learning approach (Anderson 2005; Campbell et al., 2005; Chang et al., 2005; Ling 2007; De Jong et al., 2008); the use of learning styles to capture the learner's approaches to learning (Calder 2002; Brusilovsky et al., 2003; Coffield, 2004; Dolog et al., 2004; Miller 2004; Atherton 2005; Wang et al., 2008\*; Martins et al., 2008\*; and Alves et al., 2008); the use of



semantics and LOM standards to represent learning objects (Dumbill 2000; Ogbuji 2003; Waldo 2005; and Kesteren 2007); and finally PAFS to create an effective match between the individual and the learning resources within the Repository (Bajraktarevic et al., 2003; Becks et al., 2003; Deeb, 2007; Safran et al., 2007; Chatti et al., 2007; Ghali et al., 2009).

The web-based technologies within the AIPL environment would overcome issues of exchangeability of data, and data mappings between system variables. The Learning Profiles will be stored on a local database server that will take requests and queries from the AIPL environment. By storing the Learning Profiles within a database server, the AIPL environment will be able to map internal variables from one server to another, for example: For more information see Figure 12.

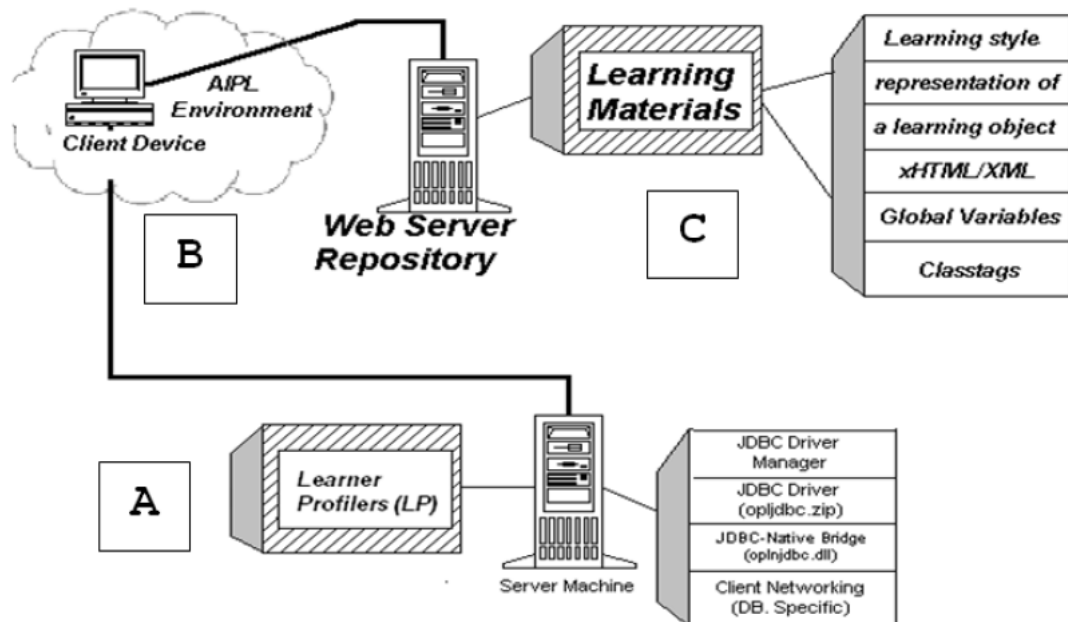


Figure 12: Representing the learner's profile (LP)

- Section A: is the representation of the learner profile, which uses a database to hold the values belonging to the individual.
- Section B: is the client end i.e. AIPL Environment
- Section C: represents the on-line Repository of learning objects

For these mechanisms to communicate directly, mapping the internal variables from one web-based technology to another was required.

- The learner profile's are stored within a PostgreSQL database
- The AIPL environment was written and designed using Java
- An on-line repository was used to hold the learning resources, which was annotated by using LOM and semantic (XML, xHTML) standards as a way of representing the learning objects, please see Section 5.3.2 Semantic Matching Algorithm for an example of mark-up.

The internal variables being used within AIPL required mapping the JDBC drivers, and PAFS together to enable communication to take place. In addition to the mapping of internal variables, the AIPL environment uses a variety of web-based adaptive technology to control access to the learner profile and monitor interoperability issues.

Aroyo et al., (2006) indicate interoperability issues exist when different information systems use formats that are not compatible across multiple systems. As indicated PAFS does deal with interoperability issues by granting access to a specific location within the on-line repository, which enables the learning object to be matched to a variety of Learning Object Standards (LOM, RDF), and metadata representation through the use of xHTML, and XML. This is achieved through the use of the Dublin Core metadata editor to generate descriptive metadata to support other repositories and systems.

The web-site for allowing this conversion can be found below:

<http://www.ukoln.ac.uk/metadata/dcdot/>.

Figure 13 is a snapshot of a learning object being used within AIPL.

```
<link rel="schema.DC" href="http://purl.org/dc/elements/1.1/" />
<link rel="schema.DCTERMS" href="http://purl.org/dc/terms/" />
  <meta name="DC.title" lang="en" content="Wiring a Kettle Plug" />
  <meta name="DC.creator" content="Robert Costello" />
  <meta name="DC.subject" lang="en" content="Wiring a Kettle Plug" />
  <meta name="DC.description" lang="en" content="Specific Exercise Based on
    Pragmatist activities: Learning Style KOLB, practical, logical and systematic" />
  <meta name="DC.publisher" content="Hull University" />
  <meta name="DC.date" content="December 2009" />
  <meta name="DC.type" scheme="DCTERMS.DCMIType" content="Text" />
  <meta name="DC.format" content="text/html" />
  <meta name="DC.format" content="23610 bytes" />
```

*Figure 13: Dublin Core Metadata*

Taken from the Dublin Core Metadata editor - <http://www.ukoln.ac.uk/metadata/dcdot/>

The above metadata representation of learning objects can also be represented within RDF, which can be seen in Figure 14.

```
<?xml version="1.0"?>
<!DOCTYPE rdf:RDF SYSTEM "http://dublincore.org/documents/2002/07/31/dcmes-xml/dcmes-xml-dtd.dtd">
<rdf:RDF
  xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-ns#"
  xmlns:dc="http://purl.org/dc/elements/1.1/">
<rdf:Description rdf:about="http://~310567/">
  <dc:title>
    Wiring a Kettle Plug
  </dc:title>
  <dc:creator>
    Robert Costello
  </dc:creator>
  <dc:subject>
    Wiring a Kettle Plug, about how to Wire a Kettle Plug, The Table of Contents, Step 1 How to identify
    the correct Screwdriver, Link to YouTube,
  </dc:subject>
  <dc:description>
    Specific Exercise Based on Pragmatist activities: LearningStyle KOLB, practical, logical and systematic
  </dc:description>
  <dc:publisher>
    Hull University
  </dc:publisher>
  <dc:date>
    December 2009
  </dc:date>
  <dc:type>
    Text
  </dc:type>
  <dc:format>
    text/html
  </dc:format>
  <dc:format>
    23610 bytes
  </dc:format>
</rdf:Description>
</rdf:RDF>
  <dc:date>
    December 2009
  </dc:date>
  <dc:type>
    Text
  </dc:type>
  <dc:format>
    text/html
  </dc:format>
  <dc:format>
    23610 bytes
  </dc:format>
</rdf:Description>
</rdf:RDF>
```

*Figure 14: Dublin Core RDF*

As stated above the AIPL environment through the use of PAFS does provide access to an

area located on the web-server that provides a link to the learning objects that use different learning standards like: RDF. However, this approach is only used for demonstration and testing purpose it would not be cost effective or stakeholder friendly to represent a large bank of learning materials in this way, as indicated by Aroyo et al., (2006). This area of ‘interoperability’ is out of the scope of this Thesis research and there is no contribution is made to literature.

### **5.2.2.3 Integration of and how to process heterogeneous profiles**

A heterogeneous profile is a profile which uses multiple items and can have many different structural variations. So for example, an individual may have a profile which contains results data from multiple institutions, or multiple learning style categorizations and another individual may have something completely different. According to Dolog et al., (2003) and Eyssautierbavay et al., (2009) heterogeneous profiles are still an unsolved issue within e-learning literature. However, according to Xu et al., (2003) and Dalsgaard (2006) it is possible for LMS and learning standards to share resources.

However, Aroyo et al., (2006) suggests that to process heterogeneous profiles web-based technologies are needed to enable this to happen. Dolog et al., (2003) and Eyssautierbavay et al., (2009) indicates that to achieve heterogeneous profiles, knowledge acquisition is needed from all researchers within the field. Simon et al., (2003) and Eyssautierbavay et al., (2009) indicates that to process heterogeneous profiles in the support of a multitude of educational environments, a personalised intelligent educational system is needed. The heterogeneous profiles must be designed to facilitate the complexities associated with dealing with a multitude of heterogeneous environments, and the flexibility of linking them into: assessment tools; learning management systems; educational repositories; and support materials such as video conferencing and interactive materials.

#### **5.2.2.3.1 Solutions provided for the processing of heterogeneous profiles**

The AIPL environment deals with heterogeneous profiles, by directly storing the learner’s profile into a database server. The design of the heterogeneous profiles (Learner Profiles) within the AIPL environment could support a multitude of cross platform educational systems; as long as the AIPL environment provides the right security privileges to enable

sharing across systems, see Figure 15.

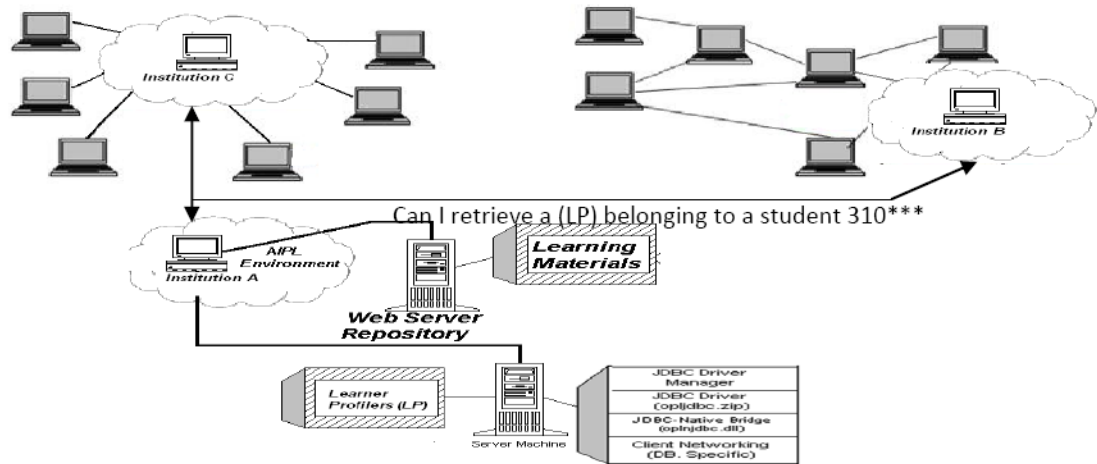


Figure 15: Heterogeneous Profiles

According to Graf et al., (2008) it is quite often that different management systems are used to store details like: students, staff, and guest details. However, modern integrated IT infrastructure requires a holistic view of the personal data that is stored and used by web applications, such as learning platforms. Graf et al., (2008) introduces concepts of using User Modelling to hold details belonging to the student, staff, and guest details, which can be held within profiles to enable heterogeneous sharing between campuses, departments etc... This concept of allowing details to be shared to compensate for re-usability, and cross system access provided the backdrop for the ideas within this Thesis belonging to Heterogeneous Profiling.

The heterogeneous profile (learner's profiles) using concepts belonging to (Graf et al., 2008) works within the AIPL environment as follows:

A student from institution A has just completed his first year and decides to move to another institution i.e. B. Institution B requests the learners profile from institution A. Once the request has been granted a direct communication link is opened on the server that holds the Learner's Profile. Once this communication is connected the learner's profile can be downloaded into a flat file format. This file will contain all the details about how the learner learns: what learning style they are; and what modules they have completed. The file can then be recreated on the other institution's database for manipulation.

#### 5.2.2.4 Learner profile cycle and Group Life

The learner profile cycle and the group life begins as soon as the individual has been enrolled into the AIPL environment. AIPL monitors all new students as soon as they login, and they are prompted for the following details, please see Figure 16.

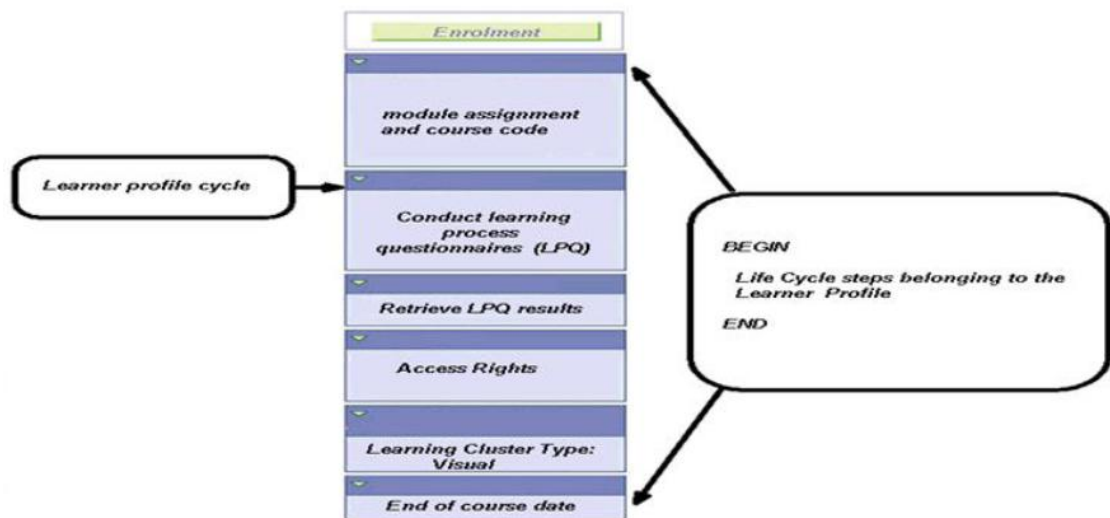


Figure 16: Life Cycle

The life cycle diagram has six features belonging to the AIPL environment, which are critical for the learner profile to work. **Module assignment and course code:** this represents what module the student is studying on to assist PAFS while filtering course content **conduct Learning Process Questionnaire:** this enables the learner to undergo two tests to indicate how they learn through the use of LPQ's.

- **Retrieve LPQ's:** The values from the LPQ are stored for later processing.
- **Access Rights:** Are used to control what materials they are allowed to view i.e. This works in conjunction with module assignment and course code.
- **Learner cluster type:** This is used to store the identification on how the learners prefer to learn. The values are retrieved from LPQ's in step 3, and sent directly to PAFS for use. Once the value from the LPQ is worked out PAFS will then use this value to identify how they learn i.e. I am a pragmatic learner.
- **End of course date:** used in two parts to control access and also to terminate the end of The life cycle belonging to the individuals.

Once the above learner's profile has been created, the group life cycle will begin. AIPL will scan through all Learning Profiles and categories the individuals into groups in

accordance with their learning styles. For more information, see Section 5.2.3 grouping learners – challenges and complexities to see how this is achieved. Once the values have been interrogated, the group value will be placed and stored into the LP, for creating clusters. AIPL will monitor the end of course date belonging to the individual learner profiles to control the grouping life cycle.

The group life cycle will be stored and maintained to track the progress of the groups. The cluster information belonging to the group life cycle can be extracted depending on people within the group, which will then be applied to different courses during their educational life cycle. Updating the individuals within the cluster profile will enable the system to keep up to date and to continue to monitor their development.

### **5.2.3 Grouping Learners – Challenges and Complexities**

This section is written to introduce the challenges and complexities associated with grouping learners within PAFS. The following layout will be used to represent a logical approach that is needed to deal with the complexities: homogenous views (Section 5.2.3.1); concept drift (Section 5.2.3.2); e-bookmarking (Section 5.2.3.3); collaborative grouping (Section 5.2.3.4); and advanced methods (Section 5.2.3.5).

#### **5.2.3.1 Homogenous Views**

According to Spiro et al., (1996) grouping individuals can vary depending on subject matter and learning capabilities. The characteristics of the individuals within group settings can be varied depending on how they learn, for example: some learners might like to learn through orderly tasks; others might like complex challenges; and some learners might not like the pedagogical approaches adopted by the domain expert. It is these homogenous views of the individuals within a group setting that can make the group either succeed or fail.

It is important that the homogenous views are compensated within any group setting by building on interests, traits and personal preferences of the learners. To overcome some of the issues associated with homogenous views, researchers like Alexander et al., (2004), Oxford (2003), Severiens et al., (1994) and Gutiérrez et al., (2003) are using learning

traits to group students.

According to Alexander et al., (2004) you can group learners through the use of cluster analysis. Cluster Analysis is where profiles can be grouped together on the basis of their expertise i.e. participant's knowledge, interests and strategic processing.

Group categories can be categorised as the following:

- **Acclimatisation cluster:** New students with low levels of domain knowledge and Individual interest within specific areas.
- **Early competence cluster:** This particular cluster relates to individuals that seek Knowledge in specific fields, interests and professions.
- **Mid-competence cluster:** Refers to knowledge and experiences that individuals already have which they can apply to deep-processing strategies or text-based strategies.
- **Proficiency cluster:** Students and staff members with a high level of academic and experience.

The research conducted by Alexander et al., (2004) through the use of cluster analysis, within grouping does work. However, grouping individuals into academic levels would not give a fair advantage to the students with very little knowledge, or mixed abilities.

Researchers like Oxford (2003) indicate that psychological and socio-cultural trends can be used as a way of grouping individuals; however, this is complex and requires a vast amount of knowledge and research into understanding the characteristics of the individuals, for example: anxiety, beliefs, support, assisting relationships and actual knowledge of the individual themselves. There are, however, more efficient ways of grouping individuals that have been demonstrated by Severiens et al, (1994) and Gutierrez et al., (2003).

Researchers like Severiens et al., (1994) and Gutierrez et al., (2003) believe that you can group individual learners into clusters belonging to their learning styles and learning theories. Severiens et al., (1994) and Gutierrez et al., (2003) indicate that by categorising individuals through the use of learning styles/theories a balance can be created within education experiences between resources and approaches to learning.



Eisenstadt et al., (1990), Leutner et al., (1998) and Boyd et al., (2004) would argue against the points of (Severiens et al., 1994; Gutierrez et al., 2003) that no matter what features applied by the domain expert to assist the individuals, the learner may still find it difficult, and even if the materials are designed accordingly this can still mislead them.

It seems that the comments made by Baroness Greenfield are similar to that of Eisenstadt et al., (1990), about applying learning styles or learning aids to individuals might not actually help them within their learning experience.

However, Genovese (2004), Litzinger et al., (2005) and Mehigan et al., (2010) would argue against the views of (Eisenstadt et al., 1990; Leutner et al., 1998), that the use of learning styles within on-line learning does improve the educational balance and also improves the learner experience.

Oxford (2003) has similar views to (Severiens et al., 1994) about using learning styles/theories to group together learners with the same learning traits. However, in addition to the research carried out by (Severiens et al., 1994; Oxford 2003) they indicate that other variables must be included like: motivation, proficiency, and achievement.

According to Oxford (2003), some of the major limitations associated with grouping are: how the learning activities are written in accordance to the behaviour of the individual set within a group environment; matching the needs of the individual/group to the right learning materials; and finally, creating and exploring relationships between tasks to engage group learning.

Whilst researchers like Severiens et al., (1994), Oxford (2003), Alexander et al., (2004), and Cristea et al., (2010), have provided a great wealth of knowledge, it is still in the early stage of academic research about how to categorise groups of individuals in successful ways.

Even though, there is not a correct procedure for grouping there is enough academic research to support the idea that certain aspects of grouping can be applied, for example: (Oxford 2003; Severiens et al., 1994; Gutierrez et al., 2003) indicate that applying learning styles and theories to groups can assist with enhancing a learner's learning experience. According to Oxford (2003), using learning styles can improve: perception,

reception, storage, and retention belong to their learning experience.

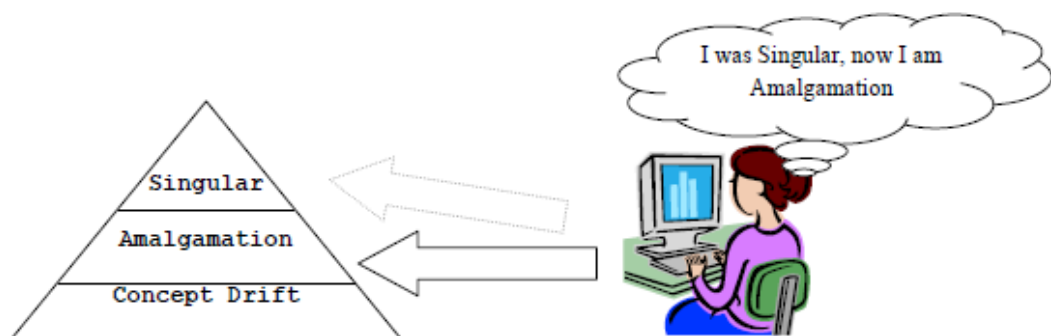
### 5.2.3.1.1 The solutions to Homogenous Views

To tackle the issues associated with homogenous views, PAFS will use the principle research that (Oxford 2003; Severiens et al., 1994; Gutierrez et al., 2003) conducted about considering learning styles as a way of grouping individuals in accordance with how they learn most effectively. By grouping individuals in accordance with their own learning styles provides a way within the AIPL environment to overcome the following problems: unfair categorisation of knowledge and expertise (i.e. all abilities are placed together); placing the learner with other learners that have similar learning traits as each other; placing the learner/s in an environment that was designed for them thus creating a more tailored learning experience.

To solve the issues associated with homogeneity within PAFS there are three levels, These are:

- 1) **Singular:** - One student has only one category i.e. Analytical
- 2) **Amalgamation:** - One student can have many values i.e. Analytical and Pragmatic or even Reflective with Analytical.
- 3) **Concept Drift:** - For more information see Section 5.2.3.2 The Concept Drift for a definition and how it works within PAFS.

Each one of these particular group clustering methods (i.e. singular, amalgamation and concept drift) can create homogenous views within PAFS. The concept of homogenous views within PAFS can be represented through a three layer triangle that enables students to change clusters over time, depending on their learning styles results. For more information see Figure 17.



*Figure 17: Three layer triangle*

By grouping the individuals into clusters of learning styles, according to Severiens et al., (1994) and Gutierrez et al., (2003) this will improve the learner's experience. To overcome the issues that (Oxford 2003) had suggested the PAFS environment will use the three layer cluster as a way of directly matching individuals with specific groups, reducing some of the limitations associated with collaborative grouping, for example: inappropriate matching and creating relationships within a dynamic moving environment.

### **5.2.3.1.2 Technical aspect of grouping**

The technical aspect of grouping used within PAFS can be found within Section 5.2.3.4 Categorising of Groups (CG) and 5.2.3.5 Advanced Methods. This approach builds upon the research carried out by (Oxford 2003; Severiens et al., 1994; Gutiérrez et al., 2003).

### **5.2.3.2 The Concept Drift**

The community-based algorithm relies on the results from the psychometric measuring which is retrieved using the LPQ. The psychometric measuring used within this algorithm has, however, divided the research community. On the one hand, some researchers argue that learning styles do not effectively improve the learning experience (Eisenstadt et al., 1990; Leutner et al., 1998; and Boyd et al., 2004) and that psychometric measuring systems are ineffective. However, reading the Learning Styles and Pedagogy in post-16 learning: A systematic and critical review report by Coffield indicates that:

*“The logic of lifelong learning suggests that students will become more motivated to learn by knowing more about their own strengths and weaknesses as learners. In turn, if teachers can respond to individuals' strengths and weaknesses, then retention and achievement rates in formal programmes are likely to rise and 'learning to learn' skills may provide a foundation for lifelong learning”* Coffield et al., (2004).

The Coffield report does question the whole concept of using learning style and indicates

*“whether a particular inventory has a sufficient theoretical basis to warrant either the research industry which has grown around it, or the pedagogical uses to which it is currently put”* Coffield et al., (2004).

Further reading into the Coffield report would indicate that their final assumption about learning styles would be that of

*“researchers and users alike will continue groping like the five blind men in the fable about the elephant, each with a part of the whole but none with full understanding”* Coffield et al., (2004).

From the authors perspective based on the Coffield et al., (2010) report it is clear that the impact of Learning Styles cannot either be proven or disproven due to the large amounts of literature supporting both claims. Due to the nature of learning styles being freely available from the internet, it is possible for the domain expert to use them to find out quickly about ones learning type, so they can adapt coursework, and learning materials.

As stated above:

*“If teachers can respond to individuals” strengths and weaknesses, then retention and achievement rates in formal programmes are likely to rise and learning to learn” skills may provide a foundation for lifelong learning”* Coffield et al., (2010)

Some researchers like Leutner et al., (1998), Genovese (2004), Boyd et al., (2004), and Litzinger et al., (2005) have indicated that many models within pedagogical theories can improve instructional design. By using a variety of different models and pedagogical approaches such as learning strategies and learning styles can arguably help improve instructional design, through modifying teaching and student self knowledge awareness about how they learn best. However, their research suggested many of the investigations carried out on learning styles lack theoretical clarity and adequate measurement instruments. Research conducted by Leutner et al., (1998) suggested that individual learning differences depend on the extent of availability, reliability and the validity of psychometric measuring. Boyd et al., (2004) furthers the debate initiated by Leutner et al., (1998) by arguing that learning styles have several weaknesses in terms of the reliability, validity, and the identification of the different characteristics of learners’ needs.

According to Leutner et al., (1998), Genovese (2004) and Litzinger et al., (2005),

psychometric measuring is a popular method for identification and analysis of the learner's needs, however, the scales used to capture individual needs sometimes lead to negative or low correlations between the needs of learners, and the actual outcome of results. Research conducted by Leutner et al., (1998) has indicated that to sufficiently test the validity of psychometric measurements it would be necessary to implement the scale based upon behavioural observation, instead of using self-based learning process questionnaires to identify the student's needs. Isaksen et al., (2007) suggested that psychometric measurements should be designed to assist the mediation between stimulus and response in relation to the scales that would best describe the characteristic ways in which individuals conceptually learn best within a learning environment.

The research conducted by Leutner et al., (1998), Genovese (2004), Boyd et al. (2004) and Litzinger et al., (2005) has indicated that psychometric measurements used in identifying learning styles are ineffective, inefficient, and lack clarity in how they are applied; however, researchers like Duff et al., (2002), Zywno (2003) Markham (2004) and Carmona et al., (2007) believe that learning styles have been widely accepted within the academic world, even though limited evidence exists concerning the psychometric properties.

Duff et al., (2002) have indicated those learning style questionnaires (LSQ) that use psychological factors serve as an indicator of how an individual interacts with and responds to the learning environment, and guarantees that some scales will be negatively correlated. However, LSQ are designed to probe the relative strengths of the individuals, therefore, it could be expected that students with a preference for particular learning activities would outperform those with preferences for other learning activities. Zywno (2003) agrees with Duff et al., (2002) by stating that learning styles are important to the individual learner, and that psychometric measurements have been rigorously tested over time. They have concluded that psychometric tools are statistically acceptable for characterising individual learning preferences. Zywno (2003) suggested that instructors that have applied psychometric learning tools to the individual have shown/demonstrated a greater statistical significance between learning styles and performance based on results retrieved from the LPQ.

According to Kovar et al., (2001) and Zywno (2003) a considerable amount of research

has been conducted in the area of learning styles and psychometric measurement tools, which has revealed that students learn better when using preferences with which they have success, and have the potential to be better learners. Kovar et al., (2001) suggests that it is important for the learner to be able to take steps to change their learning style to suit the situation by developing competence in a variety of learning styles' categories. Carmona et al., (2007) furthers the debate by arguing that psychometric measurement tools can be used to identify ways in which the individual will collect, process, and organise new knowledge/information. The research carried out by Carmona et al., (2007) suggests that the higher a psychometric value an individual obtains the closer the correlation to the learner needs. For an example of student learning needs see Table 2:

|            | Pragmatic | Analytical | Reflector | Theoretical |
|------------|-----------|------------|-----------|-------------|
| Student A: | 10        | 8          | 9         | 12          |
| Student B: | 9         | 11         | 12        | 7           |

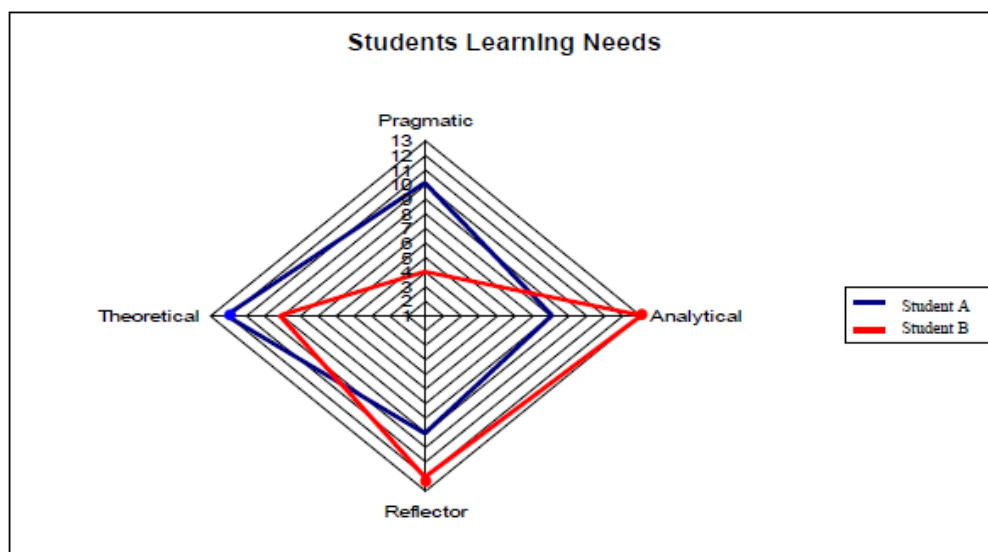
*Table 2: Student learning needs*

According to the research of Carmona et al. (2007), the table above would produce the following results:

Student A: would be classed as Theoretical

Student B: would be classed as Reflector

For a graphical representation of the table: See Graph 1 - Student learning needs.



Graph 1 - Student learning needs

However, Carmona et al., (2007) have indicated that a concept drift can occur with student **B**, where Analytical and Reflector are closely associated; in which case the student would try both possibilities to adjust accordingly to his/her needs. For more information see Table 3: Concept Drift.

|            | Pragmatic | Analytical | Reflector | Theoretical |
|------------|-----------|------------|-----------|-------------|
| Student A: | 10        | 8          | 9         | 12          |
| Student B: | 9         | 11         | 12        | 7           |

*Table 3: Concept Drift*

The concept drift is concerned with the two top values within the scale. In the table, concept drift is identified within the shaded sections.

In a concept drift, Genovese (2004) would suggest offering the student the chance to use both settings to see which one would effectively improve the learning experience. Genovese (2004) suggests that values that are low within the psychometric scales do not influence the results and the true result would be the highest number, depending on the scale used and the amount of research carried out to support the learning style in question.

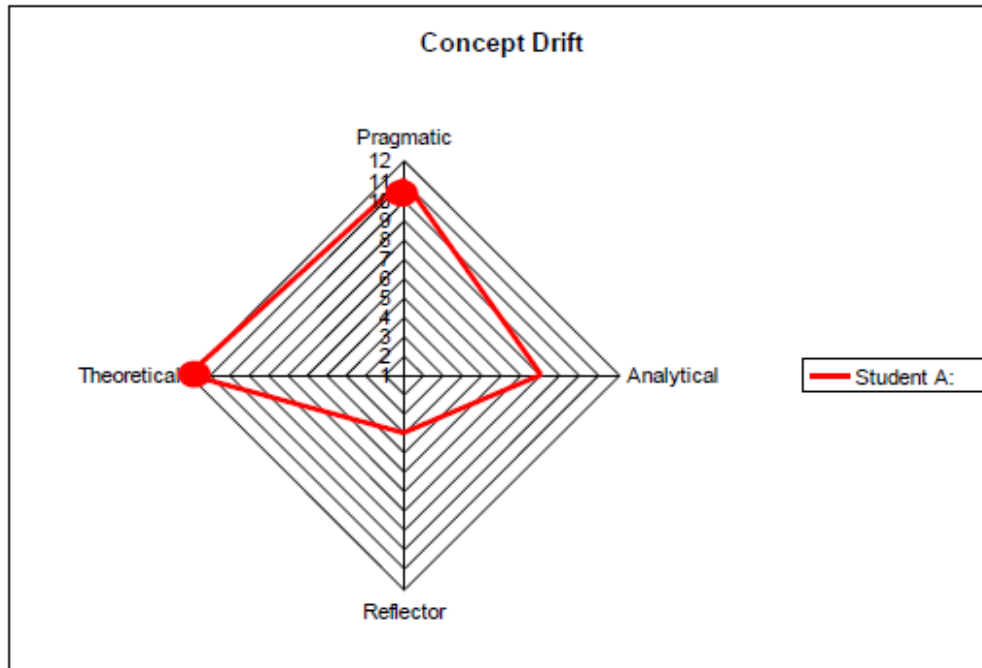
Markham (2004) suggests that the psychometric scales would not have been accepted within the academic community without the consent of, or authorisation from the American Psychological Association (APA), which is supported by local bodies such as the Australian Council for Educational Research (ACER).

According to Markham (2004), researchers that use learning styles to capture learners' behaviours must have a greater understanding, and should define how the scales within the psychometric testing have been conducted, by illustrating the consequences for, and benefits to the individual using them. Isaksen et al., (2007) suggests that learning styles seem to be more spontaneously applied without conscious deliberation, whereas strategies seem to be more a matter of choice and training.

The research associated with grouping relied upon the use of learning styles as a way of grouping individuals therefore the author thought it was important to include the issues that have divided the academic community relating to: Do learning styles work?; and How relevant are they to the individual?

### 5.2.3.2 Solution to the Concept Drift within PAFS

The Concept Drift according to Carmona et al., (2007) is when the student has been identified as having two or more high numbers that are closely associated with each other. For a graphical representation of a concept drift, see graph 2: Concept Drift.



Graph 2: Concept Drift

The concept drift can be identified on the graph by the symbols

- The circle indicates scale value belonging to each category
- The line joins the two elements together indicating the values belongs to the same student.

To overcome the issue of concept drift within PAFS a rule base was designed and implemented to calculate and categorise the psychometric values belonging to the learning process questionnaire. Once the psychometric values have been retrieved the values would be placed into a complex rule-base, such as that demonstrated in Figure 18. However, the complete version can be found in Appendix B: RuleBaseComplex.



```

IF ((Theoretical > Active) &&
      (Theoretical > Pragmatic)) &&
      (Theoretical > Reflective))
THEN
Set AIPL environment to Theoretical
Map AIPL variables (learning types, course selection, access rights)
Set location/destination of specific learning materials
Map URL locations for learning materials
Set community values
Map community values to Theoretical, grant access to communication software: chat
    facility, discussion board, and forum room.
END IF

```

Figure 18: Rule-Bases

The algorithm will use the rule-base to retrieve the highest psychometric value before placing the learner into a community that best suits the learner’s needs; however, the above rule-base must be capable of detecting a concept drift, which would flag/indicate that two high similar values have been identified.

If at any time the rule-base cannot work out the value concerning the concept drift, then the profile will adapt and retrieve the values that are stored concerning the David Kolb learning style test results. The AIPL environment was built using two learning style models, for more information see Figure 19.

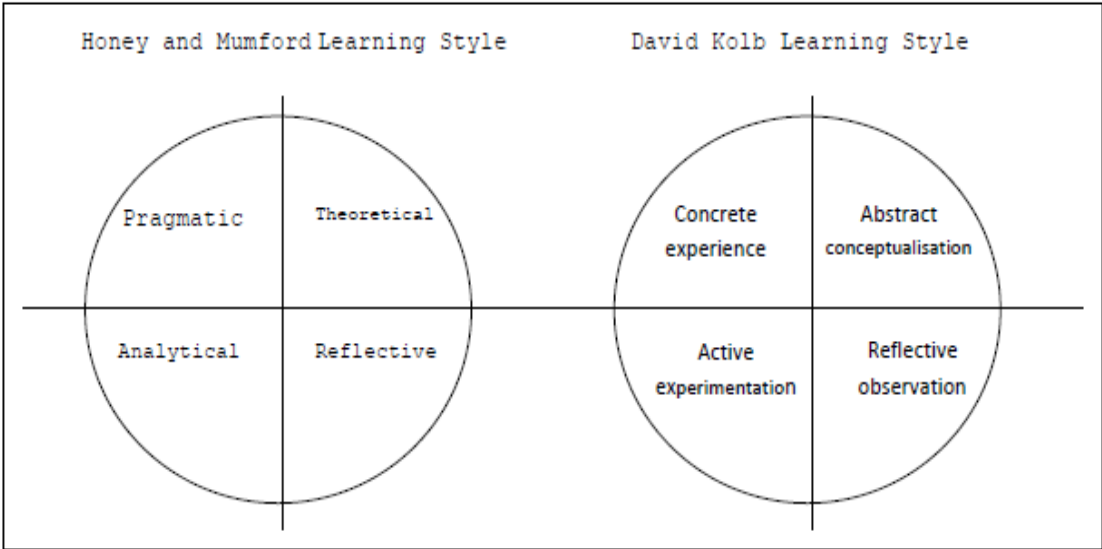


Figure 19: Two learning styles models

The first learning style has the values of 1 – 14 as seen below:

|                                  | Pragmatic | Theoretical | Reflective | Analytical |
|----------------------------------|-----------|-------------|------------|------------|
| Honey and Mumford Learning Style | 1 – 14    | 1 – 14      | 1 – 14     | 1 – 14     |

The above table from the Honey and Mumford learning style is the primary learning style that would enable the algorithm to retrieve the psychometric measurements from the individual. However, the second learning style from David Kolb will be used to aid the concept drift by enabling the algorithm to select the two highest similarities from both learning styles.

The second learning style is represented by the values of A, B & C, D to enable the matrix to calculate the difference. According to Kolb (1985) the learning style is divided into two sections, which are: Concrete Experience, and Abstract Conceptualisation (A, B) and Active Experimentation, and Reflective Observation(C, D).

- The total of As is computed as the Concrete Experience (A) score.
- Total of Bs is computed as the Abstract Conceptualization (B) score.
- Total of Cs is computed as the Active Experimentation (C) score.
- Total of Ds is computed as the Reflective Observation (D) score.

For a graphical and tabular representation of the above details see Table 4 and Graph 3.

|                           | Concrete experience | Abstract conceptualisation | Reflective observation | Active experimentation |
|---------------------------|---------------------|----------------------------|------------------------|------------------------|
| David Kolb Learning Style | 8                   | 16                         | 12                     | 14                     |

Table 4 Learning style

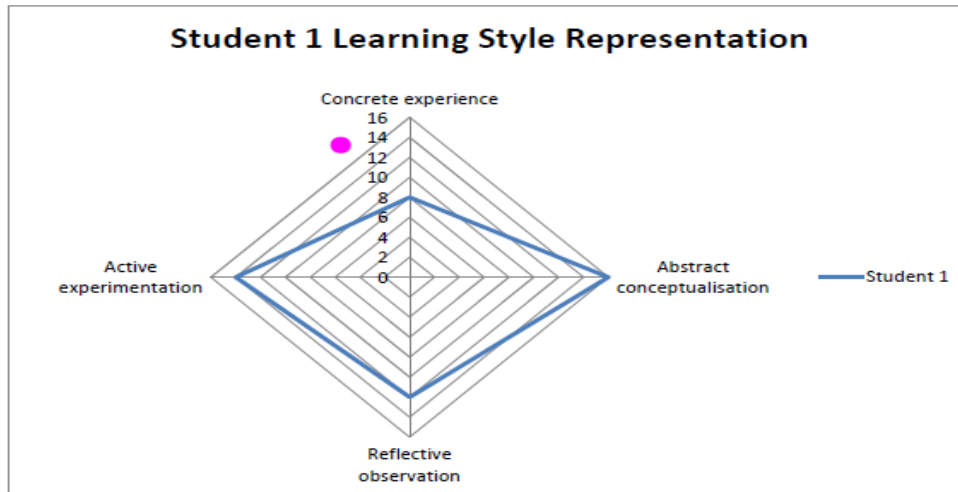


Table 4: Learning Style & Graph 3: Learning style

The tabular and graphical representation of Table 5 & Graph 3 has indicated that Abstract conceptualisation has the highest value within the psychometric scale.

According to Kolb (1985) the learning style is capable of supporting 4 different concept drifts which are:

- Abstract Conceptualization (AC) and Active Experimentation (AE)
- Concrete Experience (CE) and Reflective Observation (RO)
- Abstract Conceptualization (AC) and Reflective Observation (RO)
- Concrete Experience (CE) and Active Experimentation (AE)

To represent the concept drift, Table 5 will be used.

|                                 |    |                             |    |
|---------------------------------|----|-----------------------------|----|
| Abstract Conceptualization (AC) | 16 | Active Experimentation (AE) | 14 |
| Concrete Experience (CE)        | 8  | Reflective Observation (RO) | 12 |
| Abstract Conceptualization (AC) | 16 | Reflective Observation (RO) | 12 |
| Concrete Experience (CE)        | 8  | Active Experimentation (AE) | 14 |

Table 5: Two Learning styles

Once the rule base adjusts to accommodate the second learning style the system will record the highest values into a matrix.

According to the research carried out within Chapter 4 the two learning styles being used within this author's work can be closely correlated, for example see Table 6:

| Learning Style 1 | Learning Style 2    | Learning Style 1 | Learning Style 2           | Learning Style 1 | Learning Style 2       | Learning Style 1 | Learning Style 2       |
|------------------|---------------------|------------------|----------------------------|------------------|------------------------|------------------|------------------------|
| Pragmatic        | Concrete experience | Theoretical      | Abstract conceptualisation | Analytical       | Active experimentation | Reflective       | Reflective observation |
| 11               | 8                   | 12               | 16                         | 8                | 14                     | 4                | 12                     |

| Total value |    |                            |    |    |
|-------------|----|----------------------------|----|----|
| Pragmatic   | 11 | Concrete experience        | 8  | 19 |
| Theoretical | 12 | Abstract conceptualisation | 16 | 28 |
| Analytical  | 8  | Active experimentation     | 14 | 22 |
| Reflective  | 4  | Reflective observation     | 12 | 16 |

*Table 6: Closely correlated*

Within the matrix, applying the two learning styles together can enable the two scales to be joined enabling a more specific psychometric value to be used, for more information see graph 4: Close Correlation. As indicated early on in this Thesis, the AIPL model being presented will make it possible to map contextual learning materials to the personal learning strategy of the individuals' needs and requirements. Several researchers (Brusilovsky et al., 2003; Dolog et al., 2004; Wang et al., 2008\*; Martins et al., 2008\*; and Alves et al., 2008) have all used learning styles to adjust the learning content to suit the individual. As indicated by Alves et al., (2008) the use of learning styles within on-line learning can assist with the categorisation of individuals into groups. The facilities designed, and implemented by (Wang et al., 2008\*; Alves et al., 2008; and Martins et al., 2008\*) all use a singular Learning Style while trying to personalise the learning experience; however, due to the nature of AIPL, there will be two learning styles to enable a more in-depth understanding of the individual to assist with the adaptation of course-content and grouping.

The AIPL model is aimed at reducing mismatching between the individuals/groups to the

learning materials by gathering knowledge about the individual into a knowledge base system that uses filtering techniques to reduce learning materials/learning activities that aren't suited to the learner's specification. The benefits of blending these two learning styles together are:

- The Honey and Mumford learning style enables the domain expert to have an understanding of how the individual prefers to learn.
- The Kolb learning style enables the domain expert to have an understanding of the individual learning behaviour.
- Using the blended learning styles will enable a precise group categorisation to be performed within the on-line learning environment.
- The environment will be able to adjust to a variety of learning needs of the individual because of the blended learning styles together (how the individual prefers to learn; and what learning behaviours they have).

Each of the two learning styles was designed for a particular reason to study the behaviour of the individual, and how that individual prefers to learn. By blending these two learning styles together the domain expert will be able to extract and create a more specific image on how that individual learns and what behavioural traits they have. In accordance with Brusilovsky et al., (2003), Dolog et al., (2004), Wang et al., (2008)\*, Martins et al., (2008)\*, and Alves et al., (2008) the use of one learning style can provide an effective way of personalising the learning experience, and by blending two learning styles together, the AIPL Model will be able to provide a more in-depth understanding of how the individual prefers to learn, and will ensure a more effective learner experience.

### **5.2.3.3 E-Bookmarking**

According to Mobasher et al., (1999), enabling web personalisation via using user preferences can provide search engines with the opportunity to retrieve specific content for users through the use of: interests, personal preferences, and user traits. While keeping to the challenges and complexities associated with grouping, E-bookmarking takes into consideration homogeneous views by creating a foundation layer belonging only to learners that have similar learning traits in which a match can be adhered to. This approach will enable other learners not to get frustrated with inappropriate materials and mismatching issues, mentioned within Chapter 2, and Chapter 4.

However, in addition to using web personalisation other techniques are available to assist with grouping web-based materials: search and retrieval regarding CF; data mining techniques to extract usage patterns from users; and the clustering of user sessions to predict future user behaviour.

### 5.2.3.3.1 Solution to e-bookmarking

The quality assessment rating algorithm used in PAFS will use E-bookmarking as a technique for information retrieval to assist the individual in determining which learning materials are closely associated with their needs. To fully understand the process of the quality assessment rating algorithm, see Figure 20.

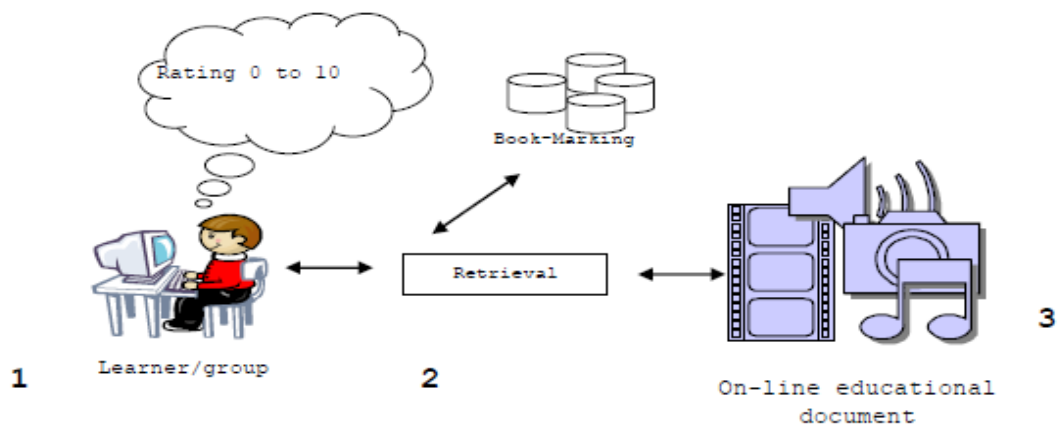


Figure 20: e-bookmarking

Figure 20 can be broken into three sections enabling a comprehensive step by step guide to be developed on how the function will work within the AIPL environment. The actual ebookmarking that the learners see within AIPL can be found within Figure 20A.

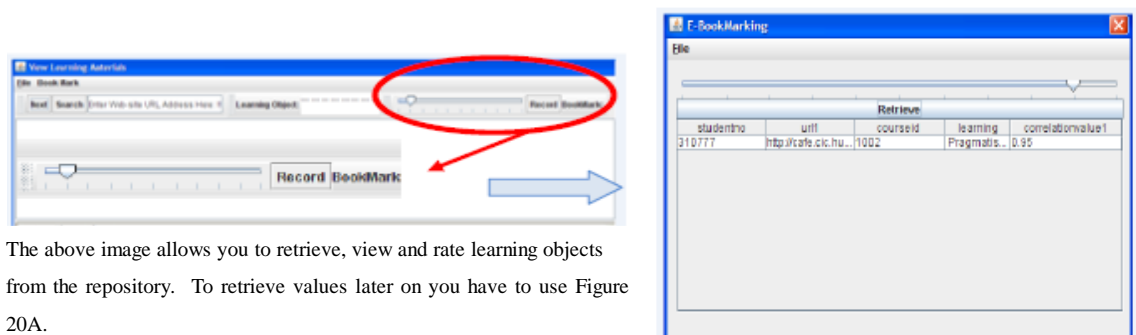


Figure 20A (Original)

Figure 20A, demonstrates the retrieval of a highly rated learning object from the repository.

## **1 – Learner**

The learner retrieves the learning materials and rates each object between zero and ten (ten being the most positive). If the learner feels that the learning object was suitable to his/her learning then he/she will rate the learning object quite highly, alternatively if not then the learning object will not be highly rated. Once the bookmark has been stored the learner can quickly retrieve the learning object through his/her favorites that are stored within the AIPL environment.

The rating system being used within e-bookmarking is similar to that of the project MERLOT and that of the recommender system by Ghauth et al., (2010). *“Highly rated objects are returned ahead of objects that have lower ratings or have not been evaluated”* (Nesbit et al., 2002). Ghauth et al., (2010) introduces a recommender system, whereby any item with similar content will be retrieved, which is based similar to that of PAFS but using rating and learning styles to classify learning objects. However, going back to the concept belonging to (Nesbit et al., 2002) within PAFS objects that have not been rated or have been given a low rating will not be automatically displayed. The PAFS e-bookmarking system does provide a feature to the individual, which allows them to override the Information Retrieval (IR) mechanism to enable access to those learning objects that either have a low rating or none at all.

## **2 – Retrieval**

Each learning material that is viewed by the individual can be rated depending on the learning experience. As mentioned above this approach is similar to that of (Nesbit et al., 2002) and the MERLOT project. However, the AIPL environment does embrace the group-learning-paradigm, which enables learners to be placed into communities best suited to their learning styles. As not clearly stated within the above Section PAFS does provide a way for allowing individuals to retrieve learning objects that have been viewed and rated within their individual community. The rating belonging to individuals within the community can be retrieved to indicate what other learners have viewed. This is similar in concept to the recommender system by Ghauth et al., (2010).

The rating system being used here bears similarity to the Pearson Correlation algorithm, which rates objects from 0.0 to 0.9, in which 0.9 is the best suited. Within AIPL the

algorithm rating system works from 0 to 10, in which 7 to 10 is the best suited. A modification to the weight-based scale has enabled a calibration to be designed:

| Rating Scale: | Specification of Search Type |
|---------------|------------------------------|
| 0 – 3         | Low Search                   |
| 4 – 6         | Medium Search                |
| 7 – 10        | High Search                  |

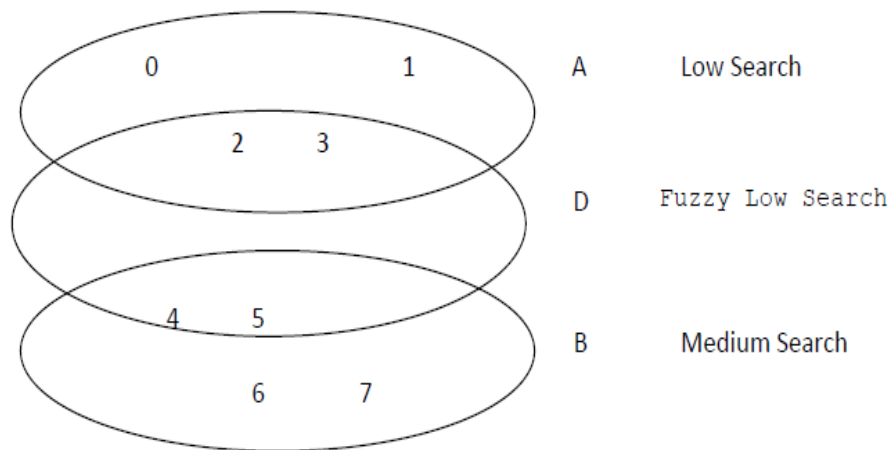
The quality assessment algorithm has an additional function which enables the learner to retrieve specific values thus enabling a more comprehensive search to be derived. For more information see Table 7: Additional Search technique.

| Rating Scale: | Search Type   | Rating Scale: | Search Type         |
|---------------|---------------|---------------|---------------------|
| 0 – 3         | Low Search    | 2 – 5         | Fuzzy Low Search    |
| 4 - 7         | Medium Search |               |                     |
| 8 – 10        | High Search   | 6 – 9         | Fuzzy Medium Search |

*Table 7: Additional Search Techniques*

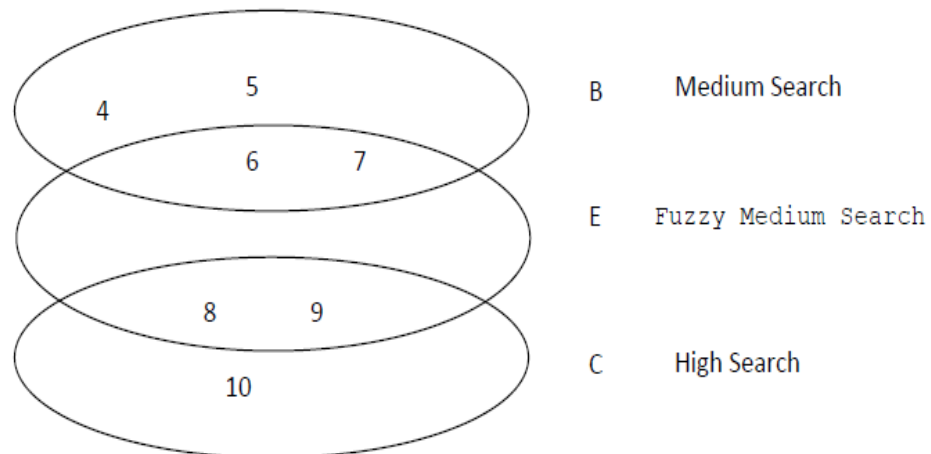
Table 7 can be represented using a Venn diagram to illustrate set operations, for more information sees Figure 21.





$$(A \cap D) = \{x \mid x \in A \wedge x \in D\} \quad \text{or} \quad (A \cap D) = \{2, 3\}$$

$$(B \cap D) = \{x \mid x \in B \wedge x \in D\} \quad \text{or} \quad (B \cap D) = \{4, 5\}$$



$$(B \cap E) = \{x \mid x \in B \wedge x \in E\} \quad \text{or} \quad (B \cap E) = \{6, 7\}$$

$$(C \cap E) = \{x \mid x \in C \wedge x \in E\} \quad \text{or} \quad (C \cap E) = \{8, 9\}$$

*Figure 21: Venn Diagram*

### 3 – Repository

The repository is used to store learning materials within the AIPL environment. The repository has the capability of enabling communities to save dynamic references from an exterior source. The e-bookmarking mechanism through the use of recommendation from the community could make it easy for homogeneous groups to share ratings belonging to the learning materials that have been viewed.

The importance of this approach provides a way for clusters to be developed from

homogeneous views. Homogeneous views within e-bookmarking can be seen as a filtering device that uses the clustering of results to be retrieved in accordance with CF.

### 5.2.3.3.2 Technical Aspects of e-bookmarking

To achieve the collaborative clustering of homogenous views within PAFS, Figure 22 expands on the theoretical work conducted by Yao et al., 2007, the Typical KR System, which can be found in Chapter 3, Section 3.5.1 Approaches to matching.

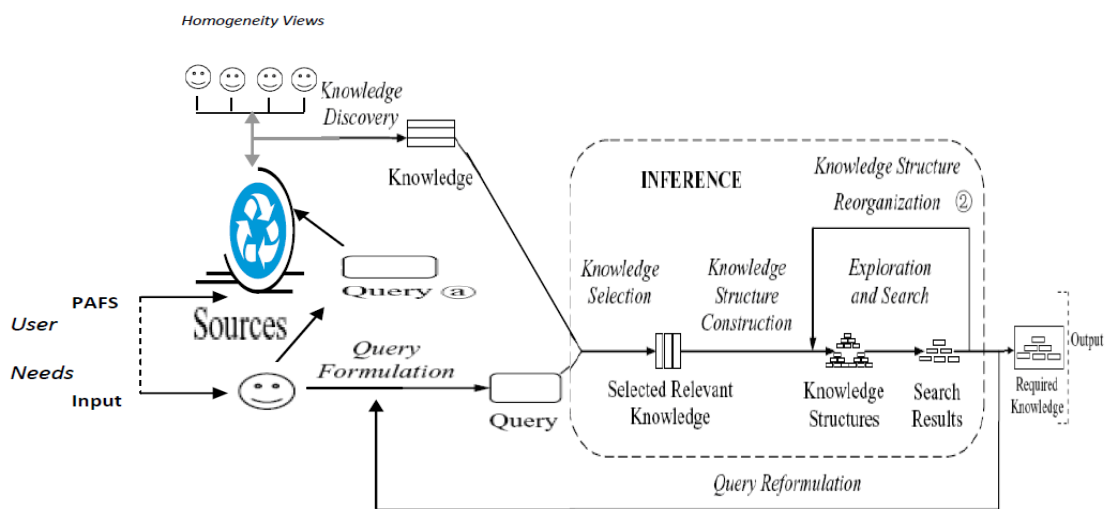


Figure 22: Approaches to Matching

To achieve the collaborative clustering and build upon the theoretical model that (Yao et al., 2007) suggested within Figure 22 the following changes were required:

**Query a:** Sends two internal state variables belonging to the individual containing how that individual wants to learn. These internal variables feed directly into the (Source) to enable the first step of retrieving the group views. This internal state variable acts like an indicator, which feeds along the process till reaching the Selected Relevant Knowledge.

**Sources:** Within PAFS the sources consist of: Rating data belonging to the learning materials; how the learners prefer to learn; and what category/s they fit in. Query a, feeds directly into the source by indicating what module the student is on and how that learner prefers to learn in accordance with their own learning style/s.

**Selected Relevant Knowledge:** The selected relevant knowledge section retrieves the

following values:

1. Search criteria: i.e. 0 to 10
2. Module course code: i.e. Internet Computing
3. Learner's category: i.e. how they learn in accordance to their own learning style/s.
4. Collaborative grouping value (linked from Learner's category)

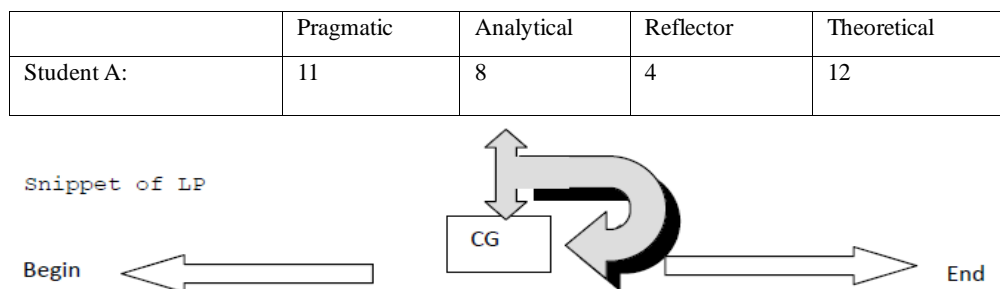
These four internal state variables are critical to the whole Personalised Adaptive Filtering System when retrieving homogenous views.

Once these internal state variables have been selected, the next important aspect is to create a knowledge structure for the algorithm to use within the search results. The search results will then be used again to filter out any unnecessary and repeated results. For more information on this technical issue see Section 5.2.3.5 Advanced Methods.

#### 5.2.3.4 Categorising of Groups (CG):

According to Tzouveli et al., (2005) and Subramaniam (2006), using groups of profiles has enabled environments to adapt to: similar groups' habits, interests, skills, projects, locations and personalised settings. The purpose of using CG within PAFS is to find any close correlations between the learning relationships of individual learners and fellow learners within a module. CG works by interrogating and comparing string parameters belonging to individual learning profiles and records them into a matrix. CG is derived from close interrogation of LPs belonging to all the students studying on a particular module, to enable comparisons to be made. Once similarities have been identified within the CG, the algorithm will group them into a matrix, for an example of the CG operational functionality see Figure 23.

*Figure 23: procedures: (original)*



The CG reads in each parameter from left to right of the LP. Once all the values belonging

to the LP have been read and recorded, the next step of the operation is to use a cycle that loops through a rule base until the highest value can be identified and it is this value which the CG uses. The following four steps are required to enable the CG to work.

**Step 1:** Placing values into a rule base see Figure 24.

Learners Style Response **Student A:**

|                        |                        |                            |                     |
|------------------------|------------------------|----------------------------|---------------------|
| Active Experimentation | Reflective Observation | Abstract Conceptualization | Concrete Experience |
| 14                     | 12                     | 16                         | 8                   |
| Activist               | Reflector              | Theorist                   | Pragmatist          |
| 8                      | 4                      | 12                         | 11                  |

*Figure 24: Matrix*

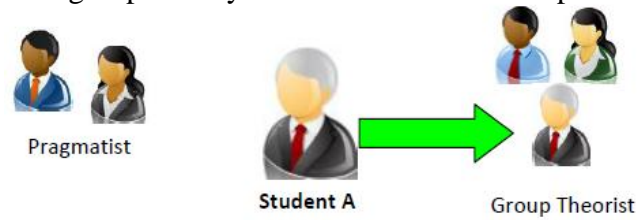
**Step 2:** The Rule Base will average out each conjoining value

|                        |                        |                            |                     |
|------------------------|------------------------|----------------------------|---------------------|
| Active Experimentation | Reflective Observation | Abstract Conceptualization | Concrete Experience |
| 14                     | 12                     | 16                         | 8                   |
| Activist               | Reflector              | Theorist                   | Pragmatist          |
| 8                      | 4                      | 12                         | 11                  |
| Average Calculation    | Average Calculation    | Average Calculation        | Average Calculation |
| $14 + 8 / 2 = 11$      | $12 + 4 / 2 = 8$       | $16 + 12 / 2 = 14$         | $8 + 11 / 2 = 9.5$  |

**Step 3:** The highest value belonging to the matrix will be extracted in this case (14)

With the category (Abstract Conceptualization & Theorist)

**Step 4:** A group will be formed or if a group already exists **Student A** will be placed into that particular cluster.



Student A Group Theorist

The Personalised Adaptive Filtering System will use the CG to overcome some of the issues associated with grouping (like unfair matching depending on experience; abilities and capabilities). According to research conducted by (Oxford 2003; Severiens et al., 1994; Gutierrez et al., 2003) matching groups based on learning preferences can improve the learning experience while studying on-line. Genovese (2004), Litzinger et al., (2005) and Mehigan et al., (2010) indicate that trying to match individuals into groups via learning preferences can assist with the development of students to gain knowledge of how other people learn. Matching individuals through learning preferences will disregard issues such as those indicated by: Alexander et al., (2004) of inappropriate grouping based on academic levels; of Leutner et al., (1998), Oxford (2003), and Boyd et al., (2004) around misleading course materials; and of Cook et al., (2004) about inappropriate goal setting towards group performance).

However, researchers like Severiens et al., 1994; Oxford 2003; Alexander et al., 2004; and Cristea et al., 2010, have provided a great wealth of knowledge about grouping using a variety of approaches, and it is still in the early stage of academic research about how to categories groups of individuals in a successful way. Spiro et al., (1996) does indicate that using learning styles within on-line learning environments can assist with matching learning materials to groups/individuals while studying on-line. The approach that was provided within CG was adopted due to the recommendation from literature that using learning preferences can assist with group development.

#### **5.2.4 Dealing with Ratings**

Yen et al., (2009) suggest that when dealing with ratings, the e-learning environment could use weights to calculate and rank the resources in accordance with personal preferences.

Once the learning objects have been ranked, the repository could provide a way for intelligent searches to retrieve specific and relevant materials in accordance with the rating. Yen et al., (2009) indicates that when dealing with rating, a large number of objects and participants are required to provide an efficient way of analysing results before learners can be assisted within the e-learning environment.

According to Almudena et al., (2009) other limitations are associated with recommendation retrieving systems for example: lack of expertise regarding querying within the domain area; lack of diversity within the retrieval of the learning materials themselves i.e. high quality of search and retrieval; and how to effectively apply a social and hybrid learning environment in retrieving specific group views.

#### **5.2.4.1 Solutions to Rating**

According to Middleton et al., (2002), Ahn (2007), Yen et al., (2009) and the cold start problem is based upon very little or no initial ratings available to represent the learning object before a recommendation system can work. There are many approaches that according to Middleton et al., (2002), Ahn (2007) and Ghauth et al., (2010)\* can be used to overcome the cold start problem, for example, bootstrapping (pre-loading of information from a group of 'experts'), ontology's (using secondary data to support assumptions made about object quality), machine learning techniques (to supplement initial data), hybrid systems (combination approaches), keyword recommendation, and content-based recommendation.

PAFS uses a rating and recommendation system and does suffer from the cold start problem. Users are able to rate resources once they have retrieved and viewed those resources, however, in the beginning resources will have limited ratings. In addition to this PAFS uses a group based recommendation system, categorising ratings data from individuals into independent group perspectives on particular learning resources, this is also subject to the cold start problem. Therefore PAFS suffers from two levels of the cold start problem. The first level is a lack of ratings data linked to individual learning materials and the second is a lack of ratings data linked to collaborative grouping. This can be best illustrated through the below example:

Clive is a pragmatist undertaking a module about Computer programming. Clive selects a resource to use from within PAFs that has not been previously rated and rates the resource. When this resource is presented to another pragmatic learner then they will view Clive's rating (generally this is as part of an aggregated total – but in this case it is a single rating). Another learner who is not pragmatic will not be presented with Clive's ratings data for this resource.

Due to the nature of the cold start problem PAFS uses a trivial approach (keyword search), which according to Ahn (2007) can assist individuals in retrieving materials which are unrated. The AIPL environment does provide a keyword search that the individual can use based upon: terminologies; key phrases; and knowledge about the topic. This approach can assist the individual in building up the rating system with the materials that were retrieved, which can assist the group from the cold start problem. Middleton et al., (2002) and Ghauth et al., (2010)\* does indicate that any additional data that can be used to assist with the cold start problems can be beneficial not just to the system but also for the individual.

*“In return for any bootstrap information the recommender system could provide details of dynamic user interests. This would reduce the effort involved in acquiring and maintaining knowledge of people's research interests”*  
(Middleton et al., 2002).

PAFS does not introduce any new concepts to the cold start problem but does use an existing approach to assist with the issue.

Dealing with the cold start problem within a community is not the only problem as indicated by Almudena et al., 2009, which refers to how to effectively group individuals. According to Severiens et al., 1994; Oxford 2003; Alexander et al., 2004; Almudena et al., (2009); and Cristea et al., (2010), there are still issues like: how to place the individual within an environment (community based); how to share homogenous views; and what factors are involved within grouping.

Section 5.2.3 deals with what factors are involved within grouping and how to place the individuals into a collaborative cluster. The research conducted by (Spiro et al., 1996; Oxford 2003; Severiens et al., 1994; and Gutierrez et al., 2003) indicates that using

learning styles to group individuals into a community does provide an effective way. This leaves a problem of how to share homogenous views.

To deal with how to share homogenous views within AIPL the learners will be placed in clusters that have the same learning traits, creating a similarity between the learners. By grouping learners into the same category this will enable homogenous views to be created. To enable other views to be shared, a rating mechanism was introduced: that focused directly on feedback regarding what they have found interesting. Even though PAFS still uses the rating and recommendation system it groups the learners with similar learning traits, thus enabling them to share more specifically focused opinions on the learning materials.

### ***5.3 The Personalised Adaptive Filtering System (PAFS)***

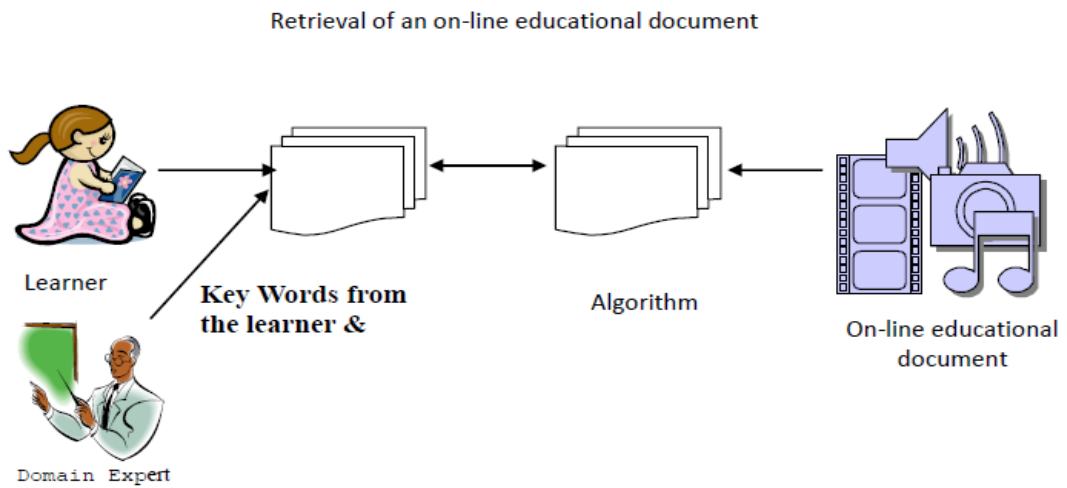
In writing this Section 5.3, the purpose is to summarise the individual functions associated with the Personalised Adaptive Filtering System. It does this through introducing the Non Semantic Matching Algorithm (Section 5.3.1), the Semantic Matching Algorithm (Section 5.3.2) and then finally the collaborative categorisation and recommendation function (Section 5.3.3).

#### **5.3.1 Non Semantic Matching**

The Non-Semantic Matching Algorithm (NSMA) is a search mechanism that enables learners to find relevant information using a pre-defined list of characters, symbols, and numbers. According to Xul et al., (2005), the keyword search is now the most popular search method for retrieving on-line documents.

Figure 25 and 25A demonstrate the overall features associated with NSMA.





*Figure 25: Features of the NSMA*

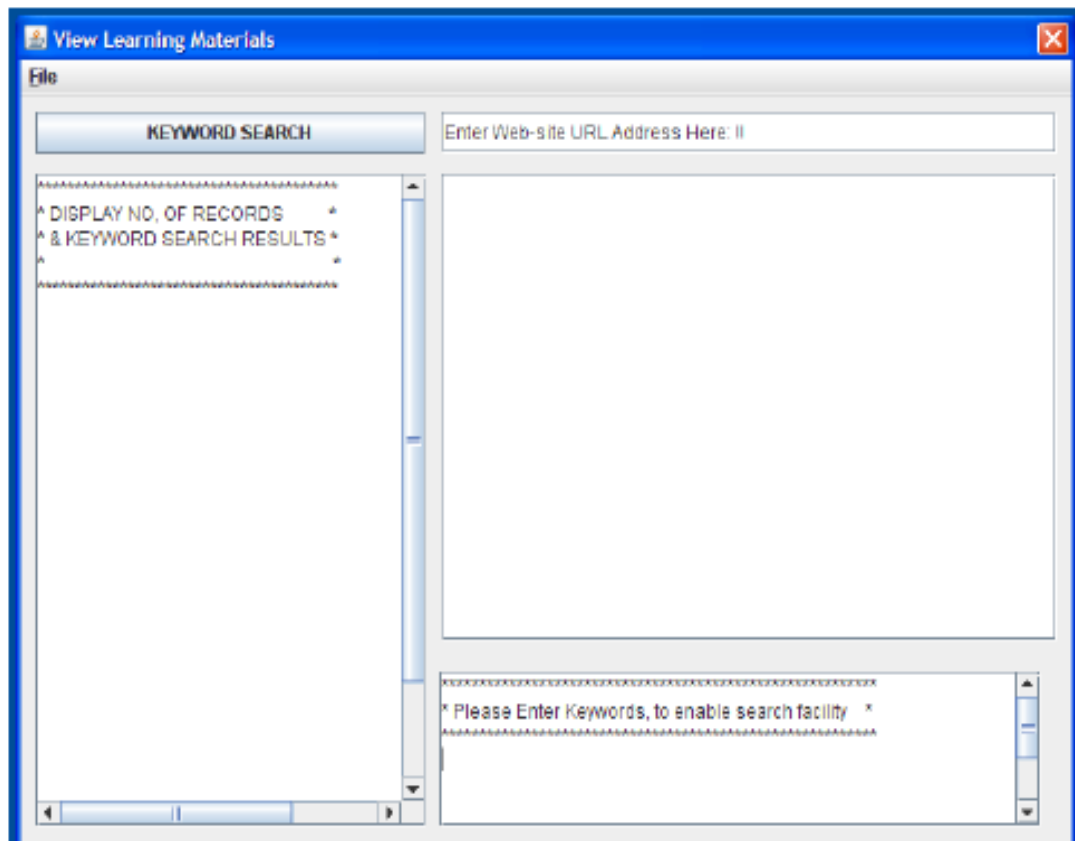


Figure 25A: Actual keyword search facility found within AIPL.

The NSMA obtains keywords from the subject domain expert and the learner. The NSMA enables the learner to add keywords that are relevant to the domain topic area. If we take an example of wiring a plug, a domain expert may choose keywords such as: {fuse, earth,

live, neutral, socket}, the individual may add keywords such as {kettle or EU} (in this example this may provide a specific context). The NSMA would then use the pre-defined keywords mentioned above to search through on-line learning resources for appropriate content.

The NSMA can also take keywords related to the learning styles of the learners, for example, for a visual learner it may use keywords related to gathering visual learning objects e.g. image, diagram etc... This is a fairly primitive search and retrieval mechanism when linked into learning styles but is worth considering.

Once the NSMA has searched through the on-line materials, the algorithm then retrieves the resources and produces a summary of its findings, from which a selection of resource is made by the individual learner.

### **5.3.2 Semantic Matching Algorithm**

The Semantic Bridging Algorithm (SBA) functions through extracting from an individual's learning profile a representation of how that individual prefers to learn, it then matches this representation against semantically marked up learning objects contained within the learning repository.

Figure 26 represents the process involved while retrieving learning materials associated with one's learning style. The SBA interrogates the learner profile and extracts relevant information i.e. how that learner prefers to learn (for example: pragmatist), once this information is found the SBA will then shift through the learning repository to find materials associated with practical, logical or systematic exercises. For the SMA, please see Figure 26 and 26A.

### Extracting metadata from the on-line educational document

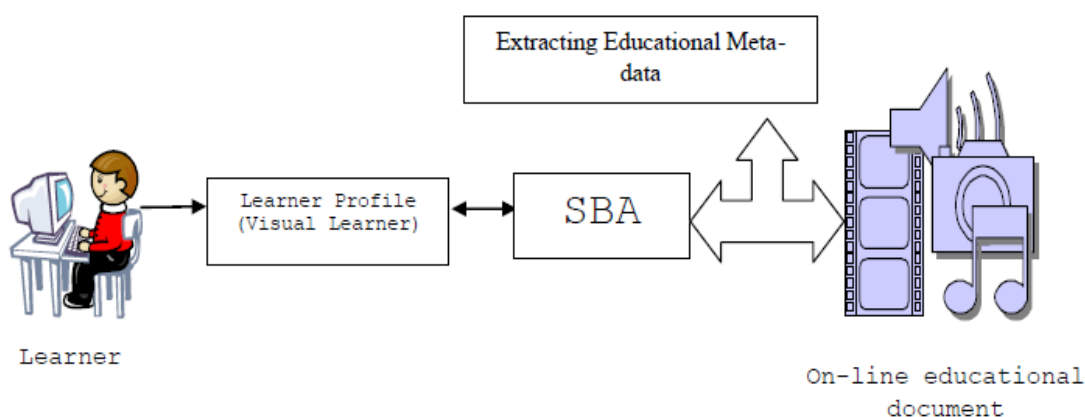


Figure 26: Semantic Matching Algorithms

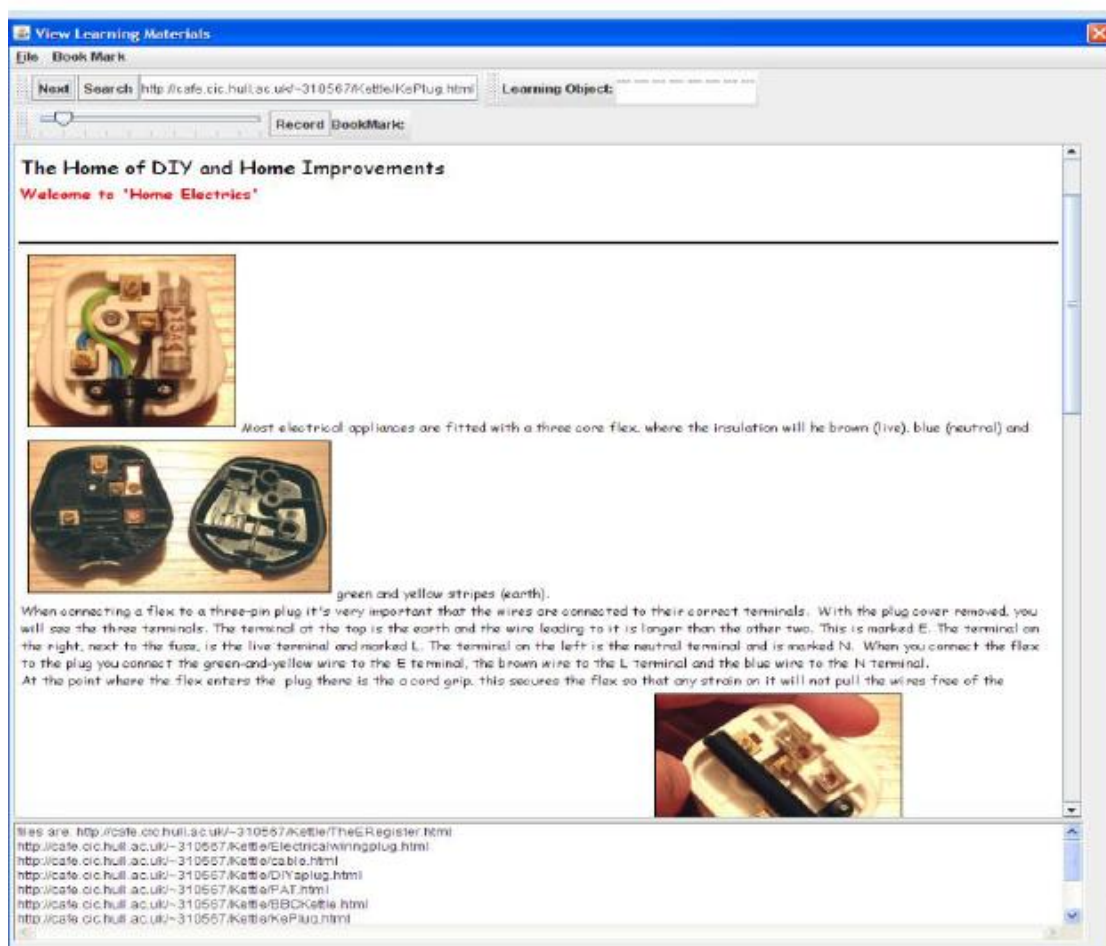


Figure 26A: Actual Semantic Matching Algorithm

To enable the SBA to shift through the learning resources, each individual learning resource needs to be marked up using LOM. This standard enables the SBA to check for matches between individual learners and learning resources.

Once the SBA has searched through the repository of materials, the function will then retrieve best matched resources and enable the individual learner to select from these.

Figure 27 is a snippet belonging to one of the learning objects used to challenge pragmatist learning within the AIPL environment.

Below are three plugs both indicating how to wire a plug, use the textboxes to select the correct cabling combination

What cable fits into Clip A

What cable fits into Clip B

What cable fits into Clip C

[JavaScript Application]

Correct Combination of Letters, Well Done!!!

The learning object above can be represented using the parent and child tag that is associated with XML. For a representation of the learning object above, please see Figure 27.

```

<?xml version="1.0" encoding="ISO-8859-1"?>
<?xml-stylesheet type="text/css" href="lss.css"?>
<xml id='xmldata' style='display:none;'>
<LearningStyle>

  <lstyle category="KOLB">
    <classification> Concrete Experience </classification>
    <activity> practical exercise </activity>
    <activity> logical exercise </activity>
    <activity> systematic exercise </activity>
  </lstyle>
  <lstyle category="Honey and Mumford">
    <classification> Pragmatist </classification>
    <activity> practical exercise </activity>
    <activity> logical exercise </activity>
    <activity> systematic exercise </activity>
  </lstyle>
</LearningStyle>
</xml>

```

*Figure 27: XML*

For an xHTML representation of the above pragmatist exercise, please see Figure 28.

```

<p> Specific Exercised Based on Pragmatist activities:
  <span class="LearningStyle" id="KOLB">
    <span class="Pragmatist"> practical, logical and systematic exercise </span>
    <span class="ConcreteExperience"> practical, logical and systematic exercise </span>
  </span>
</p>

```

*Figure 28: xHTML*

Figure 28 was extracted in accordance with the recommendations of Dumbill, 2000 and Kesteren 2007. The SBA was built to facilitate the Adaptive Information Retrieval system, by extracting relevant information (learning style categorisation) from the learner profile, which is then used to search the repository for activities and exercises that best suit the individual needs.

### **5.3.3 Collaborative Categorization and Semantic Bridging (CC&SB)**

The CC&SB function was designed to facilitate and act as an educational tool within the AIPL environment by providing the opportunity for the learner to retrieve clusters of

homogenous views (from learners with similar learning approaches). The function interrogates clusters of learners that have similar or matching learning traits through the use of the Learner Profiles. Once the grouping has been created the collaborative categorisation mechanism shifts through viewing records and ratings belonging to each individual and brings back only the highly rated learning materials from particular groups of users.



*Figure 29: CC&SB actual design*

Using CC&SB within AIPL enables other learners to retrieve materials via ratings based upon their group profile. Figure 29, shows how the learner can click a button (retrieve) which will then filter out the learning materials with a low rating. For more details regarding how Collaborative Categorization works within PAFS, see Section 5.2.4.4 Categorising of Groups.

The CC&SB requires five main concepts to work: these are:

- Section 5.2.2 Representation of the Learner Profile
- Section 5.2.4.1 Homogenous Views

- Section 5.2.4.3 E-Bookmarking
- Section 5.2.4.4 Categorising of Groups
- Section 5.2.4.5 Dealing with Ratings and Group Life

It is these five principles that the author attributes to the whole collaborative categorisation of grouping within the AIPL environment.

There are, however, complexities and challenges associated with each of the five sections mentioned, but they do have design solutions/issues that can be seen as a significant contribution from this Thesis.

## ***5.4 Overview***

Search and retrieval techniques play an important part within education: they enable learners to search for specific learning resources, and can be used to filter out any unwanted noise (inappropriate resources). Each search and retrieval approach has its own beneficial aspects and limitations associated with them. The literature search has indicated that certain filtering approaches can be grouped together to overcome issues like: improving performance relating to the retrieval of learning objects; computational issues regarding large repositories and materials; and creating clusters of homogenous views to scale down retrieval and unwanted reading materials. Combining these enables the use of: sharing knowledge; acquiring group knowledge acquisitions to support those with little or new knowledge; or to assist and develop those with existing knowledge.

The Personalised Adaptive Filtering System was designed to facilitate learning centrality, by taking the individual learner and building a solution around their needs. By grouping individuals together they can share points of views, allowing them to develop and change how they might learn over time, by encouraging them to re-evaluate their own approaches through the use of learning process questionnaires. Within this chapter, complexities and challenges were researched to indicate which problems and issues were associated with the filtering mechanism and collection of homogenous views. This chapter concludes with some of the main findings as follows:

The five principles that are required to enable collaborative categorisation of grouping to be formed are: Representation of the Learner Profile & the Learner Profile Lifecycle; Homogenous Views; E-Bookmarking; Categorising of Groups (CG) and Dealing with Ratings and Group Life.

## **Chapter 6: Experimentation**

This chapter provides detail about the Experimental suite of tests selected to evaluate the model presented in Chapter 4, and the algorithms presented in Chapter 5. This test suite includes a range of baseline tests designed to establish performance prior to system implementation, and a range of post implementation tests designed to establish change against the baseline. This suite uses a mixed methods approach evaluating technological performance, and user experience to establish support for the solution presented in this Thesis.

The chapter starts with an introduction to the Thesis question and what hypotheses are directly associated with the research. It follows this with a detailed examination of the mixed methods used to conduct the research. Finally, the chapter critically analyses the results from testing the AIPL environment.

### ***6.1 Research Questions and Hypotheses Re-stated***

This Thesis posed the following research question:

Can the underlying principle of web 2.0, that of the ‘participatory web’, be used as the basis for a model to provide more intelligent personalisation of learning content to users?

In essence, this will explore whether an intelligent environment which incorporates the ideas of social and community grouping can be developed to aid in the personalisation of learning materials to the learner.

The results from this chapter should provide supportive evidence that the theoretical concept of the AIPL model can enhance the learner’s experience.

### ***6.2 Design of Experimental Test Bed***

In this section a detailed description of each individual test is set out, to enable other researchers to follow the research conducted within this chapter.



The AIPL test suite was developed to evaluate whether the system supports learners in providing content of interest and value to their studies through the various levels of matching algorithm. The tests focused on the techniques used within the AIPL algorithm: keyword searching; semantic bridging; collaborative grouping and rating. Each technique was built using separate functions to enable a comparison to be made of the effectiveness and efficiency of matching the learner needs to the materials. According to Ardito et al., (2006) and Liebowitz et al., (2009) it also useful to measure the effect of how individual functions work together, through a more synergetic evaluation. Therefore the techniques are also evaluated collaboratively through feedback from the user.

The test bed was split into several sections including the creation of a Baseline Test (establishing a mechanism for comparison), a preliminary test (a short course on how to wire a kettle plug), a primary test (another short course module called Introduction to Java Script) and finally a comparative test with a VLE (using the same module as the primary test). Experiment A, B and C as outlined below were used to enable measurement of system performance, and user response. Experiment D focused on the measurement of user response related to comparison with another VLE.

### **6.2.1 Experiment A: Baseline Test**

To enable a system to be evaluated, it is useful to establish some form of baseline testing. Baseline tests provide a mechanism to enable correlation between ‘normal’ practice and the impact of any given change (Field et al., 2007). According to (Shepherd et al., 2000; Kindley 2002; Nordic 2006) using baseline testing within ICT situations enables critical responses to be analysed and compared. This provides evidence through the use of feedback to interpret what people liked and responded well too when using e-learning facilities. Sinner et al., (2003), indicates that the provision of baseline testing gives other researchers the opportunity to carry out similar tests. The baseline testing according to Sinner et al., (2003) is used to set and test particular behaviours of algorithms by analysing the following specifications: environmental components, environmental variables, and probability distributions.

The baseline test will initially involve test candidates finding out how they learn through

the use of a Learning Process Questionnaire (LPQ). The results of the LPQ will then be explained to the individual as well as what factors they look for, and how they should perceive the learning materials. Once the results from the LPQ have been explained the candidate will be provided with access to a repository of learning materials. They will then need to go through this repository and select relevant learning content that appeals to them in relation to a particular learning context. This baseline set of results will provide an indication of the sample set of learning materials that individuals judge as being most relevant to their learning needs, and will be used as a comparator against Experiment B and C.

For example: A candidate with a learning style category of reflector may pick out a sample set of nine learning materials from the learning materials contained in the repository. These materials they will have judged to be the most suitable, relevant, and of enough quality to help them in their learning journey.

Three instructional studies were required within this Thesis to make this research possible. The first instructional study was the introduction of a domain topic i.e. wiring a plug (learning activity). A range of learning materials was presented to students enabling them to select appropriate learning materials relevant to their approach to learning. The particular study was used to summaries (self-review), clarify, and predict materials closest to how they learn within this given topic (wiring a plug). The results belonging to the learning activity (wiring a plug) were stored for comparison against 6.3.2 Experiment B: Preliminary Test results.

The second instructional study required within this Thesis was the introduction of a module called 'Introduction to Java Script', which involved the candidates going through another repository of learning materials selecting the most relevant content to their approach to learning.

The third and final study involved comparing the AIPL environment with the Moodle VLE, shown in Section 6.3.4 Experiment D: Comparison Test. This approach allowed for a close comparison between the AIPL environment and Moodle environment with respect to: handling student queries; Human Computer Interaction (HCI) issues; pedagogical course approach; mapping of course navigation; and handling in general.

These three studies should provide an insight into how the student will interact with online learning materials based upon their individual preferences. This may lead to a significant improvement in the quality of delivery and provision. The comparison tests between the two VLE's will be able to identify reliable issues over time, and the transfer of tasks that tapped the trained skills of summarizing, questioning, and clarifying, on-line learning materials.

### 6.2.2 Experiment B, Preliminary Test

Please see Figure 30 for the 3 tests involved within Experiment B.

|        | Name of Test                         | Testing criteria |
|--------|--------------------------------------|------------------|
| Test 1 | Keyword Search                       | Wiring a plug    |
| Test 2 | Semantic meta-data contextual search | Wiring a plug    |
| Test 3 | Collaborative grouping               | Wiring a plug    |

*Figure 30: Preliminary Testing (Wiring a plug)*

Within Test 1 there were two types of tests conducted which looked at a simple generic keyword search and a more domain specific one. The response from the experiments was used to compare whether a simple generic keyword search produced the same results as a more specific one and to question how effective the retrieval filter was in both searches. The user feedback on the operation was analysed and the materials retrieved.

Test 2 involved the analysis of learning materials returned using AIPL through use of a learners profile against the baseline results from Experiment A. Precision and recall were evaluated to determine if the algorithm has performed equally well as human judgment.

Test 3 involved the students sharing their recommendations (homogeneity views) with other students that have similar learning traits. The learners were able to retrieve other views using a collaborative grouping rating mechanism to retrieve feedback from similar learner groups to enable comparisons to be made. This particular test, test 3 provided an insight into how group dynamics might affect the overall performance of sharing personal views and ratings. The test results from this Experiment were analysed to determine if mismatching was reduced in accordance to rating, and group views. Test 3 was developed to support the Thesis question.

### 6.2.3 Experiment C, Primary Test

Experiment C was created to enable comparison results to be formulated from the results found within Experiment B. This would be achieved by using a primary domain topic (Introduction to Java Script) for the testing procedure. The following tests were set out, which according to Shepherd et al., (2000); Kindley (2002); and Nordic (2006) provided the correct setting to facilitate a comparison between the preliminary (wiring a plug) and primary (Introduction to Java Script) activities. Please see Figure 31 for the three testing steps involved within Experiment C.

|        | Name of Test                         | Testing criteria            |
|--------|--------------------------------------|-----------------------------|
| Test 1 | Keyword Search                       | Introduction to Java Script |
| Test 2 | Semantic meta-data contextual search | Introduction to Java Script |
| Test 3 | Collaborative grouping               | Introduction to Java Script |

*Figure 31: Primary Testing (Introduction to JavaScript)*

The testing procedures used within Experiment C, were based upon those designed for Experiment B.

Test 1 was used to evaluate a generic and specific keyword search and compare this with the results obtained in Experiment B.

Test 2 evaluated the meta-data contextual search and enabled comparison of Precision and Recall results to the baseline presented in Experiment A and the result set obtained within Experiment B.

Test 3 enabled analysis of the results from the collaborative grouping and rating algorithm presented in Experiment C with the similar result set from Experiment B.

### 6.2.4 Experiment D: Comparison Test

This experiment looks at and explores the similarities between the AIPL environment using Introduction to Java Script and the same course being run on the Moodle environment. The comparison test will look at particular features belonging to: the course structure, the interface design and finally student thoughts about the different features offered within AIPL.

## 6.2.5 Limitations

During the transitional period from the theoretical model to the framework for testing, a variety of environmental and variable constraints were identified, which could have affected the testing stage. These factors are: 1) marking up of meta-data regarding the learning objects; 2) number of students required to set the tests for; 3) time factors, which varied during testing; and 4) corrupting the test data.

Designing the course content involved the use of LOM to represent the learning objects found within the on-line repository. The limitations and issues identified, when using LOM were: designing the correct annotation that would successfully represent the materials. This particular factor involved further complications due to the representation techniques required to mark up on-line learning objects. These are:

- How to attach the LOM standards to every learning object used throughout the tasks for each week? This involved much time wasted on the course content by going through each individual learning object to check for validation regarding the individual tasks set each week; and finally to ensure that the algorithm can identify course content that is marked up semantically.
- The number of students that are involved during the whole testing procedure will be in the range of thirty-fifty students due to the expected interest in evaluating the project in the institutional context. This small number raises concerns in relation to statistical significance, and causes some issues in relation to the collaborative group feedback algorithm, which relies on greater numbers of students viewing and rating learning objects.

However, Goldberg et al., (1994) and Cobb et al., (1998) recommends the use of small groups when trying to capture the abilities of VLE's; but, results should only be taken as a preliminary finding. Goldberg et al.,(1994), Cobb et al., (1998), Whitelock et al., (2000) and Zhang et al., (2004) have all used a variety of candidates sample sets ranging from seventeen to thirty to verify statistical significance belonging to their e-learning research.

According to Cobb et al., (1998) when testing VLE' s it is critical to the project that a diverse group of candidates are used, which will support a multitude of abilities and backgrounds. The diversity of groups can vary depending on "*background demographic information (age, gender, reading ability, numeracy, comprehension, physical disability and computer use)*" (Cobb 1998 et al., P 2).

To undertake such research varies depending on complexity and the realistic number of test benches being offered. Using a real life module that is associated with the degree classification involves students turning up on time for testing, and this would mean that consistency over the life cycle of the on-line module is ensured.

As indicated by (Goldberg et al., 1994; Cobb et al., 1998; Whitelock et al., 2000; and Zhang et al., 2004) the use of small sample sets can still produce significant evidence to support research goal.

- The time factor played an important part: it involved using a specific timetable to which each individual test was carried out; because of the size of the project, test 1 and test 2 within each Experiment were tested at the same time to check for comparison between the two. The module run time started at the beginning of the semester and ended at the end of semester, to keep within the educational life cycle. Algorithm 3 could only be applied when enough data had been recorded within the on-line system.
- It is necessary to assume that participants do not have full knowledge of the total structure of AIPL and PAFS, or the ability and inclination to go through any complex reasoning to change the results throughout the testing procedures. In addition to participants, the following issues have been identified: The testing procedures involve all learning materials being used for this testing purpose being marked up with metadata. This would ensure that a fair test can be conducted and the total learning objects retrieved for each algorithm can be recorded.

In conclusion, the limitations and issues of testing the theoretical model has given rise to many implications for future research, for example: to measure the full potential would

require testing over a longer period of time, which would produce more accurate results.

### ***6.3 E-learning Research Measurements***

This section describes experimental methods used by other researchers in the area of e-learning. Essentially, researchers suggest that experimentation in this area can be analysed through both quantitative and qualitative methods with most researchers encouraging a mixed methods approach (Bonk et al., 2000; Britian et al., 2004). Mixed methods provide the researcher with him opportunity to capture programmatic usage data whilst also capturing the essence of system use through opinion based questionnaires or interviews. Begičević et al., (2006) suggests that mixed methods allow for a closer match between experimental results and research aims.

Bonk et al., (2000) indicates that Human Computer Interaction should play an important part when testing e-learning environments, for example: learner-content interaction; learner-instructor interaction; and learner-learner interaction. Britian et al., (2004) indicates that for each of the multiple dimensions of learners' interaction, we should look to metrics for analysing adaptability and interactivity, in addition to using a variety of monitoring mechanisms. According to Britian et al., (2004) the following three elements should be used when examining e-learning environments:

- Adaptability - According to Britian et al., (2004) testing for this provides an insight into how participants react to activities associated with a learning topic, and the needs of the individual or groups of users.
- Interactivity - Cappuccio et al., (2004), Begičević et al., (2006) and Britian et al., (2004) suggest that interactivity must play an important role in analyzing students when using an on-line environment. Interactivity enables the domain expert to monitor student behaviour when using on-line materials, resources of their own, external materials, and launch and run simulations.
- Monitoring - Britian et al., (2004) suggests that monitoring through usage patterns can be broken down into three particular areas, these are: usability, observation, and data capture. Usage patterns to monitor include computer log data (e.g.

number of participants, reading time, creation time, etc.), video screen grabs, student and instructor attitudes, peer responsiveness and interactivity. Silius et al., (2003); Chen (2001); Frankli et al., (2004), Lanzilotti et al., (2006) also indicate that Human Computer Interaction, in particular, usability testing is important. They suggest that observing learners whilst on-line can provide the opportunity to gather details regarding: what stimulates the learner’s interest; what motivates the student to learn; system level perspectives on the user interface; overall system performance; and the general effectiveness of the facilities offered. The methodology used within this Thesis runs parallel to recommendations from (Bonk et al., 2000; Britian et al., 2004) for using mixed methods and that of (O’ Riordan et al., 2003; Ghauth et al., 2007; Hahsler 2010), which will use recall and precision to ensure the decision-support accuracy of the system.

According to Alvarez, precision can be defined as “*the fraction of the items retrieved by the system that are interesting to the user, and **recall** (as), the fraction of the items of interest to the user that are retrieved by the system*” (Alvarez 2002, P1).

In addition to the measurement of precision and recall, it is also useful to calculate the F Measure (Lin et al., 2004) as this improves the accuracy of results. Cambridge University Press suggests that “*a single measure that trades off precision versus recall is the F measure, which is the weighted harmonic mean of precision and recall*” (Cambridge University Press, 2008).

The mathematical formula’s used to measure precision and recall, are the following:

| Recall (R)  | F-Measure (FV)   | Precision (P)  |
|---|--|--|
| $R = TP / (TP + FN)$ Cambridge University Press (2008)  | $FV = 2PR / (P + R)$ Cambridge University Press (2008) | $P = TP / (TP + FP)$ Cambridge University Press (2008) |
| <b>Key:</b><br><br><b>TP</b> stands for <b>True Positive</b> - is used to derive the correct values within a test set, for classification purposes.<br><br><b>False Positive (FP)</b> - is used to compute the proportion of false positives between values within a test procedure.<br><br><b>FN stands for False Negative</b> - A false negative is when the outcome is incorrectly classified as negative when it is in fact positive. |  |  |

According to (Kamenský et al., 2006), the independent variables associated with



Assessment of system performance is:

- Measuring the complexity of the algorithm
- Precision
- Recall

By using the recommendation of (O’Riordan et al., 2003; Kamenský et al., 2006; Ghauth et al., 2007; Hahsler 2010) complexity will be measured using the retrieval rate of learning materials (through the use of Precision and Recall). Salton et al., (2002) and Kamenský et al.,(2006) indicate that other qualities like time factor, complexities, emotional, analytical, and structural intervention can also be used to measure: sensitivity and performance.

The independent variables that are associated with these are:

- **Emotional State:** According to Lu et al., (2008) an emotional state set is associated with the learning experience. The emotional state set can be found in Table 7: State Set

|             |  |
|-------------|--|
| Interest    | Curious about the new knowledge, attentive, eager to learn                   |
| Confusion   | Faced with problems, trying to solve the problems.                           |
| Frustration | Completely unable to understand the course material, reluctant to learn.     |
| Hopefulness | Difficulties solved, pleased with the new findings, willing to explore more. |

*Table 8: Lu et al., (2008) State Set*

An additional emotional state is the state of boredom as outlined by Chen (2000) in Table 8.

|         |   |
|---------|---|
| Boredom | <p>According to Chen (2000) to overcome boredom within on-line learning, the person has to be in a flow state of mind. This flow state of mind refers to “<i>when an activity stimulates an individual’s enjoyment and peak experience, this engagement frequently promotes psychological growth and increased personal skills</i>” Chen (2000).</p> <p>The AIPL environment does provide activities that challenge the individual through the use of pedagogical approaches and rich learning materials to capture the individual learning needs; however, in cases where this does not work AIPL does provide access to a dynamic background library in which, the student can place their own resources that is found elsewhere to enable resourcefulness.</p> |
|---------|---|

Table 8 State Set Continued

- **Analytical:** According to Bonk et al., (2000) the overall design of the e-learning environment can be measured through the analysis of interactivity, which focuses on the following independent variables:
  - Measurement of the clarity of understanding of the problem given to the students.
  - Measurement of the received feedback on how the environment handled the problem given.
  
- **Structural Intervention:** Adjusting content to optimize the learning for a specific audience becomes possible. According to Falcão et al., (2007) this is achieved by measuring the independent variables associated with the learning outcomes against the students’ own views on how successful it was.

In addition to performance evaluation according to Thulal (2003), Mutation Analysis involves a detailed look into the overall effectiveness of a system. These values or independent variables can be declared as the following: handling student’s queries, student volume in terms of assignments, the payment system for fees, and the security of the student’s account details. However, according to Nguyen et al, (2008) mutation analysis pre-focuses on how effective the system is in handling consistent data changes. For example, the number of times a statement should be executed to achieve a certain confidence with a new system. Also if there was a fault, it would be revealed by testing,

using the test-bed suite.

Neumann, (2005) has similar ideas to Thulal, (2003) about using independent variables to measure the effectiveness of a system. However, these variable factors are closely associated with interaction and how the environment can handle change. It is these small factors such as: recording event changes; executing different tasks and recording personal views (Papy et al, 2004); and how the documents are perceived, which according to Neumann, (2005) are important.

The author is interested in a variety of ideas that (Thulal 2003; Papy et al., 2004; Neumann 2005; Nguyen et al 2008) have suggested. However, the following factors were used as independent variables when using Mutation Analysis as a way of measuring effectiveness:

- Handling students queries i.e. search and filtering of learning materials.
- Recording personal views, for event changes, or tasks when dealing with the three stage evolutionary algorithm.
- Fault identification or empty searches.
- Overall design of the solution to the specification.

### **6.3.1 Summary of independent variables being monitored within this experimentation chapter**

By using performance and effectiveness (mutation analysis) as a measurement goal the author will be able to assess the effects on the performance and accuracy of the AIPL learning environment, and PAFS functions. The independent variables being used within each experiment can be broken into several parts. These are outlined in Table 9 including identification of which experiment is used to provide results for them.

| Measurement                   | Measurement Criteria  | Experiment(s) |
|-------------------------------|---|---------------|
| Performance                   | Precision   | A, B, C       |
|                               | Recall  | A, B, C       |
|                               | Complexity of the algorithm   | B, C          |
| Emotional                     | Confusion   | B, C          |
|                               | Interest  | B, C          |
| Analytical &<br>Interactivity | Measuring the clarification of understanding of the problem given to the students | B, C          |
|                               | Measure the received feedback on how the environment handled to the given problem | B, C          |
| Effectiveness                 | Handling student s query  | B, C, D       |
|                               | Recording personal views  | B, C, D       |
|                               | Fault identification  | B, C, D       |
|                               | Design of the solution to the problem specification                               | B, C, D       |

*Table 9: Independent Variables*

The above has provided a review of existing evaluation techniques used in e learning system testing. The design of the experimental test bed is described in the next section. To successfully gather the independent variables the following psychometrics measurement devices will be used: Likert' Scale; Visual-Analog Rating Scales (VAS Scales); and Self-report measures i.e. Yes/No scales. The use of Analog Rating Scales (VAS Scales) and the Likert Scale, provides an opportunity to run similar tests, in which the opposite scales will be used so that the test candidate can not formally guess the results they achieved within the previous test. According to Field et al., 2007, using two different scales will provide the methods to check for validity and accuracy between two similar tests.

For each test that was conducted within the Adaptive Intelligent Personalised Learning (AIPL) environment the measurements were taken over time for each state. This ensured that the test candidates know what was happening and their personal reviews were documented to ensure accuracy and validity.

The next section will provide an analysis of the results of the experimentation. These results will be presented in relation to each measurement factor rather than each

experiment. This will allow for analysis of the results to be presented alongside each result set.

## ***6.4 Analytical Results:***

Using the recommendations of (Goldberg et al., 1994; Cobb et al., 1998; Whitelock et al., 2000; and Zhang et al., 2004), thirty six candidates were used to undertake the tests within Experiment A and B and sixteen candidates were used to undertake the tests in Experiment C and D. The research candidates varied in: age, computer literacy skills, education, and knowledge background to enable a diverse cross section to be analysed. The results from this section have been divided into four specific areas of measurement:

Performance (6.4.1), Emotional Response (6.4.2), Analytical & Interactivity (6.4.3), and finally Effectiveness (6.4.4).

### **6.4.1 Performance Measurement**

This section focuses on analysing and discussing the results from the system performance testing outlined in Experiments A, B and C.

#### **Experiment A - Baseline Testing**

This section provides analysis of the baseline test results consisting of the result sets from each of the academic activities. These result sets will then be compared in future sections to the system based testing. The first set of baseline test results will be used for comparison in Experiment B (preliminary testing). These results can be found in Table 10. The second set of baseline test results will be used for comparison in Experiment C (primary testing). These results can be found in Table 11.

|              | Mean Precision     | Mean Recall     | Mean F |
|--------------|--------------------|-----------------|--------|
| Experiment A | 0.783              | 0.773           | 0.763  |
|              | Stdev Precision    | Stdev Recall    |        |
|              | 0.18924359         | 0.136948538     |        |
|              |                    | Human Retrieved |        |
|              |                    | 285             |        |
|              | Test candidates    | 36              |        |
|              | Mean/Average       | 7.916666667     |        |
|              | Standard Deviation | 2.811964235     |        |

*Table 10: Base line test for Experiment B, preliminary wiring a plug*

|              | Mean Precision     | Mean Recall     | Mean F |
|--------------|--------------------|-----------------|--------|
| Experiment A | 0.655              | 0.704           | 0.670  |
|              | Stdev Precision    | Stdev Recall    |        |
|              | 0.195805852        | 0.153024992     |        |
|              |                    | Human Retrieved |        |
|              |                    | 345             |        |
|              | Test candidates    | 16              |        |
|              | Mean/Average       | 21.5625         |        |
|              | Standard Deviation | 2.0320351       |        |

*Table 11: Base test results for Experiment C, Primary Introduction to Java Script*

Table 10 and 11 represent the test candidate's views while selecting relevant learning materials for Experiment A relating to Preliminary and Primary testing. Using Table 10 and 11 provides a comparison for Experiments B and C.

### **Test 1 - Keyword Search**

Using the recommendations that (Salton et al., 2002 and Kamenský et al., 2006) suggested, a two phase test was introduced. The two phase test involved using a set of

generic keywords and a more specific set of keywords that the domain expert had developed with the help of qualified electricians’.

The results from the generic search from Experiment B are shown in Table 12:

| Test 1 Primitive Keyword Search  | Mean Precision  | Mean Recall  | Mean F |
|--|-----------------|--------------|--------|
| Number of students that took part in test 1:<br>100% or 36 candidates. | 0.213           | 0.735        | 0.325  |
|  | Stdev Precision | Stdev Recall |        |
|  | 0.0562          | 0.14932      |        |

*Table 12: First test results, relating to the generic keyword search*

The first set of results indicated within Table 12, was achieved by averaging out the scores belonging to Precision, Recall, and F-Value Rate.

The results from the specific keyword search in Experiment B are shown in the Table 13:

| Test 2 Specific Keyword Search   | Mean Precision  | Mean Recall  | Mean F |
|--|-----------------|--------------|--------|
| Number of students that took part in test 2:<br>100% or 36 candidates. | 0.639           | 0.799        | 0.702  |
|  | Stdev Precision | Stdev Recall |        |
|  | 0.128           | 0.0860       |        |

*Table 13: Second test results, relating to the specific keyword search*

Looking at the results from Table 12, using a generic keyword search provided the candidates with an average threshold recall value of **0.735**, this indicates that it is relevant (Kiu et al., 2006; and Ghauth et al., 2007 suggest anything with a value over 0.6 is relevant). The results from Table 13 indicate that a specific search has increased the recall value from **0.735** to **0.799** on this occasion.

Using the recommendations from Folorunso et al., (2006), Ai et al., (2007), and Sosnovsky (2008), anything that is close to 0.7 is relevant to a retrieval search regarding Precision. The first set of results from Table 12 and 13 do not look promising for the preliminary (Wiring a Plug) test regarding precision, which only reached 0.639 within the search criteria.

To validate these results further, Experiment C was constructed. This enabled further evidence to be collected regarding system performance and compared with Experiments A and B, please see tables 14 and 15.

The results from the generic keyword search in Experiment C are shown in Table 14:

| Test 1 Primitive Keyword Search  | Mean Precision  | Mean Recall  | Mean F |
|--|-----------------|--------------|--------|
| Number of students that took part in test 2:<br>100% or 16 candidates. | 0.406           | 0.926        | 0.564  |
|  | Stdev Precision | Stdev Recall |        |
|  | 0.0297          | 0.0331       |        |

*Table 14: First test results, relating to the generic keyword search*

The first set of results indicated within Table 12, were again achieved by averaging out the scores belonging to Precision, Recall, and F-Value Rate. The results from the second specific keyword search in Experiment C are shown in the Table 15:

| Test 2 Specific Keyword Search   | Mean Precision  | Mean Recall  | Mean F |
|--|-----------------|--------------|--------|
| Number of students that took part in test 2:<br>100% or 16 candidates. | 0.790           | 0.823        | 0.803  |
|  | Stdev Precision | Stdev Recall |        |
|  | 0.062           | 0.101        |        |

*Table 15: Second test results to the specific keyword search*



These results from both tables 13, and 15, do support the idea of the more specific the search is, the more the precision rate is increased as indicated by (Fidel 1985; Klein et al., 2001; Cederberg et al., 2003).

## Test 2 - Semantic Metadata Retrieval

The semantic metadata retrieval test involved using a baseline test (see above Experiment A) to check for accuracy and performance. This approach ensured that the author was able to assess the effects on performance and accuracy of the AIPL learning environment and PAFS. To monitor the accuracy, each learning object which the candidate chose within the baseline test, was recorded and compared to the automatic retrieval tool of the semantic metadata retrieval algorithm.

## Experiment B (Wiring a Plug)

Tables 16 and 17 will demonstrate the statistical analysis of a comparison between Experiment A and Experiment B (Test 2).

|                    | Human Retrieved | Total Materials Retrieved |
|--------------------|-----------------|---------------------------|
|                    | 285.00          | 263.00                    |
| Standard Deviation | 2.8             | 1.1                       |
| Standard Error     | 0.47            | 0.19                      |

*Table 16: A comparison of Experiment A and Experiment B (Test 2)*

Taking the results from Table 16 further, the statistical significance is:

| Mean Precision | Mean Recall | Mean F |
|----------------|-------------|--------|
| 0.710          | 0.725       | 0.698  |

*Table 17: Statistical Analysis of Experiment B (Test 2)*

The first set of results from Table 16 and 17 looked promising for the preliminary (Wiring a Plug) Experiment. To validate these preliminary results further, a primary Experiment

(Introduction to Java Script module) was implemented to gather analytical responses for comparison purposes.

### **Experiment C (Introduction to Java Script)**

Tables 18 and 19 will demonstrate the statistical analysis of a comparison between Experiment A and C (Test 2).

|                    | Human Retrieved | Total Materials Retrieved |
|--------------------|-----------------|---------------------------|
|                    | 345             | 291                       |
| Standard Deviation | 2.0320351       | 3.63719214                |
| Mean/Average       | 21.5625         | 18.1875                   |

*Table 18: A comparison of Experiment A and Experiment C (Test 2)*

Looking at Table 18 PAFS has retrieved less learning materials than that of Human selection. Even though the Human selection had a higher number, PAFS still brought back relevant materials from the repository through the search facility. The next set of results will look at the results more closely by examining through the use of: Mean Precision, Mean Recall and Mean F.

| Mean Precision | Mean Recall | Mean F |
|----------------|-------------|--------|
| 0.910          | 0.911       | 0.910  |

*Table 19: Statistical Analysis of Experiment C (Test 2)*

The result from Table 18 and 19 indicates that by using a search facility tailored to the individual can increase the relevance of learning materials being retrieved. The Semantic Metadata Retrieval would search through the repository bring back anything relevant to that particular learning style categorisation i.e. (Reflector).

### **Test 3 – Collaborative grouping and Rating**

The collaborative grouping and rating retrieval test involved using a baseline test (see Experiment A) to check for accuracy and performance. This approach ensured that the author was able to assess the effects on performance and accuracy of the AIPL learning environment. To monitor the accuracy, each learning object which the candidate chose within the baseline test, was recorded and compared to the collaborative grouping and rating algorithm. Test 3 involved two experiments relating to preliminary (wiring a plug) and primary (Introduction to Java Script) which is documented through Experiment B and

C.

**Experiment B (Wiring a Plug)**

This particular experiment involved students from the preliminary investigation (wiring a plug) using the collaborative grouping and rating algorithm to search and retrieve relevant learning materials. As indicated 36 test candidates participated within this investigation and analysing Table 20 the collaborative rating overall retrieved fewer learning materials.

|                    | Human Retrieved | Total Materials Retrieved |
|--------------------|-----------------|---------------------------|
|                    | 285             | 241                       |
| Standard Deviation | 2.81964235      | 2.26551091                |
| Mean/Average       | 7.91666667      | 6.69444444                |

*Table 20: Comparison between Experiment A and B*

Table 20 demonstrated that overall fewer learning materials were retrieved compared to the baseline test, found within Experiment A. Table 21 demonstrates that Precision and Recall within this test is nearly the same, which shows that this approach has enabled a more specific search to be conducted that has assisted individuals in their on-line learning experience.

| Experiment C   | Mean Precision  | Mean Recall  | Mean F |
|--|-----------------|--------------|--------|
| Number of students that took part in the test:<br>100% or (36 n) candidates. | 0.802           | 0.695        | 0.738  |
|  | Stdev Precision | Stdev Recall |        |
|  | 0.141828856     | 0.131968094  |        |

*Table 21: Statistical analysis belonging to Experiment B*

As indicated through tables 20 and 21 this approach has reduced the total amount of learning materials being retrieved. To validate this approach another experiment was required, which can be seen in Experiment C.

**Experiment C (Introduction to Java Script)**

Looking at Table 22 by using the collaborative grouping and rating facility the students were retrieving more relevant and specific learning materials that were closely associated with their learning styles.

|  |                 |              |        |
|--|-----------------|--------------|--------|
| Experiment C   | Mean Precision  | Mean Recall  | Mean F |
| Number of students that took part in the test:<br>100% or (16 n) candidates. | 0.853           | 0.623        | 0.718  |
|  | Stdev Precision | Stdev Recall |        |
|  | 0.0601          | 0.1333       |        |

*Table 22: Statistical analysis belonging to Experiment C*

Table 23 demonstrates that using the collaborative grouping feature increases the amount of learning materials being retrieved by the individual whenever a search is being conducted.

|                    | Human Retrieved | Total Materials Retrieved |
|--------------------|-----------------|---------------------------|
|                    | 345             | 214                       |
| Standard Deviation | 2.032035105     | 3.32415403                |
| Mean/Average       | 21.5625         | 13.375                    |

*Table 23: Comparison between Experiment A and C*

The results from Table 22 and 23 does indicate that by using collaborative grouping and rating can help to reduce mis-matching and unwanted learning resources.

## **6.4.2 Emotional Response**

The author used emotional states to measure the theoretical concept of this Thesis, by analysing specific aspects of human nature i.e. Confusion and Interest. In analysing Confusion and Interest it enabled the author to take a direct look into the whole conceptual idea, and design of AIPL. Confusion and interest provide an insight into how the candidates react to the system in practice.

The results that are associated with emotions are broken into two sections, these are:

6.4.2.1 Confusion and 6.4.2.2 Interest.

### 6.4.2.1 Confusion

See Table 24 for results in relation to confusion, regarding the AIPL environment.

| Keyword Search  |    |   | Automatic Retrieval   |    |    | Collaborating grouping   |    |    |
|---|----|---|---|----|----|--|----|----|
| Did you at any time find that the keyword search was confusing? |    |   | Did you find that at any time the automatic search confusing? |    |    | Did you find that at any time the collaborative grouping search confusing? |    |    |
| Experiments   | B  | C | Experiments   | B  | C  | Experiments  | B  | C  |
| Strongly Disagree   | 20 | 6 | Strongly Disagree   | 10 | 1  | Strongly Disagree  | 15 | 2  |
| Disagree  | 16 | 9 | Disagree  | 20 | 12 | Disagree   | 14 | 12 |
| No Strong Feelings  | 0  | 1 | No Strong Feelings  | 6  | 3  | No Strong Feelings   | 5  | 2  |
| Agree   | 0  | 0 | Agree   | 0  | 0  | Agree  | 2  | 0  |
| Strongly Agree  | 0  | 0 | Strongly Agree  | 0  | 0  | Strongly Agree   | 0  | 0  |

*Table 24: Confusion Test Results*

The above Table indicates that the keyword search facility was the least difficult for candidates to use. There are some indications in the qualitative responses to the above questions related to use of the Collaborative grouping function which indicate some of the issues:

*“I found it difficult to relate to someone else search”*

*“To me some of the rating I would give would be slightly higher”.*

Table 25 will demonstrate statistical significance of the aggregated set of results from Experiment B and C linked confusion while using the AIPL environment.

| Keyword Search  |      |      | Automatic Retrieval   |      |      | Collaborating grouping   |      |      |
|---|------|------|---|------|------|--|------|------|
| Did you at any time find that the keyword search was confusing? |      |      | Did you find that at any time the automatic search confusing? |      |      | Did you find that at any time the collaborative grouping search confusing? |      |      |
| Experiments   | B    | C    | Experiments   | B    | C    | Experiments  | B    | C    |
| Standard deviation  | 2.84 | 4.09 | Standard deviation  | 7.21 | 1.73 | Standard deviation   | 6.48 | 1.16 |
| Standard Error  | 0.47 | 1.02 | Standard Error  | 1.20 | 0.43 | Standard Error   | 1.08 | 0.29 |
| Unbiased "n-1"  | 2    | 3.66 | Unbiased "n-1"  | 5.89 | 1.41 | Unbiased "n-1"   | 5.61 | 0.94 |

*Table 25: Statistical Significance Confusion*

Looking at the results from Experiments B and C belonging to the Keyword search, on average the test candidates have indicated that 97% did not find this feature confusing at all, and that 3 % had no strong feelings. However, looking at the Automatic Retrieval Search belonging to Experiments B and C, this would indicate that on average 82% of the test candidates did not find this facility confusing to use. The other 18% belonging to the Retrieval Search had no strong feelings at all towards this particular feature. The collaborating grouping Experiments B and C would indicate that on average 84% of test candidates believed that this feature was not confusing at all. 14% of the students on average had no strong feelings about the collaborative grouping and rating feature and the final 2% disagreed with the 82% by saying it was confusing to them. However, looking at all the tests belonging to B and C, the average error rate was 0.748, which would indicate that the test results produced a low rate of uncertainty amongst the test candidates.

#### **6.4.2.2 Interest**

To measure interest as an independent variable, the following aspects were analysed: how beneficial the system is; the relevance of materials being retrieved; whether the learning experience is aided; and whether the test subjects would use these facilities on another VLE.

The benefits of using a keyword search

- **Beneficial:** on average from both tests 87% of candidates found it beneficial to their learning experience.

| Keyword Search        | Question asked: Did you find that using a keyword search, beneficial? | Categorisation of feedback: |
|-----------------------|---|-----------------------------|
| Experiments           | B   | C                           |
| Strongly Disagree     | 2   | 0                           |
| Disagree              | 0   | 0                           |
| No Strong Feelings    | 5   | 2                           |
| Agree                 | 14  | 5                           |
| Strongly Agree        | 15  | 9                           |
| Standard Deviation    | 10.44   | 3.5                         |
| Unbiased "n-1" method | 8.52  | 2.87                        |
| Standard Error        | 1.74  | 0.88                        |

*Table 26: Benefits of using keyword search*

Table 26 indicates that 87% of candidates found the keyword search beneficial. The other 14% of test candidates had no strong feeling towards the information retrieval search feature.

- **Useful**

Table 27 will examine the significance belonging to how relevant and useful was the retrieval of learning objects.

| Keyword Search        | Question asked: Overall how relevant & useful did you find the keyword search? | Categorisation of feedback: |
|-----------------------|--|-----------------------------|
| Experiments           | B  | C                           |
| Poor                  | 0  | 0                           |
| Fair                  | 0  | 0                           |
| Satisfactory          | 4  | 3                           |
| Very Good             | 22   | 12                          |
| Excellent             | 10   | 1                           |
| Standard Deviation    | 9.17   | 5.86                        |
| Unbiased "n-1" method | 7.48   | 4.79                        |
| Standard Error        | 1.53   | 1.46                        |

*Table 27: Usefulness and relevance of using a keyword search*

Table 27 indicates on average, 85% of the test candidates agreed that on both experiments the keyword search brought back relevant learning objects associated with the tasks. The other 15% were satisfactory with the responses brought back from the keyword search.



- **Aid learning experience**

Table 28 demonstrates statistical significance belonging to the responses relating to how effective the keyword information retrieval tool was when aiding the candidate' s online experience.

| Keyword Search        | Question asked: The results that were brought back from using the keyword search; did this aid your learning experience? | Categorisation of feedback: |
|-----------------------|--|-----------------------------|
| Experiments           | B  | C                           |
| Strongly Disagree     | 0  | 0                           |
| Disagree              | 0  | 0                           |
| No Strong Feelings    | 4  | 4                           |
| Agree                 | 28   | 8                           |
| Strongly Agree        | 4  | 4                           |
| Unbiased "n-1" method | 11.31  | 1.89                        |
| Standard Error        | 2.31   | 0.57                        |

*Table 28: System Effectiveness*

Looking at the results from Table 28 it shows on average, 82% of test candidates from Experiment B and C would indicate that this feature has helped them with their learning experience.

- **Would use on another VLE:**

On average 85% of test candidates from Experiments B and C, indicates that they would use this facility again. Please see Table 29, for statistical significance.

| Keyword Search        | Question asked: Would you use this facility again if it was provided on another VLE/LMS | Categorisation of feedback: |
|-----------------------|---|-----------------------------|
| Experiments           | B   | C                           |
| Strongly Disagree     | 0   | 0                           |
| Disagree              | 0   | 0                           |
| No Strong Feelings    | 6   | 2                           |
| Agree                 | 16  | 10                          |
| Strongly Agree        | 14  | 4                           |
| Standard Deviation    | 5.29  | 4.16                        |
| Unbiased "n-1" method | 4.32  | 3.40                        |
| Standard Error        | 0.88  | 1.04                        |

*Table 29: Would use the feature on another VLE*

As mentioned above 85% would like to see this feature appear within another VLE, LMS or Content Management System (CMS). However, the other 15% had no strong feelings of this feature being used within another VLE/LMS/CMS.

### Semantic Metadata Search based on Interest:

- **Beneficial**

Table 30 indicates that on average 88% of candidates from Experiments B and C found it beneficial to their learning experience. The other 12% of test candidates had no strong feeling towards the information retrieval search feature.

| Metadata Search       | Question asked: Did you find that using the semantic metadata search beneficial? | Categorisation of feedback: |
|-----------------------|--|-----------------------------|
| Experiments           | B  | C                           |
| Strongly Disagree     | 0  | 0                           |
| Disagree              | 0  | 0                           |
| No Strong Feelings    | 6  | 1                           |
| Agree                 | 24   | 12                          |
| Strongly Agree        | 6  | 3                           |
| Standard Deviation    | 10.39  | 5.86                        |
| Unbiased "n-1" method | 8.49   | 4.78                        |
| Standard Error        | 1.73   | 1.10                        |

*Table 30: Benefits of using a semantic search*

- **Relevance**

The following table will examine the significance belonging to how relevant and useful was the retrieval of learning objects.

| Metadata Search       | Question asked: How relevant were the materials being retrieved in accordance to your learning needs? | Categorisation of feedback: |
|-----------------------|---|-----------------------------|
| Experiments           | B   | C                           |
| Strongly Disagree     | 0   | 0                           |
| Disagree              | 0   | 0                           |
| No Strong Feelings    | 7   | 2                           |
| Agree                 | 17  | 5                           |
| Strongly Agree        | 12  | 9                           |
| Standard Deviation    | 5   | 3.51                        |
| Unbiased "n-1" method | 4.081   | 2.87                        |
| Standard Error        | 0.83  | 2.88                        |

*Table 31: Usefulness and relevance of using a semantic search*

Looking at Table 31, on average 88% of the test candidates from Experiments B and C thought that information retrieval automatically in accordance with their learning styles was relevant. The other 12% of the test candidates had no strong feelings towards the relevance of the retrieval facility.

- **Aid learning experience**

Table 32 demonstrates the statistical significance belonging to the responses relating to how effective the metadata search retrieval facility was when aiding the candidate' s on-line experience.

| Metadata Search       | Question asked: The results that were brought back from using automatic search did this aid your learning experience? | Categorisation of feedback: |
|-----------------------|---|-----------------------------|
| Experiments           | B   | C                           |
| Poor                  | 0   | 0                           |
| Fair                  | 2   | 0                           |
| Satisfactory          | 8   | 1                           |
| Very Good             | 16  | 6                           |
| Excellent             | 10  | 9                           |
| Standard Deviation    | 5.77  | 4.04                        |
| Unbiased "n-1" method | 5   | 3.30                        |
| Standard Error        | 0.96  | 1.01                        |

*Table 32: System Effectiveness*

Looking at the responses from Table 32 it shows that from both Experiments B and C 94% of candidates on average found that this particular feature helped their learning experience. The other 6% of the test candidates found it fair in what it was trying to achieve.

- **Would use on another VLE:**

Table 33 shows the statistical significance with regards to the Metadata search facility. Looking at the results from Experiment B and C on average 85% of test candidates would like to see this feature to be used within other VLE/LMS. However, the other 15% of test candidates had no strong feelings with regards to this feature being used within on-line learning.

| Metadata Search       | Question asked: Would you use this facility again if it was provided on another VLE/LMS | Categorisation of feedback: |
|-----------------------|---|-----------------------------|
| Experiments           | B   | C                           |
| Strongly Disagree     | 0   | 1                           |
| Disagree              | 0   | 0                           |
| No Strong Feelings    | 4   | 2                           |
| Agree                 | 22  | 8                           |
| Strong Agree          | 10  | 5                           |
| Standard Deviation    | 9.17  | 4.20                        |
| Unbiased "n-1" method | 7.48  | 3.40                        |
| Standard Error        | 1.53  | 1.04                        |

*Table 33: Would use the feature on another VLE*

## Collaborating grouping and rating

- **Beneficial:** Table 34 indicates that 88% of candidates from Experiment B and C found it beneficial to their learning experience.

| Collaborative Grouping | Question asked: Did you find that using the collaborative grouping search, beneficial? | Categorisation of feedback: |
|------------------------|--|-----------------------------|
| Experiments            | B  | C                           |
| Strongly Disagree      | 2  | 0                           |
| Disagree               | 1  | 0                           |
| No Strong Feelings     | 3  | 3                           |
| Agree                  | 21   | 8                           |
| Strongly Agree         | 9  | 5                           |
| Standard Deviation     | 8.32   | 2.51                        |
| Unbiased "n-1" method  | 7.44   | 2.10                        |
| Standard Error         | 1.39   | 0.62                        |

*Table 34: Benefits of using a collaborative grouping and rating search*

Looking at Table 34, 12% of test candidates from Experiment B and C were not happy with this approach to on-line learning.

- **Relevance:** The following table (35) will examine the significance belonging to how relevant and useful was the retrieval of learning objects.

| Collaborative Grouping | Question asked: How relevant were the materials being retrieved? | Categorisation of feedback: |
|------------------------|--|-----------------------------|
| Experiments            | B  | C                           |
| Strongly Disagree      | 1  | 0                           |
| Disagree               | 2  | 0                           |
| No Strong Feelings     | 6  | 1                           |
| Agree                  | 15   | 11                          |
| Strongly Agree         | 12   | 4                           |
| Standard Deviation     | 6.14   | 5.13                        |
| Unbiased "n-1" method  | 5.49   | 4.20                        |
| Standard Error         | 1.02   | 1.30                        |

*Table 35: Usefulness and relevance of using a collaborative grouping and rating search*

Table 35, demonstrates that 88% of the test candidates from Experiment B and C thought that the information retrieved was relevant to their learning styles. The other 12% of the test candidates were divided by: no strong feeling towards the relevance of the retrieval facility; and did not like this particular approach to learning, using someone else's feedback to improve, on one own self. Looking at the qualitative responses belonging to the feedback associated with Strongly Disagree and Disagree, the test candidates have indicated the following:

“How do I know if the results that were retrieved from other people were correctly rated?”

“What makes a good learning rating, because each person might have different views?”

“I like to have my own views kept quietly!”

- **Aid Learning Experience:** 81% of candidates from Experiment B and C on average found that this approached helped their learning experience.



| Collaborative Grouping | Question asked: Did you find that using other people personal views on learning materials helpful? | Categorisation of feedback: |
|------------------------|--|-----------------------------|
| Experiments            | B  | C                           |
| Strongly Disagree,     | 0  | 0                           |
| Disagree,              | 0  | 0                           |
| No Strong Feelings     | 7  | 3                           |
| Agree                  | 17   | 6                           |
| Strongly Agree         | 12   | 7                           |
| Standard Deviation     | 5  | 3.16                        |
| Unbiased "n-1" method  | 4.08   | 2.74                        |
| Standard Error         | 0.83   | 0.80                        |

*Table 36: System Effectiveness*

According to Table 36, this approach indicates that the extra 19% of test candidates had no strong feelings with group sharing. 81% of test candidates indicate using group feedback and rating to be a positive educational experience.

- **Would use on other VLE:** 81% of candidates indicated that they would use this facility again.

| Collaborative Grouping | Question asked: Would you use this facility again if it was provided on another VLE/LMS? | Categorisation of feedback: |
|------------------------|--|-----------------------------|
| Experiments            | B  | C                           |
| Strongly Disagree      | 0  | 0                           |
| Disagree               | 4  | 1                           |
| No Strong Feelings     | 3  | 2                           |
| Agree                  | 16   | 6                           |
| Strongly Agree         | 13   | 7                           |
| Standard Deviation     | 6.48   | 2.94                        |
| Unbiased "n-1" method  | 5.61   | 2.55                        |
| Standard Error         | 1.08   | 0.74                        |

*Table 37: Would use the feature on another VLE*

Table 37 indicates from the results that from the results belonging to Experiment B and C on average 81% of the test candidates would like to see this approach applied to other VLE/LMS. The other 19% of candidates disagreed with this whole concept of sharing rating with other people on line.

Looking at the results from all three sections, on average 84% percent of the students that used the AIPL environment found it in some way interesting, and beneficial to their learning experience, while studying on-line. This particular percentage mark indicates that the theoretical concept of the AIPL model would create or improve a more tailored learning experience/approach.

### **6.4.3 Analytical & Interactivity**

This section focuses on analysing and discussing the results from the system performance testing outlined in Experiments B, C and D. To measure the feedback from the AIPL environment and compare these results to Moodle, the following aspects were developed to incorporate independent variables, these are: 6.4.3.1 pedagogical course approach; and finally 6.4.3.2 interface consistencies 'HCI'.

### 6.4.3.1 Pedagogical course approach

The pedagogical learning approach is important because this is one of the major aspects of developing a whole course structure on-line. If the course was not developed properly then the candidates' answers could be flawed with dissatisfaction, and anguish. Table 38 presents test candidates views of the presentation, accessibility and navigability of material within the system.

| Presentation of supplementary material   | Accessibility and navigational facilities  | Inter-course navigability   |
|--|--|---|
| 94% of the test candidates believed that the course content was developed and shaped for on-line learning. 6% of the students had no strong feelings towards the presentation of learning materials. | 75% of candidates agreed that the accessibility and navigational facilities were designed for individual users. 14% of test candidates had no strong feeling towards accessibility, and the other 11% found it difficult | 81% of the candidates found flicking back and forward through course materials easy; however, 14% had no feeling towards the navigation of studying online course materials. 6% found it difficult to come to terms with. |

Statistical Significant

|                    |      |                    |      |                    |      |
|--------------------|------|--------------------|------|--------------------|------|
| Standard Deviation | 9.17 | Standard Deviation | 5.60 | Standard Deviation | 7.87 |
| Unbiased           | 7.48 | Unbiased           | 4.85 | Unbiased           | 6.82 |
| Standard Error     | 1.53 | Standard Error     | 0.93 | Standard Error     | 1.32 |

*Table 38: Presentation, accessibility, and navigability*

Looking at the results from Table 38, 94% of candidates believed that the presentation of supplementary materials were suitable for viewing on-line. However, 6% of the candidates were not interested with the whole on-line learning experience. The inter-course

navigability results from Table 38 indicate that there was an 81% success rate with testing AIPL. 14% of the test candidates that were asked about inter course navigability had no strong feelings of flicking through course content. The other 6% belonging to inter-course navigability had difficulties. To expand on the 6% that had a negative the following qualitative responses were recorded:

*“I was anxious while using the on-line environment, and I just kept clicking backward button to many times.”*

*“Compared to other software that I used, I thought it could have been laid out more simple when retrieving and viewing materials.”*

#### **6.4.3.2 Interface Consistencies**

Interactivity plays an important part in evaluating the solution to the given problem; this can be evaluated by looking at how the candidates react to environmental changes in the system. These environmental changes can vary from fonts, text size, and alignment of icons, and presentational materials that could alter the thought process of the test candidates while answering the questionnaires. The following questions were asked to the students to retrieve feedback belonging to interface inconsistencies. The system was also compared against Moodle to provide results for Experiment D.

**Font was consistent throughout the AIPL Environment & Moodle Environment?**

(Results regarding preliminary and primary testing)

|             | Preliminary testing (AIPL) | Primary Testing (AIPL) | Moodle            |
|-------------|----------------------------|------------------------|-------------------|
| Experiments | B                          | C                      | D                 |
|             | Strongly Agree 12          | Strongly Agree 10      | Strongly Agree 14 |
|             | Agree 16                   | Agree 5                | Agree 2           |
|             | No Strong Feelings 8       | No Strong Feelings 1   |                   |

|                    |      |                    |      |                    |      |
|--------------------|------|--------------------|------|--------------------|------|
| Standard Deviation | 4    | Standard Deviation | 4.51 | Standard Deviation | 8.49 |
| Unbiased           | 3.27 | Unbiased           | 3.68 | Unbiased           | 2.12 |
| Standard Error     | 0.67 | Standard Error     | 1.13 | Standard Error     | 6    |

*Table 39: Font Consistency*

Looking at Table 39, 80% of the students within the preliminary testing considered that the fonts used throughout the AIPL environment were consistent, and the other 20% had no strong views about the fonts being used. Comparing the results from the preliminary testing and primary testing, there was a 14% increase in consistency. Even with 94% consistency the AIPL environment could not complete against Moodle, which achieved 100% from the test candidates.

**Text size was consistent throughout the AIPL & Moodle Environment?**

(Results regarding preliminary and primary testing)

|             | Preliminary testing<br>(AIPL) | Primary Testing<br>(AIPL) | Moodle            |
|-------------|-------------------------------|---------------------------|-------------------|
| Experiments | B                             | C                         | D                 |
|             | Strongly Agree 16             | Strongly Agree 3          | Strongly Agree 10 |
|             | Agree 15                      | Agree 12                  | Agree 6           |
|             | No Strong Feelings 2          | No Strong Feelings 1      |                   |
|             | Disagree 3                    |                           |                   |

|                    |      |                    |      |                    |      |
|--------------------|------|--------------------|------|--------------------|------|
| Standard Deviation | 7.53 | Standard Deviation | 5.86 | Standard Deviation | 5.03 |
| Unbiased           | 6.52 | Unbiased           | 4.79 | Unbiased           | 4.30 |
| Standard Error     | 1.26 | Standard Error     | 1.47 | Standard Error     | 1.26 |

*Table 40: Statistical Significance*

As indicated by Table 40, 86% of the candidates from the preliminary test believed that the text size was consistent, and easy to follow when selecting the appropriate facility. However, the other 8% totally disagreed. However, the other 6% had no strong feeling towards the text consistency. Comparing the results from the preliminary and the primary test did improve its consistency by 8%. However, looking at the results from Moodle, this learning environment had also achieved a 100% success rate similar to that of the primary grouping data.

**Did you find that the Element Placement of ICON, facilities buttons was designed to be user friendly?** (Results regarding preliminary and primary testing).

Looking at the results from Table 41, 80% of the preliminary test candidates agreed that the facilities and icons were positioned correctly in accordance with usability guidelines; the other 20% of test subjects had no strong feeling towards the GUI layout of AIPL. However, further analysis of Table 41, indicates that 69% of students belonging to the primary test found the Windows Icons Menu Pointers (WIMP) environment adequate.

Comparing this to Moodle, the result of 94%, indicates that the Moodle environment is more HCI friendly. The other 6% had no strong feeling towards Moodle.

|             | Preliminary testing: - Did you find that the Element Placement of ICON, facilities buttons was designed to be user friendly? | Primary Testing<br>- Did you find that the Element Placement of ICON, facilities buttons was designed to be user friendly? | Moodle<br>- Did you find that the Element Placement of ICON, facilities buttons was designed to be user friendly? |
|-------------|--|--|---|
| Experiments | B  | C  | D   |
|             | Strongly Agree 13  | Strongly Agree 6   | Strongly Agree 6  |
|             | Agree 18   | Agree 5  | Agree 9   |
|             | No Strong Feelings 5   | No Strong Feelings 5   | No Strong Feelings 1  |

|                    |      |                    |      |                    |      |
|--------------------|------|--------------------|------|--------------------|------|
| Standard Deviation | 6.56 | Standard Deviation | 0.58 | Standard Deviation | 4.04 |
| Unbiased           | 5.35 | Unbiased           | 0.47 | Unbiased           | 3.29 |
| Standard Error     | 1.09 | Standard Error     | 0.14 | Standard Error     | 1.01 |

*Table 41: Statistical Significance*

**Presentation of supplementary materials was suitable:** (results regarding preliminary and primary testing).

According to Table 42, the preliminary testing showed that 90% of the students believed that the supplementary materials were suitable for this activity and the other 10% were satisfied about the learning materials. Comparing this result to the primary testing and also results from Moodle indicates that: 88% of students found that material found within Moodle was suitable, and that the other 12% were satisfied with the learning materials. Comparing this result from Moodle to the primary testing would show that AIPL achieved 75% and the other 25% had no strong feeling with the learning materials.

|             | Preliminary testing: -<br>Did you find that the presentation of supplementary materials suitable for this testing? | Primary Testing: -<br>Did you find that the presentation of supplementary materials suitable for this testing? | Moodle: -<br>Did you find that the presentation of supplementary materials suitable for this testing? |
|-------------|--|--|---|
| Experiments | B  | C  | D   |
|             | Excellent 14   | Excellent 7  | Excellent 4   |
|             | Very Good 20   | Very Good 5  | Very Good 10  |
|             | Satisfactory 2   | Satisfactory 4   | Satisfactory 2  |

|                    |      |                    |      |                    |      |
|--------------------|------|--------------------|------|--------------------|------|
| Standard Deviation | 9.17 | Standard Deviation | 1.53 | Standard Deviation | 4.16 |
| Unbiased           | 7.48 | Unbiased           | 1.25 | Unbiased           | 3.40 |
| Standard Error     | 1.53 | Standard Error     | 0.38 | Standard Error     | 1.04 |

*Table 42: Statistical Significance*

The results from Table 42 show that the primary test achieved 75%, which when compared to the result from Moodle, there was a 13% decrease on the test candidates believing that the materials were suitable for testing.

The final section of results from consistency will look at the averages in general belonging to the AIPL (Preliminary and Primary Testing) and the Moodle environment.



Table 43, will demonstrate the results from the averages.

|   | Preliminary | Primary | Moodle |
|---|-------------|---------|--------|
| Experiments   | B           | C       | D      |
| Font was consistent throughout the Environment  | 86          | 75      | 94     |
| Text size was consistent throughout the Environment   | 80          | 69      | 100    |
| Did you find that the Element Placement of ICON, facilities buttons was designed to be user friendly? | 90          | 94      | 94     |
| Presentation of supplementary materials   | 80          | 94      | 88     |
| Overall result  | 84%         | 83%     | 94%    |

*Table 43: Overall Averages*

After the tests were conducted, a final question was asked to see what features of the AIPL environment, test subjects would like to be built into the Moodle environment.

The results are as follows:

|                           |   | Yes | No | Maybe |
|---------------------------|---|-----|----|-------|
| Experiment                | C |     |    |       |
| Collaborative Grouping    |   | 14  | 2  | 0     |
| Automatic retrieval of LO |   | 13  | 1  | 2     |
| Keyword Search            |   | 16  | 0  | 0     |

*Table 44: Extra Features*

As you can see from the table above, most of the students asked, would be happy to have some sort of e-learning 2.0 technology incorporated into the current Moodle Environment. This supports the work carried out by the author, by making these features more accessible and mainstream then students can benefit from a more personalised learning experience.

## 6.4.4 Effectiveness

To measure the effectiveness of the whole e-learning environment certain specific areas must be integrated into the results and these are the following: 6.4.4.1 Handling students' query; 6.4.4.2 Fault identification; 6.4.4.3 Design of the solution to the problem specification; and finally 6.4.4.4 Overall effectiveness of the AIPL environment.

Each section will provide an insight into the design features and facilities to ensure that all aspects that could possibly be covered were.

### 6.4.4.1 Handling the students' query

Handling students' queries was important to the whole of this Thesis investigation because it provided a means to test the theoretical concept of the AIPL environment. AIPL was based on learner centricity, which means placing the students needs first in regards to their learning abilities, before any internet technologies can be applied. To enable the author to analyse the results from this particular section, it is divided into three key areas: Keyword Search, Semantic Metadata search, and Collaborative grouping.

#### Keyword Search

The following questions were asked, based upon the abilities of handling students' queries.

**How did you find the functionality of the algorithm, when dealing with your query?**

The following table presents the results from questions surrounding the functionality of the algorithm.

| Experiments        | Preliminary Testing | Primary Testing    |      |
|--------------------|---------------------|--------------------|------|
|                    | B                   | C                  |      |
| Very Good          | 11                  | Very Good          | 6    |
| Excellent          | 25                  | Excellent          | 10   |
| Standard Deviation | 9.90                | Standard Deviation | 2.83 |
| Standard Error     | 1.65                | Standard Error     | 0.71 |
| Unbiased           | 7                   | Unbiased           | 2    |

*Table 45: Statistical Significance*

The results from the preliminary and primary test data show that the test candidates found the functionality of algorithm while retrieving learning materials to be very good or excellent. Looking at the results in relation to their statistical significance both had a low Standard Error Rate.

### Semantic Metadata Search

The following questions were asked, based upon the abilities of handling students' queries. **How did you find the functionality of the algorithm, when dealing with your query?**

Looking at the results, 69% of the candidates asked thought that the ability to handle user queries was excellent or very good. The extra 31% thought that the search facility was satisfactory. However, to support this concept further an additional test was applied to see if this was not just a one off result, please see Table 46 for statistical analysis.

| Experiments        | Preliminary Testing | Primary Testing    |      |
|--------------------|---------------------|--------------------|------|
|                    | B                   | C                  |      |
| Excellent          | 9                   | Excellent          | 6    |
| Very Good          | 16                  | Very Good          | 7    |
| Satisfactory       | 11                  | Satisfactory       | 1    |
|                    |                     | Fair               | 2    |
| Standard Deviation | 3.61                | Standard Deviation | 3.22 |
| Standard Error     | 0.60                | Standard Error     | 0.81 |
| Unbiased           | 2.94                | Unbiased           | 2.63 |

*Table 46: Statistical Analysis*

Studying the results from Table 46, it shows that on the primary testing data the automatic retrieval feature was given 81% compared to the 69% from the preliminary test. However, both tests produced a low standard error rate indicating a low chance of uncertainty within the test candidates when using the AIPL environment.

## Collaborative grouping

The following question was asked, based upon the abilities of handling students' queries. **How did you find the functionality of the algorithm, when dealing with your query?**

The results demonstrated that 67% of the candidates asked reported that the functionality of the algorithm was very good or excellent. 14% suggested that the handling of their request was fair, and 19% satisfactory.

| Experiments | Preliminary Test   |       | Primary Test       |       |
|-------------|--------------------|-------|--------------------|-------|
|             | B                  |       | C                  |       |
|             | Views              | Score | Views              | Score |
|             | Excellent          | 9     | Excellent          | 11    |
|             | Very Good          | 15    | Very Good          | 5     |
|             | Satisfactory       | 7     | Satisfactory       | 0     |
|             | Fair               | 5     | Fair               | 0     |
|             | Standard Deviation | 4.32  | Standard Deviation | 5.23  |
|             | Standard Error     | 0.72  | Standard Error     | 1.31  |
|             | Unbiased           | 3.74  | Unbiased           | 4.53  |

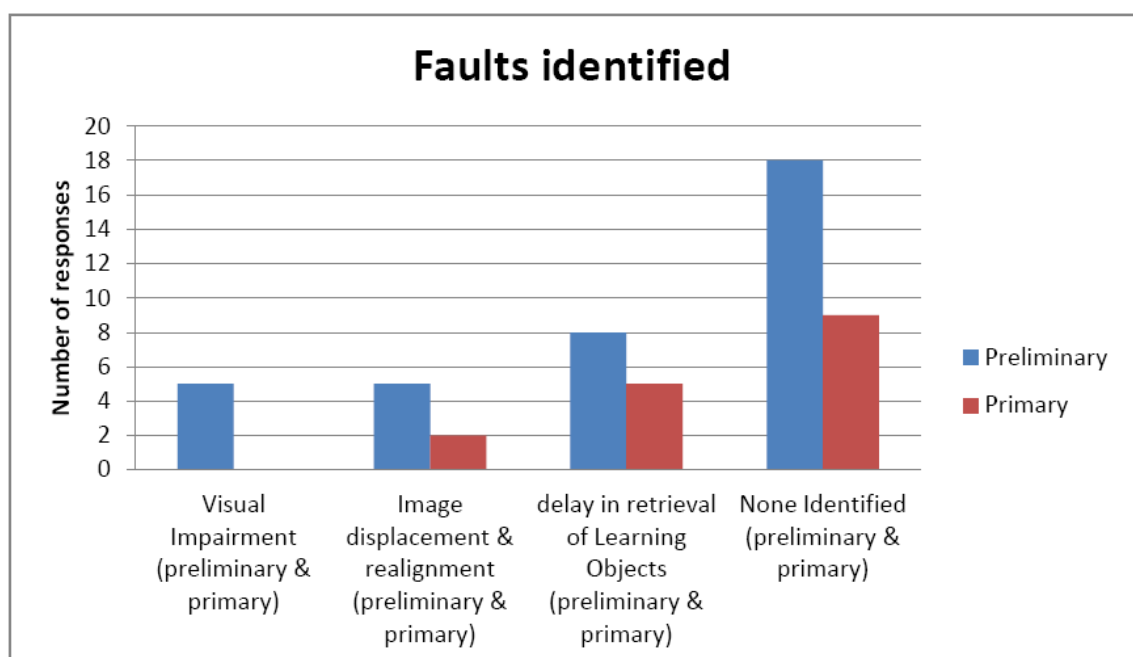
*Table 47: Statistical Analysis*

However, to expand on these results, statistical analysis was applied, which can be seen within Table 47. The results indicate that on the primary data set, test candidates found the functionality of the collaborative grouping to be Excellent (69%) or Very Good (31%). Looking at the results further, there was an increase of uncertainty even within a low number of students, compared to the low error rate belonging to the preliminary testing.

This section has demonstrated that the general conceptual thought regarding the different effectiveness and functionality of the different features has been supportive towards from the test candidates.

#### 6.4.4.2 Fault identification

According to 50% of candidates tested within the AIPL environment no faults were found. However, looking at the graph “Faults Identified”, 50% of test candidates recorded some typical errors that happened during the testing period. 22% of students recorded that during the filtering and retrieval of learning objects, they found that the AIPL environment had taken a while for the learning objects to be retrieved and displayed. 14% of the candidates also said that the image displacement and realignment was causing trouble while reading. The last 14% indicated that the font size was too small for people with long sightedness. For a graphical representation of the above statistics please see graph 4.



Graph 4: Fault identified regarding preliminary and primary data set.

Looking at Graph 4 indicates that one of the major problems associated with AIPL was The delay of the retrieval of learning objects.

#### 6.4.4.3 Design of the solution to the problem specification

To measure the design solution to the problem specification, the following questions were needed to enable an analytical approach to be used.

**Overall how effective did you find the keyword search?**

Table 48 demonstrates and expands on the results that were retrieved during the testing procedures, through the use of statistical analysis:

|             | Preliminary Test   |         | Primary Test       |         |
|-------------|--------------------|---------|--------------------|---------|
| Experiments | B                  |         | C                  |         |
|             | Views              | Score % | Views              | Score % |
|             | Excellent          | 28      | Excellent          | 38      |
|             | Very Good          | 61      | Very Good          | 50      |
|             | Satisfactory       | 11      | Satisfactory       | 12      |
|             | Standard Deviation | 9.165   | Standard Deviation | 3.055   |
|             | Standard Error     | 1.528   | Standard Error     | 0.764   |
|             | Unbiased           | 7.483   | Unbiased           | 2.494   |

*Table 48: Statistical Analysis*

The results in Table 48 indicate that 89% of the test candidates agreed that the keyword search feature was very effective in retrieving learning materials while the other 11% believed that it was satisfactory. To validate this success rate within the AIPL environment the primary test rate will now be examined. While validating the data, the keyword search feature again was rated as 88%, while the other 12% were satisfied with its effectiveness. Even looking at the standard error rating, it shows that on both accounts a low uncertainty was identified.

**Overall how effective did you find the Meta data search?**

The whole concept of the semantic metadata search facility was to fully automate the retrieval process of filtering out unnecessary learning materials that were not designed for the individual. The results demonstrate similar findings to the keyword search. About 75% of candidates believed that the whole design concept was effective. Table 49 will be used to expand further on the results, by looking into their statistical analysis and comparing the preliminary results to the primary test data.

|             | Preliminary Test   |         | Primary Test       |         |
|-------------|--------------------|---------|--------------------|---------|
| Experiments | B                  |         | C                  |         |
|             | Views              | Score % | Views              | Score % |
|             | Excellent          | 42      | Excellent          | 38      |
|             | Very Good          | 33      | Very Good          | 56      |
|             | Satisfactory       | 14      | Satisfactory       | 0       |
|             | Fair               | 11      | Fair               | 6       |
|             | Standard Deviation | 5.354   | Standard Deviation | 4.243   |
|             | Standard Error     | 0.892   | Standard Error     | 1.061   |
|             | Unbiased           | 4.637   | Unbiased           | 3.674   |

*Table 49: Statistical Analysis*

The results from the primary test set indicate that this particular feature has performed well in its effectiveness in retrieving learning materials, based upon the individual learning style. The two results have shown a 19% increase on its ability throughout both tests. The Standard Error data ranges within Table 49 have a low rate of uncertainty.

**Overall how effective did you find the collaborative grouping and rating algorithm?**

The results from Table 50 indicate that 78% of the candidates recorded that the overall effectiveness of the design specification with regards to the collaborative rating function, was excellent or very good. The other 22% believed that the retrieval tool was satisfactory. This result demonstrates that by using a collaborative rating tool to share other people's views and ratings it can effectively create a bridging mechanism between the individuals and the learning materials.

|             | Preliminary Test   |       | Primary Test       |       |
|-------------|--------------------|-------|--------------------|-------|
| Experiments | B                  |       | C                  |       |
|             | Views              | Score | Views              | Score |
|             | Excellent          | 16    | Excellent          | 5     |
|             | Very Good          | 12    | Very Good          | 7     |
|             | Satisfactory       | 8     | Satisfactory       | 4     |
|             | Standard Deviation | 4     | Standard Deviation | 1.528 |
|             | Standard Error     | 0.667 | Standard Error     | 0.382 |
|             | Unbiased           | 3.266 | Unbiased           | 1.247 |

*Table 50: Statistical Analysis*

Even though the first preliminary test had a 78% success rate, the primary test only reached 75% and the other 25% were satisfied with the overall effectiveness. It is clear the concept of using collaborative grouping to share resources has provided an effective tool within this scenario. To support this claim, further analysis belonging to Standard Error would indicate again a low uncertainty rate belonging to the test candidates.

#### **6.4.4.4 Overall effectiveness of the AIPL environment.**

##### **Overall how effective did you find the keyword search algorithm?**

Out of the 36 candidates asked, 86% of them thought that the keyword search was effective within its abilities to assist the students' learning needs. To support this claim, statistical significance was applied to study any correlation between values, please see Table 51 for tabular representation of results.



|             | Preliminary Test   |         | Primary Test       |         |
|-------------|--------------------|---------|--------------------|---------|
| Experiments | B                  |         | C                  |         |
|             | Views              | Score % | Views              | Score % |
|             | Excellent          | 39      | Excellent          | 38      |
|             | Very Good          | 42      | Very Good          | 50      |
|             | Satisfactory       | 17      | Satisfactory       | 12      |
|             | Fair               | 3       | Fair               | 0       |
|             | Poor               | 0       | Poor               | 0       |
|             | Standard Deviation | 4.97    | Standard Deviation | 3.06    |
|             | Standard Error     | 0.83    | Standard Error     | 0.76    |
|             | Unbiased           | 4.30    | Unbiased           | 2.49    |

*Table 51: Statistical Significance*

Compared to the primary test results candidates had rated the effectiveness of the AIPL environment to be 88% compared to 81% from the preliminary test. Looking at the standard error rate, both test results produced a low rate of uncertainty among the test candidates.

**Overall how effective did you find the semantic metadata search algorithm?**

For this question, the results were very distributed, 25% of the candidates believed that the effectiveness of handling the queries were high, 44% of them believed that it was very good, and 31% thought it was satisfactory. Expanding on these results further, statistical analysis was applied to enable or to identify any correlation between the results from the Preliminary and Primary testing, for a tabular representation of these results please see Table 52.

| Experiments | Preliminary Testing |       | Primary Testing    |       |
|-------------|---------------------|-------|--------------------|-------|
|             | B                   |       | C                  |       |
|             | Views               | Score | Views              | Score |
|             | Excellent           | 10    | Excellent          | 6     |
|             | Very Good           | 16    | Very Good          | 9     |
|             | Satisfactory        | 8     | Satisfactory       | 0     |
|             | Fair                | 2     | Fair               | 1     |
|             | Standard Deviation  | 5.77  | Standard Deviation | 4.24  |
|             | Standard Error      | 0.96  | Standard Error     | 1.06  |
|             | Unbiased            | 5     | Unbiased           | 3.67  |

*Table 52: Statistical Analysis*

Looking at the results from Table 52, it is clear to see that the primary testing had improved the effectiveness of the semantic metadata search by increasing the success rate to 94%. However, other factors like the standard error scale would indicate some uncertainty between the test candidates when using this particular feature.

**Overall how effective did you find the Collaborative Grouping?**

| Experiments | Preliminary Test   |       | Primary Test       |         |
|-------------|--------------------|-------|--------------------|---------|
|             | B                  |       | C                  |         |
|             | Views              | Score | Views              | Score % |
|             |                    | %     |                    |         |
|             | Excellent          | 25    | Excellent          | 31      |
|             | Very Good          | 56    | Very Good          | 44      |
|             | Satisfactory       | 8     | Satisfactory       | 25      |
|             | Poor               | 11    | Poor               | 0       |
|             | Standard Deviation | 7.79  | Standard Deviation | 1.53    |
|             | Standard Error     | 1.30  | Standard Error     | 0.38    |
|             | Unbiased           | 6.75  | Unbiased           | 1.25    |

*Table 53: Statistical Analysis*

Looking at the results from Table 53, 81% of the candidates believed that the conceptual

idea of enabling the students to retrieve queries belonging to other individuals with similar learning needs was very good/excellent. Another 11% thought it was poor while the last 8% thought it was satisfactory. However, looking at results from the primary test data, 75% of the test candidates thought it was effective when using other people views, ratings and sharing. The other 25% was satisfied with the overall effectiveness of the collaborative grouping feature.

### **Overall how effective did you find the AIPL Environment?**

The final set of data results, will look at how effective was the AIPL environment in providing a personalised experience. Table 54, will be used to indicate statistical analysis belonging to the preliminary and primary data sets, which will take into consideration 36 students point of views.

|             | Preliminary Test   |       | Primary Test       |       |
|-------------|--------------------|-------|--------------------|-------|
| Experiments | B                  |       | C                  |       |
|             | Views              | Score | Views              | Score |
|             | Excellent          | 16    | Excellent          | 7     |
|             | Very Good          | 15    | Very Good          | 6     |
|             | Satisfactory       | 5     | Satisfactory       | 3     |
|             | Standard Deviation | 6.083 | Standard Deviation | 2.082 |
|             | Standard Error     | 1.014 | Standard Error     | 0.520 |
|             | Unbiased           | 4.967 | Unbiased           | 1.700 |

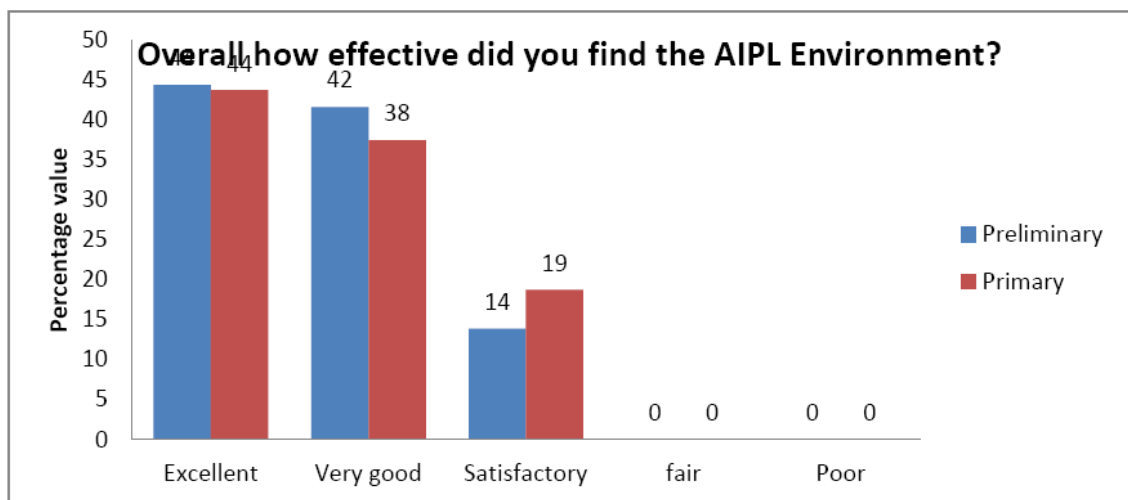
*Table 54: Statistical Analysis*

After close analysis, the results from both data sets indicate that 81-86% of candidates when asked about the overall effectiveness of the AIPL environment concluded that it performed to their level of expectation. This was to create a learner centric approach that would bridge together the individual learner and the learning materials. The other 14% were satisfied with the performance and effectiveness of the AIPL approach in providing a personalised learning experience.

## 6.5 Summary

This chapter looked at examining the whole theoretical design concept of this Thesis by using two sets of test candidates to investigate a new novel approach in matching the individual to the learning repository based upon their learning styles. The use of independent variables within this Thesis enabled statistical analysis to be performed.

Statistical analysis enabled the author to carry out research to support the Thesis question. Graph 5 demonstrates the overall effectiveness of AIPL, in creating a new approach to matching the needs of the individual to the learning resources.



Graph 5: Rating belonging to PAFS & AIPL environment

Offering the students a variety of ways of mapping their needs to the learning resources through AIPL was shown to have had a beneficial impact on their learning experience. It is also shown that 80% of the students asked found it to be beneficial and effective in creating synergy between the learner and the learning materials.

The results from these initial sets of results indicate that the approach taken to personalised one learning experience through the use of matching courseware to the individuals needs, can work. Looking at Table 40 averages belonging to testing for consistency belonging to preliminary and primary testing indicate that AIPL had the same success rate as that of Moodle.

## **Chapter 7.0 Evaluation, Critique, Contribution and Proposed Further Work**

This evaluation makes reference to the research direction outlined in Chapter 1, and explored through literature in Chapters 2 and 3. It provides an analysis of the contributions of this Thesis as presented in Chapters 4 and 5, and a critique of the experimentation outlined in Chapter 6. Finally, this chapter outlines directions for further research and further development of the system presented in this Thesis.

### ***7.1 Main Findings of Research***

In this section each of the objectives originally specified in Chapter 1 are critically reviewed in relation to the approach taken, and the main findings drawn out from their investigation and achievement.

Provide a critical overview of the current research trends within the area of e-learning and most closely linked to this Thesis, those of: adaptive learning, personalised learning and content based retrieval. Utilise the knowledge of the identified current issues in order to develop a new approach to resolving the research problem.

The critical overview concentrated to begin with on the following key areas: pedagogical approaches, e-learning, personalised learning, matching (Adaptive Information Retrieval) and learning object standards.

- According to Noy et al., (2001) matching algorithm approaches have a 74% success rate when being used by users for knowledge acquisition/retrieval.
- The research that was carried out by Eze et al., (2006) indicated that there were three possible areas of improvement within personalised learning these are:
  - i. The development of a personality component for domain profiling of the learner

- ii. Using semantic metadata to represent multimedia of specific context using xml and RDF.
- iii. In the development of the matching algorithm.

The AIPL environment expands on the theoretical work of Eze et al., (2006) by introducing a mechanism built around learning style categorisation to extract how individuals' prefer to learn (Personality Component). The learning activities found within the AIPL on-line Dynamic Background Library (DBL) are semantically constructed being written in LOM instead of RDF. The Personalised Adaptive Filtering System (PAFS) was created to expand on Eze's primitive search (profile to media context) by using an Adaptive Information Retrieval feature to match the Learning Profile to the resources found within a repository. As indicated above the research carried out by Eze et al., (2006) provided some of the theoretical inspirations for the development of AIPL and its particular features.

- Yao et al 2007, argues that keyword searches, and page ranking are inadequate when large repositories are searched, which involves individuals manually going through the results brought back one at a time. Therefore the AIPL model contains a range of search and retrieval techniques.
- Hummel et al.,(2007) indicates that their design approach for a Personalised Recommender System (PRS) required the use of: learning technology standards, metadata and the Semantic Web to mark up the learning materials, this has several limitations associated with it, these are:
  - Limited metadata mark up of learning materials using RDF/XML
  - The course management software was only capable of running a limited amount of learning activities.
  - Limitation of research focusing on stigmergy approach of allowing individuals to form their own groups instead of with assistance from the domain expert.
- Mencke et al., (2007) introduces an e-learning framework 'Learning Environment' that provides technology to enhance the performance and the effectiveness of on-line learning. According to Mencke et al., (2007) there are several issues concerned with this particular framework these are: dynamic design of the e-learning framework; complexity; and how the components react while being used within an on-line environment.
- Eze et al., (2006), Mencke et al., (2007) and Wang (2008) suggest that there are

several issues concerned with e-learning frameworks, these are:

- They do not provide a dynamic approach that is learner centric.
- They are not generally matched to a flexible pedagogical learning model.
- In all present different approaches to matching the learner to the learning materials, there is no one ‘golden bullet’ approach to matching.

Researchers like Knight et al., (1994) and Chaudri et al., (1998) believe that the use of keyword searches still need the intervention of the domain expert and learner to validate the retrieval of content. Li et al., (2004) and Hull et al., (2006) indicate that using matching algorithms is complex and that depending on the complexity and severity of the search could bring back a null search.

**Design a model based on the concepts of Adaptive Information Retrieval (AIR) for learning to facilitate the construction of a personalised content retrieval for learning environment.**

Designing a new theoretical model based on the limitations from Chapter two and three proved to be challenging, complex and fraught with difficulties and logical problems. There were four main areas, which presented substantial challenges:

1. A new pedagogical approach was based upon the ideas and concepts of researchers like (Riding et al., 1997; Santos et al. 2003; Power et al., 2005; Cristea 2005; Eze et al., 2007; Zouaq et al., 2007; Khan et al., 2007 and Melia et al., 2009), which suggest that the application of pedagogical learning approaches to learning environments can provide an opportunity to better match students requirements to learning techniques and theories designed around the learner. However, the main adaptations to the model being presented within this Thesis expand directly on (Papanikolaou et al., 2001; Stash et al., 2004 and Schippers et al., 2005) in the amalgamation of learning styles to effectively identify how an individual prefers to learn. For more information see Section 4.2.1 The Pedagogical Model.
2. The new personalised e-learning model introduced within this Thesis was inspired by the work carried out by: Anderson (2005) regarding the Community of Inquiry model, which takes the educational experience as a centre point; and that of Dong et al. in (2009), with their Cloud Computer Infrastructure that places individuals

into group-learning-paradigms. The model that Anderson (2005) proposed presents a direct focus on the educational experience, which the rest of the academic experience is built around. The model being presented by Dong et al., (2009) uses group-learning-paradigms to collectively group individuals into common interests and experience. The AIPL model uses the ideas of Dong et al., (2009) and Anderson (2005) by placing pedagogical approaches, at its center point, to harness the individual learning experience through a focus on learning activities. These activities can then be matched to the individuals or group-learning-paradigms. For more information regarding the above model, see Section 4.3.2 AIPL model.

3. The AIPL framework was built upon the work carried out by (Eze et al., 2007), expanding their primitive context-based information retrieval tool with an Adaptive Information Retrieval (AIR) mechanism. Over the years since the presentation of Eze's framework there has been a growth in the popularity and usage of social networking services. Part of the advancement that the AIPL framework brings is the introduction and the incorporation of concepts belonging to social and community grouping, and the use of community information retrieval mechanisms. Please see Section 4.1.3 Matching for more information regarding this feature.
4. AIPL presents a new novel approach to matching pedagogical content to learner preferences. The inspiration for the matching technique used within this Thesis expanded on the research carried out by (Knight et al., 1994; Becks et al., 2003; Bajraktarevic et al., 2003; Deeb, 2007; Eze et al., 2007; Chatti et al., 2007; Ullrich et al., 2008; and Ghail et al., 2009) about incorporating a variety of searches to enable matching to be performed. The main concept of the matching approach being presented within this Thesis uses and builds on the work carried out by (Tzouveli et al., 2005; Subramaniam 2006; and Yao et al., 2007) in using group-learning-paradigm profiles as a way of identifying and clustering individuals into groups. This approach uses two learning styles as a way of identifying and categorising individuals before assigning them into groups. The learning styles act as a way for the Adaptive Information Retrieval (AIR) system to search through connected on-line repositories and retrieve relevant learning activities. However, in addition to this approach, a group-learning-paradigm rating mechanism was employed to assist with the reduction of mis-matching. The validation of



individual learning style categorisation is carried out by a complex rule base. This rule base identifies Learning Process Questionnaire data and assigns individuals to groups based on their profile (Honey & Mumford and Kolb). This approach can be found in Chapter 5 A Personalised Adaptive Filtering Systems.

These four concepts mentioned above provide a solution to creating a personalized content retrieval for learning model to enable the construction of a personalised learning environment.

**Implement a prototype of the proposed model cataloguing significant design and implementation challenges faced.**

To overcome the issues that were mentioned above, the proposed model had to overcome the first issue of how to choose the correct pedagogical approach to support learners (Britian et al., 2004; Dabbagh 2005; Low 2005; Juhary 2007; Thyagarajan et al., 2007; and Svensson et al., 2007).

The design involved researching different learning theories and concepts to achieve a learner-centric approach. Using the experiential learning approach as a way of controlling the whole learning cycle provided a solid theoretical base. Once this approach was researched it was noticed that learning styles can be applied as a way of categorising and creating a tailored learner-centric approach.

Once this pedagogical approach was chosen the next challenge was how to apply this into an e-learning environment. See Figure 3 for the pedagogical approach chosen. After studying other personalised e-learning environments like: Intelligent Tutor System (Gutierrez et al., 2006); Personalising Multimedia Learning Resource (Eze et al., 2006); Personal Recommender System (Hummel et al., 2007); IDEAL (Wang 2008); and finally the personalised e-learning system called MOT 2.0 (Ghali et al., 2009). The following model was implemented called the AIPL environment see Figure 5.

Once the two models were designed the next stage was the most complex and difficult to comprehend.

This is where a number of contributions to research were achieved:

The Learning Profile (LP) being presented within this Thesis takes into consideration the research of (Ray 2000, Tzouveli et al., 2005 and Subramaniam 2006) by incorporating group-learning-paradigm profiles as a way of identifying and clustering individuals into groups. This provides a way of holding details belonging to individuals and also provides a mechanism for grouping. According to Ray (2000) this would help to build communities based upon common interests and themes. See Chapter 5, Section 5.2.2 Representation of the Learner Profile & the Learner Profile Lifecycle. The approach here has built upon the work of Tzouveli et al., (2005) and Subramaniam (2006) by applying learning styles to group-learning-paradigm profiles to enable the adaptation of the environment to how the student prefers to learn.

The AIPL environment provides a way for other institutions and e-learning environments to share academic resources through the use of heterogeneous profiles. To see how this resource could be used and shared (hypothetically), see Chapter 5, 5.2.2.3 Integration of how to process heterogeneous profiles. As indicated by Dolog et al., (2003), Xu et al., (2003), Prolog et al., (2003) and Dalsgaard (2006) there is a need for a solution to the current problems associated with heterogeneous profiles. As mentioned the heterogeneous profile is available within the AIPL environment; however, only as a demonstration of how this could work across different LMS's and VLE's, depending on the database types each institution uses.

Finally, the research has also investigated the challenges and complexities associated with grouping learners together: See Chapter 5, 5.2.3 **Grouping Learners – Challenges and Complexities**. The results from Chapter 6 associated with group learning, indicate that the use of group-learning-paradigm profiles can benefit on-line learning from sharing personal views, and rating. The findings from the preliminary and primary testing indicate that learner participants' responses concerning the factors affecting the learning materials being retrieved were useful, and beneficial when reducing mis-matching.

### **How the AIPL environment dealt with the implementation of grouping views**

According to Richardson et al., (2003), Tzouveli et al., (2005) and Subramaniam (2006)

the use of community views can assist student perceptions of learning on-line and can have a direct impact on improving their learning experience by enabling categorisation to similar groups, interests and habits. In Chapter 6 the AIPL environment was tested using the recommendations from researchers like Richards, Tzouveli and Subramaniam about using group views to see how this approach could affect the learning process. After analysing the responses within Chapter 6, in the first set of candidates 29 (80.5%) of the 36 students indicated that this approach was good/excellent when matching group's views in accordance with their learning categorisation. Comparing the preliminary test data to the primary results, 75% would agree (n=12) and the other 25% (n=4) were satisfied with this approach. The results belonging to the preliminary test data (80.5%) and that of the primary results (75%) do indicate that this approach of using group views as a way of matching the needs of the learners to the learning materials would assist the learner within the learning process.

Based upon the results presented above it shows that this approach has the potential to have an impact on student learning.

### **Evaluate the new approach using a set of learners and a set learning context.**

Evaluating the new personalised content retrieval mechanism is not as simple as matching a set of learners requirements to a set of functions in order to filtering out mis-matches. As indicated by Sherry (1996) to have a successful on-line education system, a balance must be developed to incorporate equilibrium between the learners and the learning environment. According to Baber et al., (2004) effective on-line learning requires the environment to respond to changes to the learner requirements. The relationship between the learner, the learning activities, and the requirements were complex, and the research conducted within Chapter 6 produced a positive response in accordance with matching the learner to a set of learning materials.

The results from the preliminary findings indicated that on average 85% (n=36) of the test candidates believed that matching the learning materials in accordance with their learning styles assisted their learning experience. To validate the results from the preliminary testing, another study was conducted, in which 81% of the test candidates agreed that this approach benefited their educational experience.

The analytical responses from Chapter 6 support the research carried out by (Becks et al., 2003; Bajraktarevic et al., 2003; Tzouveli et al., 2005; Subramaniam 2006 and Deeb, 2007), which indicate that matching learning materials to the learners can have a dramatic influence on the learning process.

**Critically evaluate project success/failure and approaches taken.**

Analysis of the **preliminary** and **primary** result sets demonstrates that generally candidates rated the AIPL environment as effective (over 80% of the sample) in matching the learner to appropriate learning materials. In breaking down the results further into the three categories of search (collaborative grouping/group views; keyword search and automatic retrieval of learning objects) the following analytical responses were identified.

The preliminary studies indicated that over 80% of the test candidates believed that the concept of clustering in groups based on their learning approaches assisted the learner's experience. This was supported through a further experimental study which indicated 100% of the study group believed that this approach did benefit their on-line education experience.

Studying the analytical results from the keyword search belonging to the preliminary investigation, over 80% of the test candidates believed that the keyword search was beneficial. The primary testing results indicated an increase in satisfaction (100%) with this tool. Both sets of results indicated that these search facilities assisted with their learning experience. The analytical results from the semantic metadata search algorithm both indicated that 94% of the sample found the feature to be beneficial to their educational experience.

After looking at the analytical results that were gathered from Chapter 6 the author believes that the Thesis question is supported and the new approach outlined in this Thesis for matching the learners' to the learning materials benefits and improves the learning experience.

So far by critically evaluating the project the results looks promising for this new novel

approach of personalised learning. The next set of results will look at the responses from the candidates when AIPL was compared to Moodle using the following criteria: (Human Computer Interface; Pedagogical course approach; Presentation of supplementary materials; and what features would they like to see on Moodle).

The following Table 55 demonstrates the results from the averages belonging to each question asked within Chapter 6 about consistencies between HCI, and course materials used throughout the test suite.

|   | Preliminary | Primary | Moodle |
|---|-------------|---------|--------|
| Font was consistent throughout the Environment  | 86          | 75      | 94     |
| Text size was consistent throughout the Environment   | 80          | 69      | 100    |
| Did you find that the Element Placement of ICON, facilities buttons was designed to be user friendly? | 90          | 94      | 94     |
| Presentation of supplementary materials   | 80          | 94      | 88     |
| Over all result   | 84%         | 83%     | 94%    |

*Table 55: Averages belonging to testing for consistency*

After the tests were conducted, a final question was asked to discover what features of the AIPL environment learners would like to see on other on-line learning environments and the results are contained in Table 56:

|                           | Yes | No | Maybe |
|---------------------------|-----|----|-------|
| Collaborative Grouping    | 14  | 2  | 0     |
| Automatic retrieval of LO | 13  | 1  | 2     |
| Keyword Search            | 16  | 0  | 0     |

*Table 56: Transferable Features*

Overall, the author feels that the approach that was chosen has got the potential to improve personalisation features within VLE and offers an mechanism for enabling experiential learning through collaborative grouping and rating.

## **7.2 Implications and Limitations**

Throughout this project there have been a number of limitations that have to be indicated

these are, for example: The primary test size of candidates, which involved 16 students, could have been increased to 30+ equaling the preliminary test study sample group. In addition to the test bed size the author could have broadened the test group to different disciplines to fully understand the true potential of the AIPL environment and the PAF matching mechanisms.

With hindsight the questionnaire used (see Appendix C) for evaluation of the user experience of AIPL contains a number of questions which are positively biased (e.g. did you find the keyword search useful?). The way that these questions are phrased may have impacted on the results in a positive way. A better approach to developing the questionnaire would have been to run the questionnaire past a number of individuals to check question validity; to run some preliminary testing to check that these work in practice; and then to run the series of tests.

The design of AIPL did not fully take into consideration learners with various learning barriers e.g. partially blind or visual impairments. The environment was not flexible enough to deal with the next generation of adapted learning materials. The implementation of AIPL throughout a variety of institutions (other than the two institutions where testing occurred) would have provided a greater insight into the on-line capabilities of providing personalised content retrieval for learning. Even though the AIPL environment was used to test two learning activities, one at University of Hull and one at Yorkshire Coast College, it did not provide enough detail to support how effective it could really be in cross institutional contexts.

### ***7.3 Author's Contributions***

This Thesis through the analysis, design, creation and evaluation of a system for personalised content retrieval for learning, provides contributions both theoretically and practically to the field of e-learning.

In theoretical terms, the Thesis:

- Provides an incremental enhancement to personalised content retrieval for learning through building upon research belonging to: Anderson (2005) and Dong et al in (2009), by introducing a new e-learning model called AIPL that uses a pedagogical

and group-learning-paradigm approach through learner groups and a group rating system linked to learning styles.

- A new pedagogical approach was based upon the ideas and concepts of researchers like (Riding et al., 1997; Santos et al. 2003; Power et al., 2005; Cristea 2005; Eze et al., 2007; Zouaq et al., 2007; Khan et al., 2007 and Melia et al., 2009), which suggest that by applying pedagogical learning approaches to learning environments we can better support the learner.
- A new novel approach to matching the pedagogical content to learner preferences. The inspiration for the matching technique used within this Thesis expanded on the research carried out by (Knight et al., 1994; Becks et al., 2003; Bajraktarevic et al., 2003; Deeb, 2007; Eze et al., 2007; Chatti et al., 2007; Ullrich et al., 2008; and Ghail et al., 2009) about incorporating a three stage evolutionary algorithm approach to match learning objects to learners needs based on learning styles and group categorisation.
- Provides contributions to e-learning literature in the area of PLE's (Costello and Mundy, 2009a) (Costello and Mundy, 2009b).

In practical terms, the Thesis:

- Provides a new practical solution for personalised content retrieval for learning with the development of a personalised learning environment called AIPL.
- Details the evaluation of this practical solution linked in to a learning scenario.

## ***7.4 Recommendations for Further Work***

Literature has shown that there are a variety of ways of personalising on-line learning. Within this Thesis the primary focus was on content retrieval. There are many different categories, which content retrieval can be placed into, for example: Adaptive Information Retrieval, Adaptive Hyper Retrieval, Learning Paths, Intelligent Tutoring Systems, knowledge-base and finally clustering. The retrieval mechanism used within this Thesis was based upon using AIR, which searched the user profile and matched content relevant to the learner's specification.

Further development of AIPL could be the incorporation of learning paths, and an

intelligent tutoring system, which could suggest learning materials based upon other learners activities, interests, commonly accessed features etc. A further advancement to the AIPL environment could then be to monitor each time a learner interacts with a learning activity; the learner data could then be mined for patterns depending on the learning situation, and shared across a group-learning-paradigm. This approach can be as seen as related to Intelligent Tutor Systems or Learning Paths. Understanding why that particular learning activity was accessed could provide a more specific rating system which could be applied to better support the learning experience.

Another feature that the AIPL environment did not incorporate was the design of e-Portfolios. These would require the individuals to be encouraged to update their on-line folders like (CV's, assignments, or personalised views (ratings) to belonging to on-line content). E-Portfolios could be used as a way to improve the individual learning through keeping track of their own progress, and abilities.

The author notes that at present the evaluation process defined in this Thesis is heavily focused on whether the solution presented provides an acceptable experience for online learning, through evaluation of student acceptability. Further work should be undertaken in the evaluation process to determine how much of an improvement (if any) the solution provides over other existing systems through some form of comparative study.

## ***7.5 Thesis Conclusions***

In this Thesis, the author has developed a new theoretical model called the Adaptive Intelligent Personalised Learning (AIPL) environment, to improve the learning experiences of the individuals while studying on-line. The literature review exposed problems and issues with current models that are being used within universities and colleges, for example: not using pedagogical learning approaches to structure the materials; over use of technology to demonstrate course materials; mis-matching of learning content to the users; information overload of learning resources; and not incorporating learner centricity as a centre point for on-line learning.

The AIPL model was developed to create a mapping between the individual learner and the learning materials. The results from Chapter 6 demonstrate that the overall performance of



the AIPL environment and the three-stage evolutionary algorithm (PAFS), in creating a new approach to matching the needs of the individual to the learning resource/materials was successful.

After careful analysis of the results the author found that AIPL and PAFS in general terms, improves and helps the student in their learning experience. The results demonstrate that the approach that the author took looks promising for future integration of such ideas into mainstream on-line learning environments. It is important that e-learning frameworks incorporate new theoretical concepts, and ideas, to fully harness the learning abilities of the individuals.

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## Appendices:

### Appendix A: Learning Process Questionnaires

#### Kolb Learning Inventory, Quick Activity

1. When I learn:

- I like to deal with my feelings. (CE)       I like to think about ideas. (AC)  
 I like to be doing things. (AE)       I like to watch and listen. (RO)

2. I learn best when:

- I listen and watch carefully. (RO)       I rely on logical thinking. (AC)  
 I trust my hunches and feelings. (CE)       I work hard to get things done. (AE)

3. When I am learning:

- I tend to reason things out. (AC)       I am responsible about things. (AE)  
 I am quiet and reserved. (RO)       I have strong feelings & reactions. (CE)

4. I learn by:

- feeling. (CE)       doing. (AE)  
 watching. (RO)       thinking. (AC)

5. When I learn:

- I get involved. (CE)       I like to observe. (RO)  
 I evaluate things. (AC)       I like to be active. (AE)

AE Active Experimentation Score  
CE Concrete Experience Score

RO Reflective Observation Score  
AC Abstract Conceptualization Score

*Honey and Mumford: Learning Styles Questionnaire*

1. I have strong beliefs about what is right and wrong, good and bad.
2. I often act without considering the possible consequences.
3. I tend to solve problems using a step-by-step approach.
4. I believe that formal procedures and policies restrict people.
5. I have a reputation for saying what I think, simply and directly.
6. I often find that actions based on feelings are as sound as those based on careful thought and analysis.
7. I like the sort of work where I have time for thorough preparation and implementation.
8. I regularly question people about their basic assumptions.
9. What matters most is whether something works in practice.
10. I actively seek out new experiences.
11. When I hear about a new idea or approach I immediately start working out how to apply it in practice.
12. I am keen on self-discipline such as watching my diet, taking regular exercise, sticking to a fixed routine etc.
13. I take pride in doing a thorough job.
14. I get on best with logical, analytical people and less well with spontaneous, "irrational" people.
15. I take care over the interpretation of data available to me and avoid jumping to conclusions.
16. I like to reach a decision carefully after weighing up many alternatives.
17. I'm attracted more to novel, unusual ideas than to practical ones.
18. I don't like disorganised things and prefer to fit things into a coherent pattern.
19. I accept and stick to laid down procedures and policies so long as I regard them as an efficient way of getting the job done.
20. I like to relate my actions to a general principle.
21. In discussions I like to get straight to the point.
22. I tend to have distant, rather formal relationships with people at work.
23. I thrive on the challenge of tackling something new and different.
24. I enjoy fun-loving, spontaneous people.
25. I pay meticulous attention to detail before coming to a conclusion.
26. I find it difficult to produce ideas on impulse.
27. I believe in coming to the point immediately.
28. I am careful not to jump to conclusions too quickly.
29. I prefer to have as many sources of information as possible -the more data to mull over the better.
30. Flippant people who don't take things seriously enough usually irritate me.
31. I listen to other people's point of view before putting my own forward.
32. I tend to be open about how I'm feeling.
33. In discussions I enjoy watching the manoeuvrings of the other participants.
34. I prefer to respond to events on a spontaneous, flexible basis rather than plan things out in advance.
35. I tend to be attracted to techniques such as network analysis, flow charts, branching programmes, contingency planning, etc.
36. It worries me if I have to rush out a piece of work to meet a tight deadline.
37. I tend to judge people's ideas on their practical merits.
38. Quiet, thoughtful people tend to make me feel uneasy.
39. I often get irritated by people who want to rush things.
40. It is more important to enjoy the present moment than to think about the past or future.
41. I think that decisions based on a thorough analysis of all the information are sounder than those based on intuition.
42. I tend to be a perfectionist.
43. In discussions I usually produce lots of spontaneous ideas.

44. In meetings I put forward practical realistic ideas.
45. More often than not, rules are there to be broken.
46. I prefer to stand back from a situation and consider all the perspectives.
47. I can often see inconsistencies and weaknesses in other people's arguments.
48. On balance I talk more than I listen.
49. I can often see better, more practical ways to get things done.
50. I think written reports should be short and to the point.
51. I believe that rational, logical thinking should win the day.
52. I tend to discuss specific things with people rather than engaging in social discussion.
53. I like people who approach things realistically rather than theoretically.
54. In discussions I get impatient with irrelevancies and digressions.
55. If I have a report to write I tend to produce lots of drafts before settling on the final version.
56. I am keen to try things out to see if they work in practice.
57. I am keen to reach answers via a logical approach.
58. I enjoy being the one that talks a lot.
59. In discussions I often find I am the realist, keeping people to the point and avoiding wild speculations.
60. I like to ponder many alternatives before making up my mind.
61. In discussions with people I often find I am the most dispassionate and objective.
62. In discussions I'm more likely to adopt a "low profile" than to take the lead and do most of the talking.
63. I like to be able to relate current actions to a longer-term bigger picture.
64. When things go wrong I am happy to shrug it off and "put it down to experience".
65. I tend to reject wild, spontaneous ideas as being impractical.
66. It's best to think carefully before taking action.
67. On balance I do the listening rather than the talking.
68. I tend to be tough on people who find it difficult to adopt a logical approach.
69. Most times I believe the end justifies the means.
70. I don't mind hurting people's feelings so long as the job gets done.
71. I find the formality of having specific objectives and plans stifling.
72. I'm usually one of the people who puts life into a party.
73. I do whatever is expedient to get the job done.
74. I quickly get bored with methodical, detailed work.
75. I am keen on exploring the basic assumptions, principles and theories underpinning things and events.
76. I'm always interested to find out what people think.
77. I like meetings to be run on methodical lines, sticking to laid down agenda, etc.
78. I steer clear of subjective or ambiguous topics.
79. I enjoy the drama and excitement of a crisis situation.
80. People often find me insensitive to their feelings.



## Scoring

You score one point for each item you ticked. There are no points for crossed items. Circle the questions

you ticked on the list below:

|    |    |    |    |
|----|----|----|----|
| 02 | 07 | 01 | 05 |
| 04 | 13 | 03 | 09 |
| 06 | 15 | 08 | 11 |
| 10 | 16 | 12 | 19 |
| 17 | 25 | 14 | 21 |
| 23 | 28 | 18 | 27 |
| 24 | 29 | 20 | 35 |
| 32 | 31 | 22 | 37 |
| 34 | 33 | 26 | 44 |
| 38 | 36 | 30 | 49 |
| 40 | 39 | 42 | 50 |
| 43 | 41 | 47 | 53 |
| 45 | 46 | 51 | 54 |
| 48 | 52 | 57 | 56 |
| 58 | 55 | 61 | 59 |
| 64 | 60 | 63 | 65 |
| 71 | 62 | 68 | 69 |
| 72 | 66 | 75 | 70 |
| 74 | 67 | 77 | 73 |
| 79 | 76 | 78 | 80 |

## Totals

Activist

Reflector

Theorist

Pragmatist

## **Appendix B: RuleBaseComplex**

```
BEGIN

Retrieve studentlogon

//Security control for accessing
IF studentlogon == TRUE THEN //AIPL if a member then grant
    Flag1 == TRUE //access to student
ELSE BEGIN
    Flag1 == FALSE
    DISPLAY Error Message Learning Identification Type cannot be found.
    DISPLAY Error Internal Application Fault
END IF

IF Flag1 == TRUE THEN

    Initialise learningtypeidentificationPRAG //Setting up of variable belonging
    Initialise learningtypeidentificationREFL //to part of the interrogation
    Initialise learningtypeidentificationANc //of the learner profile
    Initialise learningtypeidentificationTHE //access code to module
    Initialise modulecode //they are studying on

Retrieve learningProfileValue //Retrieve from database connection

//Extracting variables and values from the Learning Profile on
WHILE LearningProfilevalue != NULL
    modulecode == LearningProfilevalue(2)
    //set location in field for retrieval
    learningtypeidentificationPRAG == LearningProfilevalue(4)
    //set location in field for
    //retrieve
    learningtypeidentificationREFL == LearningProfilevalue(6)
    learningtypeidentificationANc == LearningProfilevalue(8)
    learningtypeidentificationTHE == LearningProfilevalue(10)
END WHILE //end loop when all records have been read

//===== CONVERT STRINGVALUESTOINTEGER =====
Initialise a, b, c, d
Initialise learningstrategy //Converting String into Integer
a integerCAST(learningtypeidentificationPRAG) //Reading from Database, which
b integerCAST(learningtypeidentificationTHE) //Learning Profile sits in
c integerCAST(learningtypeidentificationANc) //The casting converts from String
d integerCAST(learningtypeidentificationREFL) // to Integer to allow Rule base to
//extract values
```

```

//===== START OF RULE BASE IDENTIFICATION =====
IF(((a > b) && (a > c)) && (a > d))
  setvalue learningstrategy = Pragmatist //Start of RULE BASE for identifying the
ELSE IF(((b > c) && (b > a)) && (b > d)) //learner s specific learning type
  setvalue learningstrategy = Theorist
ELSE IF(((c > a) && (c > b)) && (c > d))
  setvalue learningstrategy = Activist
ELSE IF(((d > b) && (d > a)) && (d > c))
  setvalue learningstrategy = Reflector
ELSE IF((((a == b) && (a > c)) && (a > d)) || (b == a) && (b > c)) && (b > d))
  setvalue learningstrategy = Pragmatist, Theorist
ELSE IF((((a > b) && (a == c)) && (a > d)) || (b > a) && (c == a) && (d > a))
  setvalue learningstrategy = Pragmatist, Activist
ELSE IF((((a > b) && (a > c)) && (a == d)) || (b > a) && (c > a) && (d == a))
  setvalue learningstrategy = Pragmatist, Reflector
ELSE IF((((a > b) && (a > c)) && (c == d)) || (b > a) && (c > a) && (d == c))
  setvalue learningstrategy = Activist & Reflector
ELSE IF((((a > b) && (a > c)) && (b == c)) || (b > a) && (c > a) && (c == b))
  setvalue learningstrategy = Theorist, Activist
ELSE IF(a==b && a==c && a==d)
  setvalue learningstrategy = Pragmatist, Reflector, Theorist, Activist
ELSE IF((((((((a == b) && (a == c)) && (a > d)) || (a == b)) && (a == c)) && (a > d)) || (b == a)
&& (c == a) && (d > a))
  setvalue learningstrategy = Pragmatist, Theorist, Activist
ELSE IF((((((((a == b) && (a == c)) && (a < d)) || (a == b)) && (a == c)) && (a < d)) || (b == a)
&& (c == a) && (d < a))
  setvalue learningstrategy = Pragmatist, Theorist, Activist
ELSE IF((((((a == b) && (a < c)) && (a < d)) || (b == a) && (b < c)) && (b < d))
  setvalue learningstrategy = Pragmatist, Theorist
ELSE IF((((((a < b) && (a == c)) && (a < d)) || (b < a) && (c == a)) && (d < a))
  setvalue learningstrategy = Pragmatist, Activist
ELSE IF((((((a < b) && (a < c)) && (a == d)) || (b < a) && (c < a) && (d == a))
  setvalue learningstrategy = Pragmatist, Reflector
ELSE IF(a < b && b == d && c < b)
  setvalue learningstrategy = Theorist, Reflector
END IF

Function call identification (learningstrategy, modulecode) String

ELSE BEGIN

  DISPLAY Error
  DISPLAY ERROR PLEASE LOGIN

END IF

END

```

```

//===== START OF FUNCTION CALL =====

STRING collaborative_retrieval_values(Learningstrategyarraylist, modulecode)
BEGIN

    Initialise Displayarraylearningobjects[]

Retrieve LearningMaterials //Retrieve Learning Materials
WHILE LearningMaterials != NULL //from DATABASE
    IF ((LearningMaterials == Learningstrategyarraylist) && (LearningMaterials == modulecode))
    THEN

        READ LearningMaterials
        SET displayarraylearningobjects[ ] = LearningMaterials

    ELSE

        //Store any materials that is
        DISPLAY ERROR
    END IF //filtered into array list for displaying
END WHILE

    FORLOOP displayarraylearningobjects [ ] != NULL

        NEXT //Display Filtered Results
        DISPLAY LearningMaterials

    ELSE BEGIN
        DISPLAY not designed to your learning needs
    END IF

END FORLOOP

END

```

## Appendix C: Questionnaires

**Can you name any Learning Management System?**

**Have you had any experience of a VLE/LMS before either at college or another university?**

**Do you find VLE/LMS useful, within the context of learning on-line?**

Poor  
Fair  
Satisfactory  
Very Good  
Excellent

**Did you find the keyword search useful, while searching through learning materials?**

Strongly Disagree  
Disagree  
No Strong Feelings  
Agree  
Strongly Agree

**Did you find that using a keyword search, beneficial?**

Strongly Disagree  
Disagree  
No Strong Feelings  
Agree  
Strongly Agree

**The results that were brought back from using the keyword search, did this aid your learning experience?**

Strongly Disagree  
Disagree  
No Strong Feelings  
Agree  
Strongly Agree

**Would you use this facility again if it was provided on another VLE/LMS?**

Strongly Disagree  
Disagree  
No Strong Feelings  
Agree  
Strongly Agree

**Overall how effective did you find the keyword search algorithm?**

Strongly Disagree  
Disagree  
No Strong Feelings  
Agree  
Strongly Agree

**Did you find that at any time the keyword search was confusing?**

Strongly Disagree  
Disagree  
No Strong Feelings  
Agree  
Strongly Agree

**How did you find the functionality of the algorithm, when dealing with your query?**

Poor  
Fair  
Satisfactory  
Very Good  
Excellent

**How relevant were the materials being retrieved in accordance to your learning needs?**

Strongly Disagree  
Disagree  
No Strong Feelings  
Agree  
Strongly Agree

**Did you find that using the semantic metadata search beneficial?**

Strongly Disagree  
Disagree  
No Strong Feelings  
Agree  
Strongly Agree

**Would you use facility again if it was provided on another VLE?**

Strongly Disagree  
Disagree  
No Strong Feelings  
Agree  
Strongly Agree

**Overall how effective did you find the semantic metadata search algorithm?**

Poor  
Fair  
Satisfactory  
Very Good  
Excellent High

**Did you find that at any time the semantic search confusing?**

Strongly Disagree  
Disagree  
No Strong Feelings  
Agree  
Strongly Agree

**How did you find the functionality of the algorithm, when dealing with your query?**

Poor  
Fair  
Satisfactory  
Very Good  
Excellent

**Did you find that using other people personal views on learning materials helpful?**

Strongly Disagree  
Disagree  
No Strong Feelings  
Agree  
Strongly Agree

**How did you find the functionality of the algorithm, when dealing with your query?**

Poor  
Fair  
Satisfactory  
Very Good  
Excellent

**How relevant were the materials being retrieved?**

Strongly Disagree  
Disagree  
No Strong Feelings  
Agree  
Strongly Agree

**Did you find that using the collaborative grouping search, beneficial?**

- Strongly Disagree
- Disagree
- No Strong Feelings
- Agree
- Strongly Agree

**Would you use this facility again if it was provided on another VLE/LMS?**

- Strongly Disagree
- Disagree
- No Strong Feelings
- Agree
- Strongly Agree

**Overall how effective did you find the Collaborative Grouping?**

- Poor
- Fair
- Satisfactory
- Very Good
- Excellent

**Did you find that at any time the collaborative grouping alg 3 confusing?**

- Strongly Disagree
- Disagree
- No Strong Feelings
- Agree
- Strongly Agree

**Overall how effective did you find the keyword search?**

- Excellent
- Very good
- Satisfactory
- fair
- Poor

**Overall how effective did you find the auto retrieval tool?**

- Excellent
- Very good
- Satisfactory
- fair
- Poor

**Overall how effective did you find the AIPL Environment?**

- Excellent
- Very good
- Satisfactory
- fair
- Poor

**Overall how effective did you find the Collaborative Grouping?**

- Poor
- Fair
- Satisfactory
- Very Good
- Excellent

**Did you identify any problems errors within the AIPL environment and if so what where they?**

**Do you find that the Font was consist throughout the AIPL Environment?**

- Strongly Agree
- Agree
- No Strong Feelings

Disagree  
Strongly Disagree

**Did you find that the text size was consistent throughout the AIPL Environment?**

Strongly Agree  
Agree  
No Strong Feelings  
Disagree  
Strongly Disagree

**Did you find that the Element Placement of ICON, facilities buttons were designed to be user friendly?**

Strongly Agree  
Agree  
No Strong Feelings  
Disagree  
Strongly Disagree

**Did you find that the presentation of the AIPL environment was consistent throughout the VLE?**

Strongly Agree  
Agree  
No Strong Feelings  
Disagree  
Strongly Disagree

**Did you find that the presentation of supplementary materials suitable for this testing?**

Strongly Agree  
Agree  
No Strong Feelings  
Disagree  
Strongly Disagree

**Did you find that the Accessible and navigable home or course map suitable?**

Strongly Agree  
Agree  
No Strong Feelings  
Disagree  
Strongly Disagree

**Did you find that the Intercourse navigability suitable for online usage?**

Strongly Agree  
Agree  
No Strong Feelings  
Disagree  
Strongly Disagree

**Did you find that using a keyword search aided in reducing materials?**

Strongly Disagree  
Disagree  
No Strong Feelings  
Agree  
Strongly Agree

**Did you find that using a Metadata search aided in reducing materials?**

Strongly Disagree  
Disagree  
No Strong Feelings  
Agree  
Strongly Agree

**Did you find that using the collaborative group and rating algorithm aided in reducing materials?**

Strongly Disagree  
Disagree  
No Strong Feelings  
Agree  
Strongly Agree



**How do you think the AIPL environment could be improved?**

**What have you learnt from using the AIPL environment? Please list topics or themes that have helped you in your research?**

**How would you rate the overall effectiveness of the AIPL environment between 1 (Excellent) and 5 (Poor)**

Poor (5)

Fair (4)

Satisfactory (3)

Very Good (2)

Poor (5)

Fair (4)

Satisfactory (3)

Very Good (2)

**How would you rate the overall effectiveness of the Metadata Search, between 1 (Excellent) and 5 (Poor)**

Poor (5)

Fair (4)

Satisfactory (3)

Very Good (2)

Excellent (1)