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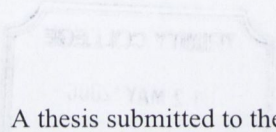
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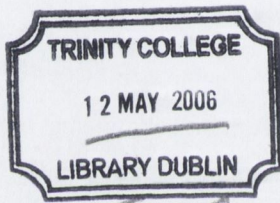
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On the Dynamic Multiple Intelligence Informed Personalization of the Learning Environment



A thesis submitted to the
University of Dublin, Trinity College
for the degree of
Doctor of Philosophy

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December, 2005

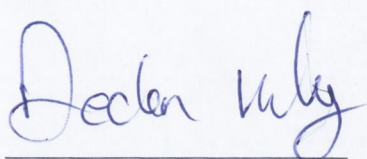


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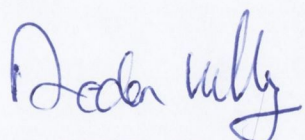
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Acknowledgments

Firstly, I would like to thank my supervisor, Brendan Tangney, for all his help, support and guidance throughout my academic endeavours.

Secondly, I would like to thank all the members of the CRITE research group, who provided many hours of discussion and were instrumental in the development of the ideas presented in this thesis. In particular, I would like to mention Ann Fitzgibbon and Inmaculada Arnedillo-Sánchez who provided crucial comments at critical times in the Ph.D. research journey.

Thirdly, I would like to express gratitude to Stephan Weibelzahl and Peter Brursilovsky who provided insightful comments on different papers submitted during the course of the research and on early drafts of the thesis. In addition, I would like to express thanks to the many anonymous reviewers of papers I have submitted to conferences and to the many different people I have met at conferences who have provided extremely useful comments.

I would also like express gratitude to all the teachers and students who participated in the different studies including the students from John Scottus School, St. Dominics (Cabra), St. Benildus College (Stillorgan) and all the participants in Discovering University (National College of Ireland, 2004).

Above all, I would like to thank my parents who have been incredibly supportive throughout my academic career. Thank you so much.

Abstract

Educational research informs us “one size does not fit all” (Reigeluth, 1996). It states that learners, reflecting individual traits, possess different learning characteristics, process and represent knowledge in different ways, prefer to use different type of resources and exhibit consistent observable patterns of behaviour (Riding & Rayner, 1998). Research also suggests that it is possible to diagnose a student’s learning traits and that some students learn more effectively when instruction is adapted to the way they learn (Rasmussen, 1998).

Within the field of technology enhanced learning, adaptive educational systems offer an advanced form of learning environment that attempts to meet the needs of different students (Brusilovsky, 2003). Such systems capture and represent, for each student, various characteristics such as knowledge and traits in an individual learner model. Subsequently, using the resulting model it dynamically adapts the learning environment for each student in a manner that attempts to best support learning.

However, there are many unresolved issues in building adaptive educational systems that adapt to individual traits. Major research questions still outstanding include: what is the appropriate educational theory with which to model individual traits, how are the relevant learning characteristics identified and in what way should the learning environment change for users with different learning characteristics (Brusilovsky, 2001)? This thesis describes how the adaptive intelligent educational system, EDUCE, addresses these challenges and demonstrates how dynamic adaptive presentation of content can improve learning.

Firstly, EDUCE uses Gardner’s theory of Multiple Intelligences (MI) as the basis for modelling learning characteristics and for developing different Multiple Intelligence informed versions of the same instructional material (Gardner, 1983). The theory of Multiple Intelligences reflects an effort to rethink the theory of measurable intelligence embodied in intelligence testing and suggests that they are eight different intelligences that are used to solve problems and fashion products.

The thesis also describes how EDUCE’s novel predictive engine dynamically identifies the learner’s Multiple Intelligence profile from interaction with the system and makes predictions on what Multiple Intelligence informed resource the learner prefers. Based on data coming from the learner’s interaction with the system, the predictive engine uses a novel set of navigational and temporal features that act as behavioural

indicators of the student's learning characteristics. Empirical studies conducted validated the performance of the predictive engine.

Empirical studies were also conducted to explore how the learning environment should change for users with different characteristics. In particular it explored: 1) the effect of using different adaptive presentation strategies in contrast to giving the learner complete control over the learning environment and 2) the impact on learning performance when material is matched and mismatched with learning preferences. Results suggest that teaching strategies can improve learning performance by promoting a broader range of thinking and encouraging students to transcend habitual preferences. In particular, they suggest that students with low levels of learning activity have most to benefit from adaptive presentation strategies and that surprisingly learning gain increases when they are provided with resources not normally preferred.

In summary, the main contributions of this research are:

- The development of an original framework for using Multiple Intelligences to model learning characteristics and develop educational resources.
- A novel predictive engine that dynamically determines a learner's preference for different MI resources.
- Results from empirical studies that support the effectiveness of adaptive presentation strategies for learners that display low levels of learning activity.

Related Publications

- Kelly, D., Durnin, S., & Tangney, B. (2005a). *'First Aid for You': Getting to know your Learning Style using Machine Learning*. Paper presented at the Fifth IEEE International Conference on Advanced Learning Technologies, ICALT'05, Kaohsiung, Taiwan, 1-4.
- Kelly, D., & Tangney, B. (2002). *Incorporating Learning Characteristics into an Intelligent Tutor*. Paper presented at the Sixth International Conference on Intelligent Tutoring Systems, ITS'02., Biarritz, France, 729-738.
- Kelly, D., & Tangney, B. (2003a). *A Framework for using Multiple Intelligences in an Intelligent Tutoring System*. Paper presented at the World Conference on Educational Multimedia, Hypermedia & Telecommunications. EDMedia'03, Honolulu, USA, 2423-2430.
- Kelly, D., & Tangney, B. (2003b). *Learner's responses to Multiple Intelligence Differentiated Instructional Material in an Intelligent Tutoring System*. Paper presented at the Eleventh International Conference on Artificial Intelligence in Education, AIED'03, Sydney, Australia, 446-448.
- Kelly, D., & Tangney, B. (2004a). *Empirical Evaluation of an Adaptive Multiple Intelligence Based Tutoring System*. Paper presented at the Third International Conference on Adaptive Hypermedia and Adaptive Web Based Systems, AH'04, Eindhoven, Netherlands, 308-311.
- Kelly, D., & Tangney, B. (2004b). *Evaluating Presentation Strategy and Choice in an Adaptive Multiple Intelligence Based Tutoring System*. Paper presented at the In Individual Differences Workshop: Third International Conference on Adaptive HyperMedia and Adaptive Web Based Systems, AH'04, Eindhoven, Netherlands, 97-106.
- Kelly, D., & Tangney, B. (2004c). *On Using Multiple Intelligences in a Web-based Educational System*. Paper presented at the Fifth Annual Educational Technology Users Conference, EdTech'04, Tralee, Ireland.
- Kelly, D., & Tangney, B. (2004d). *Predicting Learning Characteristics in a Multiple Intelligence based Tutoring System*. Paper presented at the Seventh International Conference on Intelligent Tutoring Systems, ITS'04, Maceio, Brazil, 679-688.
- Kelly, D., & Tangney, B. (2005a). *Adapting to Intelligence Profile in an Adaptive Educational System*. *Journal Interacting With Computers*, in press.
- Kelly, D., & Tangney, B. (2005b). *Do Learning Styles Matter?* Paper presented at the Sixth Annual Educational Technology Users Conference, EdTech'05, Dublin, Ireland.
- Kelly, D., & Tangney, B. (2005c). *Matching and Mismatching Learning Characteristics with Multiple Intelligence Based Content*. Paper presented at the Twelveth International Conference on Artificial Intelligence in Education, AIED'05, Amsterdam, Netherlands, 354-361.
- Kelly, D., Weibelzahl, S., O'Loughlin, E., Pathak, P., Sanchez, I., & Gledhill, V. (2005b). *e-Learning Research and Development Roadmap for Ireland, e-Learning Research Agenda Forum, Sponsored by Science Foundation Ireland*. Dublin.
- Stynes, P., Kelly, D., & Durnin, S. (2004). *Designing a learner-centred educational environment to achieve learner potential*. Paper presented at the Fifth Annual Educational Technology Users Conference, EdTech'04, Tralee, Ireland.

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1 Introduction

1.1 Motivation

Educational research informs us “one size does not fit all” (Reigeluth, 1996). It informs us that the learning characteristics of students differ (Honey & Mumford, 1986). It suggests that students, reflecting their individual traits, process and represent knowledge in different ways, prefer to use different type of resources and exhibit consistent observable patterns of behaviour (Riding & Rayner, 1998). Research also suggests that it is possible to diagnose a student’s learning traits and that some students learn more effectively when instruction is adapted to the way they learn (Rasmussen, 1998).

Within the field of technology enhanced learning, adaptive educational systems offer an advanced form of learning environment that attempts to meet the needs of different students (Brusilovsky & Peylo, 2003). Such systems, for each student, capture and represent various user characteristics such as knowledge, background and traits in an individual learner model. Subsequently, using the resulting model it dynamically adapts the learning environment for each student in a manner that best supports learning. Typical strategies that could be used to adapt the environment include adapting the presentation of content in order to hide information not relevant to the user’s knowledge and providing navigation support using annotated links that suggest the most relevant path to follow (de Bra, 2002).

Several adaptive educational systems that adapt to different traits have been developed (Specht & Oppermann, 1998; Gilbert & Han, 1999; Stern & Woolf, 2000; Panpankilolaou et al, 2003). However, building adaptive educational systems that adapt to individual traits is not easy. Major research questions still outstanding include: what is the relevant educational theory with which to model individual traits, how are the relevant learning characteristics identified and in what way should the learning environment change for users with different learning characteristics? (Brusilovsky, 2001)

This thesis describes how the adaptive intelligent educational system, EDUCE, addresses these challenges. Firstly, it describes how EDUCE uses Gardner's theory of Multiple Intelligences (MI) as the basis for modelling learning characteristics and for designing instructional material (Gardner, 1983). Secondly, it describes how EDUCE's novel predictive engine dynamically identifies the learner's Multiple Intelligence profile from interaction with the system and makes predictions on what Multiple Intelligence informed resource the learner prefers. Lastly, it describes empirical studies conducted with EDUCE, that explore how the learning environment, and in particular the presentation of content, should change for users with different characteristics.

1.2 Adapting to Individual Differences

Individual differences between learners have been found to predict performance and thus, adaptive educational systems attempt to improve performance by adapting to these differences. Educationalists interested in the relationship of performance to individual differences have typically sought answers using the trait concepts of intellectual ability and learning styles. Traits are the psychological constructs that describe how individuals generally behave over the long term and have been found to be indicators of learning performance (Cooper, 2002).

Learning style, with its roots in the psychoanalytic community, can be defined as the habitual manner in which a person approaches or responds to learning tasks that is consistent over long periods of time and across many areas of activity (Riding & Rayner, 1998). It describes how learners process and represent knowledge, how they behave when dealing with the demands of specific learning situations and how they interact with different educational material. The concept of learning styles is of interest as some researchers report that they can be used to predict performance in ways that go beyond intelligences (Marton & Booth, 1997; Sternberg & Grigorenko, 1995).

Intellectual abilities have been also found to be predictors of performance with students demonstrating measurable differences in intelligence and ability levels (Neisser et al, 1995). Gardner's theory of Multiple Intelligences, with its root in cognitive science, reflects an effort to rethink the theory of measurable intellectual ability embodied in intelligence testing (Gardner, 1983, 1993, 2000). Gardner defines intelligence as the "biopsychological potential to process information that can be activated in a cultural setting to solve problems or create products that are of value in a culture". The Multiple Intelligence theory suggests that there are eight different ways to demonstrate this

intelligence with each having its own unique characteristics, tools, and processes that represent a different way of thinking, solving problems, and learning. The eight intelligences include the logical/mathematical, linguistic/verbal, visual/spatial, bodily/kinesthetic, musical/rhythmic, interpersonal, intrapersonal and naturalist intelligence. There is current debate about the existence of a ninth intelligence, the existential or spiritual intelligence, but Gardner has not formally included it in his model yet (Gardner, 2000). Furthermore, Gardner (1983) suggests that everybody possesses the different types of intelligences to different degrees and that they operate together in an orchestrated way. He suggests that even though different intelligences do tend to be stronger in some people, everybody has the capacity to activate all the intelligences and in different situations distinct intelligences or a combination of intelligences may be used.

Comparing the constructs of styles to abilities or intelligences, abilities refer to things one can do such as to execute skills or strategies, whereas styles refer to preferences in the use of abilities (Messick, 1996). In other words, abilities are concerned with how much and styles with how. Hence, high amounts of ability are always preferable to low amounts, whereas each pole of a style dimension indicates different characteristics. Moreover, an ability is usually limited to a particular domain of content such as verbal or musical whereas style cuts across domains of ability. For example, learners with the wholist cognitive style tend to organise information globally and prefer to have an overview picture first before delving down into the details (Riding & Rayner, 1998). Regardless, if the content is verbal or musical, the wholist learner will use the same style and prefer to have an overview first.

Several adaptive educational systems that adapt to individual traits have been developed (Papanikolaou et al., 2004). Such systems attempt to build a learner model that represents the student's learning characteristics by getting feedback from questionnaires, analysing navigation paths, assessing answers to questions, allowing the user to update their own student model and supporting the student in making specific adaptations such as sorting links. Subsequently, the resulting model is used as the basis for adapting the learning environment in different ways. For example, the system may modify the presentation of content to match the student's preferred cognitive approach or by annotating the links of the current page to make it easier to choose where to go next (de Bra, 1998).

Adaptive educational systems that support individual traits can be classified according to how they diagnose learning traits and by the way in which they adapt the environment.

When diagnosing traits, some systems use self-report measures where the students complete specially designed psychological tests (Papanikolaou et al, 2003) while others observe the learning behaviour and use inference techniques to detect patterns (Gilbert & Han, 1998a). To adapt the learning environment, some systems change the content of instruction and sequencing of material (Carver et al., 1999) while others change the navigation support to help the learner move about in the knowledge domain (Triantafillou et al., 2004). However, despite the variety of systems developed, it is still unclear on how to best diagnose learning characteristics and change the environment for different learners.

The development of intelligent techniques for diagnosis and adaptation is one promising approach that can address the issues of how to diagnose learning traits and how to adapt the learning environment. These techniques are based on observing the learner's behaviour, inferring learning preferences from those observations and subsequently, dynamically customising the learning environment (Jameson, 2003). For example, a system may contain fragments of different media types representing the same content, and by analysing the characteristics of previous resources that have been selected calculate the probability of one resource being wanted over other resources (Stern & Wolf, 2000).

As differences in style and intelligences have been well documented, it would seem logical that different styles of teaching would have different impacts on individual learners. However this has been difficult to demonstrate conclusively. Research is divided on the application of research in learning traits to the development and design of technology enhanced learning environments. On the one hand, some studies show that learning improves and the quality of material is enhanced when individual differences are taken into account (Rasmussen, 1998; Riding & Grimley, 1999; Graf, 2003b). In contrast, other studies have reported no differences in learning outcomes for learners of different style (Ford & Chen, 2000, Shih & Gamon, 2002). One reason for these conflicting results is that it is difficult in practice to match learning characteristics with instructional environments and it is not clear how the matching should take place. The research challenge in developing such environments is to identify the salient individual differences that affect learning and put interventions in place to give all learners the opportunity to fulfil their potential. One promising approach that can address this challenge is the development of adaptive educational systems and in particular, the development of intelligent techniques for diagnosis and adaptation.

1.3 EDUCE Adaptive Educational System

Despite the insight provided by research into individual trait differences, the educational promise of developing adaptive educational systems that accommodate such differences is only sporadically realised in practice (Brusilovsky, 2001). Building such systems is not easy and outstanding research issues include: what is the appropriate educational theory with which to model individual traits, how is it possible to diagnose relevant learning characteristics and what is the best way to adapt the learning environment for different learners? (Brusilovsky, 2001; Papanikolaou & Grigoriadou, 2004)

EDUCE is an adaptive educational system that attempts to address these challenges by using the Multiple Intelligence theory as its pedagogical framework and by using a predictive engine to dynamically diagnose learning characteristics. The word “educere” originates from the Latin “educere” meaning to “lead out, bring out or develop from latent or potential existence”. Through the provision of a variety of instructional strategies, EDUCE aims to motivate and engage the learner in spontaneous, creative and ingenious ways in order to draw out the latent knowledge. The theory of Multiple Intelligence supports the motivation behind EDUCE, in that intelligence is not a fixed static entity, but something that resides inside a person, and can be enhanced significantly through education and awareness.

In the past 20 years since the theory of Multiple Intelligences was introduced, it has been found to be a useful construct in many settings such as education and training, career guidance and development, counselling and personal development (Mantzaris, 1999). In particular, research has suggested that the impact of the Multiple Intelligence in the classroom has been significant (Campbell & Campbell, 2000). One reason for this is that the different intelligences are not abstract concepts, but are easily recognizable through experience. Intuitively, it is possible to understand the differences between musical and linguistic, or spatial and mathematical intelligences. As a consequence, it offers a rich structure and language in which to develop content and model the student. Currently, the application of Multiple Intelligence to adaptive educational systems is still very limited and in the early stages of research (Dara-Abrams, 2002). This is somewhat surprising given that Gardner predicted back in 1983 that “the potential utility of computers in the process of matching individuals to modes of instruction is substantial” and that “the computer can be vital facilitator in the actual process of instruction” (p391). For these reasons, and the fact that the research on learning styles is inconclusive,

EDUCE uses the Multiple Intelligence theory with which to model individual traits and to provide the basis for developing different versions of content.

In order to diagnose learning characteristics and provide the basis for adapting the environment, EDUCE uses a novel predictive engine. The predictive engine dynamically identifies the learner's Multiple Intelligence profile from interaction with the system and makes predictions on what Multiple Intelligence informed resource the learner prefers. Based on data coming from the learner's interaction with the system, the predictive engine uses a novel set of navigational and temporal features that act as behavioural indicators of the student's learning characteristics. These features describe how different Multiple Intelligence resources are used by identifying which resource was selected first and how many times each category of resource was used. The predictive engine, with these features as input and the Naïve Bayes algorithm (Duda & Hart, 1973) as its inference engine, dynamically detects patterns in the learning behaviour and determines the learner's preferences.

Figure 1-1 illustrates the overall architecture of EDUCE (Kelly & Tangney, 2004d). The typical adaptive educational systems contain student, domain, pedagogical and presentation models (Wenger, 1987). In order to adapt to individual learning traits, two special features are incorporated into EDUCE: a novel predictive engine and the use of the Multiple Intelligence theory to develop content and model the student. The different components have the following functions:

- The domain model is a representation of the material to be learnt. It includes principles, facts, lessons and problems. In EDUCE, the principles of Multiple Intelligences are used to develop different versions of the same content.
- The student model represents the student's knowledge of the domain, the background of the user and learning behaviour of the student. In EDUCE, the student model also includes the Multiple Intelligence profile. For each student two Multiple Intelligence profiles are represented: a static and dynamic profile. The static profile is generated from a Multiple Intelligence inventory completed by the student before using the system. The dynamic profile is constructed online by observing the student's behaviour and navigation.
- The presentation model handles the flow of information and monitors the interactions between the user and the system.

- The pedagogical model uses adaptive presentation and navigation techniques to determine what next to present to the student in terms of content and style using different pedagogical strategies.
- The predictive engine, using the Naïve Bayes algorithm and the dynamic student profile, determines the learner's preference for different Multiple Intelligence resources during a tutorial and can be used to inform the pedagogical strategy.

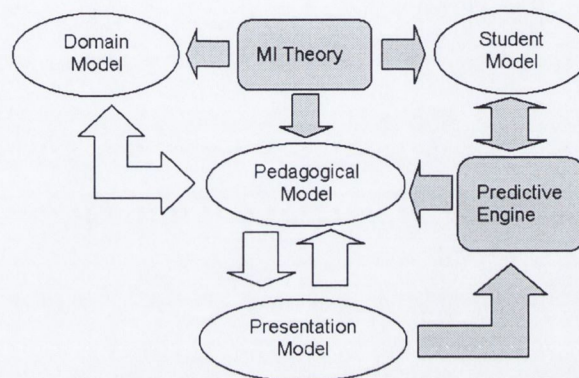


Figure 1-1: EDUCE Architecture

1.4 Research Goals and Contributions

As mentioned above, the research goal of this thesis was to develop an adaptive educational system, EDUCE, that supports individual learning traits, that dynamically determines the learner's profile from interaction with the system, and to empirically evaluate the effect of different adaptive presentation strategies. To achieve this research goal, three main critical research questions were identified.

1. What learning theory can effectively categorise and model individual trait differences in learning?

This was addressed by developing an original framework for using Multiple Intelligences in an adaptive educational system. The Multiple Intelligence theory was used to model learning characteristics and to provide a range of matching educational resources.

2. How is it possible to identify learning characteristics from observations of the learner's behaviour?

This was addressed by developing, using the Naïve Bayes algorithm, a novel predictive engine. The predictive engine dynamically identifies and constructs the learner's Multiple Intelligence profile and makes predictions on what resource the learner prefers. The predictive engine also uses a novel set of navigational and temporal features that act as behavioural indicators of the student's learning characteristics. The performance of the predictive engine was validated with empirical studies.

3. How should the learning environment change for users with different learning characteristics?

This was addressed by using different pedagogical and adaptive presentation strategies. Primarily, these strategies involved selecting a Multiple Intelligence resource from a range of available resources and by enabling/disabling navigation links. In particular, empirical studies were conducted to explore:

- (a) The effect of using different adaptive presentation strategies in contrast to giving the learner complete control over the learning environment and
- (b) The impact on learning performance when material is matched and mismatched with the student's learning preferences.

In achieving the research goal, the main contributions of this research can be summarised as:

- The development of an original framework for using Multiple Intelligences to model learning characteristics and develop educational resources in an adaptive educational system.
- A novel predictive engine that dynamically determines a learner's preference for different MI resources in an online learning environment.
- Results from empirical studies that support the effectiveness of adaptive presentation strategies for learners with low levels of learning activity.

The research in this thesis may be significant for researchers and practitioners. For researchers, it demonstrates that adaptive presentation strategies are important for learners who are not inclined to explore different learning options. For practitioners, it demonstrates how teaching in different ways can affect learning.

1.5 Structure of the Dissertation

In the construction of an adaptive educational system such as EDUCE some key issues need to be addressed. First, there is the need to develop a model for using Multiple Intelligences and to develop content that reflects the principles of Multiple Intelligences. Second, there is the need to develop adaptive technologies that intelligently model the student and allow for flexible delivery in presentation. Finally, there is the need to analyse using experimental studies the effect on learning performance when using different adaptive presentation strategies. The following chapters describe in detail each of these different stages:

Chapter 2 provides the literature review on individual trait differences and adaptive educational systems. It also presents a critique of existing research in order to support the architecture, design and implementation of EDUCE.

Chapter 3 describes the principles, architecture, design and implementation of EDUCE. It outlines the model for incorporating Multiple Intelligence theory into its design (Kelly & Tangney, 2002). It also outlines the pedagogical taxonomy for developing content that reflects the principles of Multiple Intelligence (Kelly & Tangney, 2003a).

Chapter 4 describes the intelligent predictive engine within EDUCE that dynamically determines a learner's Multiple Intelligence profile and predicts the resources they prefer to use (Kelly & Tangney, 2004d). It describes the novel set of navigational and temporal features that act as behavioural indicators of the student's learning characteristics. It also describes how the inference engine, using the Naïve Bayes algorithm, operates online with no prior information and dynamically detects patterns in the learning behaviour.

Chapter 5 describes the experimental studies that were carried out to validate the design and construction of EDUCE. It describes the validation process to ensure the content created reflected the principles of MI. It also describes the experimental study that compares the performance of the predictive engine with the actual behaviour of students using the learning resources without any guidance from EDUCE (Kelly & Tangney, 2003b; Kelly & Tangney, 2004d)

Chapter 6 describes the experimental design of the study that explored the effect of adaptive presentation strategy on learning performance (Kelly & Tangney, 2004a).

Chapter 7 presents an analysis and discussion of the experimental results. In particular it evaluates the results in terms of the effectiveness of adapting to learning characteristics

using different presentation strategies (Kelly & Tangney, 2005a; Kelly & Tangney, 2005c). Results suggest that teaching strategies can improve learning performance by promoting a broader range of thinking and encouraging students to transcend habitual preferences. In particular, they suggest that students with low levels of learning activity have the most to benefit from adaptive presentation strategies and that learning gain increases when they are provided with resources not normally preferred.

Chapter 8 concludes with an overview, summary and directions for future work.

2 Background and Related Work

2.1 Introduction

“Today, as in the past, it appears that of all the branches of psychology, differential psychology – the study of individual and group behavioural differences – is the most germane to discussion of the problems of education” (Jensen, 1972).

It is obvious to state that some students achieve higher results than others, learn faster in certain environments, stay longer periods in education and apply knowledge more effectively in different circumstances (Slavin, 2003). However, it is more difficult to explain why. The psychology of individual differences attempts to understand the reasons for different levels of performance by examining the different characteristics that students express when learning (Cooper, 2002).

Different learning characteristics have been well documented. Students, reflecting their individual traits, express different characteristics in the way they process and organise information, in their predispositions towards particular learning modes and in their patterns of behaviour when learning. (Gardner, 1983; Riding & Rayner, 1998; Sadler-Smith & Smith, 2004). It would seem logical, therefore, that learning environments that accommodate these learning characteristics would improve performance. However, this has been difficult to demonstrate conclusively, with some studies reporting increases in learning outcomes (Riding & Cheema, 1991; Moore & Scevak, 1997; Rasmussen, 1998; Riding & Grimley, 1999; Ford & Chen, 2001, Graf, 2003b) whilst others reporting no differences (Ford & Chen 2000, Shih & Gamon, 2002). The reason for these conflicting studies is that matching learning characteristics with instructional environments is difficult and it is not clear what should be matched and how should the matching take place (Messick, 1996). The challenge in developing such environments is in identifying the salient individual differences that affect learning, and putting interventions in place to give all learners the opportunity to fulfil their potential (Cronbach, 1977).

Technology enhanced learning solutions offer the potential to provide learning environments that support and acknowledge individual differences. Technology can

enable learners to acquire knowledge and skills at a time, place and pace that are appropriate for their own particular circumstances. In particular, adaptive educational system that adapt the content and/or environment to the learning characteristics of each individual learner offer an alternative to the traditional educational approach of “one size fits all” (Brusilovsky & Peylo, 2003).

Subsequently, the question arise: how can developments in individual difference theory and instructional design be integrated together in the design of adaptive educational systems to make a positive impact on learning outcomes? To answer this question, it is necessary to review:

- The aspects of individual differences that need to be taken into account
- How technology enhanced learning environments can accommodate individual differences through the use of appropriate instructional design and adaptive strategies

The structure of the chapter is organised to address these two questions. Section 2 will review the nature and dimensions of individual differences and in particular the trait dimensions of intelligence or ability, and style. Section 3 will review how technology enhanced learning environments can support individual trait differences, and in particular the potential offered by adaptive educational systems.

Section 4 summaries the chapter and argues that the use of the Multiple Intelligence framework of individual differences offers an unexplored dimension in the design of adaptive educational systems. It also argues that adaptive educational systems, through the use of adaptive presentation and navigation techniques, can support individual differences in learning. Furthermore, it suggests that machine-learning techniques provide the opportunity to diagnose individual differences by detecting patterns in observable learning behaviour.

2.2 Learning Theory and Individual Differences

Considerable research has been undertaken to discover the nature and dimensions of individual differences. The following sections outline the various psychological constructs that have been proposed. In particular, it provides an overview of the various intelligence and learning style theories, and highlights the debate surrounding their impact on education. The purpose of the overview is to provide the basis for reviewing technology enhanced learning environments that acknowledge the role of individual trait

differences and for positioning the research undertaken as part of this thesis, the adaptation of content using the Multiple Intelligence theory.

2.2.1 Individual Difference Frameworks

The psychology of individual differences involves the study of psychological constructs, their interaction with environmental stimuli and the resulting observable behaviour (Boyle, 2004a). These psychological constructs can be divided into two groups: traits and states (Cooper, 2002). Traits are descriptions of how individuals generally behave over the long term. For example, a person who can easily remember songs and sing in tune is generally regarded as having musical ability. States are short lived, lasting for minutes or hours rather than months or years, such as the joy of doing well in an examination.

Individual behaviour can be described as the function of individual differences in traits such as intellectual abilities and personality characteristics, and states such as dynamic motivational and transitory mood states (Anastasi, 1965, Boyle, 1988). Intellectual ability traits describe the level of cognitive performance in some area and refer to thinking skills such as how well an individual can read maps, visualise shapes and solve crossword puzzles. Personality traits reflect a person's style of behaviour and refer to characteristics such as extroverted, shy, punctual or anxious. Motivational states are forces that influence our behaviour for a short time, for example desire for food that subsides after a meal. Moods or emotions refer to transient feelings, such the exhilaration of getting married (Cooper, 2002).

However, research into individual differences has been hindered by the problem of elucidating a generally agreed upon taxonomy of psychological constructs. There have been many attempts to derive a universally agreed upon taxonomy of trait and state dimensions, but much controversy still exists as to the major dimensions within each of the ability, personality trait, motivation and mood domains. An example of this debate can be seen within the personality domain where several models of personality traits exist including Cattell's Sixteen Personality Factor model (Cattell et al., 1970), the Five Factor Model (Goldberg, 1990) and Eysenck's Three factor model (Eysenck & Eysenck, 1985). Eysenck's model proposes three main aspects of personality, namely introversion versus extraversion, neuroticism versus emotional stability and psychoticism (or tough mindedness) versus tender minded. Introverted individuals are reserved and pessimistic, while extraverted individuals are social, talkative and optimistic. Highly neurotic people

are moody, touchy and anxious while people low on neuroticism are relaxed, even-tempered and calm. Individuals high in psychoticism are emotionally cold, cruel, risk takers and manipulative while tender minded individuals are warm, socialized individuals. In comparison, the Five Factor Model describes five personality factors, extroversion, neuroticism, openness, agreeableness and conscientiousness.

In the context of learning, educationalists interested in the relationship of performance to individual differences have typically sought answers using the trait concepts of intellectual ability and learning styles. Intellectual abilities have been found to be predictors of school performance with students expressing measurable differences in intelligence and ability levels (Neisser et al., 1995). The concept of learning styles is also of interest as some researchers report that they can predict performance in ways that go beyond abilities (Marton & Booth, 1997; Sternberg & Grigorenko, 1995). The concept of learning style is similar to that of personality in that it reflects a person's style of behaviour when learning, and lies in the area of psychology at the interface between abilities and personality (Sternberg, 2001).

Comparing the constructs of styles to abilities or intelligences, abilities refer to things one can do such as to execute skills or strategies, whereas styles refer to preferences in the use of abilities (Messick, 1996).

In other words, abilities are concerned with how much and styles with how. Hence, high amounts of ability are always preferable to low amounts, whereas each pole of a style dimension indicates different characteristics. Moreover, an ability is usually limited to a particular domain of content such as verbal or whereas style cuts across domains of ability. For example, learners with the wholist cognitive style tend to organise information globally and prefer to have an overview picture first before delving down into the details (Riding & Rayner, 1998). Regardless, if the domain is verbal or musical, the wholist learner will use the same style and prefer to have an overview first.

The concepts of intellectual abilities and styles of learning have been much explored and offer a strong basis on which to develop learning environments that support individual differences. In contrast, the constructs of motivation and mood are less understood and still in need of more research (Cooper, 2002; Vincente & Pain, 2002). Subsequently, this research is based on the development of learning environments that accommodate individual traits such as intelligences and style. The following two sections provide a brief overview of the various taxonomies that have been proposed for the intelligence and style constructs.

2.2.2 Abilities and Intelligence

Individuals differ from one another in their ability to apply reasoning, to understand concepts, to adapt effectively to their environment and to learn from experience. Different concepts of 'intelligence' have been proposed to give clarity on these differences and what it means to be intelligent. However, no such concept has yet answered all the important questions and none commands universal agreement. For example, back in 1986 when two dozen prominent theorists were asked to define intelligence, two dozen different definitions were given (Sternberg & Detterman, 1986). However, a couple of years later in 1994, a consensus definition for intelligence was agreed by 52 experts and published in the Wall Street Journal (Gottfredson, 1997). It defined intelligence as a very general capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience. This is somewhat different from Descartes definition as intelligence being the ability to judge true from false (Diogenes Laertius, 1924). Another very often cited definition is Wechsler's statement that "intelligence is the aggregate or global capacity of the individual to act purposefully, to think rationally, and to deal effectively with his environment" (Wechsler, 1958). This broad definition encompasses a range of abilities such as writing a sonnet, adding numbers, designing a building, reading a map, structuring an essay, inventing a joke or diagnosing a fault in a computer.

Wechsler's definition is in contrast to the definition of intelligence as a very general capability and illustrates the key debate that surrounds the concept of intelligence. This debate revolves around the issue of whether there is a general aptitude or intelligence that indicates the level of performance in all areas. Critics (Gardner, 1983; Sternberg, 1996) of the general intelligence level point out that people can vary in their aptitude for learning specific types of knowledge taught in specific ways. For example, a person can be good at calculus but may not be able to write an essay or paint a picture.

In attempts to establish the nature of intelligence two main approaches are used: the psychometric and cognitive approach (Borich, 1997). Both approaches attempt to define the number of abilities, what these abilities are and how they are related. The approaches can be described as follows:

- The empirical approach or psychometric approach attempts to understand the structure of intelligence. Psychologists who use this approach are interested in analysing the structure of intelligence and asking such questions as "Is intelligence one general ability or many specific abilities?". They attempt to define the number

of abilities and the relationship between them. They tend also to agree that tests which contain questions that are clearly right or wrong is the best way to learn about intelligence. The approach involves measuring an individual's performance on a wide range of tasks, correlating the scores on the test items and using factor analysis to determine the underlying structure and main dimensions of abilities. An example of such an "intelligence" test is the Wechsler Intelligence Scales for Children or WISC III (Wechsler, 1991).

- The cognitive approach attempts to understand the process of intelligence. Using this approach psychologists try to understand what people do when they are engaged in intelligent behaviour. They believe understanding the underlying process of intelligence is more important than describing its structure. They also believe that the best way to explore the nature of intelligence is not through standardized tests, but instead by having people solve problems and examine the process they use to do so.

The following two sections will briefly review the concepts of intelligence that have resulted from both approaches.

2.2.2.1 Psychometric Approach

Spearman (1904) was the first to perform an empirical study of the structure of abilities using factor analysis. He constructed some primitive tests of vocabulary, mathematical ability, visualization and matching colours. He found, despite variations in a persons abilities from task to task, just one intelligence factor which he called g (for general ability). He proposed based on his studies, that there was some basic thinking ability that determines the level of performance across all learning situations.

Thurstone, from his empirical studies came to a different conclusion (Thurstone, 1938). He proposed 12 independent primary mental abilities which included spatial ability (visualising shapes and mental rotation), word fluency (dealing with isolated words), numerical facility, perceptual speed (searching), induction (finding rules given exemplars) and deduction (applying a rule).

Other researchers proposed even more primary mental abilities. Hakstian & Cattell (1978), proposed a hierarchical model of intelligence. This model incorporates a general intelligence level g, which in turn influences six second order factors which also in turn influences 20 primary abilities. To assess the 20 primary abilities they use a test called the Comprehensive Ability Battery (Hakstian & Cattell, 1976). The test assesses primary

abilities as diverse as originality (thinking of creative uses for objects), mechanical knowledge and reasoning, verbal ability, numerical ability, fluency of ideas (being able to produce ideas quickly), perceptual speed (speed in comparing two strings of characters), spelling and aesthetic judgement (for works of art). From an analysis of the correlations between these primary abilities, six 'second-order' factors were identified. The two most important factors in this model are fluid intelligence and crystallised intelligence. Fluid intelligence is the raw reasoning ability and covers memory, spatial ability and inductive reasoning whereas crystallised intelligence requires knowledge and influences verbal comprehension and mechanical knowledge (Boyle, 1988). The other four factors in this model were retrieval (Gr), (the speed with which ideas are produced), visualization (Gz), perceptual speed (Gps) (speed with which two strings of characters can be compared) and memory capacity (Gm).

More recently, Carroll in one seminal study attempted to determine if there was one common general intelligence with a hierarchical arrangement of specialised abilities below it (Carroll, 1993). He found, after the re-analysis of virtually all data sets collected in the 20'th century, a hierarchy of structures. At the lowest level of the hierarchy he discovered around 70 narrow primary abilities. Correlations between primary abilities allow them to be clustered together to define eight broad intelligences at the second stratum and these broad abilities clustered to define a general intelligence at the third stratum.

2.2.2.2 Cognitive Approach

Three main theories need to be mentioned when discussing the cognitive approach to understanding intelligence: Multiple Intelligences (Gardner, 1983), Triarchic Theory (Sternberg, 1989) and social/emotional intelligence (Goleman, 1995). The following three sections will outline the main concepts behind each of these theories.

Gardner's Theory of Multiple Intelligences

One very popular model based on the cognitive approach, is Gardner's theory of Multiple Intelligence (Gardner, 1983, 1993, 2000). In his theory, Gardner defines intelligence as the "biopsychological potential to process information that can be activated in a cultural setting to solve problems or create products that are of value in a culture" (Gardner, 2000). This definition implies that, depending on the setting or domain, different intelligences are used to solve problems and fashion products such as compositions, music or poetry. It is also important to note that Gardner considers

intelligences as something that cannot be seen or measured but instead are potentials that will or will not be activated depending upon the values of a particular culture and the opportunities available in that culture.

Gardner derives his concept of intelligence not only on work with normal children and adults but also by studies of gifted persons in various domains, of valued abilities in diverse cultures and of individuals who have suffered selective forms of brain damage. Gardner suggests that no single model of cognitive functioning will be found to underlie all human problem solving. Rather, cognitive processes will vary depending on the task the student is involved in. He proposes that there are eight different ways to demonstrate intelligence with each having its own unique characteristics, tools, and processes that represent a different way of thinking, solving problems, and learning. These eight intelligences are described as the logical/mathematical, linguistic/verbal, visual/spatial, bodily/kinesthetic, musical/rhythmic, interpersonal, intrapersonal and naturalist intelligences. There is current debate about the existence of a ninth intelligence, the existential or spiritual intelligence, but Gardner has not formally included it in his model yet (Gardner, 2000).

Gardner suggests that everybody possesses the different types of intelligences to different degrees and that they operate together in an orchestrated way. He also suggests that even though different intelligences do tend to be stronger in some people, everybody has the capacity to activate all the intelligences and in different situations different intelligences or a combination of intelligences may be used.

Sternberg's Triarchic Theory of Intelligence

Sternberg (1989, 1990) also proposes that the best way to study intelligence is to examine how people solve problems that are important to them in their environments. But contrary to Gardner, he believes that regardless of the type of problem people are confronted with, they use a common set of cognitive processes to solve them. He believes that whether the problems involve mathematical, spatial or linguistic or interpersonal issues, the same cognitive processes are used. He suggests that when solving problems that require intelligence, three factors come into play: the context in which "intelligent" behaviour takes place is important (contextual sub-theory); the role of novelty and experience in solving the task (experiential sub-theory); and the underlying processes of intelligent behaviour (componential sub-theory).

However, recognising that problems in traditional intelligence tests did not adequately measure intelligence, Sternberg proposed his triarchic theory of intelligence. His triarchic

theory proposes three fundamental aspects of intelligence: analytic, creative and practical. He suggests that mainstream tests only measure analytic intelligence using analytic problems that are clearly defined, which come with all the information needed to solve them, have only a single right answer reached by a single method and are disembedded from ordinary experience. In contrast, he suggests practical intelligence is measured by practical problems that require problem formulation, require information seeking, have various acceptable solutions and are embedded in everyday experience.

Sternberg states that you can make learners more intelligent by giving them real world problems that are important to solve, by teaching them general cognitive strategies that can be used to solve any problem, by teaching metacognitive skills to help them regulate their use of cognitive strategies and by showing them how to acquire knowledge so that these skills become automatic.

Social and Emotional Intelligences

One type of intelligence, which has been part of the intelligence field since its inception, is the concept of social intelligence (Walker & Fole, 1973). Thorndike originally defined intelligence as the ability to understand and manage people, and as the ability to perceive one's own and other's internal states, motives, and behaviours (Thorndike & Stein, 1937). However social intelligence was not universally accepted and in 1960, Cronbach came to the conclusion that despite 50 years of intermittent investigation, social intelligence was undefined and unmeasured (Cronbach, 1960).

A subset of social intelligence called emotional intelligence has now seen a resurgent of interest (Goleman, 1995). Emotional intelligence is defined as the ability to monitor one's own and others' feelings and emotions, to discriminate among them and to use this information to guide one's thinking and action (Salovey & Mayer, 1990). Emotional intelligence is also part of Gardner's view of social intelligence, which he refers to as the inter- and intra-personal intelligences and which includes knowledge about the self and about others (Gardner, 1983).

2.2.2.3 Intelligence: The Debate

There is an ongoing debate in the research community about how many distinct types of intelligences exist and how it is possible to describe them. The classical viewpoint is that intelligence could be measured by giving tests with right and wrong answers, and characterising the ability that underlies intelligence with a unitary trait, for example the

IQ test score (Cronbach, 1960). Proponents of the classical viewpoint argue that intelligence tests act as predictors of school performance, particularly at primary school level, and are predicative of accomplishments such as social status after school (Brody, 1992; Cattell, 1987; Detterman 1994). They also argue that test scores remain stable throughout childhood and adolescence, that is the scores in relation to others of the same age (Moffitt et al., 1993). Nevertheless intelligence scores tend not to be a significant predictor at university level, as other variables such as motivation, self concept, attitudes and beliefs come to the fore in predicting success and failure (Neisser et al., 1995).

However, there are many disputes over the utility of intelligence testing and the concept of *g*, the general intelligence level. Some theorists are critical of the entire psychometric approach (Ceci, 1990, Gardner, 1983, Gould, 1978) while others regard it as firmly established (Carroll, 1993, Eysenck, 1973, Hernstein & Murray, 1994, Jensen, 1972). Critics do not dispute the stability of test scores, or the fact that they predict certain forms of achievement effectively, especially school achievement. Rather, they do argue that to base a concept of intelligence on test scores alone is to ignore many important aspects of mental ability. They reason that tests cannot assess wisdom, creativity, practical knowledge and social skill. They also argue that there is more than one general aptitude where all abilities are correlated with each other (Gardner, 1983; Snow, 1992; Sternberg, 1996). They do not support the idea that good or poor performance in one area guarantees similar performance in another and argue that correlations are not consistent enough support to support the concept of one general intelligence (Gaustafsson, 1994; Lohman, 1989). It appears the debate on the concept and nature of intelligence will continue to evolve.

2.2.3 Learning Style

In addition to intelligence, personality is the second dimension of individual traits. Students have different natures and personalities, each having a set of specific qualities. The concept of style is associated with individuality and invariably used to describe an individual quality, form, activity or behaviour sustained over time. Just as students have different personalities, they also have different styles of learning. For example, students differ in the way they learn the names of people they meet. If they learn better when they see it written down, they may be a visual learner, a person who learns best by seeing or reading. If they learn a name better by hearing it they may be an auditory learner. The

manner in which a person habitually approaches or responds to learning tasks is defined as their personal learning style (Riding & Rayner, 1998).

There have been many conceptual frameworks into which the various constructs for learning style may be usefully categorised (Curry, 1983; Riding & Rayner, 1998; Sternberg & Grigorenko, 2001). For example, Curry (1983) organised the various learning style constructs into different layers making an analogy with the concentric layers of an onion. She identified 21 different models of styles and later commented that “Like the blind men in the fable about the elephant, learning styles researchers tend to investigate only a part of the whole and thus have yet to provide a definitive picture of the matter before them” (Curry, 1990).

More recently, Riding & Rayner (1998) have proposed an overall framework that integrates more fully the various models of style. The framework describes a number of models and comprises of

- The cognitive-centred approach (cognitive styles). This reflects the work of experimental psychologists investigating the area of individual differences in cognition and perception.
- The activity (learner) centred approach (learning styles). This reflects the work of educationalists addressing environmental and process-based issues related to meeting individual differences in the classroom. Here the focus is on the learner’s active response to the learning task.

One important theme running through the framework is the relative stability of style versus the adaptive nature of strategy. The framework also separates out phenomena that reflect an individual’s habitual processing mode (cognitive style) and behaviour (learning style) from those that are responses to a given context (learning strategy) as they interact with learning tasks.

The following two sections will briefly review the theories of style that have resulted from both approaches.

2.2.3.1 Cognitive-centred approach to styles: Cognitive Styles

The cognition centred approach attempts to elucidate the processes generating individual differences. Table 2-1 displays the two distinct families of cognitive style (Riding & Rayner, 1998):

- The wholist/analytic dimension that relates principally to how people think and process information. It describes how individuals tend to cognitively organise information in wholes or parts. For example, some individuals will process information into its component parts while others will retain a global or overall view of information.
- The verbal/imagery dimension relates principally to how people mentally represent information: It describes how individuals tend to represent and recall information in pictures or words. For example, verbalisers tend to present information in words, while imagers tend to present information in pictorial form.

One example of a prominent cognitive style is Witkin's field-dependence/field-independence model (Witkin & Asch, 1948). Field-independence refers to a tendency to articulate figures as discrete from their backgrounds and an ability to differentiate objects from the surrounding environment. It describes how much a learner's comprehension of information is affected by the surrounding perceptual or contextual field (Witkin et al., 1977).

When learning, field-dependent and field-independent learners use different approaches (Witkin et al., 1977; Wapner & Demick, 1991; Jonassen & Grabowski, 1993). Field-independent individuals are highly analytic and are able to extract the necessary cues to complete a task. They tend to discern figures as discrete from their background, to focus on details, and to be more serialistic in their learning. They operate within an internal frame of reference and thrive in situations where they need to actively structure their own learning. On the other hand, field-dependent individuals process information globally and attend to the most salient cues regardless of their relevance. They tend to see patterns as a whole and have difficulty separating out specific aspects of a situation or pattern. They typically see the global picture, ignore the details, and approach a task more holistically. They also operate within an external frame of reference and prefer situations in which structure and analysis is provided for them. To support the existence of the theory, a recent study reports that matching instructional presentation style to the student's field-dependence/field-independence cognitive style can have significant effects on learning outcomes (Ford & Chen, 2001).

2.2.3.2 Learning-centred tradition of style: Learning Styles

The learning-centred tradition of style has its focus on the learning process and in particular the aspects of the process which relate to individual differences as the person

interacts with their environment. Its primary interest is in the impact of individual differences upon pedagogy and the enhancement of learning achievement. Table 2-2 displays the different learning style theories which are categorised into the following groups (Riding & Rayner, 1998):

- The learning process based on experiential learning
- The learning process based on orientation to study
- Instructional preferences
- Cognitive skills and learning strategy development

The first three groups of style are generally concerned with the process of learning and its context. They are characterised by a specific focus on individual differences in the process of learning rather than within the individual learner. The fourth group is more concerned with developing a repertoire of cognitive skills and abilities.

One very popular model based on the process of learning is the Kolb learning style theory (Kolb, 1976). Kolb describes learning style as the individual's preferred method for assimilating information. His theory is grounded in the theory of experiential learning and is rooted in the proposition that learning is a process whereby knowledge is created through the transformation of experience (Kolb, 1984). He identifies four stages in the learning process: concrete experience, reflective observation, abstract conceptualisation and active experimentation. Each of these learning modes has unique learning characteristics. In the active experimentation phase, learners learn primarily by manipulating the environment, while in the reflective observation learners typically learn by introspection and internal reflection on the external world. In the abstract conceptualisation phase learners comprehend information symbolically and conceptually, whilst in the concrete experience phase learners respond primarily to the qualities of the immediate experience.

Kolb's learning style theory consists of two dimensions: perceiving and processing. The first describes a continuum between concrete and abstract thinking, the second an active or reflective information processing activity. The two dimensions combine together to describe four types of learning style:

- Divergers who process information concretely and reflectively
- Convergers who process information abstractly and reflectively
- Assimilators who process information abstractly and actively

- Accommodators who process information concretely and actively

Each of the different types of learners has different strengths and weaknesses. Divergers need to be personally engaged in the learning activity whilst convergers need to follow detailed sequential steps. Assimilators need to be involved in pragmatic problem solving whereas accommodators process information concretely and actively and, need to be involved in risk taking and experimentation. In addition, Kolb's theory of learning embraces the notion that the individual ultimately learns to use each learning style to cope with the learning task. To support the learning theory, a recent study has presented evidence in favour of Kolb's orthogonal style dimensions (Sadler-Smith, 2001).

2.2.3.3 Styles: The Debate

Educationalists with an interest in style regard this field as an underdeveloped aspect of teaching and learning which may be the key to greatly enhancing levels of performance (Riding & Cheema, 1991; Grigorenko & Sternberg, 1995). However, cognitive and learning styles has come in for much criticism, with researchers commenting that the style construct has largely evolved from theories generalised on single experiments and little empirical evidence (Vernon, 1963). Some have gone as far as to reject the style construct as an illusion or at best, a construct which is impossible to operationalise and therefore undeserving of further research (Freedman & Stumpf, 1980; Tiedemann, 1989).

Critics highlight that only a limited number of studies have demonstrated that students learn more effectively when learning style is accommodated (James & Blank, 1993, Stellwagen, 2001). They argue that for a learning style theory to be useful, it needs to show how it can enhance performance. Concerns also exist over the instruments that measure styles. There exists many instruments that measure style, for example, the LSI "Learning Style Inventory" (Kolb, 1976), the LSQ "Learning Style Questionnaire" (Honey & Mumford, 1986) and the ASI "Approaches to Study Inventory" (Entwhistle, 1979). However, some feel that the usefulness or validity of learning style models and instruments has not been definitively established (Bonham, 1988a; Bonham, 1988b; Kavale & Forness, 1987). Another particular concern is that most learning style theories label students into a few discrete categories (Grasha, 1990; Stellwagen, 2001). Indeed it may be necessary to recognize that individuals develop and practice a qualitative mixture of learning styles that evolve as they learn and grow and which vary by discipline (Silver, Strong, & Perini, 1997).

2.2.4 Individual Differences: Summary

As has been highlighted, individual differences in style and intelligence have been well documented. Therefore, it would seem logical that different styles of teaching would have a different impact on individual learners. However this has been difficult to demonstrate conclusively. In particular, research is divided in the application of leaning and cognitive styles to the development and design of technology enhanced learning environments. On the one hand, some studies show that learning improves and the quality of material is enhanced when individual differences are taken into account (Rasmussen, 1998; Riding & Grimley, 1999; Graf, 2003). In contrast, other studies have reported no differences in learning outcomes for learners of different style (Ford & Chen 2000; Shih & Gamon, 2002). Some reasons for these contrasting studies include difficulties in assessing learning style, the arbitrary classification of learners into categories and questions around the construct validity of style (Riding & Rayner, 1998).

In contrast, there is evidence to support the concept of intelligence as a predictor of learning performance. Rather with the concept of intelligence, there is debate on whether there is single general intelligence level that can be measured through psychometric approaches or multiple intelligences which are determined by observing what people do when problem solving. In particular, the theory of Multiple Intelligences offers potential to provide a framework for a broad range of individualised pedagogical strategies while building on research that demonstrates how intelligence can be a predictor of learning performance. Thus, this research has adopted the concept of Multiple Intelligences as the relevant educational theory upon which to develop adaptive educational systems.

Table 2-1: Cognitive Styles (Adapted from Riding & Rayner, 1998)

Dimension	Description	References
<i>Wholist/Analytic dimension</i>		
Field-dependency/ Field-independency	Dependency on surrounding field or context when analysing a structure or form which is part of the field	Witkin & Asch (1948a, 1948b)
Levelling-Sharpening	Tendency to oversimplify perceptions and to assimilate detail rapidly or to perceive task in a differentiated manner with little assimilation	Klein (1954)
Impulsivity-reflectiveness	Tendency for a quick as against a deliberate response	Kogan et al. (1964)
Converging-Diverging	Narrow, focused, logical, deductive thinking rather than broad open-ended associational thinking to solve problems	Guilford (1967)
Holist-Serialist thinking	Tendency to work through learning tasks incrementally or adopt a global approach building broad descriptions	Pask & Scott (1972)
Concrete Sequential/concrete random/abstract sequential/abstract random	Learn through concrete experience and abstraction either randomly or sequentially	Gregorc (1982)
Assimilator-explorer	Preferences for seeking familiarity or novelty in the process of problem-solving and creativity	Kaufmann (1989)
Adaptors-innovators	Adaptors prefer conventional, established procedures and innovators new perspectives whilst problem solving	Kirton (1994)
Reasoning-intuitive active-contemplative	Preference for developing understanding and/or insight and learning activity that allows active participation or passive reflection	Allison & Hayes (1996)
<i>Verbal-imagery dimension</i>		
Abstract versus concrete thinker	Preferred level and capacity of abstraction	Harvey et al. (1961)
Verbaliser-visualiser	The extent to which verbal or visual strategies are used to represent knowledge and thinking	Paivio (1971); Riding and Taylor (1976)
<i>Integration of the wholist-analytic and verbal-imagery dimensions</i>		
Wholist-analytic, verbal-imagery	Tendency for the individual to process information in parts or as a whole and think in words or pictures	Riding & Cheema (1991)

Table 2-2: Learning Styles (Adapted from Riding & Rayner, 1998)

Dimension	Description	References
<i>Style models based on the learning process</i>		
Concrete experience/reflective observation/abstract conceptualisation/active experimentation	A two-dimensional model comprising perception (concrete/abstract thinking) and processing (active/reflective information processing)	Kolb (1976)
Activist/theorist/pragmatist/reflector learners	Preferred models of learning which shapes an individual approach to learning	Honey & Mumford (1986)
<i>Style models grounded in orientation to study</i>		
Meaning/reproducing/achieving/holistic orientation; later developed to include deep, strategic, surface, lack of direction, academic self confidence	Model of the processes underlying individual orientation to learning	Entwistle (1979)
Surface-deep-achieving/intrinsic-extrinsic-achievement orientation	Integration of approaches to study with motivational orientation	Biggs (1978)
Synthesis-analysis/elaborative processing/fact retention/study methods	Quality of thinking which occurs during learning relates to distinctiveness, transferability, and durability of memory and fact retention	Schmeck et al. (1977)
<i>Style models based on instruction preference</i>		
Environmental/sociological/emotional/ physical/psychological elements	Learner's response to key stimuli: environmental (light, heat); sociological (peers, pairs, adults, self); emotional (structure, persistence, motivation); physical (auditory, visual, tactile); psychological (global-analytic, impulsive-reflective).	Dunn et al. (1978)
Participant-avoidant/collaborative-competitive/independent-dependent	Social interaction measure which has been used to develop three bipolar dimensions in a construct which describes a learner's typical approach to the learning situation	Grasha & Riechmann (1975)
<i>Style models based on cognitive skills development</i>		
Visualisation/verbal symbols/sounds/emotional feelings	Learning style defined in terms of perceptual modality	Reinert (1976)
Field-dependency/scanning focus/breadth of categorisation/cognitive complexity/reflective-impulsivity/levelling-sharpening/ tolerant-intolerant	A cognitive profile of three types of learners reflecting their position in a bi-polar analytic-global continuum which reflects an individuals cognitive skills development	Letteri (1980)
Cognitive skills/perceptual responses/ study and instructional preferences	Identifies 24 elements in a learning style construct grouped into 3 dimensions.	Keefe & Monk (1986)

2.3 Technology Enhanced Learning Environments

Despite inconclusive research evidence, technology enhanced learning solutions offer the potential to provide environments that support and acknowledge individual differences. These solutions typically come in two forms: traditional hypermedia systems and adaptive educational systems.

Hypermedia systems offer not just one linear path through the educational material but a multitude of branches in which a learner can explore a subject matter at their own pace. These systems give control to the learner in what they read and the order in which they read it, and as such provide the flexibility that allows learners to express their individual differences in learning. Adaptive educational systems are an extension of hypermedia systems in that they structure the learning environment and personalise instruction to individual students by building a model of the student's goals, interests and preferences (Brusilovsky et al., 1998). For example, adaptive annotation or the augmentation of links with some forms of comments can assist field-dependent learners who habitually attend to the most vivid or salient features (Chen & Macredie, 2002). Adaptive educational systems offer great potential to take advantage of individual differences to improve learning. However in the design of adaptive educational systems, significant challenges exist. How can the system build and diagnose the student's learning characteristics and how can they adapt the learning environment to suit the student's needs?

The focus in this section is to give an overview of the research on technology enhanced learning environments that support individual differences in learning. First, it reviews the different categories of adaptive intelligent educational systems and in particular the role of adaptive hypermedia. Second, it reviews several studies that have tried to evaluate the impact of individual differences in hypermedia systems. Last, it reviews a number of sample adaptive educational systems illustrating the design issues in building such systems, and in particular how adaptive hypermedia can support individual differences.

2.3.1 Overview of Adaptive and Intelligent Systems

Traditional educational systems tend to adopt a 'one size fits all approach' and treat all students in the similar manner. However, this raises problems where they are students with different levels of knowledge, goals and preferences. Adaptive and Intelligent Educational Systems overcome this problem by building a model of the goals,

preferences and knowledge of each individual student, and by subsequently using the generated model to dynamically adapt the learning environment for each student in a manner that best supports their needs (Brusilovsky, 2001). They attempt to be more intelligent by incorporating and performing some activities traditionally executed by a human teacher – such as coaching students or diagnosing misconceptions (Mitrovic, 2003). They also attempt to be adaptive to different ways of learning by modifying the presentation of materials to the student's level of knowledge (De Bra & Calvi, 1998) or suggesting a set of relevant links to progress further (Brusilovsky et al., 1998).

The distinction between Adaptive Educational Systems and Intelligent Educational Systems can be sometimes blurred, but different emphasis can be identified in each. In adaptive systems, the emphasis is on providing a different environment for each different student or group of students by taking into account information accumulated in the individual or group student models. In intelligent systems, the emphasis is on the application of techniques from the field of Artificial Intelligence to provide broader and better support (Brusilovsky & Peylo, 2003).

To help categorise the diverse range of adaptive and intelligent educational systems, the term 'technologies' is used to describe the different ways in which technology adds adaptive or intelligent functionality (Brusilovsky, 1996). Brusilovsky & Peylo (2003) propose five major groups of technologies: Adaptive Hypermedia, Intelligent Tutoring, Adaptive Information Filtering, Intelligent Class Monitoring and Intelligent Collaboration Support.

The major Intelligent Tutoring technologies are curriculum sequencing, intelligent solution analysis and problem solving support. Curriculum sequencing addresses the question of what content to present. Its goal is to help the student find the most suitable path through learning material (Weber & Brusilovsky., 2001). Intelligent solution analysis deals with solutions to educational problems. Intelligent analysers do more than tell whether a solution is correct or not. They can find out what exactly is wrong or incomplete, identify what piece of incorrect knowledge may be responsible for the error and provide suitable feedback (Mitrovic, 2003). The purpose of interactive problem solving support is to provide the student with intelligent help on each step of problem solving, from giving a hint to executing the next step for the student (Melis et al., 2001).

The goal of Adaptive Information Filtering (AIF) is to find a few items that are relevant to user interests from a large pool of documents. It adapts Web searches by filtering and ordering the results, and by recommending the most relevant documents in

the pool using link generation. There are essentially two different AIF technologies – content based filtering and collaborative filtering. In the content-based approach, the behaviour of a user is predicted from their past behaviour, while in the collaborative approach, the behaviour of the user is predicted from the behaviour of other like-minded people. MLTutor (Smith et al., 2003) is an example of applying content based AIF to education while WebCOBALT (Mitsuhara et al., 2003) is an example of collaborative AIF. AIF is now becoming popular, as the Web provides an abundance of non indexed open corpus educational resources.

Intelligent collaborative learning technologies help to support collaborations between students, who in web based education may rarely meet in person. Three types of technologies may be defined within this area: adaptive group formation and peer help, adaptive collaboration support, and virtual students. Technologies for adaptive group formation and peer help attempt to use knowledge about collaborating peers to form matching groups for different kinds of collaborative tasks (Greer et al., 1998). Adaptive collaboration support technologies attempt to provide interactive support in the collaboration process by using knowledge about good and bad collaborations (Soller et al., 2003). Virtual student technology attempt to introduce different kinds of virtual peers into a learning environment (Chan et al., 1990).

Intelligent class monitoring technologies attempt to identify students who need additional attention or who need to be challenged. Such technologies use AI techniques to analyse the large volume of data that web based systems can collect when tracking student actions (Maceron & Yacef, 2003).

Adaptive Hypermedia encompasses two major technologies: adaptive presentation and adaptive navigation. Adaptive presentation adapts the content to be presented by dynamically generating the content for each individual student according to their needs (Weber & Brusilovsky, 2001). Adaptive navigation supports the student by changing the appearance of links. For example, it can adaptively sort, annotate or partly hide the links of the current page to make it easier to choose where to go next (de Bra, 1996).

As has been described, there is a diverse range of technologies available in the development of adaptive and intelligent educational systems. This research has selected Adaptive Hypermedia technologies as the most appropriate, as they provide the techniques and methods to support individual differences in learning.

2.3.2 Adaptive Hypermedia

Traditional static hypermedia applications provide the same page content and the same set of links to all users. Adaptive hypermedia systems build a model of the goals, preferences and knowledge of each individual user, and use this model to adapt to the need of the users. For example, in an adaptive educational hypermedia system, a student can be given a presentation that is adapted specifically to their knowledge of the subject. Other adaptive hypermedia systems include on-line information systems, on-line help systems, information retrieval hypermedia, and systems for managing personalized views (Brusilovsky, 2001).

Adaptive decisions are usually made taking into account the various characteristics of the users. These features can include the user's goals, tasks, knowledge, background, preferences, hyperspace experience, interests and individual traits. Adaptive educational systems capture and represent these characteristics in a learner model for each individual learner (Kobsa, 2001). Observing learner's behaviour is in many cases the basis for the diagnosis of user characteristics such as knowledge level and preferences. Knowledge level can be based on the learner's navigation through the domain. For example it can be based on the web pages visited (history-based) or by the submission of assessment tests (knowledge-based) (Eklund & Sinclair, 2000). Individual traits such as personality, cognitive and learning styles can also be captured but challenges remain in how to exploit this information (Brusilovsky, 2001).

Information in the learner model is used as the basis for making adaptation decisions. The two distinct areas of adaptation that exist, adaptive presentation and adaptive navigation support, cover a broad range of techniques (Brusilovsky, 1998, 2001). Adaptive presentation includes text, multimedia and modality adaptation. Adaptive navigation support includes direct guidance, link hiding, sorting, generation, annotation, and hypertext map adaptation. Figure 2-1 displays the different adaptive hypermedia technologies and their associated techniques.

Different systems use the different techniques for a variety of reasons. Active-Math (Melis, et al., 2001) and C-Book (Kay & Kummerfeld, 1994) use adaptive presentation techniques to:

- Hide information that is not relevant to the user's level of knowledge and provide additional explanations required by novices (additional explanations)

- Provide explanations of pre-requisite explanations not known to user before presenting a concept (prerequisite explanations)
- Explain similarities and differences about current concept and related ones (comparative explanations)
- Explain the same part of a concept in different ways (explanation variants)

In addition, ELM-ART (Weber & Brusilovsky, 2001) and AHA (De Bra et al., 1998) are two systems that use adaptive navigation techniques to

- Help find the shortest way to information goals (global guidance). For example, using the next button to go to the node with the most relevant educational material according to the model of the user
- Help make one navigation step by suggesting the most relevant links to follow from the current position (local guidance)
- Help understand what is around or relative to current position in hyperspace (local orientation support). This is done by providing information about nodes available or limiting the number of navigation opportunities
- Help understand the structure of the overall hyperspace and the position in it (global orientation support). This is done by providing visual landmarks, global maps, link hiding and annotating
- Organize the electronic workplace for the learner (personalized views)

Together adaptive presentation and adaptive navigation provide a rich range of techniques and methods for developing adaptive educational systems that accommodate individual differences.

2.3.3 Empirical Studies on Learning Styles

When compared with adaptive educational systems, there have been a greater number of studies that have examined the influence of individual differences on behaviour and performance in hypermedia learning environments (Chen & Paul, 2003). Hence a number of these studies will be reviewed to give some understanding of the issues involved when designing and evaluating such environments. The majority of these studies undertaken usually have three themes underpinning them:

- How do learners with different characteristics use hypermedia environments?

- How are individual differences related to learning performance?
- Can individual differences in learning be supported by different instructional designs?

Typically these studies would investigate the influence of cognitive and learning style on issues such as nonlinear learning, learner control, navigation tools, learning effectiveness, and matching/mismatching (Chen & Macredi, 2002).

This section presents a small sample of studies that have attempted to evaluate the impact of individual differences on learning behaviour and performance. In particular, it reviews hypermedia systems that have used the field-dependent/field-independent cognitive style in order to illustrate the debate on how learners with different styles can use hypermedia systems and achieve different learning outcomes.

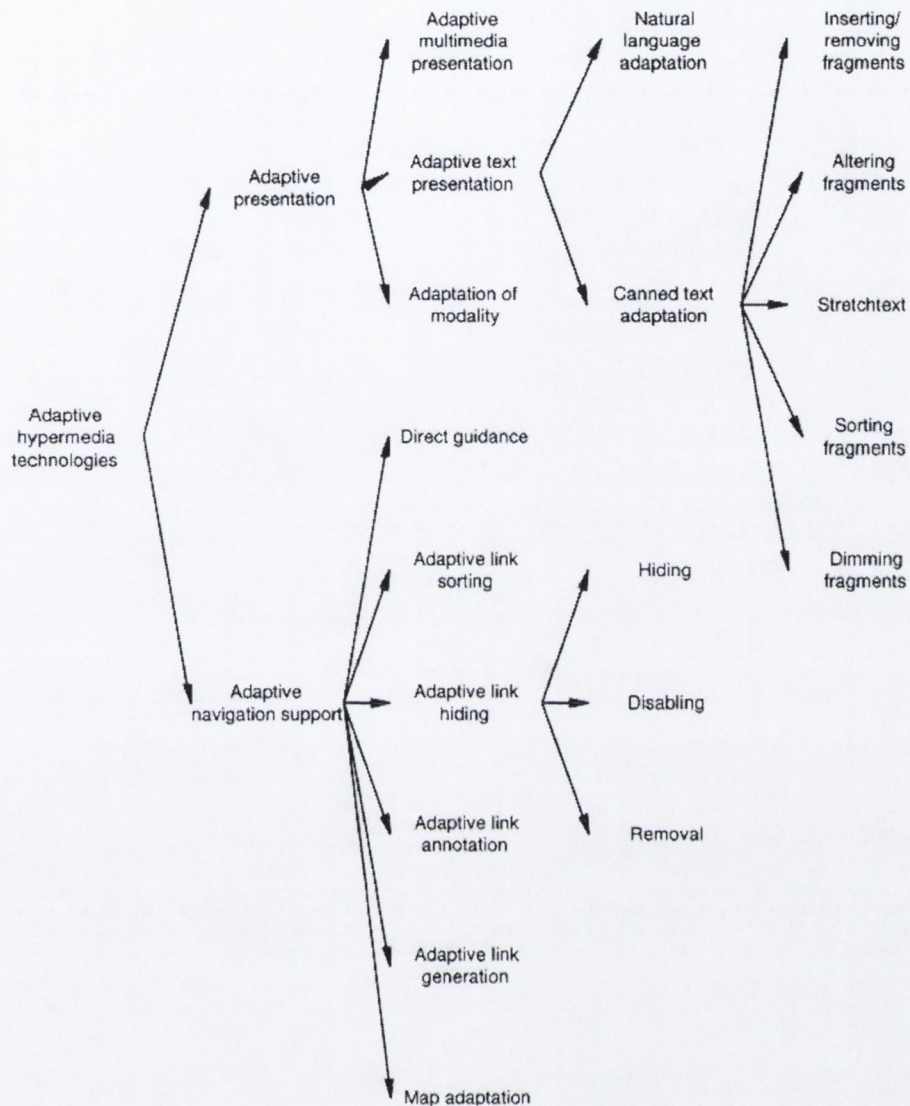


Figure 2-1: The taxonomy of Adaptive Hypermedia Technologies, (adapted from Brusilovsky, 2001)

2.3.3.1 Field-Dependent/Field-Independent Cognitive Style

When learning, field-dependent and field-independent learners use different approaches (Witkin et al., 1977; Wapner & Demick, 1991; Jonassen & Grabowski, 1993).

Three main categories of differences can be defined:

- Is the approach to learning active or passive?

- Is learning internally or externally directed?
- Is the approach analytic or global?

Field-independent learners thrive in situations where they need to actively structure their own learning and operate within an internal frame of reference. They also tend to be more analytic and proceed in a serialistic fashion, giving attention first to low level detail before building up an overview later. On the other hand, field-dependent learners take a more passive approach and operate within an external frame of reference. They tend to take a global approach, first concentrating on establishing an overview of what is to be learned, before attending to lower level procedural detail.

Correspondingly, research studies have attempted to explore how the different features of hypermedia systems support both types of learners. These features include non-linear learning, learner control and navigation tools.

Several studies have examined the aspect of non-linear learning and report that field-independent learners prefer non-linear pathways and field-dependent learners prefer linear pathways. For example, Dufresne and Turcotte (1997) designed a hypermedia system to teach students the use of Microsoft Excel. They developed a free access version of the system that supported non-linear learning and a restricted version that supported linear learning. Using both versions of the system, they investigated the preferences of field-dependent and field-independent learners for linear and nonlinear pathways through hypermedia systems. They found that field-dependent students who used the free access version of the hypermedia system (nonlinear format) spent more time completing the test than those who used the restricted version (linear format). They also found that field-independent students also consulted the user guide for a longer period than field-dependent students in the restricted version, while field-dependent students consulted it for longer in the free access version. The study indicates that field-dependent learners spend less time learning and less time consulting the user guide when they had a fixed path to follow in learning programmes. They concluded that not all learners appreciate non-linear learning, with field-independent learners relatively capable of defining their own learning path while field-dependent learners seem to prefer following a fixed path. This may be due to the fact that field-independent learners tend to be more analytical, defining their own structure, and relatively more active in their learning behaviour. On the other hand field-dependent learners prefer some externally provided structure as they tend to rely on external stimuli and have more difficulty in separating the individual parts from the whole.

Other studies have examined the impact of learner control on navigation patterns and the use of navigational tools. For example, Ford and Chen (2000) examined student learning in a hypermedia system that taught HTML. The content of the tutorial was divided into seven hierarchical levels. Navigational control was provided in the form of: (a) an overall topic map, (b) a keyword search, (c) a top level menu, (d) section buttons for the three main sections, (e) subject categories, for example, overview and examples, (f) next/previous and back/forward buttons and (h) hyperlinks. During the course of the study they recorded the frequency of navigation tools selected: including hyperlinks, buttons, map and index; and the frequency of subject categories selected: including overview, examples and detailed techniques.

On analysing the results, they found significant differences in navigation strategies used by field-dependent and field-independent learners. Relatively field-independent learners made greater use of the index to locate a particular item and in contrast, field-dependent learners preferred to use the map to get the whole picture of the context. Field-independent learners made greater use of the back/forward buttons learning in a serialist manner while field-dependent learners spent a greater proportion of the time studying higher levels in the subject content hierarchy preferring to get an overview of the content. They also found that field-dependent and field-independent students preferred to use different resources. Field-dependent students preferred to learn HTML with examples, while field-independent students preferred to see detailed descriptions of each HTML command.

However despite the differences found in learning strategies and navigation patterns, they found no significant correlation between field-dependent/field-independent students and their learning outcomes. Some reasons they proposed, which equally apply to other studies, were:

- Differences in learning behaviour may not matter in terms of learning performance when learning takes place in a relatively unconstrained learning environment which allows high levels of learner control over navigation
- Types and levels of support provided in hypermedia environments (menu of contents, back/forward navigation buttons) may provide sufficient support for field-dependent to overcome their limitations in imposing effective structure on their learning
- Measures used to assess learning outcomes may not have been sufficiently sensitive to determine the effects of different learning strategies

- The sample number in the study was too small

Despite the results of this study, in which field-dependence/field-independence had no correlation with learning outcome, Ford & Chen (2001) conducted another study that examined the effect of matching instructional strategies with levels of field-dependence. Two versions of hypermedia learning systems were designed with program control paths. A depth-first version presented each topic fully before the next topic, which was also presented in the same way. In contrast the breadth first version gave an overview of all the material prior to introducing detail. They proposed that the depth-first sequence maps relatively well to the serialist strategy preferred by field-independent learners, and the breath-first sequence maps onto the top-down approach preferred by field-dependent learners. Their results showed, with statistical significance, that students whose cognitive styles were matched to the design of hypermedia learning systems attained higher post-test and gain scores on conceptual knowledge. Field-dependent learners in the breadth-first version performed better than those in the depth-first version. In contrast, field-independent learners in the depth-first version outperformed those in the breadth-first version. Their results indicate that learning in matched conditions may in certain contexts be significantly more effective than learning in mismatched conditions.

Bringing together the results of previous studies, Chen & Macredie (2002) proposed a learning model that illustrates how the field-dependence/field-independence cognitive styles influence student learning in a hypermedia system. Table 2-3 illustrates the model and shows how different learning characteristics can be supported with the different features of hypermedia systems. Based on this model, they made recommendations for the design of navigation support and user-interfaces in hypermedia systems. For example, to support field-independent learners with their analytic approach and independent learning, they should be provided with tools such as index and query searching that facilitate the location of particular items. To support the global approach of field-dependent learners, they should be provided with a main menu or map that show the whole picture of the context and which serve as an anchor to organise information.

Table 2-3: Characteristics and learning patterns of field-dependent and field-independent individuals (adapted from Chen & Macredie, 2002)

		Field-Dependent Individuals	Field-Independent Individuals
Hypermedia Learning Systems	Non-Linear Learning	Passive Approach: Provide Guided Navigation	Active Approach: Provide Free Navigation
	Learner Control	Externally Directed: Support Guided Learning	Internally Directed: Support Independent Learning
	Multiple Tools	Global Fashion: Supply Map	Analytic Fashion: Supply Index

In order to evaluate this model Mitchell et al. (2004) investigated the learning performance and user perception of students using different hypermedia interfaces. They developed three interfaces: a field-independent and field-dependent interface that supported different cognitive styles, and a normal interface that supported both cognitive styles. The normal interface was a richly linked hypermedia system accompanied by different navigation tools such as a map, an index and a menu. The field-dependent interface organised the content in a breadth first manner, disabled links to restrict navigation choices and provided a hierarchical map. In contrast, the field-independent interface organised the content in a depth first manner, provided rich links to support free navigation and provided an alphabetical index.

During the course of the study, each student used two interfaces: the normal interface and a second interface that either matched or mismatched their cognitive style. They reported that for those who were matched to their cognitive styles, there was no interface preference between the normal interface and the matched interface.

However, for those who were mismatched, they were significantly more likely to prefer the normal interface. Furthermore, analysis of learning performance as measured by learning gain between pre- and post-test showed no significant difference between those who were matched and mismatched. In fact, the results indicate that those who were mismatched performed marginally better.

The authors of the study suggest that wrongly adapted interfaces may cause problems for users and appropriately adapted interfaces may be no more effective than a well-designed interface for all users. They also pose the question whether it is possible to create a single interface that can be suitable for both field-dependent and field-independent users. They suggest that trying to create distinct interfaces for different levels

of field-dependent may do more harm than good. In addition as field-dependency is measured on a continuous scale and is only superficially grouped into distinct categories, it is difficult to decide categorically the preferences for any given user, particularly if the user achieved an average score on the scale. They conclude by stating that further research is needed to re-interpret what the ideal interface might be for field-dependent and field-independent users and to determine if one interface could satisfy all learners.

In another study, Shih & Gamon (2002) also report no difference in learning outcomes and suggest that the web provides an equally effective environment for students regardless of field-dependent/field-independent cognitive style. They examined how students learned in Web-based courses on biology and zoology by analysing learning strategies, patterns of learning and achievement. Learning patterns were measured by identifying how often the students accessed different functions in the hypermedia environment and how long the students used the courseware. Learning strategies were analysed by identifying how students understood, integrated and retained new information. These strategies included metacognition, resource management, rehearsal, organisation and elaboration. They report that student's learning styles and patterns of learning, did not have an effect on achievement measured by class grade. Additionally, field-independent students did not differ significantly from field-dependent students in their use of learning strategies and patterns of learning. They conclude that students with different learning styles and backgrounds learned equally well, and did not differ in their use of learning strategies and patterns of learning.

In summary, it appears that field-dependent and field-independent learners do express differences in learning behaviour. It seems that learners react differently to non-linear learning, prefer different levels of learner control, exhibit different navigation patterns and prefer different navigation tools. However, further research is required to determine how instructional design can support these differences and improve learning performance.

2.3.3.2 Additional Learning Style Studies

Many other research studies have investigated different styles, trying to measure the impact of style on learning behaviour and learning outcomes. Graff (2003b) investigated whether different hypertext architectures could be matched to an individual's cognitive style to facilitate learning. Three hypertext architectures were employed: linear, hierarchical, and relational; and the wholist-analytic/verbaliser-imager cognitive style was used. Their findings revealed that for certain hypertext architectures, learning may be

facilitated when the architecture is matched to the cognitive style of the user. Riding and Grimley (1989) also investigated the effect of the wholist-analytic/imager-verbaliser cognitive style when using different presentations. The report that overall, imagers generally learn best from pictorial presentations whereas verbalizers learn best from verbal presentation. Rasmussen (1998) also argues that learning styles can be used to facilitate and enhance student performance in hypermedia learning environments. In a study examining the influence of the Kolb learning styles, they report that learners who tended toward abstractness on the perception dimension of the Kolb learning style performed better than those individuals who tended toward concreteness. Furthermore, Ross and Schultz (1999) investigated the impact of the Gregorc learning style model. Their results indicated that patterns of learning did not differ significantly based on the learner's dominant learning style. However, they report that learning style significantly affected learning outcome and argue that abstract random learners may perform poorly with certain forms of computer-aided instruction

In one of the few studies exploring the concept of different intelligences, Howard et al. (1999) examined the effect that various intelligences (or abilities, as defined by Sternberg, 1989) had on using multimedia when learning science. They categorized students according to their strongest ability (either analytic, creative, or practical) and examined how each group succeeded at cooperative learning tasks. The learning tasks consisted of conducting research investigations on the topic of the universe and current astronomical questions. The study also observed how the learner's attitudes towards science were influenced. The results indicate that students achieved equal success regardless of what their strongest intelligence was. In addition, they found evidence that those who were more practical or creative in their abilities benefited by developing more positive attitudes towards science.

As indicated by the research studies, it still remains inconclusive about how individual differences affect learning performance. Studies do appear to demonstrate that learners with different characteristics do exhibit differences in learning behaviour such as navigation. However, how these different characteristics relate to learning performance is still not clear. Further empirical studies are needed to explore the relationship between learning performance, individual differences and technology enhanced learning environments. In particular, more research is needed on the application of multiple intelligences to technology enhanced environments. A promising research direction is in the area of adaptive educational systems, which by building a dynamic model of each

individual learner has the potential to address the problem of how to match individual differences with instructional methods.

2.3.4 Adaptive Educational Systems

Several adaptive educational systems adapting to individual traits such as style and intelligence have been developed. Such systems are built on the hypotheses that learning behaviour is related to learning characteristics and that learning performance can be improved if the individual traits are supported. The two critical issues in the design of such systems are:

- Diagnosis of learning style and construction of the learner model
- Adaptation of environment in different ways for learners with different characteristics.

These two issues are examples of the generic processes of user model acquisition and user model application that are found in general user-adaptive systems (Jameson, 2003). Accordingly systems can be classified by how they address these two issues.

Diagnosis

The diagnosis of learning characteristics is the process of inferring the student's internal characteristics from their observable behaviour. This diagnosis encompasses three aspects: 1) the initialisation of the learner model, 2) the selection of appropriate measures to serve as indicators of learning preferences, and 3) the analysis of observable behaviour. Two main approaches to student diagnosis can be identified:

1. The simpler approach in the diagnosis of learning characteristics is the use of self-report measures (Riding & Rayner, 1998). This approach is usually used to initialise the learner model by getting the student to complete specially design psychological tests. Examples of such systems are INSPIRE (Papanikolaou et al., 2003), AES-CS (Triantafillou et al., 2003) and CS3838 (Carver et al., 1999). In addition, several systems such as INSPIRE and AES-CS allow the user to directly manipulate the learner model and express their own point of view about their learning style. Such systems that allow the user to explicitly set their own preferences are described as adaptable, in contrast to adaptive systems which automatically adapt to information in the learner model (Chen & Magoulas, 2005).

2. The second approach is to base the diagnosis of learning characteristics on the behaviour of the learner. Examples of such systems are ARTHUR (Gilbert & Han, 1999b), iMANIC (Stern & Wolf, 2000) and ACE (Specht & Opperman, 1998). In this case, the diagnosis is based on real data coming from the learner's interaction with the system. However with this approach, inference techniques are needed to analyse the behavioural indicators (Jameson, 2003).

Adaptation

The second critical issue involves the design of adaptation: what to do for different learners and how to do it using different adaptation technologies. Two main classes of systems can also be identified:

1. Systems that adapt the content of instruction. Such systems will primarily use adaptive presentation technologies and techniques to adapt the content and sequencing of material. ARTHUR and CS383 are examples of systems that use multiple types of resources. These systems demand the development of multiple types of educational material for each particular section of the course. ACE and INSPIRE are examples of systems that adapt the sequencing of material. These systems reuse the same content but present it in a different sequence.
2. Systems that adapt to the learner's cognitive thinking (i.e. thinking, perceiving and remembering). Such systems will use adaptive navigation technologies and techniques to support the learner's orientation and navigation. AES-CS is an example of such a system which uses learning style information to decide which navigational aids will help the learner move about in the knowledge domain.

To illustrate the different approaches used in diagnosis and adaptation, several examples of systems will be described in more detail using the following criteria:

- Underpinning educational theory: The underpinning theory that provides the framework through which it is possible to categorise learners and the domain, and guide decisions about what the system should do for different learners
- Diagnosis: The approach used to diagnose learning characteristics and construct the learner model
- Adaptation: The adaptation technology describes what is done for different learners and how it is done.

- Empirical Studies: The goals of such studies concentrate on the effectiveness and efficiency of adaptation by measuring performance, learning time, navigation patterns and learner's subjective evaluation. These studies consider different dimensions: (1) the relationship between matching and mismatching instructional approaches with individual differences (Ford & Chen, 2001; Bajraktarevic et al., 2003); (2) the learning performance and time of learners with different styles in matched sessions (Triantafyllou et al., 2003); (3) the navigation patterns of learners with different profiles in matched sessions (Papanikolaou et al., 2003).

2.3.4.1 Adaptive Systems with Diagnosis based on Self Report

The systems reviewed in this section construct the learner model using self-report measures. The systems have been selected to illustrate how adaptive presentation or navigation techniques can be used. For example, CS383 (Carver et al., 1999) and CUMAPH (Habieb, 2004) both modify the presentation of content. AES-CS (Triantafyllou et al., 2003) uses adaptive navigation techniques to support the learner's orientation. INSPIRE (Papanikolaou et al., 2003) uses both adaptive presentation and navigation to support different learning styles. Two systems that adapt to abilities are also presented. Arroyo (2004) adapts the presentation of hints to cognitive abilities whereas Dara-Abrams (2002) adapts the presentation of content to intelligence. Table 2-4 provides a summary of the different systems.

CS383 modifies the presentation of content for each student using the Felder & Silverman learning style model. Learners submitted a questionnaire proposed by Soloman and were classified as sensing/intuitive, visual/verbal and sequential/global learners. For example, sensing learners like to learn facts while intuitive learners like to learn concepts and sequential learners like to learn step-by-step while global learners like to learn the big picture first. The system provided a rich set of multimedia content with each media type rated on a scale from 0 to 100 to determine the amount of support it gave for each learning style. This rating was combined with the student profile to produce a unique ranking of each media type from the perspective of the student's unique profile. Subsequently, the media elements were presented in a sorted list ranked from the most to least relevant based on their effectiveness to each student's learning style. The key factor with this approach is determining what type of media is appropriate for the different styles and scoring the ratings for each media element. However, despite some media

being inherently appropriate to certain learning styles, for example graphics for visual learners, it is not always clear how to rate media elements against other learning styles such as the sensing/intuitive dimension. Despite only an informal assessment being conducted over a 2-year period using an end of course survey some useful feedback was received. Different students rated different media components as best and worse, indicating that students have different preferences. Instructors also noticed dramatic changes in the depth of student knowledge with substantial increases in the performance of the best students.

Similarly, CUMAPH (Habieb-Mammar & Tarpin, 2004) adapts the presentation of content, but in this instance to cognitive profile. This cognitive profile is based on working memory (visual, verbal, auditory), long and short term memory, categorisation, comprehension, visual/spatial exploration, form recognition and glossary. To determine the cognitive profile, students complete interactive exercises before the tutorial. In the tutorial, each element of content such as a concept or explanation has different versions with different amounts of verbal, visual and musical media. For each element, a rating for each media type is assigned, indicating how much verbal, visual or musical content it contains. The adaptive presentation technique, using an arithmetic formula, selects the combination of elements that best fits the cognitive model. Again the challenge with this approach is ensuring that the ratings for each element are accurate and match appropriately to the visual, verbal and auditory indicators. In an evaluation with 39 students, they created a real profile based on visual, verbal and auditory indicators and a randomised profile. They based the adaptation on the randomized profile and showed that when the randomized profile was similar to the real profile, the results were better. The results indicate that adaptive presentation can contribute to improvements in performance of students.

INSPIRE illustrates how systems can use adaptive presentation techniques without having to create multiple versions of each resource. By submitting a questionnaire students were classified either as activists, pragmatists, reflectors or theorists according to Honey & Mumford's theory. After submitting the questionnaire students were also able to directly manipulate the learner model. During the tutorial the system can adapt the order of presentation of multiple types of resources according to different instructional strategies. These resource types vary from activities, examples, exercise, theory presentations to questions. Depending on the instructional strategy resources are presented in a different sequence. For example, if the learner is an activist, the instructional strategy would be to provide the activity resource first and provide links to

the other resources in a suitably ordered sequence. A formative study was conducted with 23 students, the main objective of which was to provide evidence about the way learners that belong to different learning style categories select and use educational resources. During the study, learners were matched with instructional strategies that were deemed beneficial. For the different learning style categories, the navigation traces and studying behaviour, such as the time spent and hits on resources, were analysed. The results indicate that different learners use resources in different ways and that the studying behaviour of specific learners was representative of their learning style category.

Table 2-4: Adaptive Systems with Diagnosis based on Self-Report

Author(s)	Educational Theory	Diagnosis	Adaptation	Empirical Studies
Carver et al. 1999 (CS383)	Sensing/intuitive, visual/verbal, and sequential/global (Felder & Silverman, 1988)	Learners submit questionnaire proposed by Soloman (1992)	Adaptively presents media elements in a sorted list ranked from the most to least conducive based on their effectiveness to each student's learning style	Informal assessment over 2 years using end of course survey, Different students rated different media components as best and worse
Habieb-Mammar et al. 2004 (CUMAPH)	Cognitive model based on working memory(visual verbal, auditory) and other features	Interactive Exercises	Adaptively selects and presents multimedia combination for content that bests fist cognitive model	39 students. Based adaptation on a generated randomized profile. When randomized profile similar to real profile, results better
Triantafillou et al. 2003, 2004 (AES-CS)	Field-dependent/Field-independent Cognitive Style	Questionnaire plus direct manipulation of learner model by learner	Adapts amount of control (system vs. learner), contextual organisers (advance vs. post), lesson structure support, approach (global vs. analytical), navigational tools and feedback	64 students. Field-dependent learners performed better with adaptive system than with traditional system
Papanikolaou et al. 2003 (INSPIRE)	Activists, Pragmatists, Reflectors & Theorists (Honey & Mumford, 1986)	Questionnaire plus direct manipulation of learner model by learner	Adapt the method and order of presentation of multiple types of resources (activity, examples, exercise, theory, question) according to different instructional strategies	Formative study with 23 subjects. Indicates that studying behaviour of specific learners were representative of learning style categories.
Arroyo et al. 2004 (Wayang Outpost)	Cognitive abilities: spatial ability and maths proficiency	Computer based pre-tests	Adapt hints using either spatial or computational approach	95 students. Providing hints to student's cognitive skills yields higher learning.
Dara-Abrams (2002)	Multiple Intelligences	Questionnaire plus direct manipulation of learner model by learner	Adapts text and multimedia presentation	Formative evaluation with 33 students. Positive feedback from participants on content

AES-CS is an example of a system that adapts navigational aids based on the cognitive style of the learner. Before the tutorial, students are asked to complete a questionnaire in order to determine their field-dependent/field independent cognitive style. In addition, students have the facility to directly manipulate the learner model throughout the tutorial if they so wish. During the tutorial, the system adapts learner control, contextual organisers and lesson structure support. Control options vary between learner control where the learner can proceed through the course in any order via the menu and program control where the system guides the user with adaptive navigation support. Contextual organisers may be either advance, before presentation of a topic, or post, after presentation of a topic. Lesson structure support can be provided through either a concept map or graphic indicator. A summative evaluation of the system was conducted with 64 students. One group used the adaptive AES-CS and the other group used a traditional hypermedia environment. The results suggest that learners, and in particular field-dependent learners, performed better with the adaptive system than with the traditional system.

A different approach is to adapt the presentation of hints to cognitive abilities (Arroyo et al., 2004). Wayang outpost is an adaptive tutor for maths that, among other features, adapts the type of hints to spatial ability and maths proficiency. Using computer based pre-tests, it determines the cognitive skill level in spatial ability and maths fact retrieval, maths fact retrieval being a measure of the student's proficiency with math facts. When a student seeks help, the system provides hints using either a spatial or computational approach. The spatial approach uses spatial tricks and visual estimations of angles and lengths, and the computational approach uses arithmetic formulas and equations. An evaluation was conducted with two groups of 95 students. Students were assigned to one of two versions of the system, spatial or computational. They report that students with low spatial and high maths retrieval profiles learn more with computational help whereas students with high-spatial and low-retrieval profiles learn more with spatial explanations. The results suggest that adapting the presentation of hints to student's cognitive abilities yields higher learning.

Dara-Abrams (2002) is another example of a system that adapts to abilities. It is one of the very systems where adaptation is based on the theory of Multiple Intelligences. Using an online questionnaire, the system identifies the three most developed intelligences. In addition during the tutorial, students can also inspect and change the user model. As the

student proceeds through a tutorial, the system adapts the presentation of content using different variations of Multiple Intelligence informed multimedia. A formative evaluation using questionnaires with 33 students was conducted. Positive feedback was received indicating that a multi-intelligent approach to content development can improve the learning environment.

A number of other systems that diagnose learning characteristics using self-report measures also exist (e.g. Martinez & Bunderson, 2000; Wolf, 2003; Bajraktarevic et al., 2003; Castillo et al., 2003). Most of them adapt to a particular learning style theory rather than to a theory of intelligence. However, one area for future research with all these systems is in evaluation. Significant empirical studies are needed to determine their impact the learning performance and the benefit of adaptivity for learning.

2.3.4.2 Adaptive Systems with Diagnosis based on Observable Behaviour

Instead of using self-report measures to diagnose learning characteristics, it is possible to base the diagnosis on observations of learning behaviour. With this approach data coming from the learner's interaction with the system is analysed to determine their learning characteristics. The systems reviewed here illustrated how it is possible to use different types of behavioural indicators as the basis of the analysis. For example, ACE (Specht & Opperman, 1998) adapts the sequence of material based on the learner's performance in tests and the requests for different material. ARTHUR (Gilbert & Han, 1999b) is another system that adapts the instructional style to performance in tests, but in this instance by matching the performance of one learner with another. In contrast, iMANIC adapts the presentation of content just by analysing the student's preferences for different kinds of resources. Table 2-5 provides a summary of these systems.

Table 2-5: Adaptive Systems with Diagnosis based on Observable Behaviour

Author(s)	Educational Theory	Diagnosis	Adaptation	Empirical Studies
Specht & Opperman 1998 (ACE)	Preferences about sequencing of materials	Based on learners requests for material and on the success of currently used strategy as determined by performance in tests	Adapt sequence of material according to teaching strategy e.g. learning by example	Studies have evaluated adaptive components and have shown improvements in efficiency and effectiveness of learning compared to classical static hypermedia
Gilbert & Han 1999b (Arthur)	Style of instruction with which students achieve satisfactory performance	Based on learner's performance in tests	Adapts choice of multimedia resources: visual-interactive, auditory-text, auditory-lecture, and text style	Majority of learners (81 % out of a group of 21 students) complete the course while performing at a mastering level on quizzes found at the end of each lesson
Stern & Wolf 2000 (iMANIC)	Preferences for: media, type of instruction, level of content abstractness, ordering of content	Adapts to learner's selection of different types of resources	Presentation of content using stretch text which allows certain part of page to be opened or closed. Also sequencing of content objects for a concept.	Evaluated accuracy of classification. Possible to learn parameters for each student within few slides that achieved optimal classification.

ACE illustrates how both adaptive presentation and navigation are used to adapt the sequence of material to the success of the currently used teaching strategy. Within the system, two levels of adaptation take place: sequencing of learning units and sequencing of learning materials within each unit. Each unit consists of different types of learning material such as introduction, text, example, animation, simulation, test, summary, graphic, animation and video. Depending on the particular teaching strategy (such as learning by doing, reading text or learning by example) materials are sequenced in different ways. The particular teaching strategy is chosen by monitoring the learner's request for material, and on the success of the currently used strategy. The success of a strategy is mainly determined by the learner's performance in the tests where repeated occurrences of high performance raise the preference value of the strategy. Empirical studies conducted with the different adaptive components have shown that the efficiency and effectiveness of learning has improved when compared to classical static hypermedia.

ARTHUR is another system that illustrates how to dynamically adapt instructional style to learner's performance in tests. However, in this instance multiple versions of the same resource are created using different instructional styles and different types of media. The range of styles varies from visual-interactive, auditory-text, auditory-lecture to plain text. After each concept, the learner is presented with a quiz. If the learner scores less than 80 % in the quiz they will be provided with material of alternative instructional style, otherwise the instructional style currently used is presumed to match the learner's learning style. To determine the instructional style an inference engine, based on case-based reasoning, matches the current user performance against the history of previous users. For example if a student shows a similar pattern in missing questions to a previous student, they will be classified as having similar learning styles, and will be allocated an instructional strategy which worked for the previous student. Empirical studies were conducted to determine how many learners could complete a course while performing at a mastery level on quizzes found at the end of each lesson. It was found that the majority of learners, 81 % out of a group of 21, completed the course and were successfully at mastering the course content. This suggests that providing a range of instructional strategies was beneficial to learners. However, it would be interesting to determine with further studies the impact of the different instructional strategies on different learners.

In contrast, iMANIC is a system that adapts the presentation of content to the learner's selection of different types of resources. Multiple resources are categorised according to the instructional type (explanation/ example/ definition), media type (text/picture), place in topic (beginning/end), abstractness (concrete/abstract) and place in concept (beginning/middle/end). The different resources are adaptively presented using stretch text which allows certain parts of a page to be opened or closed. As the student interacts with the system, they can open and close resources indicating which resources are preferred. When presenting the next concept, this interaction data is analysed using the Naïve Bayes algorithm to determine which resources are wanted and should be presented first. A limited evaluation was performed to determine how accurate the classifier was at predicting student behaviour. The results indicate that it was not possible to use same teaching strategy for all students as the classification algorithm did not achieve the best accuracy using the same parameters for every student. However, the results suggest that it was possible to learn for each student within a few slides the parameters that achieve optimal classification. The results also suggest that students have strong preferences for particular resources and that the Naïve Bayes algorithm may be suitable technique for

determining these preferences. However, it would be interesting to evaluate with further studies if the system has any impact on learning performance.

Compared to the number of systems that diagnose learning characteristics by self-report, there are few systems that dynamically diagnose by observing the learner's behaviour. The problem in developing such systems is that not only is there the need to validate the effectiveness of the adaptation strategies, there is also the need to identify appropriate behavioural indicators and validate the accuracy of the inference techniques that analyse the interaction data.

2.3.5 Technology Enhanced Learning: Summary

The two critical issues in the development of systems that adapt to individual differences are the diagnosis of learning style and the adaptation of the learning environment. One promising approach that can address these issues is the development of intelligent techniques for diagnosis and adaptation. These techniques are based on observing the learner's behaviour, inferring learning preferences from those observations and subsequently, dynamically customising the learning environment.

One of the significant factors influencing the effectiveness of such techniques is the selection of appropriate measures of behaviour that are indicative of learning style preferences. Such measures may include (Papanikolaou & Grigoriadou, 2004):

- Navigational indicators such as the number of hits on particular resources, the preferred format of presentation and navigation patterns
- Temporal indicators such the time spent on different types of resources
- Performance indicators such as the number of attempts on exercises and or the score obtained in tests

Another significant factor is the identification of appropriate inference methods that can analyse the behavioural data. Such methods range from Bayesian and logic based methods to machine learning techniques such as rule based learning, neural networks, probability learning, instance-based learning and content-based/collaborative filtering (Zuckerman & Albrecht, 2001; Jameson, 2003). The reason for choosing a particular method will depend on the computational complexity, amount of input data required, handling of noise and uncertainty, knowledge acquisition effort and validity (Webb et al., 2001).

Further research is needed for the promise of dynamic diagnosis and adaptation to be realised. It still remains a challenge to identify the features of behaviour that are most indicative of learning characteristics and are worth modelling. It is also necessary to identify appropriate inference techniques that analyse the data and validate the accuracy of such techniques. Furthermore, large-scale empirical studies are also needed to determine the impact on learning performance of different dynamic adaptation strategies.

2.4 Conclusions

A number of conclusions can be drawn from the literature reviewed. The study of individual trait differences may hold the key to understanding why some students perform better than others. Technology enhanced learning environments, and in particular adaptive educational systems offer the potential to support individual differences in learning. Research has examined the impact of learning styles on learning but it has been difficult to prove conclusively how learning styles can be supported and improve learning outcomes. In contrast, there is much evidence that shows how intelligence is a predictor of learning performance. In particular, the theory of Multiple Intelligences offers the potential to provide a framework for a broad range of individualised pedagogical strategies, while building on research that demonstrates how intelligence can be a predictor of learning performance. Furthermore, diagnosing learning characteristics can be challenging and intelligent techniques that analyse patterns in observable learning behaviour offer a promising solution. This section summarises the main conclusions of the literature review and argues that this research addresses the challenges in building adaptive educational systems that support individual trait differences in a novel manner.

2.4.1 Individual Differences and Technology Enhanced Learning

The study of individual differences is central to understanding how some students perform better than others. Learners exhibit different learning characteristics in the way they process and organise information, in the way they behave while learning and in their predispositions towards particular learning modes. Considerable research has been undertaken to discover the impact of individual traits on learning environments. However the results are inconclusive, with some studies finding that learning improves when individual difference are taken into account, whilst others finding no differences. One

reason for these conflicting studies is that it is difficult in practice to match student characteristics with instructional environments.

Adaptive Educational Systems offer the opportunity to address the issue of how to match individual differences with instructional methods or learning environments. Such systems adapt the content and environment to the knowledge, goals, interests and other features of the learner such as individual differences in style and intelligence. However in the design of adaptive educational systems, significant challenges exist.

First, it is necessary to determine what the system adapts to, how learning characteristics are diagnosed and how a model of the student is built. Second, it is necessary to define what and how the system adapts, what can be done for learners with different characteristics and how can the learning environment be tailored to support the student's needs.

2.4.2 Multiple Intelligences and Learning Styles

Two main categories of individual traits in learning that are consistent over the long term can be identified: intelligences and style. Comparing intelligences to style, individual differences in intelligence refer to the ability with which one can do something, whereas styles refer to preferences in the use of abilities.

Much research has been conducted on the integration of learning styles in the design of adaptive educational systems. However, it has been difficult to demonstrate conclusively how the concept of learning style can be supported and how it can improve learning outcomes. Some reasons for this include (Riding & Rayner, 1998):

- The lack of a unifying framework or organising theory to understand different styles in relation to each other
- Difficulty in developing valid methods for objectively assessing dimensions of style
- Arbitrary classification of individuals into categories, theories classify people but people are flexible and do not fit neatly in predefined types
- Questions around the construct validity of style with statistical analyses providing mixed support

In contrast, there is much evidence to support the concept of intelligence as a predictor of learning performance. Instead with intelligence, there is much debate about how

intelligence can be measured and on the concept of a single general intelligence level where all abilities are correlated. Critics argue that good or poor performance in one area in no way guarantees similar performance in another and that the full range of intelligent behaviour is not completely captured by any single general ability (Snow, 1992; Sternberg, 1996).

In particular, Gardner (Gardner, 1983, 1993, 2000) proposes the concept of Multiple Intelligences, a theory which describes how different intelligences are used to solve problems and fashion products. In the past 20 years since the theory of Multiple Intelligences was introduced, it has been found to be a useful construct in many settings such as education and training, career guidance and development, counselling and personal development (Mantzaris, 1999). In particular, research has suggested that the impact of the Multiple Intelligence theory in the classroom has been significant (Campbell & Campbell, 2000). It should be noted however that the theory of Multiple Intelligence has many critics who state that the intelligences should be described as special talents and that there is no empirical basis for the different intelligences (Klein, 1997; Traub, 1998).

Despite the critics, the theory of Multiple Intelligence has remained very popular. One reason for this is that the different intelligences are not abstract concepts, but are easily recognizable through experience. Intuitively, it is possible to understand the differences between musical and linguistic, or spatial and mathematical intelligences. As a consequence, it offers a rich structure and language in which to develop content and model the student. Currently, the application of Multiple Intelligence to adaptive educational systems is still very limited and in the early stages of research (Dara-Abrams, 2002). This is somewhat surprising given that Gardner predicted back in 1983 that “the potential utility of computers in the process of matching individuals to modes of instruction is substantial” and that “the computer can be vital facilitator in the actual process of instruction” (Gardner, 1983, p391). Hence, this research proposes that the use of the Multiple Intelligence framework of individual differences in the design of adaptive educational systems offers an unexplored dimension that may enhance learning.

2.4.3 Intelligent Techniques for Diagnosis and Adaptation

The diagnosis of Multiple Intelligence profile can be achieved by either self-report or by observing the behaviour of the learner. The self-report diagnosis can be achieved through the use of the MIDAS questionnaire (Shearer, 1996). It should be first noted that

the issue of the adequacy of psychometric measurement instruments is of critical importance and is continuously debated (Meyer et al., 2001; Messick, 1996; Bonham, 1988b). Gardner (1996) himself opposes the use of Multiple Intelligence tests as he argues they cannot assess aptitudes such as wisdom, creativity, practical knowledge and social skills. However he has endorsed the MIDAS instrument as having the potential to be very useful to students and teachers. The MIDAS instrument has been used in a wide a number of studies and has proved to be consistent and reliable (Shearer, 1996).

The second approach is to diagnose the Multiple Intelligence profile by observing the patterns in learning activity. With this approach, every action the learner makes, such as selecting a navigation link or playing a sound file, is recorded and analysed. The problem here is that the volume of data recorded can be enormous. Hence to effectively identify patterns in learning behaviour, intelligent techniques based on machine learning or statistics are required. The key challenges with this approach are the identification of behavioural features that are most indicative of learning characteristics and the selection of appropriate intelligence techniques of analysis and inference.

There exists a variety of methods for inference such as neural networks, rule based learning and probability learning. However, one of the key criteria for success in using these methods is the identification of suitable input features. As it remains a challenge to identify behavioural features that are representative of learning characteristics, the effective use of such methods is not easy. Several systems using machine-learning techniques have adapted to knowledge level indicators, which can be more easily determined by analysing performance in tests. For example, if a student is performing well in tests it can be presumed that the current instructional style is working (Gilbert & Han, 1999b). Alternatively, other indicators such as navigational and temporal indicators can also be used. For example, the probability of one resource being wanted over other resources can be calculated by analysing the characteristics of previous resources that have been selected (Stern & Wolf, 2000).

To dynamically diagnose the Multiple Intelligence profile of the learner, this research proposes a novel set of input features that are based on navigational and temporal features. These features describe how different Multiple Intelligence resources are used and include such information as to which resource was selected first and how many times each category of resources was used. The research also proposes a novel way of using these input features with the Naïve Bayes algorithm to dynamically determine a Multiple Intelligence profile.

To develop an adaptive system that incorporates the Multiple Intelligence concept, adaptive hypermedia offers two major technologies: adaptive presentation and adaptive navigation. Adaptive presentation can be used to dynamically assemble different Multiple Intelligence informed educational content. Adaptive navigation can be used to help the student move around a knowledge domain rich in Multiple Intelligence informed resources. Both technologies provide a rich range of techniques and method that support Multiple Intelligence based adaptation. Several systems have demonstrated such technologies enhance the learning performance of students (Triantafilliou, 2004) which suggests they will also be of benefit in Multiple Intelligence based adaptation.

2.4.4 Research Challenges

Adaptive educational systems that adapt to different learning characteristics offer great opportunities to enhance learning for all types of learners. However, building such systems is not easy and outstanding research issues include how to diagnose relevant learning characteristics and how to adapt the learning environment for different learners. This review suggests that the theory of Multiple Intelligences is an un-explored dimension in the design of adaptive educational systems, that there is a need for intelligent techniques that can diagnose learning characteristics and that adaptive hypermedia techniques can be used to improve learning performance.

This thesis proposes that the EDUCE adaptive educational system addresses these challenges in a novel manner. In summary, it demonstrates:

- How the use of the Multiple Intelligence theory can be used to model learning characteristics and provide a complementary range of educational material (chapter 3). In this chapter the theory of MI is also explained in much greater detail.
- How EDUCE's predictive engine, using the Naïve Bayes algorithm, can dynamically identify the learner's Multiple Intelligence profile and make predictions as to what Multiple Intelligence informed resource the user prefers (chapter 4)
- How to adapt the presentation of material using different pedagogical strategies (chapter 3)

Using EDUCE it is possible to explore different educational issues as: different levels of adaptivity that vary from full learner control to system control, the use of self report

versus behavioural observations to determine learning characteristics, and the matching and mismatching of pedagogical strategies with learning characteristics.

More specifically, this research, through empirical studies, examines two research questions: (chapter 6 and chapter 7):

1. The effect of using different adaptive presentation strategies in contrast to giving the learner complete control over the learning environment and
2. The impact on learning performance when material is matched and mismatched with learning preferences.

2.5 Summary

This chapter has briefly reviewed how adaptive educational systems offer the potential to provide learning environments that support individual differences. First, it reviewed the nature and dimensions of individual differences in intelligence and style. Second, it reviewed technology enhanced learning environments that acknowledge the role of individual differences. Last, it argued that EDUCE addresses, in a novel manner, the challenges in developing an adaptive system by using the Multiple Intelligence theory of individual differences and by being able to dynamically diagnose learning characteristics from observable behaviour.

3 EDUCE

3.1 Introduction

This chapter describes the principles, architecture, design and implementation of EDUCE. Firstly, it outlines the model for incorporating the Multiple Intelligence theory into the design of EDUCE. Secondly, it describes in detail the Multiple Intelligence theory and the MIDAS instrument used to assess Multiple Intelligence profiles. Subsequently, it describes the domain model, student model, presentation model, predictive engine and pedagogical model. Finally, it outlines the technical implementation of EDUCE.

3.2 Overall Architecture

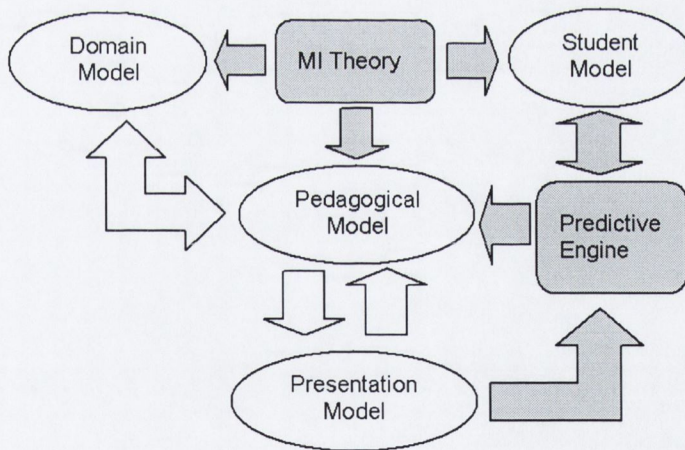


Figure 3-1: EDUCE Architecture

Figure 3-1 illustrates the architecture of EDUCE (Kelly & Tangney, 2002, 2004d). It consists of a student model, a domain model, a pedagogical model, a predictive engine and a presentation model. The different components have the following functions:

- The domain model is a representation of the material to be learnt. It includes principles, facts, lessons and problems. In EDUCE, the principles of Multiple Intelligences are used to develop different versions of the same content.
- The student model represents the student's knowledge of the domain, the background of the user and learning behaviour of the student. In EDUCE, the student model also represents the Multiple Intelligence profile. Two Multiple Intelligence profiles are represented: a static and dynamic profile. The static profile is generated from a Multiple Intelligence inventory completed by the student before using the system. The dynamic profile is constructed online by observing the student's behaviour and navigation.
- The presentation module handles the flow of information and monitors the interactions between the user and the system.
- The predictive engine, using the Naïve Bayes algorithm, dynamically determines the learner's preference for different Multiple Intelligence resources during a tutorial and can be used to inform the pedagogical strategy.
- The pedagogical model uses adaptive presentation and navigation techniques to determine what next to present to the student in terms of content and style using different pedagogical strategies.

Typical adaptive educational systems contain student, domain, pedagogical and presentation models (Wenger, 1987). The special features of EDUCE are its predictive engine and its use of the Multiple Intelligence theory to develop content and model the student. Using the Multiple Intelligence concept, different content can be created to explain the same concept in multiple ways. As a student uses the different resources available it becomes possible to build a Multiple Intelligence profile. The predictive engine can, using the constructed student model, predict student preferences and inform the pedagogical strategy. Using the predictive engine, EDUCE has the flexibility to experiment with different pedagogical strategies customised to the individual student.

3.3 Multiple Intelligences

Almost eighty years after the first intelligence tests were developed, Howard Gardner challenged the commonly held belief that there was something called “intelligence” that could be objectively measured and reduced to a single number or “IQ” score. Arguing that our culture had defined intelligence too narrowly, he proposed in the book “Frames of Mind” (Gardner, 1983) the existence of at least seven basic intelligences. More recently he has added an eight (Gardner, 1999) and discussed the possibility of a ninth (Gardner, 2000). In this theory of multiple intelligences, Gardner sought to broaden the scope of human potential beyond the confines of the IQ score. He questioned the validity of determining an individual’s intelligence through the practice of psychometric tests. Instead Gardner suggested that intelligence has more to do with “the ability to solve problems and fashion products that are of value within one or more cultural settings” (Gardner, 1983, p. 160). Subsequently, he updated the definition of intelligence to the “biopsychological potential to process information that can be activated in a cultural setting to solve problems or create products that are of value in a culture” (Gardner, 1999, p. 33).

With this broader perspective, intelligence can be viewed as a functional concept that can work in a variety of ways. With his MI theory, Gardner provided the means for grouping the broad range of human capabilities into eight comprehensive categories or “intelligences” (Gardner, 1983; Armstrong, 2000):

- **Verbal/Linguistic Intelligence (VL):** This involves having a mastery of the language and includes the ability to manipulate language to express oneself. It involves the capacity to use words effectively, either orally (e.g. as a story teller, orator, or politician) or in writing (e.g. as a poet, playwright, editor or journalist). It includes the ability to manipulate the syntax or structure of language, the phonology or sounds of language and the semantics or meaning of language. It include the ability to use language in a pragmatic manner such as in rhetoric (using language to convince others to take a specific course of action), mnemonics (using language to remember information), explanation (using language to inform), and meta-language (using language to talk about itself)
- **Logical/Mathematical Intelligence (LM):** This consists of the ability to detect patterns, reason deductively and think logically. It involves the capacity to use numbers effectively (e.g. as a mathematician, tax accountant, or statistician) and to

reason well (e.g. as a scientist, computer programmer, or logician). This intelligence includes the ability to understand and manipulate logic patterns, relationships, propositions (if-then, cause-effect), classifications and generalizations.

- **Visual/Spatial Intelligence:** This is the ability to manipulate and create mental images. It involves the ability to perceive the visual-spatial world accurately (e.g. as a hunter, scout or guide), to perform transformations on those perceptions (e.g. as an interior decorator, architect, artist, or inventor) and to recreate visual expressions (e.g. an artist or sculptor). It involves sensitivity to colour, line, shape, form, space, and the relationships that exist between these elements. It includes the capacity to visualise and to graphically present visual or spatial ideas.
- **Musical/Rhythmic Intelligence:** This encompasses the capability to recognise and compose musical pitches, tones and rhythms. It involves the capacity to perceive (e.g. as music aficionado), discriminate (e.g. as a music critic), transform (e.g. as a composer), and express (e.g. as a performer) musical forms. This intelligence includes sensitivity to the rhythm, pitch or melody, and timbre or tone colour of a musical piece.
- **Bodily/Kinesthetic Intelligence:** This is the ability to learn by doing and using mental abilities to co-ordinate bodily movements. This involves the ability to use one's whole body to express ideas and feelings (e.g. as an actor, a mime, an athlete, or a dancer) and facility in using one's hands to produce or transform things (e.g. as a craftsperson, sculptor, mechanic, or surgeon). This intelligence includes specific physical skills such as coordination, balance, dexterity, strength, flexibility, and speed.
- **Interpersonal Intelligence:** This is the ability to work and communicate with other people. It involves the ability to perceive and make distinctions in the moods, intentions, motivations and feelings of other people. This can include sensitivity to facial expressions, voice, and gestures; the capacity for discriminating among many different kinds of interpersonal cues; and the ability to respond effectively to those cues in some pragmatic way, such as influencing a group of people to follow a certain line of action.
- **Intrapersonal Intelligence:** This involves knowledge of the internal aspects of the self such as knowledge of feelings and thinking processes. It involves self-

knowledge and the ability to act adaptively on the basis of that knowledge. This intelligence includes having an accurate picture of one's strengths and limitations; awareness of inner moods, intentions, motivations, temperaments, and desires; and the capacity for self-discipline and self-understanding.

- **Naturalist Intelligence:** This involves the ability to comprehend, discern and appreciate the world of nature. It involves having expertise in the recognition and classification of the numerous species – the flora and fauna – of an individual's environment. This also includes sensitivity to other natural phenomena (e.g. cloud formations and mountains) and in the case of those growing up in an urban environment, the capacity to discriminate among the nonliving forms such as cars and music CD covers.

To derive the eight intelligences, Gardner did not use psychological tests. Rather, based on a synthesis of significant bodies of scientific evidence, Gardner defined eight criteria that each intelligence had to meet to be considered as a full intelligence. These criteria were grounded in the disciplines of biological sciences, logical analysis, developmental psychology and traditional psychological research (Gardner, 1983).

From the biological sciences came two criteria:

- **The potential of isolation by brain damage:** Each intelligence has a relatively autonomous brain system where damage to one part of the brain does not affect other parts. For example, a person may have brain damage and be seriously impaired in the ability to write or read yet still have tremendous capacity for drawing.
- **An evolutionary history and plausibility:** Each intelligence has its roots deeply embedded in the evolution of human beings and other species. For example, musical intelligence can be studied through early musical instruments or through the wide variety of bird songs.

From logical analysis came two criteria:

- **An identifiable core operation or set of operations:** Each intelligence has a core set of operations that serve to support the activities of that intelligence. For example, in bodily/kinesthetic intelligence, core operations include the ability to imitate the physical movements of others.

- **Susceptibility to encoding in a symbol system:** Each intelligence must have the ability to be symbolized and possess its own unique symbol or notational systems. For example, the verbal/linguistic intelligence has a number of spoken or written languages.

Two of the criteria came from developmental psychology:

- **A distinct developmental history along with a definable set of expert “end-state” performances:** Each intelligence-based activity has its own development trajectory; that is each activity has its own time of arising in early childhood, its own time of peaking during one’s lifetime, and its own pattern of rapidly or gradually declining as one gets older. For example, logical/mathematical intelligence peaks in adolescence and early adulthood with higher math insights declining after age 40. Intelligences can also be best seen working at their peak by studying “end-states” of intelligences in the lives of exceptional individuals. For example, spatial intelligence can be seen at work through Michelangelo’s Sistine Chapel paintings.
- **The existence of savants, prodigies and other exceptional people:** Intelligences can be seen operating at high levels in savants. Savants are individuals who demonstrate superior abilities in one intelligence while their other intelligences function at a low level. For example, there are savants who draw exceptionally well or who have amazing musical memories.

The final two criteria were drawn from traditional psychological research:

- **Support from experimental psychological tasks:** It is possible to witness each intelligence working in isolation from one another by looking at specific psychological studies. For example, certain individuals may have a superior memory for words but not for faces. People can demonstrate different levels of proficiency across the eight intelligences in each cognitive area.
- **Support from psychometric findings:** It is possible to look at standardized tests for support of the theory of multiple intelligences. Standardized tests provide measures of human ability and are typically used to ascertain the validity of other theories of intelligence and learning styles. For example, the Wechsler Intelligence Scale for Children includes subtests that require linguistic, logical/mathematical and spatial intelligence (Sattler & Saklofske, 2001).

In addition to the descriptions of the eight intelligences and their theoretical underpinnings, certain points of the MI theory need to be mentioned. Each person possesses all eight intelligences which operate together in unique ways to each person. Most people can develop each intelligence to an adequate level of competency if given encouragement, enrichment and instruction. Intelligences usually work together in complex ways and only have been taken out of context in MI theory only for the purposes of examining their essential features. Finally, there are many ways to be intelligent within each category. There is no standard set of attributes that one must have to be considered intelligent in a specific area, MI theory emphasises the rich diversity of ways in which people show their gifts within intelligences as well as between intelligences.

3.4 MI Assessment: MIDAS

The MI theory is a significant departure in the traditional understanding of intelligence and as a result requires a different form of assessment. Instead MI theory requires a different approach to the measures, instruments, materials, context and purpose of assessment (Torff, 1997). Broad ranges of measures need to explore the different aspects of intellectual activity and value intellectual capacities in a wide range of domains. Instruments need to assess the unique capacities of each intelligence and engage the key abilities of a particular intelligence. Materials need to engage students in meaningful activities and learning. The context of learning should be an ongoing process fully integrated into the natural environment. The purpose of assessment should be to identify strengths as well as weaknesses and provide feedback that will uncover and develop an individual's competence.

Gardner, when asked to comment on measures of multiple intelligences, stresses the importance of the distinction between preferences and capacities, of drawing on observations and of using complementary approaches to assessment. It is significant to note that he has never developed a MI assessment test and the only MI assessment program he has been involved in has been Project Zero (Chen, Krechevsky, & Viens, 1998). This project developed domain-specific assessment tasks and observational guidelines as an example of the application of MI theory to assessment. Empirical results from the project report that intellect is structured in terms of specific relatively independent abilities.

Despite the issues involved in developing MI profiles, a number of attempts have been made to develop questionnaires that provide insight on MI strengths and weakness; the

most recognised being the MIDAS questionnaire developed by Shearer (1996). The purpose of the MIDAS or Multiple Intelligence Development Assessment Scales profile is to provide information that the student can use to gain a deeper understanding of their skills, abilities and preferred teaching style. It is described not as a test, but as an “untest” that empowers the student to reflect. Indeed, it even states that scores it provides are not absolute and it is up to the student to decide if these scores are a good description of their intellectual and creative life. The profile can be described as the general overall intellectual disposition that includes the skill, involvement and enthusiasm for different areas. Moreover, the MIDAS is the only MI questionnaire that Gardner has given support to and in 1996 he commented:

“I think that it (MIDAS) has the potential to be very useful to students and teachers alike and has much to offer the educational enterprise. Branton Shearer is to be congratulated for the careful and cautious way in which he has created his instrument and continues to offer guidance for its use and interpretation”

(Gardner, 1996)

The inventory itself consists of 93 questions. Some sample questions are illustrated in Table 3-1. From the responses entered, a MI profile is generated. It is important to remember that the MIDAS is an assessment that describes abilities in terms of strengths and weaknesses. The results are based on the perceptions of the student. The scores are not like test scores because they are not based on a comparison to other people. Basically the scores answer the questions “How much developed skill and ability the student have in the area described?”

An important part of the student model in EDUCE is the representation of Multiple Intelligence profile. Considering the issues in assessing MI strengths and weaknesses, EDUCE uses both a static and dynamic approach to create a static and dynamic MI profile. The static profile is generated from the MIDAS inventory which is completed by the student before using the system. The dynamic profile is constructed online by observing the student’s navigation and selection of MI resources. Both profiles inform the pedagogical strategies that adaptively present MI informed content.

Table 3-1: Sample Questions from the MIDAS

<p>Mathematical/Logical Question</p> <p>Q. When you were young, how easily did you learn your numbers and counting?</p> <p>A = It was hard B = It was fairly easy C = It was easy D = It was very easy E = I learned much quicker than most kids F = I don't know</p>	<p>Visual/Spatial Question</p> <p>Q. Do you like to decorate your room with pictures or posters, drawings etc?</p> <p>A = Not very much B = Sometimes C = Many Times D = Almost all the time E = All the time F = I don't know or I haven't had the chance</p>
<p>Verbal/Linguistic Question</p> <p>Q. How hard was it for you to learn the alphabet or learn how to read?</p> <p>A = It was hard B = It was fairly easy C = It was easy D = It was very easy E = I learned much quicker than all the kids F = I don't know</p>	<p>Musical/Rhythmic</p> <p>Q. Did you ever learn to play an instrument or take music lessons?</p> <p>A = Once or twice B = Three or four times maybe C = For a couple of months D = Less than a year E = More than a year F = I never had the chance</p>

3.5 Domain Model

The domain model is a representation of the material to be learnt and includes principles, facts, lessons and problems. In EDUCE, the principles of Multiple Intelligences provide the guidelines for representing the domain knowledge and developing different versions of the same content.

The domain model is structured in two hierarchical levels of abstraction, concepts and learning units. Concepts in the knowledge base are divided into sections and sub-sections. Each section consists of learning units that explain a particular concept. Each learning unit is composed of a number of panels that correspond to key instructional events. Learning units contain different media types such as text, image, audio and animation. Within each unit, there are multiple resources available to the student for use. These

resources have been developed using the principles of Multiple Intelligences. Each resource uses dominantly the one intelligence and is used to explain or introduce a concept in a different way.

Currently, EDUCE contains content in the subject area of Science for the age group 12 to 15. Science was chosen as it is a rich subject which benefits from different modes of representation and has been successfully applied to Science education in schools (Goodnough, 2001). Two tutorials were developed for EDUCE: Static Electricity and Electricity in the Home. From the Static Electricity tutorial, an example of a concept would be Electric Forces. The learning units used to explain this concept would include: (a) conductors and insulators, (b) how electrons move, (c) charge imbalance, (d) opposite charges attract and (e) charging neutral objects.

It must be remembered when developing content that Multiple Intelligences is just a theory that describes the broad range of abilities that people possess. Indeed it is a theory with a set of principles that structures and suggests a pedagogical model but does not prescribe a particular set of instructional strategies. Moving from a theory of intelligence to implementation as a pedagogical practice requires an act of interpretation. Consequently, there has been a considerable amount of research done in articulating different techniques that can access each of the intelligences (Campbell & Brewer 1991; Armstrong 1993; Campbell et al., 1996; Carroll, 1999; Lazaer, 1999; Wahl 1999).

A particular challenge is to develop a broad range of computer-based content that supports the eight intelligences. Some of the intelligences lend easily to online implementation while others are more difficult. Verbal/linguistic intelligence is traditionally the intelligence employed in academic textbooks and the classroom, and creating online material for the student to read and listen is straightforward. Likewise there are clearly defined instructional strategies, such as the use of pictures, which stimulate the visual/spatial intelligence. Logical/mathematical based material that encourages the student to think critically and logically can also be easily created using puzzles and maths problems. With a bit of creativity it is possible create material using musical/rhythmic instructional strategies through songs and raps. Material that stimulates the naturalist intelligence can be created using extensive references to living things and the natural phenomena. The bodily/kinesthetic intelligence it quite difficult to implement online as it places the emphasis on learning by doing. However, in conjunction with the other intelligences, it can be developed through the use of kinesthetic imagery and virtual reality software. Interpersonal and intrapersonal intelligences can be activated, not

primarily by the content itself, but by available features in the learning environment. Communication tools can be used to encourage students to collaborate and interact, thereby stimulating the interpersonal intelligence. To stimulate the intrapersonal intelligence, opportunities can be provided for the student to reflect, plan and set goals.

Currently EDUCE uses four of the intelligences: Logical/Mathematical, Verbal/Linguistic, Visual/Spatial and Musical/Rhythmic. The three intelligences, LM, VL and VS were chosen as they reflect the abilities that are traditionally designated as intelligences (Gottfredson, 1997). The musical/rhythmic intelligence was chosen because it is not considered as an intelligence that can be easily used to deliver and inform the design of content yet the emotive power of music is widely acknowledged (Carroll, 1999). The other four intelligences are outside the scope of this research.

From the research literature available, a pedagogical taxonomy of instructional strategies for developing MI theory has been derived. The taxonomy describes a set of practical techniques, methods, tools, media and instructional strategies for cultivating each of the four intelligences. Figure 3-2 illustrates EDUCE's pedagogical taxonomy for developing MI material (Kelly & Tangney, 2003a). It describes the range of instructional approaches that will cultivate each of the intelligences. Table 3-2 explains in more detail how each instructional approach can be implemented.

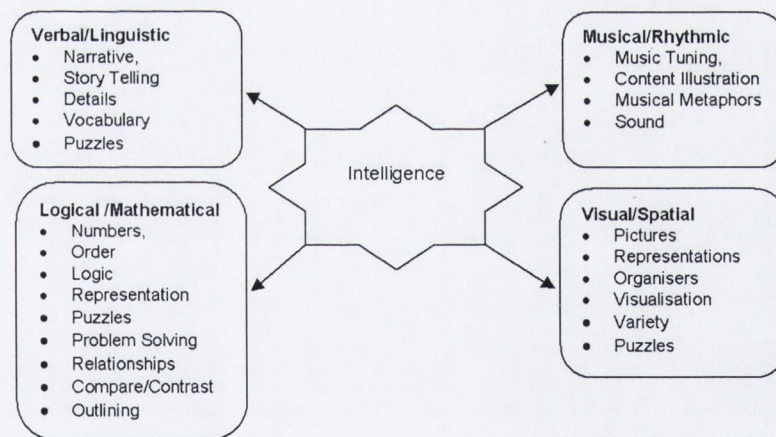


Figure 3-2: Pedagogical Taxonomy for developing MI material

Verbal/linguistic intelligence can be encouraged through the use of descriptive writing, creative writing, the use of facts and details, an emphasis on vocabulary, the development of listening skills and through word puzzles. Descriptive writing involves narrating the

steps in procedures and problem solving. It also includes summarising and repeating content in written form. Creative writing aims to motivate, inspire and explain through the use of story telling, history, folklore, parables, wordplay, metaphors, myths, legends, plays, prose, poetry or novels. Facts and details involve the use of specifics such as names, places and trivia and can be used to encourage linguistic analysis. Vocabulary focus involves placing the emphasis on a few accurate key words, the origins of words and the definition of terms in order to capitalize on verbal capacity for clarifying concepts. Listening involves the use of audio recordings to carry the sound, rhythm and music of language into the ear. Puzzles involves the use of word puzzles and games that play on the meaning and structure of words

Logical/mathematical intelligence can be promoted through the use of number, order, logic, visual representation, maths representation, puzzles, problem solving, causal knowledge, classification and outlining. Number includes the use of mental arithmetic, calculations and measurements that encourages mental maths, numerical thinking and precision. The arrangement and detection of order can be promoted through the identification of steps, procedures, sequences and patterns. Logic includes the use of scientific, deductive and inductive logic. This can be best realised by examining how reasoning processes operate and how truthful conclusions may be reached. Syllogisms, Venn diagrams and analogies may be employed. Visual representation through the use of graphs, charts, pie charts, tables, grids, matrices can make mathematical relationships easier to understand. Mathematical representation involves the use of abstract symbols, codes and formulas to represent and communicate concrete objects and concepts. Logic puzzles and games can awaken and arouse reasoning and logical thinking. Problem solving may be promoted through the use of estimation, prediction, exploration and heuristics. Understanding causal knowledge involves the use of questioning, creating meaningful connections between ideas and understanding cause-effect relationships. Classification and the arrangement of information into rational frameworks include comparing and contrasting concepts, attribute identification, categorisations and ranking. Outlining explains concepts in logical frameworks using logical explanations, logical thought maps and sequence charts.

Table 3-2: Implementation techniques for developing MI content

Verbal/Linguistic Intelligence	
Descriptive Writing	Summaries, procedures, problem solving, narrative
Creative Writing:	Stories, history, wordplay, metaphors, myths, legends, plays, prose, poetry
Details:	Facts, names, places, trivia
Vocabulary focus:	Key words, origins and definitions of terms
Listening:	Verbal recordings
Puzzles:	Word puzzles and games
Logical/Mathematical Intelligence	
Numbers:	Mental arithmetic, calculations, measurements,
Mathematical Order:	Steps, procedures, sequences, patterns
Logic:	Scientific, deductive, syllogisms, Venn diagrams, inductive, analogies
Visual Representation	Graphs, charts, pie charts, grids, matrices
Maths Representation:	Codes, symbols, formulas
Puzzles:	Logic puzzles and games
Problem Solving:	Estimations, predictions, exploration
Causal knowledge:	Questioning, cause and effect, logical meanings and relationships
Classification:	Compare/contrast , attribute identification, categorisations, ranking
Outlining:	Logical explanations, logical thought maps, sequence charts
Visual/Spatial Intelligence	
Pictures:	Drawings, maps, diagrams, artwork, photography, videos, slides, movies
Visual organisers:	Flowcharts, visual outlines, concept maps, mind maps
Internal Visualisation:	Visual thinking exercises, imaginations, guided imagery, visual memory
Visual variety:	Patterns, designs, colour, texture, geometric designs, unusual positions
Puzzles:	Visual puzzles, mazes, games
Musical/Rhythmic Intelligence	
Music tuning:	Background music, mood setting, sound breaks, jingles
Content illustration:	Songs, raps, chants
Musical metaphor:	Tones, notes, rhythms, clapping
Sounds:	Instrumental, environmental, nature

Visual/spatial intelligence can be cultivated through the use of pictorial representation, visual organisers, internal visualisation, visual variety and puzzles. Pictorial representations support written language with drawings, maps, diagrams, artwork, photography, videos, slides and movies. Visual organisers involve the use of flowcharts, visual outlines, concept maps and mind maps to visually illustrate verbal statements.

Internal visualisation techniques include the use of visual thinking exercises, imagination, guided imagery and visual memory to mentally construct visual imagery. Visual variety involves the creative use of patterns, designs, colour, texture and geometry as a learning tool. Visual puzzles, mazes and games can be used to arouse and awaken visual competencies.

Musical/rhythmic intelligence can be encouraged through the use of music tuning, content illustration, musical metaphor and sounds. Music tuning involves the use of background music, mood setting music, sound breaks and jingles to relax, invigorate and focus attention. Content illustration employs the use of songs, raps, chants and lyrics to convey information and content. Musical metaphors convey concepts through the use of tones, notes, rhythms and clapping. Instrumental, environmental and nature sounds can be used to musically augment concept and ideas.

Figure 3-3 to Figure 3-10 show specific examples of these instructional strategies and techniques. Figure 3-3 and Figure 3-4 emphasis the verbal/linguistic intelligence using explanations, descriptions, highlighted keywords, term definitions and audio recordings. Figure 3-5 and Figure 3-6 illustrate logical/mathematical intelligence using number, pattern recognition, relationships, questioning and exploration. Figure 3-7 and Figure 3-8 give examples of visual/spatial intelligence with the use of photographs, pictures, visual organisers and colour. Figure 3-9 and Figure 3-10 accentuate the musical/rhythmic intelligence using musical metaphors, raps and rhythms.

Using the pedagogical taxonomy and associated implementation techniques, a set of educational material has been developed with the help of a subject expert. Two tutorials on Static Electricity and Electricity in the Home were developed. For the Static Electricity tutorial there 5 sections, 14 learning units and 4 MI resources per unit giving a total of 56 MI resources. For the Electricity in the Home tutorial there 5 sections, 15 learning units and 4 MI resources per unit giving a total of 60 MI resources. All resources developed were validated and identified as compatible with the principles of MI theory by expert practitioners. The validation process is described in Chapter 5.

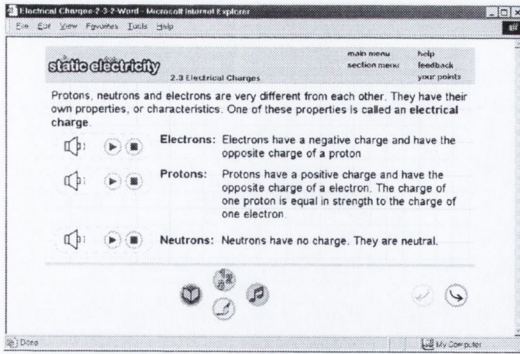


Figure 3-3: Verbal/Linguistic Intelligence

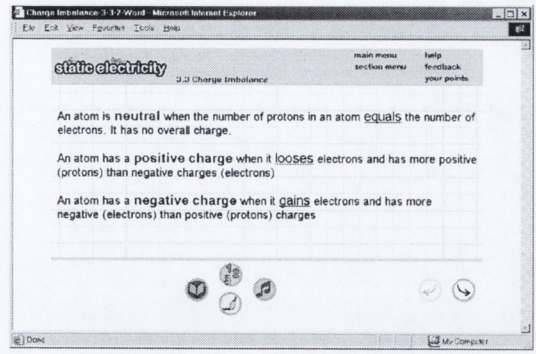


Figure 3-4: Verbal/Linguistic Intelligence

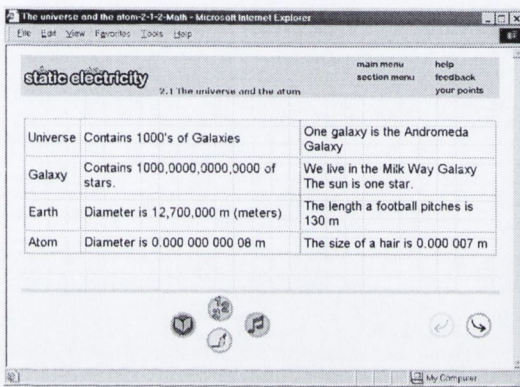


Figure 3-5: Logical/Mathematical Intelligence

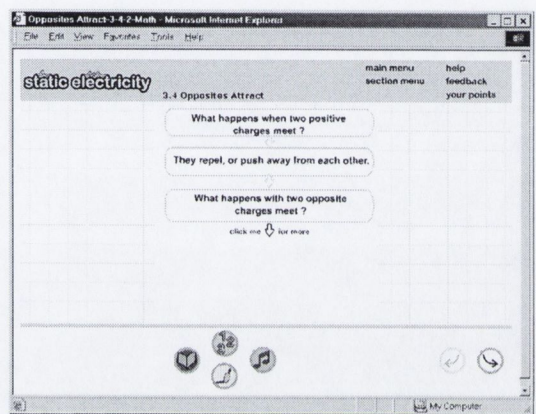


Figure 3-6: Logical/Mathematical Intelligence

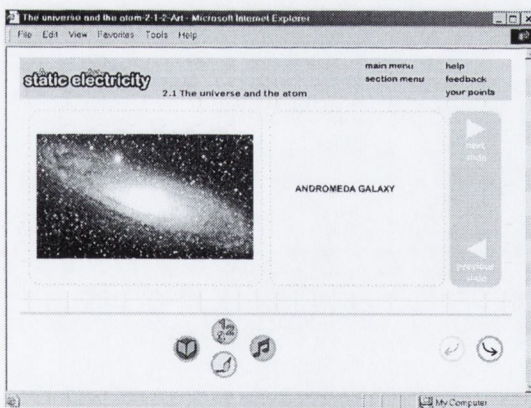


Figure 3-7: Visual/Spatial Intelligence

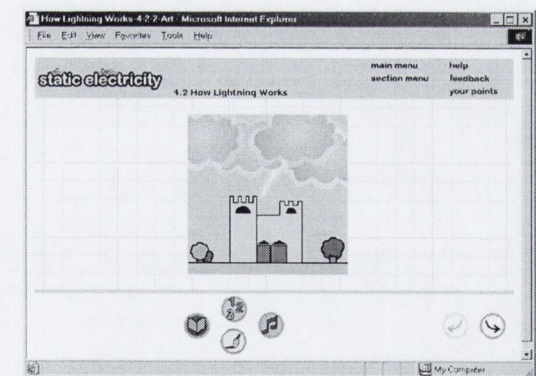


Figure 3-8: Visual/Spatial Intelligence

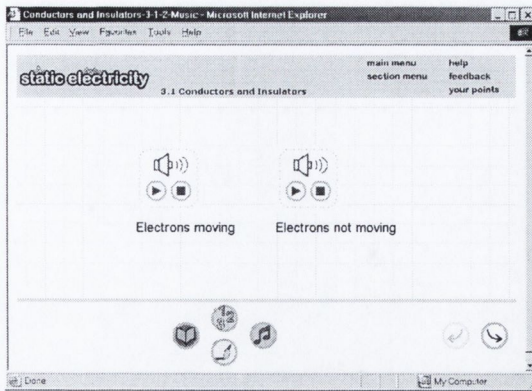


Figure 3-9: Musical/Rhythmic Intelligence

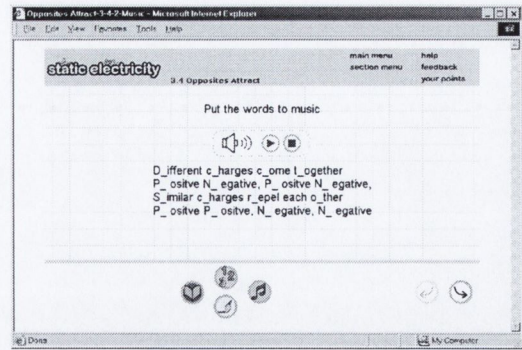


Figure 3-10: Musical/Rhythmic Intelligence

3.6 Student Model

The student model is the source of information for an adaptive educational system to adapt to individual differences. In EDUCE, a student model is constructed for each particular learner. During the student's interaction with the system, all information is recorded and used to provide a complete description of the learner's knowledge, characteristics and preferences.

The student model in EDUCE has the following characteristics:

- It employs an overlay model that follows the domain structure and which records learner's knowledge level on the various concepts and learning units.
- It records information that describes the student's interaction with the content, in particular the MI resources, and represents the learning characteristics of the student.
- It represents the navigation history, a record of the navigation path the student has taken through the educational material and time spent on each learning unit.
- It represents the student attitudes to the learning environment by recording responses to reflective feedback questions during and after the tutorial
- It stores general information about the learner, such as username, gender, sex, prior ability and previous computing experience.
- It is dynamically updated during interaction to reflect the learner's current state.

The special feature of the EDUCE student model is the use of the MI concept to provide the basis for modelling learning characteristics. EDUCE dynamically builds a Multiple Intelligence based profile of the student's learning characteristics by observing, analysing and recording the student's interaction with MI differentiated material. In particular, the model uses the following criteria as indicative of learning behaviour:

- Did the student spend a minimum amount of time using the resource? The assumption made is that if the student spends a brief amount of time using a resource they have not engaged with the material and have just glanced at it before moving onto the next screen.
- Did the student spend a long time using the resource? When a student spends a longer time than normal using a resource, it is assumed that the resource appeals and engages him.
- Which resource did the student use first? A student with strong preferences will choose the most favourite resource first.
- Did a student use only one resource or multiple resources? Some students have no distinct preference and instead use a broad spread of resources that examine a concept in different ways
- Did the student use the resource more than once? Going back to the same resource is indicative that the student has strong preferences for it.
- Did the student attempt a question after viewing the resource? Using particular types of resources may motivate the student to answer questions.
- Did the student attempt a question after viewing the resource and get it right? Certain types of resources may encourage deeper learning and understanding.

This information attempts to capture what the student spends time on, what is first viewed, what is repeatedly viewed and what helps in answering questions. To complement the dynamic Multiple Intelligence profile, EDUCE also holds a static MI profile of each student that is completed using the MIDAS inventory.

3.7 Presentation Module

In the teaching of a concept, key instructional events are the elements of the teaching process in which learners acquire and transfer new information and skills (Gagné et al.,

1992). The EDUCE presentation model, using a summarized version of the Gagné model, has four key instructional events, as shown in Figure 3-11.

- *Awaken*: The main purpose of this stage is to attract the learner’s attention
- *Explain*: Different multiple intelligences are used to explain the concept in different ways
- *Reinforce*: This stage reinforces the key message in the lesson
- *Transfer*: Here learners convert memories into actions by answering interactive questions

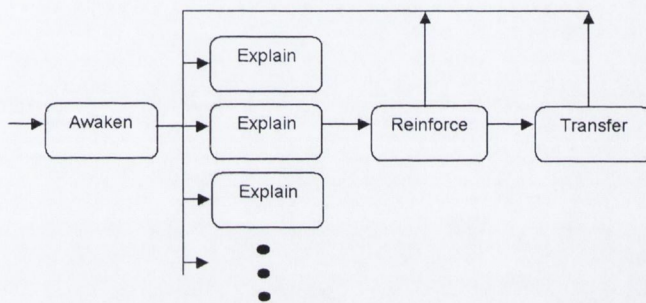


Figure 3-11: Events in Presentation Module

Figure 3-12 shows the Awaken stages in the unit – “Opposites Attract”. It shows a picture of a bulldog and a poodle. It tries to stimulate curiosity and introduces the concept of “opposites attract” through a visual image. It leads the learner into the topic by encouraging inquiry and by giving the learner an opportunity to construct an initial understanding of the topic.

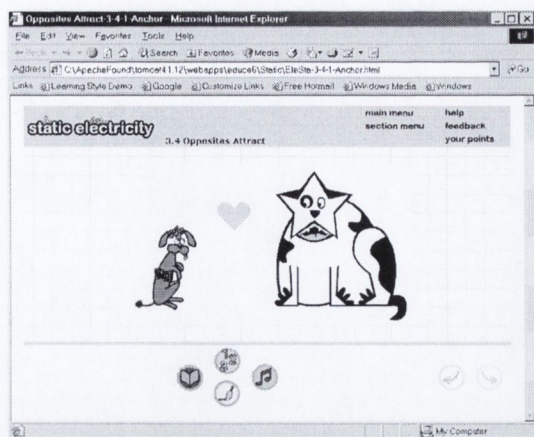






Figure 3-12: The Awaken stage of “Opposites Attract”

At the Awaken, Reinforce and Transfer stages, the learner can access different MI resources using the following four symbols.

Table 3-3: Symbols for MI Resources

	LM		VL		VS		MR
---	----	---	----	---	----	--	----

As students choose between Multiple Intelligence differentiated materials EDUCE automatically builds a model of the learning characteristics and preferences. This model provides EDUCE with the opportunity to facilitate learning by providing an individualised learning path.

The Explain stage in the event model provides for a choice of MI differentiated material. The objective at this stage is to allow for multiple representations of the same content. Different learners can choose different paths through the material. A learner may use one and move through the unit, may return to a second alternative representation if difficulties in understanding arise, or may proceed to view them all to get a complete picture of the content from different angles. Sometimes the material is the same, just represented differently; other times it presents information that is not available in the other representations. At other times, it is used as an entry point into the material. The Reinforce stage is used to summarise the key content message of the learning unit. It may be a short summary or it may be an explanation of the key concept. The Transfer stage

consists of short questions requiring one-word answers, fill in the blank questions and multi-choice questions. All answers to questions are available at the preceding Reinforce stage. If the learner does not remember the answer it is possible to navigate back to the Reinforce stage or to any of the MI differentiated material at the Explain stage.

Additional navigation options are provided through a main menu and a section menu. Through these menus students have the opportunity to move from one concept to next according to their learning strategy and goal.

Learner support is also provided through a feedback and "points" menu. A feedback menu provides information about the current dynamic MI profile in terms of how many resources have been chosen and how much time has been spent in each MI category. A "points" menu provides feedback on the number of interactive questions that have been attempted and answered correctly.

EDUCE also allows the learner to personalise the environment, as research suggests that learners appear to benefit from learner control opportunities (Hannafin & Sullivan, 1996). It gives the learner two modes of operation, with adaptivity and without:

- *Adaptive*: This is the default level where the system takes the initiative and adaptively guides the learner to particular resources based on the student model. The student is first adaptively guided to a specific MI resource type but has the option to go back and view alternative resources. The adaptive strategy can be based on either the dynamic or the static MI profile.
- *Free*: Adaptivity is turned off and the learner takes the initiative when selecting resources. The student has the choice to view the different MI resources in any order. No adaptive presentation decisions are made as the learner has complete control.

On entry to EDUCE and at any time throughout the tutorial, students select the level of learner control and system guidance they would like. The two options determine the navigation paths available from the Awaken stage. With the *Free* option, links to all MI resources are available. With the *Adaptive* option, on first looking at the Awaken stage, the links to all MI resources are not available and only the next button may be chosen. On choosing the next button, the learner will be directly guided by EDUCE to a particular MI resource using information in the student model.

3.8 Predictive Engine

The predictive engine dynamically determines the learner's preference for different Multiple Intelligence resources and informs the pedagogical strategy. Being able to predict student behaviour provides the mechanism by which instruction can be adapted and by which to motivate a student with appropriate material. As the student progresses through a tutorial, each learning unit offers four different types of resources. The student has the option to view only one, view them all or to repeatedly view some. The prediction task is to identify at the start of each learning unit which resource the student would prefer.

Figure 3-13 illustrates the main phases of the prediction process and their implementation within EDUCE. The input representation model to the learning scheme consists of fine-grained features that describe the student's interest in and use of different resources available. The predictive engine employs an Artificial Intelligence based classification algorithm, Naïve Bayes (Duda & Hart, 1977) to analyse the input data. It operates online using no prior information. At the resource classification phase, a model of each individual student's preferences is created. During student/system interaction, EDUCE monitors the student's actions, updates the student model, and makes predictions on learning preferences. Chapter 4 will describe in greater detail the architecture and implementation of the predictive engine.

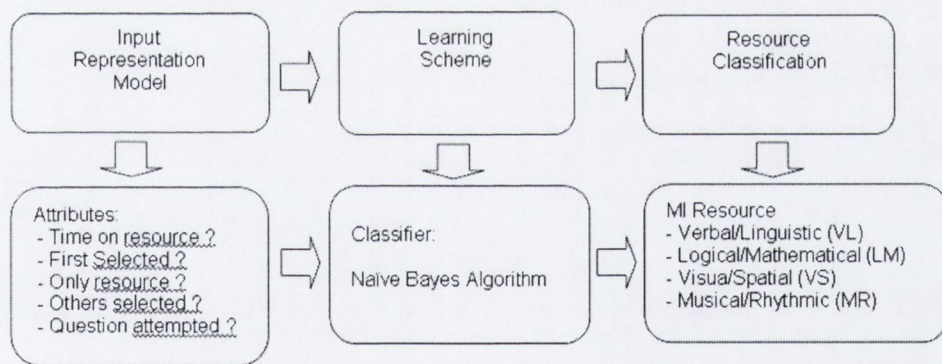


Figure 3-13: The different stages in the predictive engine and their implementation within EDUCE

3.9 Pedagogical Manager

EDUCE has the flexibility to use different pedagogical strategies due to the availability of a rich student model, the availability of a predictive engine that can detect preferences and MI inspired material that can stimulate the learner in different ways. Such strategies include: providing students with a broad choice of resources, providing students with a restricted set of resources, using system guidance instead of supporting learner control, and guiding students to resources they may not prefer. These strategies are implemented by dynamically tailoring the environment using information in the student model and the output from the predictive engine.

Adaptivity is implemented using two adaptation technologies: adaptive presentation at the content level and adaptive navigation support at the link level (Brusilovksy, 2001).

Adaptive presentation is implemented using page variants. Page variants involve keeping two or more variants of the same page with different presentations of the same content. There is a variant for each of the four intelligences: verbal/linguistic, visual/spatial, logical/mathematical and musical/rhythmic. When presenting a page, EDUCE selects the page variant using information in the student model.

Adaptive navigation support techniques help students find paths through the educational material by adapting the presentation of links. Adaptive navigation is implemented using direct guidance and link hiding. With direct guidance the student selects the next button, and the next page is presented without having to make a choice. Link hiding restricts the navigation space by hiding links to pages not relevant to that particular learner.

3.10 Technical Implementation

EDUCE is implemented as a web based adaptive intelligent educational system using Java servlet and XML technology. The domain model is stored in XML format and an XML file stores the educational content for each section of material. Individualized student models are stored dynamically and persistently within a MySQL database. The predictive engine has been developed using Java and the Weka package (Witten & Frank, 2000). The pedagogical manager is implemented in Java. It is responsible for analyzing feedback from the student, updating the student model, retrieving information from the student model, communicating with the predictive engine and making decisions about which instructional strategy to use. The presentation module receives input from the

pedagogical manager and manages the presentation of information through the use of XSLT style sheets. It observes monitors and handles all feedback from the student in the form of links activated, buttons pressed and text entered. Appendix C describes further the implementation of EDUCE and includes implementation details for the domain knowledge representation, presentation model, pedagogical model and predictive engine.

3.11 Summary

The chapter has described the architecture, design and implementation of EDUCE. It described in detail the Multiple Intelligence theory and how it is incorporated into the design of EDUCE. It also described the different components of the EDUCE architecture: the domain model, student model, presentation model, predictive engine and pedagogical model. The next chapter will describe in detail the architecture and implementation of the predictive engine.

4 Predictive Engine

4.1 Introduction

Using Artificial Intelligence techniques, the predictive engine dynamically determines the learner's preference for different Multiple Intelligence resources and informs the pedagogical strategy on what content to present. The core of the engine is a statistical based algorithm called Naïve Bayes.

The chapter describes the architecture and implementation of the predictive engine (Kelly & Tangney, 2004d). Firstly, it provides some general background on predictive statistical methods in general and on the Naïve Bayes algorithm in particular. Secondly, it outlines the overall architecture of the predictive engine. Next, it describes the novel set of navigational and temporal input features that are used as input to the learning algorithm. Last, it describes how the classification of the preferred resource takes place online with no prior information using the Naïve Bayes algorithm.

4.2 Predictive Statistical Models

Student modelling involves inferring information about the student from observable behaviour such as actions or speech. One approach to user modelling is to use handcrafted rules by analysing several instances of the problem at hand. This approach is a resource intensive process, and gives models that are not adaptable and are difficult to construct in the presence of uncertainty. Statistical models are an alternative approach to developing handcrafted rules. Statistical models are concerned with the use of observed sample data to make statements about an unknown, dependent parameter (Larson, 1969). In predictive statistical models for student modelling, this parameter represents an aspect of a student's future behaviour, such as goals, preferences or future actions.

The Artificial Intelligence area of machine learning has generated a variety of techniques which can be described as predictive statistical models (Zukerman & Albrecht, 2001). These techniques use both the content-based and collaborative approach to make

predictions and adapt the behaviour of the systems. The content-based approach is based on the belief that each user demonstrates a particular behaviour in a given situation, and that this behaviour is repeated under similar circumstances. With this approach, a predictive model is built for a user based on data from their past behaviour. The collaborative approach is based on the belief that people within a particular group tend to behave similarly under a given set of circumstances. In this approach, a model is built using data from a group of users. Thus, in the content-based approach, the behaviour of a user is predicted from their past behaviour, while in the collaborative approach, the behaviour of the user is predicted from the behaviour of other like-minded people.

Predictive statistical models span a range of techniques that include linear models, Markov models, neural networks, rule-induction methods and Bayesian networks. Linear models take weighted sums of known values to produce a value for an unknown quantity. They have a simple structure, which allows them to easily learn and generalize. These models have been used to predict the time intervals between a user's successive logins (Orwant, 1995). Markov models predict the next event from the probability distribution of observed events in the past and have been used to predict user's requests for pages on the WWW (Zukerman et al., 2001). Neural networks can express non-linear decision surfaces using different network structures, weights of the edges between nodes and non-linear thresholds. It has been used in the identification of individual learning styles (Lo & Shu, 2005). Rule induction consists of learning sets of rules that predict the class of an observation from its attributes, given information about the class of each observation. In one application, it has been used to learn rules that predict features of subtraction errors performed by students (Chiu & Webb, 1998). Bayesian networks are directed acyclic graphs where the nodes correspond to random variables. The nodes are connected by directed arcs, which represent causal links between the nodes. Each node has a conditional probability distribution that assigns a probability to each possible value of this node for each combination of the values of its parent nodes. Bayesian networks have been used in systems to predict the type of assistance required by users performing spreadsheet task (Horwitz, 1998).

However, there are a number of critical issues that need to be addressed when applying machine learning to student modelling. The issues include (Webb et al., 2001):

- The need for large data sets – the learning algorithm may not build a model with acceptable accuracy until it sees a relatively large number of examples

- The need for explicitly labelled data – learning algorithms require labelled data that may not be readily apparent
- Concept drift – attributes that characterize a user are likely to change over time and the learning algorithm needs to be able to adjust to these changes quickly
- Computational Complexity – to be of practical use, learning algorithms need to be efficient and quick

Despite these issues, there has been some successful work on the application of machine learning to student modelling. For example, Net-tutor (Quafafou, 1995) uses rough set theory to map features of the teaching action such as interactivity level and type of presentation to expected amounts of learning. Assert (Baffes & Mooney, 1996) uses theory refinement to build its model of student misconceptions. The system observes when a student obtains an incorrect result, and modifies a correct rule base to be consistent with the student's behaviour. In addition, Advisor (Beck & Woolf, 2000) constructs a model of how a student will respond to a particular teaching action in a given situation. Subsequently, it uses this model to determine a policy for teaching actions that try to achieve a customizable teaching goal. Advisor uses linear regression to construct the model of the student and reinforcement learning to reason with the model. While acknowledging these successful applications, there is much further research required in the application of machine learning to student modelling as it is still unclear which modelling technique is most suitable in light of the available data and features of a given problem.

4.3 Naïve Bayes

Before choosing a learning algorithm it is first necessary to define its purpose and in particular the prediction task. In EDUCE, the prediction task was defined as the ability to predict preferences for different MI versions of resources based on observations of student behaviour. In addition, certain requirements for the learning algorithm were also defined. These included the ability to:

- Operate with no prior knowledge about the user.
- Construct student model based on user's own data
- Develop a predictive model for each individual student based on his or her interaction data.

- Continually refine the predictive model with further observations of the student.

With these requirements in mind, the learning mechanism chosen was the Naïve Bayes algorithm (Duda & Hart, 1973). It is an algorithm that works well with sparse datasets, can be used to create individual predictive models and can be used with datasets that are dynamically updated (Witten & Frank, 2000).

In addition, the Naïve Bayes algorithm has been applied to a range of problems in education. For example, the Adaptive Bayes algorithm (Castillos, 2003) predicts resources as appropriate or not appropriate based on the resource's characteristics and student's learning style. Adaptive Bayes uses an incremental adaptive version of Naïve Bayes that includes an updating scheme making it possible to adapt the current model to new data. The algorithm uses input features based on learning style and resource characteristics. These features include 3 dimensions of the Felder Silverman model (Felder, 1988): Visual/Verbal, Sensing/Conceptual and Global/Sequential; and two features that describe the resource characteristics: learning activity and resource type. The output predictions are used to generate two ranked lists labelled "appropriate reading" and "other resources" (non-appropriate reading). In evaluations, the performance of Adaptive Bayes was compared with non-adaptive versions. The results suggest that Adaptive Bayes had better accuracy when taking changes in the student's learning style into account. However, in the evaluation of the algorithm, artificial datasets were generated to simulate changes in learning style and there is no dynamic diagnosis of learning style. In addition, it would be of interest to see the effect on learning when the algorithm is used in experiments with students.

In contrast, the iMANIC system (mentioned in Ch2) dynamically predicts student preferences for different types of resources and adapts the presentation of content accordingly (Stern & Woolf, 2000). Multiple resources are categorised according to the instructional type (explanation/ example/ definition), media type (text/picture), place in topic (beginning/end), abstractness (concrete/abstract) and place in concept (beginning/middle/end). The different resources are adaptively presented using stretch text that allows certain parts of a page to be opened or closed. As the student interacts with the system, they can open and close resources indicating which resources are preferred. When presenting the next concept, this interaction data is analysed using the Naïve Bayes algorithm to determine which resources are wanted and should be presented first. In results from a limited evaluation study, it was reported that it was possible to

learn for each student within a few slides the parameters that achieve optimal classification. One drawback with this system is that there is no explicit educational theory underpinning the categorisation of resources or learning characteristics. In addition, there are some problems in using the place in topic and place in concept attributes as the Naïve Bayes algorithm assumes all input features to be independent. These attributes are not independent from attributes such as media type, as a student may prefer a picture before text and so the media type preferred will be dependent on its place in the topic presentation. Finally, it would be of interest to see what impact the iManic system has on student learning using an experimental study.

The limitations of the Adaptive Bayes and iManic systems provide the motivation for the design of the predictive engine in EDUCE. Firstly, it needs to support an explicit educational theory that provides the framework for modelling learning characteristics. Secondly, it needs to take as input an appropriate set of navigational and temporal input features that are indicative of learning characteristics. Next, it should be able to dynamically diagnose learning characteristics as the input data continually changes. Finally, it needs to be easily integrated into an adaptive learning environment so that it can be evaluated in an experimental study.

4.4 Engine Architecture

Machine learning can be described as the extraction of implicit, previously unknown and potentially useful information from data (Mitchell, 1997). It detects patterns and regularities in data and represents them as structural descriptions that can be used to make predictions. EDUCE's predictive engine is based upon the assumption that students do exhibit patterns of behaviour appropriate to their particular learning characteristics and that it is possible to describe those patterns. By observing the student's pattern of behaviour, it attempts to build an individual predictive model of each student's learning characteristics that can inform the adaptive presentation of content.

Patterns in data are identified using machine learning algorithms and techniques. These algorithms require input in the form of instances that are independent examples of the concept to be learnt. Instances are characterised by a pre-determined set of attributes or features that measure the different aspects of the instance using different values. The output from the learning algorithm is the predicted class of the instance.

Figure 4-1 illustrates the main phases of the predictive engine within EDUCE. Both the prediction process and its implementation are illustrated. The input representation model to the learning scheme consists of fine-grained features that describe the student's interest in and use of different resources available. The predictive engine employs the Naïve Bayes classification algorithm to analyse the input data. It operates online using no prior information. At the resource classification phase, a model of each individual student's preferences is created. During student/system interaction, EDUCE monitors the student's actions, updates the student model, and makes predictions on learning preferences.

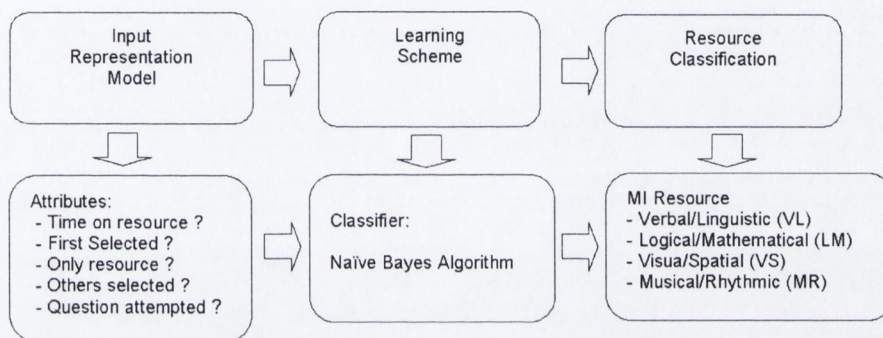


Figure 4-1: Phases of the EDUCE's predictive engine

4.5 Input Model and Resource Classification

The input representation model consists of a set of features that describe the student's learning characteristics. Rather than modelling the static features of the learning resources, it consists of a set of dynamic navigational and temporal features that are indicative of how different resources are used. The attributes and values selected were:

- NormalTime {Yes, No}: Yes if students spent more that 2 seconds viewing a resource otherwise No. The assumption is made that if a student has spent less than 2 seconds they have not had the time to use it. The value is also No if the student does not select the resource. 2 seconds was chosen as in experimental studies it provided the optimal classification accuracy.
- LongTime {Yes, No}: Yes if the student spends more that 15 seconds on the resource otherwise No. The assumption is that that if the student spends more that

15 seconds he is engaged with the resource. 15 seconds provided the optimal classification accuracy.

- FirstChoice {Yes, No}: Yes if the student views the resource first otherwise No
- OnlyOne {Yes, No}: Yes if this is the only resource the student looks at otherwise No
- Repeat {Yes, No}: Yes if the student looks at the resource more than once otherwise No
- QuestAtt {Yes, No}: Yes if the student looks at the resource and attempts a question otherwise No.
- QuestRight {Yes, No}: Yes if the student looks at the resource and gets the question right otherwise No.

These attributes describe the set of instances upon which the classifier makes a prediction. When making a prediction, the classifier is given a new instance and is asked to predict the value of the output attribute or the class of the instance. This attribute is defined as:

- Resource {VL, LM, VS, MR}: The name of the resource: Verbal/Linguistic, Logical/Mathematical, Visual/Spatial and Musical/Rhythmic. This is the feature the learning scheme will classify.

Thus, the prediction task is to predict the probability that a particular resource type is wanted given instances that describe how the previous resources were used.

4.6 Learning Scheme

The predictive engine employs the Naïve Bayes classification algorithm to analyse the input data and make predictions. The formula for the Naïve Bayes classifier can be expressed as (Mitchell, 1997):

$$v_{NB} = \underset{v_j \in V}{\operatorname{argmax}} P(v_j) \prod_i P(a_i | v_j)$$

v_{NB} is the target value which can be any value v_j from the finite set V . $P(a_i | v_j)$ is the probability of the attribute a_i for the given class v_j . The probability for the target value of a particular instance, or of observing the conjunction $a_1, a_2 \dots a_n$, is the product of the probabilities of the individual attributes. $a_1 \dots a_{n-1}$ are the input attributes and a_n is output

attribute or the class of the instance. The algorithm works on the assumption that all attributes are uncorrelated, statistically independent and normally distributed.

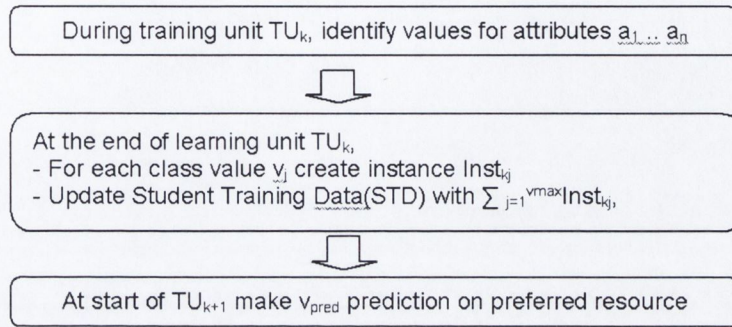


Figure 4-2: Algorithm describing how instances are created and predictions made

Figure 4-2 illustrates the algorithm that describes how instances and predictions are made. During each learning unit TU_k observations are made about how different resources are used. At the end of the learning unit TU_k one instance is created for each target class value $v_1 \dots v_j$. For example, the instances $\sum_{j=1}^{v_{max}} Inst_{ij}$ generated for one student after the interaction with one particular learning unit and four resources are given in Table 4-1. The training data is next updated with these new instances. The entire training data set for each student consists of all the instances generated, with equal weighting, from the learning units that have been used.

Table 4-1: Example instances after interaction with one learning unit.

Normal Time	Long Time	First Choice	Only One	Repeat	Quest Att	Quest Right	Resource
Yes	Yes	Yes	No	No	Yes	Yes	VS
Yes	No	No	No	Yes	Yes	Yes	VL
Yes	Yes	No	No	No	Yes	Yes	MR
No	No	No	No	No	No	No	LM

At start of the next learning unit TU_{i+1} the predictive engine is asked to make a prediction v_{pred} on the preferred resource. This is achieved by asking the predictive engine to classify the instance that describes what the student spends time on, what he views

first, what he repeatedly views and what helps him to answer questions, namely the instance illustrated in Table 4-2:

Table 4-2: The instance classified against each resource

Normal Time	Long Time	First Choice	Only One	Repeat	Quest Att	Quest Right	Resource
Yes	Yes	Yes	Yes	Yes	Yes	Yes	?

The range of target values for the output attribute is {VL, LM, VS, MR}, one for each class of resource. For each possible target value the Naïve Bayes classifier calculates a probability on the fly. The probabilities are obtained by counting the frequency of various data combinations within the training examples. The target class value chosen is the one with the highest probability.

An example of how these probabilities are calculated is as follows. Using data consisting of only instances that are illustrated in Table 4-1, the probability for VL is

$$\prod_i P(a_i | VS) = 1/1 \times 1/1 \times 1/1 \times 0/1 \times 0/1 \times 1/1 \times 1/1 \times 1/4$$

To avoid any attribute occurring zero times (and a multiplication by 0 which result in 0 probability) a Laplace estimator is used. This involves adding 1 to the numerator and compensating by adding 1 for each attribute value to the denominator (e.g. Yes/No values for Normal Time will result in 2 been added to the denominator). This results in:

$$\prod_i P(a_i | VS) = 2/3 \times 2/3 \times 2/3 \times 1/3 \times 1/3 \times 2/3 \times 2/3 \times 2/8 = 0.003658$$

In addition

$$\prod_i P(a_i | VL) = 2/3 \times 1/3 \times 1/3 \times 1/3 \times 2/3 \times 2/3 \times 2/3 \times 2/8 = 0.001829$$

$$\prod_i P(a_i | MR) = 2/3 \times 2/3 \times 1/3 \times 1/3 \times 1/3 \times 2/3 \times 2/3 \times 2/8 = 0.001829$$

$$\prod_i P(a_i | LM) = 1/3 \times 1/3 \times 1/3 \times 1/3 \times 1/3 \times 1/3 \times 1/3 \times 2/8 = 0.000114$$

The maximum of these probabilities is returned as the predicted preferred resource. In addition the resource with the lowest probability is returned as predicted lowest preferred resource.

4.7 Summary

The chapter has describes the architecture and implementation of the predictive engine. The central component of the engine is the Naïve Bayes classifier. It has described the input features and the prediction task. It has also illustrated the main phases in the prediction algorithm and described how the classification of the preferred resource is calculated. The following Chapter 5 describes empirical studies conducted to compare the predictive accuracy of the engine with the actual behaviour of students.

5 Validation

5.1 Introduction

The previous two chapters have described the development of EDUCE. Chapter 3 has described how the principles of MI can be used to model the student and develop content. Chapter 4 has described the development of the predictive engine and how it dynamically diagnoses MI preferences based on observable behaviour. Before conducting experiments to determine what pedagogical strategies EDUCE should use two studies were carried out. First, a study was conducted to validate that the content developed reflected the principles of MI. Second, a study was conducted to compare the performance of the predictive engine with the actual behaviour of students (Kelly & Tangney, 2003b, Kelly & Tangney 2004d). This chapter describes both the content validation and predictive engine validation studies.

5.2 Content Validation

The resources used by EDUCE have been developed using the principles of MI. In particular, the resources have been developed using the pedagogical taxonomy outlined in Chapter 3. The team of developers included the author, a Science teacher and an instructional developer. Two expert MI practitioners subsequently assessed the developed resources with a view to determining how accurate they reflected MI principles:

- Expert 1 - Branton Shearer, the author of the MIDAS questionnaire
- Expert 2 - Anne Fleischmann, a teacher and MI practitioner for more than 10 years

Each MI informed resource was developed to reflect the principles of one particular intelligence. The validation process involved, for each resource, identifying the dominant intelligence and specifying in percentage terms how much the different intelligences were employed. For example a resource categorised as verbal/linguistic could be rated as activating the VL intelligence 70 % of the time and activating other intelligences 30 % of the time.

5.2.1 Procedure

The MI experts were asked to navigate through the content in the Static Electricity tutorial and rate the content in terms of each intelligence it activated. The experts were asked to indicate, as a %, how much each resource activates each of the four intelligences: Verbal/Linguistic (VL), Logical/Mathematical (LM), Visual/Spatial (VS) and Musical/Rhythmic (MR). The total sum of four percentages should add up to 100 %. For example, in section 1 unit 1 (S1_U1) there are four options: a VL, LM, VS and MR option. Table 5-1 shows how the VL option has been given a rating of: 70% VL, 10% LM, 20% VS, and 0% MR. This rating describes that the VL resource highly activates the VL intelligence (70%) and to a lesser extent activates the VS and LM intelligences (30 %).

The experts were also asked if suggestions could be made to improve the content. For example, Table 5-1 illustrates how the VL option for Section 2 Unit 1 (S2_U1) has been given a rating of 60% VL, 10% LM, 30% VS, and 0% MR. An example of a suggestion to make it more VL orientated could be to remove the picture

Table 5-1: Sample Ratings for the VL option

Unit	VL Option				LM Option				VS Option				MR Option			
	VL	LM	VS	MR	VL	LM	VS	MR	VL	LM	VS	MR	VL	LM	VS	MR
S1_U1	70	10	20	0												
S2_U1	60	10	30	0												

5.2.2 Ratings

Table 5-2 and Table 5-3 illustrate the ratings for Expert 1 and 2 respectively. Despite some disagreements among the experts, the ratings suggest that according to the MI experts, the resources activate the intelligences they were designed to activate. For example, expert 1, on average, rates the VL resources as activating the VL intelligence by 88%, the LM resources the LM intelligence by 67 %, the VS resources the VS intelligence by 86 % and MR resources the MR intelligence by 83 %. Similarly, expert 2 on average rates the VL resources as activating the VL intelligence by 93%, the LM resources the LM intelligence by 76 %, the VS resources the VS intelligence by 83 % and MR resources the MR intelligence by 82 %. Table 5-4 summarizes these results.

5.2.3 Conclusions

It can be concluded that the different categories of MI resources activate the relevant intelligence. For the VL, VS and MR option it is very clear that they activate the appropriate intelligence. The LM option did not receive the same high rating, maybe because in promoting the LM intelligence it was necessary to use words that activate the VL intelligence and diagrams that reflect the VS intelligence. It is also interesting to note that the main secondary intelligence used by each resource is the VL intelligence. When developing the MR and VS resources it is still necessary to use some words reflecting the traditional importance of verbal ability.

Table 5-2: Ratings of Expert 1 for MI Content

Unit	VL Option				LM Option				VS Option				MR Option			
	VL	LM	VS	MR	VL	LM	VS	MR	VL	LM	VS	MR	VL	LM	VS	MR
S1_U1	100				30	70					100		20			80
S2_U1	100				30	70					100					100
S2_U2	70	30			40	60			15	15	70		30			70
S2_U3	80	20			15	70	15		20		80		30			70
S3_U1	100				35	65					100					100
S3_U2	100				35	65				15	85					100
S3_U3	80	20			25	75				25	75		25			75
S3_U4	100				25	75					100		15			85
S3_U5	60	40			35	65				40	60		15			85
S4_U1	100				35	65					100		15			85
S4_U2	85	15			35	65					100		25			75
S5_U1	85	15			35	65					100		15			85
S5_U2	85	15			35	65				35	65		25			75
S5_U3	85	15			35	65				35	65		25			75
Average	88					67					86					83

Table 5-3: Ratings of Expert 2 for MI Content

Unit	VL Option				LM Option				VS Option				MR Option			
	VL	LM	VS	MR	VL	LM	VS	MR	VL	LM	VS	MR	VL	LM	VS	MR
S1_U1	100				30	70					100				30	70
S2_U1	95		5		20	80			5		95					100
S2_U2	60	40			25	50	25		10		90		30			70
S2_U3	70	20	10			80	20						20			80
S3_U1	100				20	80			10		90		5			95
S3_U2	100				20	80					100		5			95
S3_U3	80	20			10	60	30			50	50		20			80
S3_U4	90			10	20	80			5		95		20			80
S3_U5	100				20	80			10		90		20			80
S4_U1	100				20	80			20		80		20			80
S4_U2	100				20	80			100				20			80
S5_U1	100				20	80			30		70		20			80
S5_U2	100				20	80			60		40		20			80
S5_U3	100				20	80			10		90		20			80
Average	93					76					83					82

Table 5-4: Average Ratings for the dominant intelligence.

	VL Option	LM Option	VS Option	MR Option
Expert 1	88	67	86	83
Expert 2	93	76	83	82
Average	90.5	71.5	84.5	82.5

5.3 Predictive Engine Validation

The predictive engine predicts the most preferred and least preferred resource based on observations of student behaviour. In order to evaluate the accuracy of these predictions an experimental study was conducted (Kelly & Tangney, 2003b, Kelly & Tangney 2004d). The objective of the study was to compare the actual behaviour of students with predictions by the predictive engine. During the study, students had access to all MI informed resources. The performance of the predictive engine was analysed by comparing at the start of each learning unit the predicted preferred resource with the actual resources used by the student in that unit. The predictive engine based its

predictions on all observations of the student's behaviour in the learning units preceding the learning unit for which the prediction was made.

5.3.1 Data Collection

The evaluation study was conducted with 25 participants from the same school. The 25 female students were between the ages 12 and 16 and came from two different classes. The teachers described one half as below average academic achievers and the other half as high academic achievers. About half the participants had studied Static Electricity before and the other half had not. The study was conducted in the school computer laboratory. The results of tests undertaken in the study did not contribute towards the student's science grade mark and the motivation for the students in using the material was for fun and exploration.

During the study, participants navigated through the Static Electricity tutorial with the free version of EDUCE. With this version adaptivity is turned off and the learner takes the initiative when selecting resources. The student has the choice to view the different MI resources in any order. No adaptive presentation decisions are made as the learner has complete control. Note also that in the version of EDUCE used for this study the questions were fill-in the blanks as opposed to multi-choice questions. To avoid problems with spelling mistakes later versions of EDUCE used multi-choice questions.

Before using EDUCE, students were given a two-minute demonstration on how to navigate through the tutorial. Each student interacted with EDUCE for an average of 40 minutes giving a total of 3381 observations over the entire group. 840 of these interactions were selections for a particular type of resource. In each learning unit students had a choice of four different modes of instruction: VL, VS, MR, and LM. As no prior knowledge of student preference was available, the first learning unit experienced by the student was ignored when doing the evaluation.

For individual predictive modelling, one approach is to load all of the student's data at the end of a session and evaluate the resultant classifier against individual selections made. The other approach is to evaluate the classifier predictions against user choices made only using data up to the point the user's choice was made. This approach simulates the real behaviour of the classifier when working with incomplete profiles of the student. The second approach was used as this reflects the real performance when dynamically making predictions in an online environment.

5.3.2 Evaluation

The evaluation consisted of a number of different investigations, which were made to determine answers to the following questions:

1. Is it possible to predict if the student will use a resource in a learning unit?
2. Is it possible to predict when the student will use a resource in a learning unit?
3. What range of resources did students use?
4. How often does the prediction of students preferred type of resource change?
5. Can removing extreme cases where there is no discernable pattern of behaviour help in the prediction of the preferred resource?

5.3.2.1 Evaluation 1: Predicting if resource will be used

Each learning unit has up to four types of resources to use. At the start of each unit, the student's most preferred type of resource was predicted based on previous selections the student had made. After the student had completed the learning unit, it was investigated to see if the student had used the predicted preferred resource. In 75 % of cases the prediction was correct. In other words EDUCE was able to predict with 75 % accuracy that a student will use the predicted preferred resource. The results suggest that there is a pattern of behaviour when choosing among a range of resources and that students will continually use their preferred resource.

5.3.2.2 Evaluation 2: Predicting when the resource will be used

In each learning unit, the student can determine the order in which resources can be viewed. Is it possible to know at what stage the student will use his preferred resource? When inspecting the learning units where the predicted preferred resource was used, it was found that in 78 % of cases the predicted preferred resource was used first, i.e. in the 75% of cases where the prediction was correct the predicted resource was visited first 78% of the time. The results suggest that it is a challenging classification to predict the first resource a student will use in a learning unit. However when the student does use the predicted preferred resource, it will with 78 % accuracy be the first one used. Figure 5-1 illustrates these results ($58\% = 78 \times 75$). The analogy is that of shooting an arrow at a

target. 75 % of the time the target is hit and when the target is hit, 78 % of the time it is a bulls-eye!

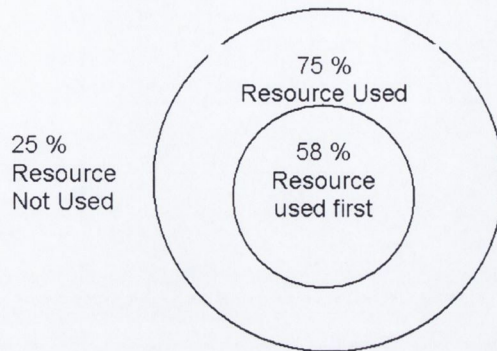


Figure 5-1: The classification accuracy of predicted preferred resource.

5.3.2.3 Evaluation 3: Changes in predicted preferred resource

To determine the extent of how stable the predicted preferred resource is, an analysis was made of the number of times the prediction changed. The average number of changes in the preferred resource was 1.04. The results suggest that as student's progress throughout a tutorial they identify quite quickly which type of resource they prefer as the predicted resource will on average only change once per student.

5.3.2.4 Evaluation 4: The range of resources used

Did students use all available resources or just a subset of those resources? By performing an analysis of the resources selected from those available in each unit, it was found that students on average used 40 % of the available resources. This result suggests that students identified for themselves a particular subset of resources which appealed to them and ignored the rest. But did all students choose the same subset? To determine which subset was used, a breakdown of the resources used against each class of resource was calculated. Table 5-5 displays the results. The even breakdown across all resources suggests that each student chose a different subset of resources. (If all students chose the same subset of VL and LM resources, VS and MR would be 0 %). It is interesting to note that the MR approach appeals to the most number of students and the LM approach appeals to the least number of students.

Table 5-5: Breakdown of resources used

VL	LM	VS	MR
25 %	16 %	27 %	33 %

5.3.2.5 Evaluation 5: Without extreme cases

Inspecting students with extreme preferences, both very strong and very weak, reveals some further insights, into the modelling of learning characteristics. With one student with a very strong preference for the VL approach, it could be predicted with 100 % accuracy that she would use the VL resource in a learning unit, and that with 92 % accuracy that she would use it first before any other resource. On analysing students with very weak preferences it appears that some students seem to have a complex selection process not easily recognisable. For example with one student, it could only be predicted with 33 % accuracy that she would use her predicted preferred resource in a learning unit and only with 11 % accuracy that she would use it first. In this particular case, the results suggest that she was picking a different resource in each unit and not looking at alternatives.

Some students will not display easily discernable patterns of behaviour and these outliers can be removed to get a clearer picture of the prediction accuracy for students with strong patterns of behaviour. After removing the 5 students with the lowest prediction rates the prediction accuracy for the rest of group was recalculated. This resulted in an accuracy of 84 % that the predicted preferred resource will be used and in an accuracy of 65 % that the predicted preferred resource will be used first in a learning unit. The results suggest that strong predictions can be made about the preferred class of resource. However predicting what will be used first is still a difficult classification task.

5.3.3 Conclusions

The results of the evaluation reveal that it is possible using EDUCE's predictive engine to model the students learning characteristics. In particular, they reveal that it is possible to make strong predictions about a student's preferred resource type. The results suggest that it is possible to predict with a relatively high degree of probability that the student will use the predicted preferred resource in a learning unit. However it is a more difficult task to determine if the predicted preferred resource will be used first before any other resource. The results also suggest that predictions about the preferred resource are

relatively stable, that students only use a subset of resources and that different students use different subsets. Combining the results together suggest that learning characteristics can be modelled and that the characteristics are different for alternative groups of students.

5.4 Summary

This chapter has described two studies conducted to validate that the content developed for EDUCE reflected the principles of MI and to evaluate the performance of the predictive engine. The content validation study confirmed, using two MI experts, that the different categories of MI resources activated the relevant intelligence. The results from the study evaluating the performance of the predictive engine confirm that it is possible to model learning characteristics and predict the student's preferred resource to a reasonable level of probability. The studies indicate that if a student selects a particular resource category, it is indicative of their interest in that particular intelligence category. They also indicate that by observing past selections it is possible to predict future selections. The two studies together provide the empirical grounding for experimental studies that evaluate different pedagogical and adaptive presentation strategies.

6 Experimental Design

6.1 Introduction

EDUCE uses the MI theory as the educational theory with which to model individual traits. In addition, the predictive engine incorporated into EDUCE can dynamically determine the learner's profile and make predictions on what the resource the learner prefers. However the question that remains is in what way should the learning environment change for users with different learning characteristics?

To get some insight into how the learning environment should change empirical studies were conducted using EDUCE. These studies explored:

- The impact on learning performance when using different adaptive presentation strategies in contrast to giving the learner complete control over the learning environment
- The impact on learning performance when material is matched and mismatched with learning preferences

The following sections explain the experimental design and procedure (Kelly & Tangney, 2004a). Section 2 describes the experimental design and includes the definition of the independent and dependent variables. Section 3 describes the experimental procedure and the typical student experience of the experiment. Section 4 describes how tracking data for the participants is generated and how this information is processed to identify specific measurements that are indicative of individual traits. Section 5 describes the context in which two studies were conducted. The following chapter 7 presents and discusses in detail the results of these studies.

6.2 Experimental Design

In the design of adaptive systems, there is debate on where the locus of control between student and system should reside. Systems that facilitate student control assume that the learner knows best about how to construct their own learning experience. Adaptive systems are based on the premise that intelligent decisions can be made on behalf of the student by the computer to adapt and personalise the learning environment.

However, there are several issues with the concept of student control. Students need to learn how to make critical choices when self-matching to educational treatments. Students also need to distinguish between what they want and what they need (Glaser, 1977). Likewise with adaptivity and system control, there are issues around how best to adapt the learning environments. Individual traits can be viewed as characteristics or aptitudes that promote a student's performance in one kind of environment as opposed to another. With this approach the belief is that it is better to provide treatment that matches aptitude, an approach that is formalised in aptitude-treatment interaction (ATI) (Cronbach & Snow, 1977). An alternative belief is that the systematic alternation of educational approaches can develop a broad range of competency by increasing the flexibility of thinking and reducing the restrictiveness of habitual thinking (Entwhistle, 1982). It is still not clear whether it is better to match individual differences with instructional methods to optimise performance or mismatch to strengthen desirable style and broaden the potential range of competence (Sternberg, 1997).

In order to investigate the issues of matching versus mismatching and adaptivity versus learner control, two independent variables are defined: level of choice and presentation strategy. When looking at the definitions of these variables it is useful to remember that within each learning unit there are multiple MI based learning resources for the student to use.

The independent variable level of *choice* provides for four different levels of choice and adaptivity. These are:

- *Free* – student has the choice to view any resource in any order. No adaptive presentation decisions are made as the learner has complete control.
- *Adaptive Single* – student is only able to view one resource. This is adaptively determined by EDUCE based on an analysis of the static MI profile.
- *Adaptive Inventory* - student is first given one resource but has the option to go back and view alternative resources. The resource first given to the student is determined by EDUCE based on the analysis of the MI inventory completed by the student. The *Inventory* choice level is the same as the *Single* choice level but with the option of going back and viewing alternative resources.
- *Adaptive Dynamic* – the student is first given one resource but has the option to go back and view alternative resources. The resource first given to the student is determined by using the dynamic MI profile that is continuously updated based on

the student's behaviour. The predictive engine within EDUCE identifies the most preferred and least preferred resource from the online student computer interaction.

Four different versions of EDUCE correspond to the four different levels of choice. The single, inventory and dynamic versions can be considered as adaptive systems as the system takes the initiative in deciding which resource to present.

The independent variable *presentation strategy* encompasses two main strategies for delivering material. These strategies are:

- *Most preferred*: - showing resources the student prefers to use or matching resources with preferences
- *Least preferred*: - showing resources the student least prefers to use or mismatching resources with preferences.

The presentation strategy, using the dynamic and static MI profiles, determines which resource is shown first to the student.

Experiments were designed in such a manner to explore the effect of different adaptive presentation strategies and to determine the impact on learning performance when resources were matched with preferences. In particular they were set up to explore the impact of the two independent variables, presentation strategy and level of choice, on the dependent variable, learning performance.

The dependent variable *learning performance* is defined by the learning gain and learning activity:

- The learning gain, or more specifically the relative learning gain, is the percentage improvement of the post-test score on the pre-test score. Each student sits the pre-test and post-test before and after the tutorial. The pre-test and post-test consist of the same 10 multi-choice questions, which are mostly factual questions. These questions also appear throughout the tutorial.
- Learning activity is a measure of the interest in exploring different learning resources. It is determined by the navigation profile, the number of the different panels visited and the number of different resources used. Three categories are defined for activity level: low, medium and high. The cut points for each category are determined by dividing students into three equal groups based on their activity level.

Learning activity is analysed to provide informed explanations on learning gain. The influence of other variables such as dominant intelligence is also examined. The dominant intelligence is the highest-ranking intelligence as determined by the MIDAS inventory. Table 6-1 summarises the variables used in the study and their values.

In addition, the original design of EDUCE incorporates a rich set of links to support non-linear learning. These links include navigation options that are provided through a main menu and a section menu. Through these menus students have the opportunity to move from one concept to next according to their learning strategy and goal. However, the purpose of the experimental design is to evaluate presentation strategy with different learner and adaptive controlled environments. Thus, links were disabled to ensure that students progressed in a linear manner through the content. As a result, students can only navigate to different MI resources and go back or forward. This restricted navigation path makes it possible to observe students making decisions about which MI resource to use and examine the effect in isolation.

Table 6-1: Variables used and their values

<i>Variable</i>	<i>Value</i>
Presentation Strategy	Least Preferred, Most Preferred
Choice Level	Free, Adaptive Single, Adaptive Inventory, Adaptive Dynamic
Relative Learning Gain	(Post test score-pre test score)/pre test score
Activity Level	% of resources used
Activity Groups	Low, Medium and High Activity
Dominant Intelligence	Highest ranking intelligence as recorded by MIDAS Inventory

6.3 Experimental Procedure

For each student the experiment will consist of 4 sessions of approximately 25 minutes. The sessions are as follows:

Table 6-2: Different sessions in the experiment

Session 1	Session 2 Tutorial Sitting 1	Session 3 Tutorial Sitting 2	Session 4
MI concept introduced, students complete the MIDAS Inventory and questions on background	Computer based tutorial on the topic of “Static Electricity” or “Electricity in the home”	Computer based tutorial on the topic of “Electricity in the Home” or “Static Electricity”	Reflection on MI profile created.

The sessions are conducted over three or four days. In Session-1, students are introduced to the MI concept and complete the MIDAS MI Inventory. In Session-2, students explore one tutorial on electricity. Before the session, the students are given a 2 minute induction on how to navigate through EDUCE. The session is preceded by a pre-test and followed by a post-test. The pre-test and post-test have the same 10 multi-choice questions. Session-3 repeats the same format as Session-2, except that the student explores a different tutorial. Session-2 and Session-3 are conducted on different days. During Session-2 and Session-3, the groups using the adaptive versions receive the most preferred and least preferred presentation strategies on different days. In Session-4 students are asked to reflect on their experiences and their MI profile. This session was recorded by video camera or audio tape.

Students are randomly assigned to one of the four groups defined by the levels of choice. Students assigned to the *free* group experience the same learning environment during Session-2 and Session-3, however the tutorial content is different. Different students use the “Static Electricity” (ELE-STA) tutorial first, while others use the “Electricity in the Home” (ELE-HOME) tutorial. Students assigned to the adaptive versions experience both presentation strategies of least preferred (LEAST) and most preferred (MOST). Some students receive the least preferred presentation strategy first, whilst others received the most preferred presentation strategy. To ensure order effects are balanced out, students are also assigned to systematically varying sequence of conditions. The design of the experiment can be described as a mixed between/within subject design with counterbalance (Mitchell & Jolley, 2004).

Figure 6-1 illustrates how for the adaptive dynamic group students are assigned to systematically varying sequence of conditions.

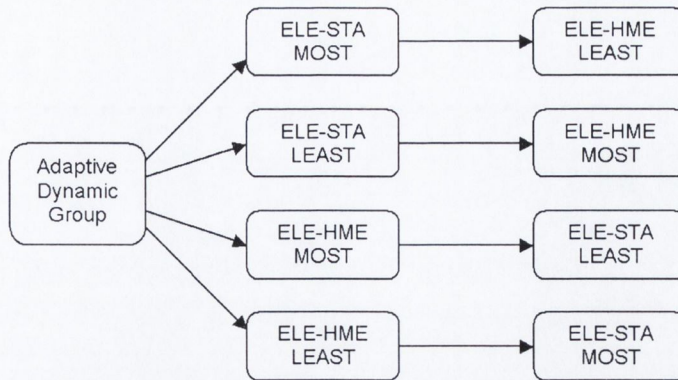


Figure 6-1 Systematic varying sequence of conditions for 4 groups of students in the adaptive *dynamic* group.

6.4 Tracking Data

As students interact with EDUCE tracking data is generated. This section describes how this data is processed in order to identify specific measurements that are indicative of individual traits. It describes how participant background is elicited and how the dominant intelligence is identified using the MIDAS inventory. It also identifies how the relative gain, activity level, activity groups and engagement is calculated.

6.4.1 Participant Background

At beginning of session 1, participants were asked several questions on their background. These questions included:

- Age ?
- Male/Female ?
- Do you have a computer at home ? Yes/No
- Do you use the internet ? Yes/No
- Do you play games on the computer ? Yes/No
- Have you studied electricity in school ? Yes/No

6.4.2 MIDAS MI Profile

The MIDAS inventory, previously described in chapter 3, is used to determine a student's preferences and aptitudes for the different intelligences. The inventory itself consists of 93 questions. A sample question is illustrated in Figure 6-2. It is completed after a student logs in for the first time.

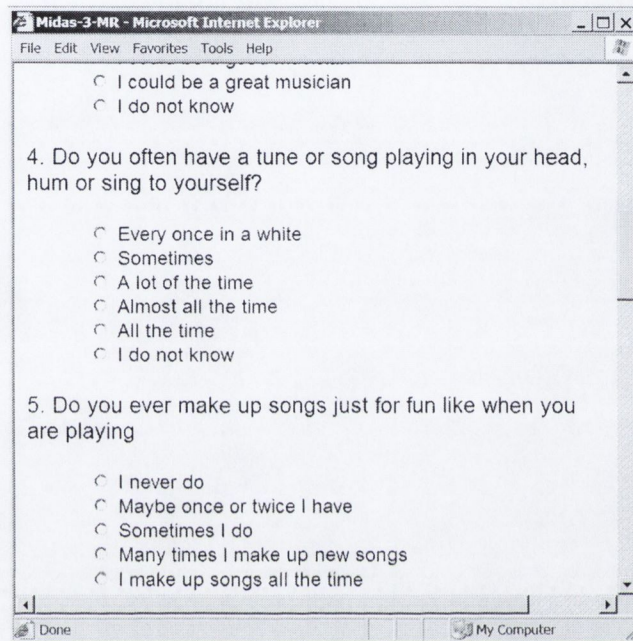


Figure 6-2: MIDAS questions online

From the responses entered, a MI profile is generated using the scoring engine that comes as part of the MIDAS inventory. From this MI profile, the dominant intelligence or highest-ranking intelligence is identified.

6.4.3 Relative Gain

The relative learning gain is the percentage improvement of the post-test score on the pre-test score. Before and after each tutorial, students sit a pre-test and post-test. The test consists of 10 multi-choice questions, each question with four options. Figure 6-3 illustrates a sample question from the pre-test. The relative gain is calculated by subtracting the pre-test score from the post-test score and dividing by the pre-test score.

$$\text{Relative Learning Gain} = \frac{(\text{Post Test Score} - \text{Pre Test Score})}{\text{Pre Test Score}} \times 100$$

The calculation of the relative gain allows for the influence of the pre-test score to be taken into account when analysing learning performance.

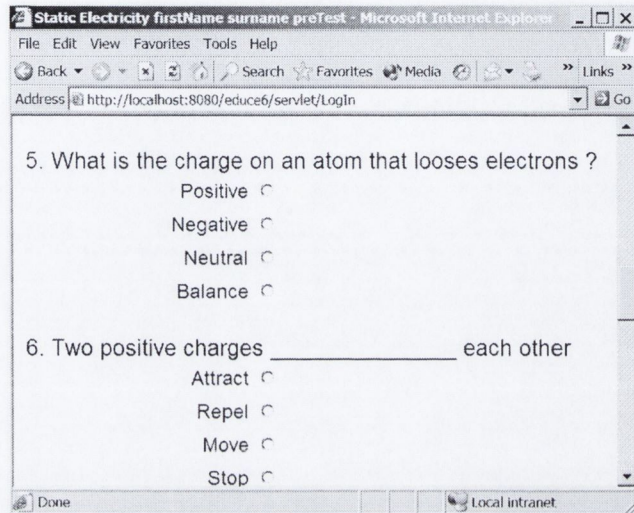


Figure 6-3: Sample question from pre-test

6.4.4 Activity Level and Activity Groups

Learning activity is used as a measure of the interest in exploring different learning resources. Each time, a learner generates an event such as navigating to a screen or pressing a button, the event is logged with a time-stamp. From these events, it is possible to calculate the number of times each type of MI resources is used and the percentage of all MI resources used.

Figure 6-4 illustrates how a student can access one of four different MI resources during a learning unit on static electricity. In total, the ELE-STA tutorial contains 14 learning units and, as each learning unit contains four MI resources, a total of 56 MI resources. The ELE-HOME tutorial contains 16 learning units and 64 MI resources. Students can navigate to a minimum of one and a maximum of four resources in each unit.

For example, in the ELE-STA tutorial a student may use 28 resources, or 2 per unit, which would give an activity level of 50 % ($26/58=.5$). It was observed that some

students randomly selected a resource and moved on quickly without studying or using it. To prevent this navigation behaviour from influencing the results, all resources used for less than 2 seconds were not included in calculations.

Three categories are defined for the activity level: low, medium and high. The cut points for each category were determined by dividing students into three equal groups based on their activity level. The activity level is considered as an indicator of the general interest in exploring different MI resources.

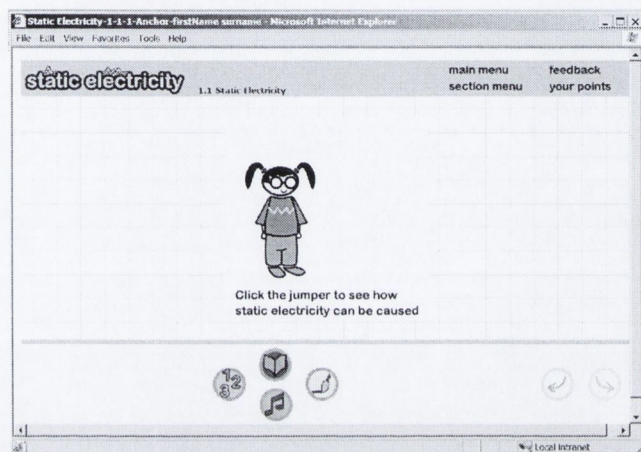


Figure 6-4: A choice of four different MI resources during a learning unit

6.4.5 Categories of Resources

In addition to the overall activity level, the preference for each intelligence category is also identified. This is obtained by keeping count of the number of resources used in each intelligence category across all the learning units. For example, a student in the ELE-HOME tutorial may have used 4 VL, 4 LM, 8 VS and 12 MR resources. As there is a maximum of 16 resources for each category in this tutorial, the profiles of resources used would be 25 % VL, 25 % LM, 50 % VS, 75 % MR, as illustrated in Table 6-3.

Table 6-3: Profile of resources used in a session

Resources Used	VL	LM	VS	MR
Count	4	4	8	12
%	25	25	50	75

From these profiles it is possible to analyse, both on the individual and group level, which resources are preferred and not preferred by different students. Also recorded was the amount of time spent with each resource category. The profile of resources used is considered as an indicator of the learner's interest in different MI resource types.

6.4.6 Qualitative Feedback

Qualitative feedback was received from students in order to determine perceptions and preferences. Feedback was received at a number of points during the experiment. These included:

1. At the end of each learning unit where students were asked:
 - Which option helps them remember most and why?
 - Which option do they prefer and why?
2. At the end of the tutorial sessions where students were asked to reflect on:
 - What were the differences between the options?
 - After going to your favourite choice did you try other options?
3. After both tutorial sessions, when a verbal feedback session took place and students were asked questions such as:
 - Which option do they prefer and why?
 - Which option did they remember and why?
 - If they had to choose only one option, which one would it be?
 - What are the differences between the icons?
 - What was the best part of the sessions on the computer?

This session was recorded either by video or mini-disc.

6.5 Participants

Two studies were conducted with EDUCE, in order to explore how the learning environment should change for users with different characteristics.

In Study 1, 70 boys and girls participated in the study. The ages ranged from 12 to 17, with an average age of 14. The students were participating in a "Discovering University"

programme being run in the author's place of work. The objective of the programme was to give students the experience of third level education and to encourage them to continue education in university. The students attending this programme would primarily be from areas designated as disadvantaged in terms of the number of students who participate in third level education. The study itself was conducted in the computer laboratories in the college and took place within the 'Computer' sessions on the Discovering University programme. No reward incentives were provided to the students who participated.

In Study 2, 47 boys from one mixed ability school participated in the study. The ages ranged from 12 to 14 with an average age of 13. The study was conducted as part of normal class time and integrated into the daily school curriculum. No reward incentives were provided to the students who participated.

6.6 Summary

Two studies were conducted with EDUCE, in order to explore how the learning environment, and in particular the presentation of content, should change for users with different characteristics. The first study explored the differences between dynamic adaptive and free learner control. The second study explored the differences between the different variations in adaptive control. With the first study the *free* and adaptive *dynamic* versions of EDUCE were used, and with the second study the adaptive *single*, *inventory* and *dynamic* versions were used. In both studies, students using the adaptive versions received the least and most preferred presentation strategies in different sessions.

The two studies together provided insights into how an adaptive educational system can best adapt the learning environment to individual learning traits. The following chapter 7 will present and discuss in detail the results of these studies.

7 Results

7.1 Introduction

Adaptive Educational Systems, having diagnosed learning traits, need to make pedagogical decisions on how best to adapt the learning environment. This chapter describes the results of two empirical studies conducted with EDUCE that explore how the learning environment, and in particular the presentation of content, should change for users with different characteristics. Using quantitative and qualitative methods, the results were analysed to explore the following research questions:

- The effect of the independent variables, choice (learner and adaptive) and presentation strategy, on learning performance
- The relationship between learning activity or number of MI resources used and performance
- The relationship between the MI Profile, as determined by the MIDAS inventory, and performance
- The relationship between the MIDAS results and observable behaviour when choosing resources
- The relationship between the particular MI resources used and performance

The goal of the quantitative and qualitative analysis was to evaluate the hypotheses that:

- Providing content with the preferred presentation strategy would improve performance
- Adaptive control, with diagnosis of traits based on observable behaviour, would improve performance more than other forms of adaptive control and learner control
- High level of MI resource use and learning activity would improve performance

The results of the analysis confirmed some of these hypotheses but some surprising results were also revealed. The following sections will present and discuss these results. Firstly, section 7.2 presents the results of the study that investigated the differences between adaptive and learner control on learning performance. Secondly, section 7.3 presents the results of the study that investigated the differences between different types

of adaptive control on learning performance (Kelly & Tangney, 2005a, 2005c). Both studies also investigated the relationship between matching/mismatching student preferences to learning resources and learning performance. Finally, section 7.4 discusses the results of the two studies together and concludes with recommendations on how Adaptive Educational Systems could adapt the learning environment to individual traits.

7.2 Study A: Adaptive Dynamic versus Learner Control

In Study A, 70 students (33 boys and 37 girls) participated in the study. The ages ranged from 12 to 17, with an average age of 14. The students were participating in a "Discovering University" programme and took place in June 2004. The objective of the programme was to give students an experience of third level education and to encourage them to continue education in university. The students attending this programme would primarily be from areas designated as disadvantaged in terms of the number of students who participate in third level education. The study itself was conducted in the computer laboratories within the college and took place within the 'Computer' sessions on the Discovering University programme. No reward incentives were provided to the students who participated.

In this study, two versions of EDUCE were used:

- *Free*: student has the choice to view any resource in any order. No adaptive presentation decisions are made as the learner has complete control.
- *Adaptive Dynamic* – the student is first given one resource but has the option to go back and view alternative resources. The resource first given to the student is determined by using the dynamic MI profile that is continuously updated based on the student's behaviour. The predictive engine within EDUCE identifies the most preferred and least preferred resource from the online student computer interaction.

The two versions correspond to the two values (free and adaptive dynamic) of the *choice* independent variable. Students were randomly assigned to one of the two versions. 39 students (18 boys and 21 girls) were assigned to the free version and 31 students (15 boys and 16 girls) were assigned to the dynamic version. Each student sat through two tutorials. The students using the dynamic version experienced both least and most preferred presentation strategies in different tutorials. The students using the free version experienced two different tutorials in which they had complete learner

control and were free to navigate to any resources. A summary of the analysis is provided in Table 7-1.

Table 7-1: Summary of analysis for Study 1

Analysis	Conclusion
Independent variables: choice and presentation strategy	Higher learning performance (relative learning gain) when adaptively presented with resources not preferred
Learning Activity	High activity levels or use of MI resources correlate with higher post-test scores
Learning Activity	Students in adaptive group with medium activity levels had larger increases in learning gain with the least preferred presentation strategy
Time on Task	Time-on task using MI resources correlated with activity level and no additional insights provided
MI Profile	MI Profiles did not influence post-test scores
MIDAS Results vs. Behaviour	For students with LM, VS and MR profiles, their preferred resource matches results of MIDAS inventory
Resources Used	For Free group, high use of VL resources and low use of MR resources result in greater post-test scores. For adaptive group, high use of VL resources results in greater post-test scores, nothing conclusive to say about use of MR resources.

7.2.1 Influence of Different Tutorials

The design of the experiment involved each student sitting through two tutorials, one tutorial on Static Electricity (ELE-STA), the other on Electricity in the home (ELE-HOME). Some sat through the ELE-STA tutorial first, others the ELE-HOME tutorial. Analysis was conducted to determine if the tutorials were at the same level of difficulty.

A paired-samples t-test was conducted to compare the post-test and relative gain scores of the ELE-STA and ELE-HOME tutorials for all students. There was no significant difference in the post-test scores for the ELE-STA ($M=56.57$, $SD=23.77$) and ELE-HOME ($M=55.86$, $SD=21.77$) tutorials. There was also no significant difference in the relative gain scores for the ELE-STA ($M=70.1$, $SD=109.7$) and ELE-HOME ($M=47.36$, $SD=76.93$) tutorials. The results suggest that both tutorials were at a comparable level of difficulty.

7.2.2 Choice and presentation strategy

The results were analysed to compare the effect of different adaptive presentation strategies in contrast to giving the learner complete control over the learning environment. It was expected that students would have greater learning gain with adaptive presentation strategies than with free learner control, and in particular when adaptively guided to resources they preferred.

Each student sat through two tutorials on the computer designated as Tutorial Sitting 1 and Tutorial Sitting 2. Different students would experience a different tutorial and presentation strategy at each tutorial sitting. Note that for each tutorial sitting there are three groups. Group 1 receives the free version and have complete learner control, Group 2 is adaptively guided to resources they prefer and Group 3 is adaptively guided to resources they do not prefer.

Two sets of analysis were conducted. First, to explore the effects of the two independent variables, choice and presentation strategy, a one-way ANOVA was conducted to compare the post-test and relative gain scores for each tutorial sitting. Second, as each student in the adaptive group experiences both least and most preferred presentation strategies at different tutorial sittings, a paired samples t-test was conducted to investigate the effect of presentation strategy on post-test and relative gain scores.

7.2.2.1 Choice/Presentation Strategy for All Groups

For the post-test scores at Tutorial Sitting 1, there was no statistically significant difference at the $p < .05$ level for the three groups. At Tutorial Sitting 2, there was a statistically significant difference: $F = (2, 67) 4.175$, $p = .02$ between Group 1 and Group 2. Post-hoc comparisons using the Tukey HSD test indicated that the mean score for Group 2 ($M = 70.7$, $SD = 15.8$) was significantly different from Group 1 ($M = 53.3$, $SD = 22.4$). The post-test scores for Tutorial Sitting 1 and Tutorial Sitting 2 are displayed in Table 7-2. At Tutorial Sitting 2, the mean score for Group 2 was greater than the score for Group 3 which was in turn greater than the mean scorer for Group 1. In contrast, at Tutorial Sitting 1, the mean score for Group 3 was greater than that for Group 2 with both having means greater than Group 1.

On evaluating the post-test scores, the results for Tutorial Sitting 1 and 2 appear contradictory. In both sittings, adaptive presentation strategies in place of complete learner control result in higher performance, but in each sitting it is a different

presentation strategy. The results for Tutorial Sitting 1 suggest that students who are adaptively guided to resources they do not prefer achieve higher post-test scores. In contrast, the results for Tutorial Sitting 2 suggest that students who adaptively guided to resources they prefer achieve higher scores.

On analysing the relative gain scores, there was no statistically significant difference at the $p < .05$ level for the three groups at both tutorial sittings. The relative gain scores for Tutorial Sitting 1 and 2 are displayed in Table 7-3. It can be observed that a pattern appears for both sittings, with the mean score for Group 3 being greater than the score for Group 2 which in turn is greater than the mean score for Group 1.

The relative gain scores suggest that adaptive presentation strategies result in higher scores than free learner control. The pattern that emerges in the results, somewhat surprisingly, suggests that students achieve the greater relative gain when adaptively presented with resources they do not prefer.

Table 7-2: Post-Test for free and adaptive (least/most) presentation strategies

Group – Choice	Post-Test: Tutorial Sitting 1			Post-Test: Tutorial Sitting 2		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
1. Free	53.33	22.39	39	52.30	20.32	39
2. Dynamic: Adaptive Most	53.75	25.00	16	70.67	15.80	15
3. Dynamic: Adaptive Least	61.33	25.87	15	56.87	26.00	16
Total	55.14	23.64	70	57.25	21.86	70

Table 7-3: Relative Gain for free and adaptive (least/most) presentation strategies

Group – Choice	Relative Gain: Tutorial Sitting 1			Relative Gain: Tutorial Sitting 2		
	Mean	Std. Dev.	N	Mean	Std. Dev.	N
1. Free	46.02	76.28	39	59.70	91.94	39
2. Dynamic: Adaptive Most	50.21	75.95	16	61.95	43.82	15
3. Dynamic: Adaptive Least	68.54	103.18	15	84.79	167.94	16
Total	51.56	81.62	70	65.91	106.23	70

7.2.2.2 Presentation Strategy and the Adaptive Group

Since each student in the adaptive group experienced both least and most preferred presentation strategies at different tutorial sittings, it is possible to analyse the impact, within subject, of presentation strategy on learning performance. A paired samples t-test was conducted to investigate the effect of presentation strategy on post-test and relative gain scores in the adaptive dynamic group.

The analysis revealed no statistically significant difference for post-test and relative gain scores using different presentation strategies. However, it is interesting to note, as shown in Figure 7-1, that the relative gain for the least preferred presentation strategy ($M=77.2$, $SD=139.6$) was greater than that for the most preferred presentation strategy ($M=55.5$, $SD=62.8$). The results suggest that students achieve higher learning performance when presented with resources they do not prefer.

The results together suggest that higher learning performance is achieved when students are adaptively presented with resources they do not prefer. Despite there being no significant difference in the post-test scores, the relative gain scores suggest that, within-subject, students achieve higher performance when presented with resources they do not prefer.

7.2.3 Learning activity

To investigate the reasons for the differences in learning gain, the learning activity and the number of resources used was analysed. The purpose of this analysis was to explore if students using a large variety of resources had the same learning gain as students who used only a minimum. Analysis was conducted for the adaptive and free groups separately.

7.2.3.1 Adaptive Group

The learning activity of the adaptive group was analysed to investigate the reasons for the difference in learning gain between the least and most preferred presentation strategies. It was expected that the activity level would increase with the least preferred presentation strategy as students would move to more preferred resources, and that higher learning activity would result in increased learning gain for all students.

Presentation Strategy and Relative Gain: Adaptive Dynamic Group

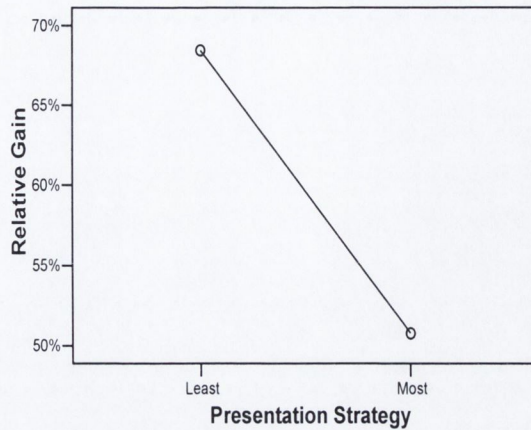


Figure 7-1: Presentation Strategy and Relative Gain: Adaptive Dynamic Group

The overall activity level was first calculated as the average of the resources used with the least and most preferred presentation strategies. Three categories were defined for activity level: low, medium and high. The cut points for each category were determined by dividing students into three equal groups based on their activity level. Table 7-4 displays the cut points for the different groups.

Typically, a student in the low activity group would look at less than one resource per learning unit (a student needs to use a resource more than 2 seconds for it to be included in the calculations, 2 seconds was chosen as in experimental studies it provided the optimal accuracy for the predictive engine), a student in the medium activity group would on average look at one resource per unit and a student in the high activity group would on average look at between one and two resources per unit.

Table 7-4: Activity Groups

Activity Group	Cut-Points	Average	Resources used per learning unit
Low	≤ 22	19	Less than one resource
Medium	> 22 and ≤ 26	25	One resource
High	> 26	31	Between 1 and 2 resources

First, to explore the effect of activity level and presentation strategy on post-test score a two way mixed between-within ANOVA was conducted. There was no statistically significant main effect for presentation strategy or for the interaction between presentation strategy and activity level. However, there was a significant between-subject effect for activity level: $F=3.718 (2, 28)$, $p=.037$, partial eta squared = .21. Figure 7-2 illustrates this effect and shows how students with high and medium activity levels obtained the highest scores in both the least and most preferred sitting. It suggests that learners who are interested in exploring different learning options achieve higher post-test scores.

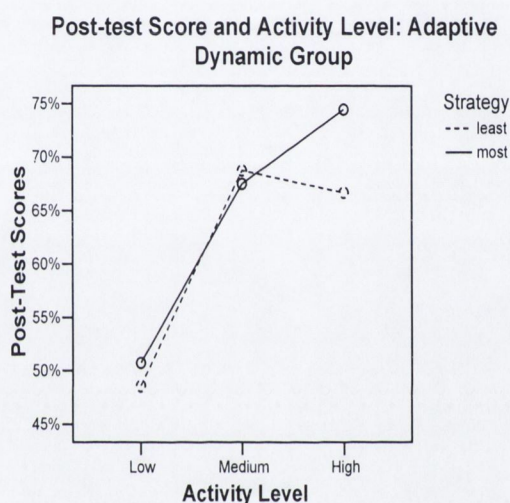


Figure 7-2: Activity Groups and Post-test Scores: Adaptive Dynamic Group

Second, to explore the effect of activity level and presentation strategy on relative gain a two way mixed between-within ANOVA was conducted. The means and standard deviations of the relative gain scores are presented in Table 7-5. There was not a significant within-subject main effect for presentation strategy. However, there was a within-subject interaction effect between presentation strategy and activity level: Wilks Lambda: 0.619, $F = 8.309 (2, 27)$, $p = 0.002$, partial eta squared=0.381. There was also a significant between-subject effect for activity level: $F=6.817 (2, 270)$, $p=0.004$, partial eta squared=0.336.

The within-subject interaction effect and between-subject effect was primarily due to the fact that medium activity learners had a higher relative gain at the least preferred sitting than at the most preferred sitting. This was in contrast to low and high activity learners who achieved a slightly higher learning gain at the most preferred sitting.

Figure 7-3 plots the relative gain for the different activity groups with the least and most preferred presentation strategy. It shows how students with medium activity have higher relative learning gain when given least preferred resources. Students with low and high activity have the slightly higher relative gain in the most preferred conditions. The results indicate that students with medium learning activity levels benefit most when they are encouraged to use resources not normally used or preferred.

Finally, analysis was also conducted to determine if presentation strategy had an impact on learning activity for the different activity groups. Figure 7-4 shows how activity levels remain similar with both the least and most preferred presentation strategies, with a slight decrease in learning activity in the most preferred condition. It suggests the presentation strategy did not influence learning activity and that the difference in learning gain for medium activity learners may be dependent on the type and variety of resource provided.

The results indicate that the presentation strategy had a different effect for students with different levels of activity. Students with high and low activity levels were not influenced by presentation strategy. In contrast, the presentation strategy had a significant impact on medium activity students, who had larger increases in learning gain when encouraged to use resources not normally preferred.

Table 7-5: Relative gain for different activity groups

Activity	Rel. Gain in Least Condition		Rel. Gain in Most Condition		N
	Mean	Std. Dev.	Mean	Std. Dev.	
Low	19.62	58.17	32.44	67.81	13
Medium	220.83	196.14	58.75	30.22	8
High	32.72	60.50	86.03	68.36	9
Total	77.21	139.56	55.53	62.80	30

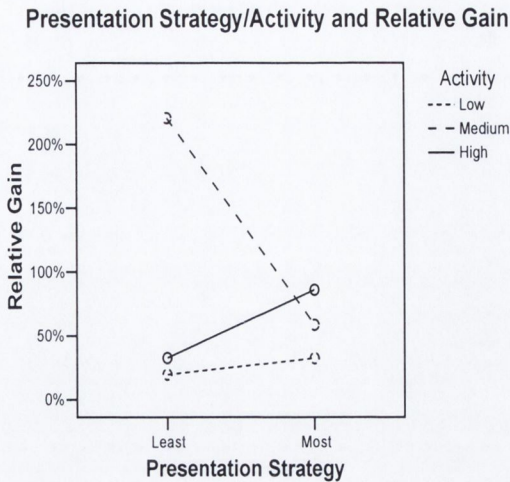


Figure 7-3: Relative gain for different groups in least/most preferred conditions

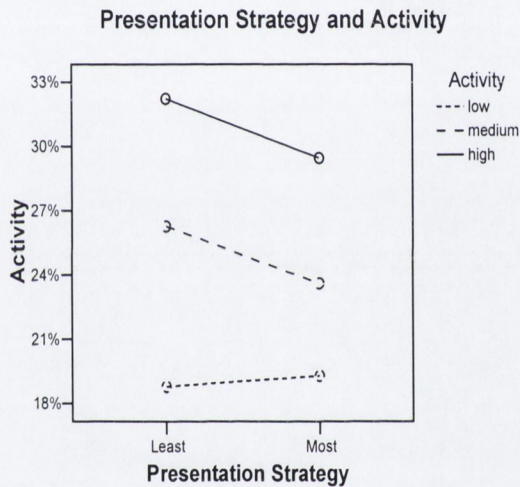


Figure 7-4 Activity and least/most presentation strategy for different activity groups

7.2.3.2 Free Group

Activity levels in the free group were also analysed to determine the relationship between activity and learning performance. Students were divided into three groups: low, middle and high, based on their average activity level over the two sittings. A one-way ANOVA was conducted to explore the impact of activity level on post-test score and relative gain score. However, no significant differences were found between the activity

groups. A paired-samples t-test was also conducted to compare the activity level between the first sitting and the second sitting. Again, no significant difference was found.

Together the results for the adaptive group and the free group suggest that the presentation strategy had a different effect for students with different levels of activity. It appears that students with medium activity levels had larger increases in learning gain when encouraged to use resources not normally preferred. The implications are that students with certain types of learning characteristics have the most to benefit from adaptive presentation strategies.

7.2.4 Time-on-Task

To determine if learning performance was related to the time spent using resources, analysis was conducted on both the time spent using each MI category of resources and the total time spent using all MI resources. For the complete tutorials, students spent an average of 17 minutes on each tutorial, with a total of 34 minutes over the two tutorials

First, the time spent using each MI category was analysed. For each category, the time spent on resources was correlated with the activity level (number of resources used) at $p < 0.01$ level. As a result, the analysis of time spent on resources did not provide any additional insights proved by the analysis of activity level and learning performance.

Next, the total time spent using MI resources was analysed. Interestingly, when conducting a paired-samples t-test, it was found that the free group spent significantly more time, $p < 0.05$, on MI resources during the second tutorial sitting ($M=338.53$, $SD=198.1$) than on the first tutorial sitting ($M=277.69$, $SD=182.83$). The result suggests that students spent more time using MI resources at the second tutorial sitting.

For the adaptive group there was no difference in time between the sittings with the least preferred ($M=245.1$ & $SD=118.83$) and most preferred ($M=239.13$ & $SD=153.58$) presentation strategy. This suggests that the adaptive presentation strategy had no substantial impact in the time spent on resources.

Analysing the time spent on MI resources over the 2 days, it was found that the free group ($M=616.23$, $SD=343.33$) spent more on time MI resources than the adaptive group ($M=484.22$, $SD=223.45$). This results suggests that adaptivity reduces time spent on MI resources, which is interesting given the fact that despite the less time spent, the learning performance is comparable.

The results together suggest that time-on-task did not provide any additional insights into differences in learning performance. However, it is interesting to note that the free group spent more time on MI resources than the adaptive group, however this did not reach statistical significance.

7.2.5 Students with Medium Activity Levels

On using quantitative analysis techniques, it was found that students with medium activity levels had higher learning performance when guided to resources they least preferred. A deep analysis was performed on this group of students to help identify reasons for this surprising behaviour. As part of this analysis, differences between the least and most preferred strategies in the number and range of resources used were assessed. Also evaluated, was the qualitative feedback from several students in this group.

First, the number of resources used or activity level was analysed. It was found that the activity level with the least preferred strategy (29.38 %) was greater than with the most preferred strategy (23.25 %). Students used more resources with the least preferred strategy than with the most preferred strategy. It suggests that the least preferred strategy encouraged students to use more resources.

Next, the range and spread of resources used was evaluated. Table 7-6 illustrates the average use of resources and indicates that this group of students used all categories of resources and not just one type. UseVL is the percentage of VL resources used and AvUseVL is the average of UseVL for all students.

Table 7-6: Average use of resources in the different MI Categories

	AvUseVL	AvUseLM	AvUseVS	AvUseMR
Least Preferred Strategy	29	31	25	32
Most Preferred Strategy	18	26	18	32

The range was found by calculating for each student the Euclidean distance between their use of resources and the average use of resources by all students.

$$\text{Distance} = \text{ABS} (\text{UseVL}-\text{AvUseVL}) + \text{ABS} (\text{UseLM}-\text{AvUseLM}) \\ + \text{ABS} (\text{UseVS}-\text{AvUseVS}) + \text{ABS} (\text{UseMR}-\text{AvUseMR})$$

If the distance between the student's use of resources and the average is great, it indicates that some categories of resources were not used very much and other categories were used greatly. This suggests that the range of resources used is not very wide. In contrast, if the distance between the use of resources and the average is small, it suggests that all categories of resources are used as each resource is used at close to the average level. On calculating the distance, it was found that the range of resources used with the least preferred strategy was greater than with the most preferred strategy. It suggests that students used a greater variety of resources with the least preferred strategy.

The qualitative feedback from the four students with the maximum gain with the least preferred strategy was next explored. The four students are labelled Student A, B, C and D. Qualitative feedback was received from the students by asking for feedback at the end of each learning unit. Students were asked which option helps them remember most and why. Also, at the end of the entire session, students were asked to reflect on a number of questions such as

- What were the differences between the options?
- After going to your favourite choice did you try other options?

Student A

Student A mainly used the MR resource category with the most preferred presentation strategy. Table 7-7 illustrates how 93 % of MR resources were used. The feedback given was also very positive about MR.

- "I preferred the music because i like music and the art helps you learn because its more visual"
- "because it (MR) is funny"

This feedback matches the results from the MIDAS inventory where the two most preferred intelligences were VS and MR (which was also at the same level as LM).

In contrast the range of resources used with the least preferred presentation strategy increases. Table 7-7 illustrates how the MR category is used less and other categories are used more. Interestingly despite using a wider range of resources, the student when asked which resource he preferred typically answered that MR was the preferred resource.

The results suggest that the least preferred presentation strategy encouraged the student to use a broader range of resources in addition to the preferred MR and that using a broader range of resources resulted in greater learning performance.

Table 7-7: Use of MI resource categories for Student A

	UseVL	UseLM	UseVS	UseMR
Most Preferred Strategy	7	14	14	93
Least Preferred Strategy	23	15	23	15

Student B

With the most preferred presentation strategy, Student B was guided mainly to VL resources. In addition to using primarily the VL resource category, the student also used a number of MR resources. However, when asked what did she remember and prefer, the feedback only mentioned the MR and VS resources.

- “because i love music and i love drawings or painting”
- “because I learn better that way (VS, MR)”

This feedback matches the results from the MIDAS inventory where the two most preferred intelligences were VS and MR.

With the least preferred strategy, the learning activity and range of used resources increased. As illustrated in

Table 7-8, more LM, VS and MR resources were used with the least preferred strategy. However, despite using a broader range of resources, the student still used MR resources more than any other resource and identified MR as her favorite as indicated by the comments:

- “because i love music and it helps me because i am deslexic”
- “because I like music the best”

The feedback suggests that regardless of the strategy used, the student identified MR resources as the preferred resource. It appears that the effect of the least preferred presentation strategy was to increase learning activity and encourage the student to explore a broader range of resources, which resulted in greater learning performance.

Table 7-8 Use of MI resource categories for Student B

	UseVL	UseLM	UseVS	UseMR
Most Preferred Strategy	36	14	14	21
Least Preferred Strategy	23	23	31	46

Student C

With the most preferred presentation strategy, Student C used only the one resource type, the VL resource category. He did not bother to explore any other resource categories. The feedback given when asked what did he prefer highlighted VL as the preferred resource type. This feedback matches the results from the MIDAS inventory where the most preferred intelligence was VL.

With the least preferred strategy, the learning activity and range of used resources increased. As illustrated in

Table 7-9, more LM and MR resources were used with the least preferred strategy. The feedback received, during this strategy, indicated that MR was the preferred resource type.

Again, it appears that the effect of the least preferred presentation strategy was to increase learning activity and encourage the student to explore a broader range of resources, resulting in greater learning performance.

Table 7-9 Use of MI resource categories for Student C

	UseVL	UseLM	UseVS	UseMR
Most Preferred Strategy	50	0	0	0
Least Preferred Strategy	50	50	0	50

Student D

With the most preferred strategy, Student D used mostly the one resource type, the VL resource type. However, the feedback given on preferences, mentioned in particular VS resources:

- For VS: 'its very colourful'

With the least preferred strategy, the learning activity and range of used resources increased. As illustrated in Table 7-10, more VL, LM, VS and MR resources were used with the least preferred strategy. The feedback received, during this strategy, indicated different resources as the preferred resource type:

- On MR resources: ‘because i learn more from listening’
- On VL: ‘i learned a bit from reading’
- On VS: ‘it helps me remember best’

The comments indicate that the student learns from a variety of approaches. The results also suggest that the effect of the least preferred presentation strategy is to encourage greater use of different resources types and increase learning activity.

Table 7-10 Use of MI resource categories for Student D

	UseVL	UseLM	UseVS	UseMR
Most Preferred Strategy	50	0	21	14
Least Preferred Strategy	31	23	38	31

Altogether, the results suggest that this group of learners have aptitudes for a broad range of resources. They suggest that, using the least preferred presentation strategy, it is possible to encourage students to experiment with different options and increase learning activity. It seems that that encouraging students to step outside habitual preferences and promoting a broader range of thinking maybe a strategy for increasing learning performance.

7.2.6 MI Profile and Performance

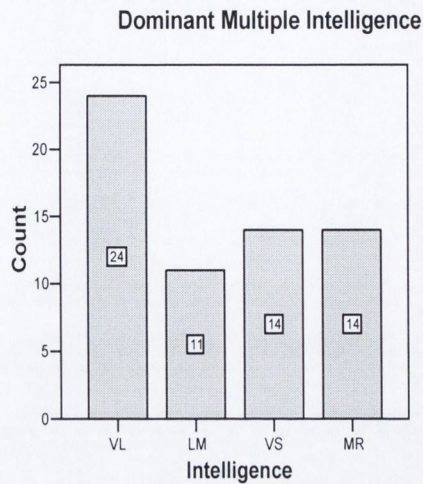


Figure 7-5: Highest ranking intelligence for students

As part of the study, all students completed the MIDAS inventory to determine their MI profile and highest-ranking intelligence. For the 63 students who completed the inventory (7 students did not) the results were: Verbal/Linguistic 24 students, Logical/Mathematical 11, Visual/Spatial 14 and Musical/Rhythmic 14 students, as illustrated in Figure 7-5. The results were next analysed to determine if students of a particular MI profile had greater learning performance than other MI profiles. It was expected that due to the nature of the post-test (multi-choice questions) that verbal linguistic students would have higher scores.

A one-way ANOVA was first conducted to explore the impact of highest-ranking intelligence on average post-test score, average relative gain and activity level. The results were not statistically significant, for post-test score: $F(3, 59) = .404, p = .751$; for relative gain: $F(3, 58) = 1.062, p = .372$; for activity level: $F(3, 59) = .71, p = .55$. Table 7-11 displays the average post-test score and relative gain for each intelligence group.

VS students had a slightly higher post-test score than all other students. The results suggest that despite VS students doing slightly better, there was no significant difference for students with different MI profiles and that no conclusions could be drawn about the performance of students with different MI profiles on standard tests.

The results suggest students with particular MI profiles do not have higher learning performance. It also suggests that the post-test mechanism did not unfairly bias a

particular MI category and that other factors may explain the difference in learning performance.

Table 7-11: Average post-test score and relative gain for each intelligence group

Intelligence	N	Post-test	Std. Dev.	Relative Gain %	Std. Dev.
VL	24	55.4	19.1	61.4	87.4
LM	11	57.7	19.9	59.2	60.5
VS	14	59.3	21.0	74.5	57.4
MR	14	51.1	24.1	29.4	51.2
Total	63	55.7	20.6	56.7	69.8

7.2.7 MI Profile: MIDAS vs. Behaviour

The EDUCE environment allows for a comparison to be made between the results of the MIDAS inventory and the behaviour of students when choosing MI informed resources. To compare the MI profiles generated from the MIDAS inventory and observed behaviour, the resources used by different students in the free group were analysed. With this group, no adaptivity was provided and students were free to choose whatever resource they wished. On analysing the MIDAS inventory, the dominant intelligence for each student was identified:

- 12 students were Verbal/Linguistic (VL),
- 6 students were Logical/Mathematical (LM),
- 8 students were Visual/Spatial (VS) and
- 9 students were Musical/Rhythmic (MR).

The use of the four different resource types for each of these groups was compared, where 'use' of a resource is defined as the percentage of available resources used. Table 7-12 displays the average of the different resources used for each intelligence group. Figure 7-6 to Figure 7-9 display the statistics in graph form. The preference by each intelligence group for each resource category was as follows

- VL resources, used by the LM group the most, followed by the MR, VS and VL groups

- LM resources, used by the LM group the most, followed by VL, MR and VS groups
- VS resources, used by the VS group the most, followed by LM, VL and MR groups
- MR resources, used by the MR group the most, followed by VS, LM and VL groups

For LM, VS, MR groups, their preferred resources matched the results of the MIDAS inventory. For the VL group, their learning behaviour indicated that their preferred resource type was LM. It seems students identified as VL by the MIDAS inventory did not use VL resources more than any other resources. One reason for this could be the novelty factor associated with some of the other types of resources causing VL students to choose other types of resources.

In summary, students on average use the resource type that reflects their dominant intelligence greater than other students. This is the case with LM, VS and MR students, the exception being VL students. In general VL resources are the least popular with students, which suggests that to capture the attention of students, resources that engage other intelligences are needed.

Table 7-12: Use of Difference Resources by different MI groups

Dominant Intelligence	Mean			
	Use VL	Use LM	Use VS	Use MR
VL	10.8	21.0	21.4	29.5
LM	29.4	28.6	27.2	47.3
VS	11.4	9.6	29.4	53.6
MR	13.2	20.4	18.2	66.1
Total	14.7	19.5	23.4	57.7

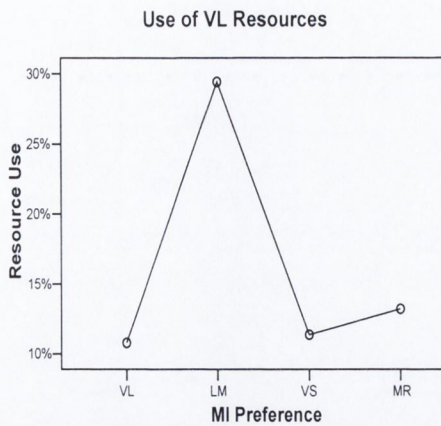


Figure 7-6: Use of VL Resources by MI groups

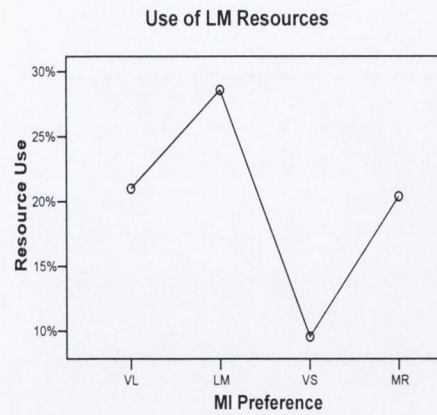


Figure 7-7: Use of LM Resources by MI groups

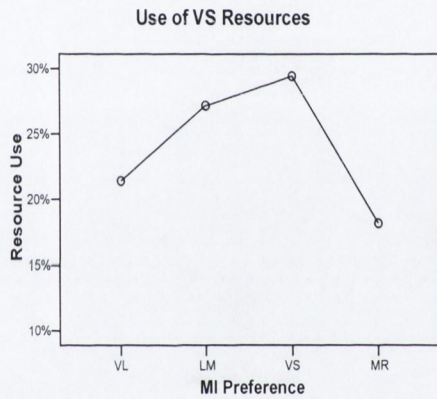


Figure 7-8: Use of VS Resources by MI groups

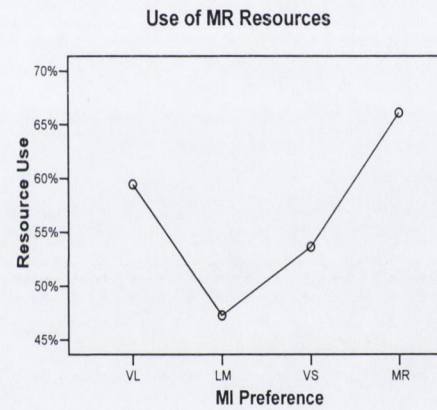


Figure 7-9: Use of MR Resources by MI groups

7.2.8 Resources Used

The type of resource predominantly used by a student may be a factor in learning performance. The following two sections examine how, for the free and adaptive group, the use of different types of resources influence learning performance.

7.2.8.1 Free Group

On analysing the resources used by students, it is found that Musical/Rhythmic resources are very popular. Thus, the question arises: do particular types of resource have

greater influence on learning performance? To answer this question, analysis was conducted on the resources used by students in the free group. Only students in the free group were used because with the adaptive dynamic group, the adaptive presentation strategy was a factor in the choice of resources.

To conduct the analysis, standard multiple regression was performed to indicate how much variance in the post-test and relative gain score could be attributed to the amount each resource category was used. The independent variables in the analysis were the amount of each resource type used (UseVL, UseLM, UseVS, UseMR) averaged over two sittings. The dependent variables were the average post-test and the relative gain over two sittings.

Table 7-13 displays the statistics for how much each resource category was used. As illustrated MR resources are very popular, with on average each student using 58 % of MR resources available, 24 % of VS resources, 19 % of LM resources and only 14 % of VL resources. MR resources, it appears are very attractive to students and indicates the power of music to stimulate students, but it needs to be further examined to determine how this preference influences learning performance.

Table 7-13: Resources used by students in the Free group

Resource Used	N	% Used	Std. Dev.
VL	39	14.1	16.9
LM	39	18.7	25.0
VS	39	23.9	22.4
MR	39	57.8	32.7

Before regression was conducted, the VL, LM, VS variables were transformed to reduce skewness, reduce the number of outliers and improve the normality, linearity and homoscedasticity of residuals. Square root transformations were used on all three variables.

Table 7-14 displays the means and standard deviations and Table 7-15 displays the correlations between the variables. It can be noted from the correlations that the independent variables have strong correlations with the dependent variable but also have strong correlations with each other. In particular there is a negative correlation between

the use of the MR resource type and the other resource types indicating that some students are using the MR resource type without considering any other.

Table 7-16 displays the unstandardised regression coefficients (B) and intercept, the standardized regression coefficients (Beta), the semipartial correlations (sr_i^2), R^2 , and adjusted R^2 . R for regression was significantly different from zero, $F(4, 34) = 3.235$, $p < 0.05$. Only two of the independent variables contributed significantly to the prediction of post-test score, (square of) VL use ($sr_i^2 = .092$) and MR use ($sr_i^2 = .125$). The four independent variables in combination contributed another .059 in shared variability. Altogether 28 % (19 % adjusted) of the variability in the post-test score was predicted by knowing scores on all the independent variables.

Table 7-14: Means and standard deviations for independent (VL, LM, VS transformed) and dependent variables.

Variables	Post-Test Score	Sqrt(UseVL)	Sqrt(UseLM)	Sqrt(UseVS)	UseMR
Means	52.82	3.42	3.75	4.42	57.63
St. Dev.	18.27	1.86	2.41	2.34	32.74

Table 7-15: Correlations between independent and dependent variables

		Post-Test	UseVL	UseMR	UseVS
Pearson Correlation	Post-Test				
	UseVL	.359			
	UseMR	-.410	-.184		
	UseVS	.217	.579	-.446	
	UseLM	.297	.471	-.463	.270
Sig. (1-tailed)	Posttest	.			
	Use VL	.012			
	Use MR	.005	.131	.	
	Use VS	.092	.000	.002	
	LM SR	.033	.001	.001	.048

Table 7-16: Standard multiple regression on Use of resources on Post-Test scores

Variables	B	Beta	sr_i^2 (unique)
UseVL	62.19	.428	.092
UseMR	-2.5	-.454	0.125
UseVS	-1.7	-.218	
UseLM	-.428	-.056	
Intercept	62.19		
	$R^2 =$.276	
	Adjusted $R^2 =$.19	
	$R =$.525	
	**p	<0.03	
	^a Unique Variability =	.217	Shared Variability = .059

To further analyse from a different perspective the influence of the MRUse variable, students were divided up into three groups determined by how much they used the MR resource type: high, medium and low. A one-way ANOVA was conducted to explore the impact of MRUse on the average post-test score. The results were statistically significant: $F(2, 36) = .4974, p = .012$. Post-hoc comparisons using the Tukey HSD test indicated that the mean score for the low use MR group ($M = 64.6, SD = 6.91$) was significantly different from the medium ($M = 45.77, SD = 19.0$) and high use MR group ($M = 47.08, SD = 20.47$). The results suggest that students who did not just use the MR resource to the exclusion of all others had the greater learning performance.

A similar analysis was performed on the VLUse variable. Students were again divided into three groups determined by the amount of use of the VL resource type: high, medium and low. A one-way ANOVA was conducted to explore the impact of VL use on the average post-test score. The results were statistically significant: $F(2, 36) = 3.56, p = .039$. Post-hoc comparisons using the Tukey HSD test indicated that the mean score for the high use VL group ($M = 63.8, SD = 13.67$) was significantly different from the low use VL group ($M = 46.92, SD = 18.66$). The results suggest that students who used the VL resource a lot had the greater learning performance.

However despite the relatively strong prediction on resource use with the post-test score, nothing significant was found in relation to the relative gain score. When performing linear regression, the independent variables together contributed only 4 % (negative adjusted R^2) of the variance in relative gain score. Similarly, exploring the relationship between high use of VL and MR resources with relative gain also yield nothing significant. It seems other factors besides the resources may influence the relative learning gain.

Summarising the results above, it seems that for this group of students, high use of the VL resource type and low use of the MR resource type result in greater learning performance. However this does not explain why there is no relationship between the use of these resources and the relative gain. It is significant to note the popularity of the MR resources and a promising research challenge is to identify how the motivating power of MR can be used to enhance learning performance.

7.2.8.2 Adaptive Group

The results for the free group suggest that adaptive strategies should guide students away from MR to VL and other resources. To evaluate this hypothesis, the resources used by the adaptive group are analysed. The resources used with the most and least preferred strategy are analysed separately.

First, analysis was conducted on the use of resources when the most preferred presentation strategy was used. Examining the relationships between the use of different resource categories, it was discovered that the only significant correlation was between the use of LM and MR resources [$r=-.393$, $n=31$, $p=.029$]. This result suggests that high use of MR resources is correlated with low use of LM resources, which also agrees with the results for the free group.

The relationship between the use of the different resources and the post-test score was next analysed. No significant correlations were found between the use of VL or MR resources and post-test scores. Indeed the only correlation that approached significance was the relationship between the use of VL resources and post-test score [$r=-.343$, $n=31$, $p=.059$] and in this case it was a negative correlation. This result surprisingly suggests that high use of VL resources result in a low post-test score, a direct contradiction to what was reported in the free group. One reason for this could be that VL resources were not initially presented as it was not the preferred resource for the majority of students and

subsequently students did not bother to use them. No significant correlations were found between the use of resources and relative gain.

Second, analysis was conducted on the use of resources when the least preferred presentation strategy was used. Significant correlations were found between the use of VL and LM resources [$r=.487$, $n=31$, $p=.005$] and VL and VS resources [$r=.404$, $n=31$, $p=.024$]. This suggests that high use of VL resources is correlated with high use of LM and VS resources, which supports the results for the free group.

When examining the relationship between the use of resources and post-test scores, no significant correlations were found. However, the positive correlations between the use of VL, LM or VS resources and post-test scores approached significance: for VL [$r=.318$, $n=31$, $p=.082$], for LM [$r=.32$, $n=31$, $p=.08$] and for VS [$r=.348$, $n=31$, $p=.055$]. The correlation between use of MR resources and post-test score was very weak [$r=.002$, $n=31$, $p=.992$]. The results suggest that high use of VL, LM or VS resources are related to high post-test scores. No significant correlations were found between use of resources and relative gain.

Table 7-17: Correlations for least and most preferred strategies

	Significant Correlations	Amount
Most Preferred Strategy	Use of LM and MR	$r=-.393$, $n=31$, $p=.029$
	Use of VL and Post-Test	$r=-.343$, $n=31$, $p=.059$
Least Preferred Strategy	Use of VL and LM	$r=.487$, $n=31$, $p=.005$
	Use of VL and VS	$r=.404$, $n=31$, $p=.024$
	Use of VL and Post-Test	$r=.318$, $n=31$, $p=.082$
	Use of LM and Post-Test	$r=.32$, $n=31$, $p=.08$
	Use of VS and Post-test	$r=.348$, $n=31$, $p=.055$

The results are summarised together in Table 7-17. With the least preferred strategy, high use of VL, LM and VS resources is related to high post-test scores. With the most preferred strategy, low use of VL resources is related to high post-test scores. With the least preferred strategy, the use of VL, LM and VS resources are related to each other and with the most preferred strategy, high use of MR resources is correlated with low use of LM resources.

Returning to the original hypothesis that the best adaptive presentation strategy is to guide students away from MR to VL and other resources, the results from the least preferred sitting are in agreement. These results suggest that the use of VL, LM and VS resources can result in higher learning performance. In contrast, it was found that with the most preferred strategy low use of VL resources is correlated with high post-test scores. It appears that students, when given options, did not choose the VL resource type and were able to learn from other resources. Concerning the use of MR resources, nothing definitive can be said as no significant correlations with post-test score were discovered.

Examining the results for the free and adaptive group together, there are indications that students who prefer to work with VL resources achieve higher post-test scores (except for the adaptive group with the most preferred strategy) but this could be related to the verbal mode of assessment based on written multi-choice questions. No indications could be found about how the use of different resources is related to relative gain. It is clear that MR resources are extremely popular. MR resources seem to captivate students, maybe because of the novelty effect or because music conveys an emotional power that normal text does not. Further research is required to understand how the power of music can be tapped into for education purposes and how music can be best employed to enhance learning performance.

7.2.9 Qualitative Feedback

Qualitative feedback was received from students in order to determine perceptions and preferences. Feedback was received at a number of points during the experiment:

1. At the end of each learning unit, students were asked:
 - Which option helps them remember most and why?
 - Which option do they prefer and why?
2. At the end of the tutorial sessions, students were asked to reflect on:
 - What were the differences between the options?
 - After going to your favourite choice did you try other options?

A sample of the feedback received is presented here to give an indication of how different students preferred different options.

First the responses to the feedback questions during the tutorial are illustrated in Table 7-18. The responses indicate the diverse nature of student preferences and inclinations.

Some students comment that they “learn more from reading” while others remember pictures better “because the picture stays in your head”. Some students prefer the logical/mathematical approach because “numbers are an easy way to remember” and “it goes through step by step”. In addition, some students prefer the musical approach because “it is catchy and it just sticks in your head” and “music sings the answers for you”. It is clear from the feedback that different students prefer different approaches to learning.

Second, the responses to the reflection questions at the end of each tutorial sitting are illustrated in Table 1-19. It summarizes student’s understanding of the differences between resource categories and provides insights into why different options were tried.

Some students are clearly able to articulate the differences between resource categories and provide comments such as “they’re all the same points just shown in different ways through music, pictures etc” and “you can see one, hear one, read one, learn one”. As to why students tried different options after their favourite one, the main reasons seem to be “curiosity” and “to see if they were good”. The comments suggest that one benefit in providing multiple MI resources is that it can support a learning environment that encourages curiosity and interest.

The feedback together suggests that students do have different strengths and preferences and the challenge is to find out best to adapt to this diversity. It suggests that a wide approach to learning is necessary so that all students can find something attractive and beneficial.

Table 7-18: Feedback to questions during tutorial: What do you prefer and remember?

<p>Comments on VL:</p> <ul style="list-style-type: none"> • because it tells you everything you need to know • its explained easier • because i take things in more when reading • because it stays in your head longer • i learn more from reading • because it was easy 2 read and understand • i learned a bit from reading • because i like reading • because it is easier to understand than the music because the person that is speaking i can't understand them • it helps you remember more because there is a person talking to you 	<p>Comments on VS:</p> <ul style="list-style-type: none"> • because it explains it more in drawings for us • i found this mode most useful because the information was given in small portions so it was not very difficult to remember • you can see whats happening. • because the picture stays in your head • it put a picture in my head • the picture was better because then it was easier 2 remember • because it is easy to remember pictures • it helps me remember best • it is easier to understand • because of the way you see it. • because it shows you a diagram of how it works
<p>Comments on LM:</p> <ul style="list-style-type: none"> • because i thought it was explained very well and layed out very well • it helped me remember better because it gives you all the steps • its easy to understand and it's explained well • because it explained it in a simpler form • the maths i prefer because it showed exactly how electricity works • it tells u in easy language i hate the listenin coz they cant sing and u cant understand wat dey r sayin • because numbers are an easy way to remember • because i found it is easy to use and i like to work with numbers • this is because it goes through step by step • because it gives you an answer with another question so helps me remember and it takes less time to learn. 	<p>Comments on MR:</p> <ul style="list-style-type: none"> • it did because i could listen to the different sounds it was fun • it is catchy and it just sticks in your head • because music sing the answers for you • because it stuck in my head • i remembered the music one because it is very catching • i remembered the music the best because of the rap and the way it went • because you could hear the sounds • because we make a rap song using the words below • this is a fun way of learning and the music helps you remember the stuff • coz i like music and i remember songs better than reading or looking • easier to remember the sound stays in your head • because songs are easy to remember • because it tells you about it in the song

Table 7-19: Feedback to questions during tutorial: What do you prefer and remember?

“What were the differences between the options?”	“After going to your favourite choice did you try other options ?”
<ul style="list-style-type: none"> • zsome are better than others • there is none • there different activitys • they are different every time • some are more interesting than others • there is different stuff in each one • you can see one ,hear one ,read one,learn one • you could see hear and look • they're all the same points just explained in different ways • they're all the same points just shown in different ways through music, pictures etc • they show you different things • different types of learning 	<ul style="list-style-type: none"> • yes because i wanted to see what the oters are like • yes cos i wanted to • havent got a favourte • yeah to see what the others were like • yes because i liked them all • no because i didnt want to • yes to see what they were like • yes to see if they were good • noting else to do • i triedall of them to see what they were like • yes , just to look • yes i just tryed them all • I just tried them all • yes to see hat they were like • curiosity • no, they seemed boring • no the sounds help me remember

7.2.10 Summary

Study A was conducted primarily to explore the effect of presentation strategy and level of choice on learning performance. In particular, its goal was to determine differences in performances between students who have complete learner control over the learning environment and students who use an adaptive system that matches and mismatches resources with preferences. Despite the short duration and limitations of the study, a vast amount of experimental data was obtained and subsequently analysed to produce tentative results.

To explore the effects of choice and presentation strategy, the results of all students at each tutorial sitting were first compared. It was found that adaptive presentation strategies resulted in higher post-test and relative gain scores, though the differences were not statistically significant. Next, for the adaptive group, the effect of the least and most preferred presentation strategies was compared. Despite, there being no significant difference in the post-test scores, the relative gain scores surprisingly suggest that students achieve higher learning performance with the least preferred presentation strategy. It suggests that students achieve greater performance levels when adaptively presented with resources they do not prefer.

To investigate the reasons for the difference in learning gain with the least/most preferred presentation strategies, the learning activity of the adaptive dynamic group was analysed. Students were divided into groups defined by their learning activity or the number of resources they used during the tutorial.

On examining the post-test scores, the results indicate that students with high and medium activity levels obtain the highest scores with both the least and most preferred presentation strategies. It suggests that learners who are interested in exploring different learning options achieve higher post-test scores.

The relative gain scores indicate that students with medium learning activity levels benefit most when they are encouraged to use resources not normally used. Medium activity learners typically use just the one resource that is presented first and do not explore other different options. Surprisingly the same effect was not observed with students with low levels of activity. One reason for this may be that the activity level was so low it indicates that the presented resource was not used, hence it did not matter which strategy was in use.

A further analysis was conducted to determine if presentation strategy had an impact on learning activity for the different activity groups. No significant difference in activity was observed between the least and most preferred strategies. The result indicates that presentation strategy may not influence learning activity and that differences in learning gain for medium activity learners may be dependent on the type and variety of resource provided.

The results for the adaptive group suggest that the presentation strategy had a different effect for students with different levels of activity. It appears that students with medium activity levels had larger increases in learning gain when encouraged to use resources not

normally preferred. The implications are that students with certain types of learning characteristics have the most to benefit from adaptive presentation strategies.

A related measure to activity level is the time spent using MI resources. However the analysis of the time spent using each MI resource category and the total time spent using all MI resources did not provide any further insights into differences in learning performance. However, it is interesting to note that the free group spent more time on MI resources than the adaptive group, but this did not reach statistical significance.

To further investigate the differences in learning performance for medium activity level students, a deep analysis was performed on the qualitative feedback and the resources used. The analysis revealed that, for this group of learners, there was a broad range of preferences for different resources. It suggests that the least preferred presentation strategy encourages students to experiment with different options and increase learning activity. It seems that encouraging students to step outside habitual preferences and promoting a broader range of thinking maybe a strategy for increasing learning performance.

Using the highest-ranking intelligence as identified by the MIDAS inventory, no significant results were found on the impact of intelligence on post-test, relative gain and activity level. Students with different highest-ranking intelligences did not score significantly higher than other students.

In addition, the MI profiles generated from the MIDAS inventory were compared with the observed behaviour of students in the free group. With this group, no adaptivity was provided and students were free to choose whatever resource they wished. It was found that students on average use the resource type that reflects their dominant intelligence. This is the case with LM, VS and MR students, the exception being VL students. In general VL resources are the least popular with students, which suggests that to capture the attention of students, resources that engage other intelligences are needed.

Furthermore, the use of the different MI resources was investigated to determine its influence on performance. It was found for the free group, that high use of the VL resource type and low use of the MR resource type resulted in greater learning performance. However no relationship was discovered between the use of resources and the relative gain.

These results suggest that adaptive strategies should guide students away from MR to VL and other resources. Analysis of the dynamic group did indicate that the use of VL,

LM and VS resources could result in higher post-test scores. However, concerning the use of MR resources, no significant correlations with post-test score were discovered and no conclusions could be drawn. In addition no relationships were discovered between the use of resources and relative gain.

It is significant to note the popularity of the MR resources however it is not clear how they can be best employed to enhance learning performance. MR resources seem to captivate students, maybe because of the novelty effect or its emotional power. A promising research challenge is to identify how the motivating power of music can be used to enhance learning performance.

Extensive qualitative feedback was also received from students in order to gauge perceptions and preferences. This feedback was elicited by asking what did students prefer and remember. The responses included: "learn more from reading", "picture stays in your head", "numbers are an easy way to remember" and "music sings the answers for you". The responses indicate the diverse nature of student preferences and inclinations. It is clear from this feedback that different students prefer different approaches to learning.

It was also clear that some students were able to easily articulate the differences between resource categories with comments such as "they're all the same points just shown in different ways through music, pictures etc". The comments also reveal that the main reason for trying different options after their favorite one was curiosity.

Taken together, the results suggest that using adaptive presentation strategies to provide students with a variety of resources can enhance learning performance and the learning experience for learners with certain types of characteristics. In particular the use of adaptive presentation strategies can benefit learners who are not inclined to explore different options and who just use the resource that is presented first. Such learners can benefit from adaptive presentation strategies that guide them to resources not normally used. The results also suggest that students do have different strengths and preferences and the challenge is to find out how best to adapt to this diversity. It suggests that a wide approach to learning is necessary so that all students can find something attractive and beneficial.

7.3 Study B: Adaptive Control

Whereas Study A investigated the differences between adaptive and learner control, Study B investigated the differences between different types of adaptive control on learning performance. In this study, 47 boys from one mixed ability school participated in the study. The ages ranged from 12 to 14 with an average age of 13. The study was conducted as part of normal class time and integrated into the daily school curriculum. The study took place from March to May, 2004. No reward incentives were provided to the students who participated.

In this study, three versions of EDUCE were used:

- *Adaptive Single* – student is only able to view one resource. This is adaptively determined by EDUCE based on an analysis of the static MI profile. .
- *Adaptive Inventory* - student is first given one resource but has the option to go back and view alternative resources. The resource first given to the student is determined by EDUCE based on the analysis of the MI inventory completed by the student. The *Inventory* choice level is the same as the *Single* choice level but with the option of going back and viewing alternative resources.
- *Adaptive Dynamic* – the student is first given one resource but has the option to go back and view alternative resources. The resource first given to the student is determined by using the dynamic MI profile that is continuously updated based on the student's behaviour. The predictive engine within EDUCE identifies the most preferred and least preferred resource from the online student computer interaction.

The three versions correspond to three values (adaptive single, inventory and dynamic) of the *choice* independent variable. Students were randomly assigned to one of the three versions. 20 students were assigned to the adaptive single version, 18 students to adaptive inventory and 9 students to the adaptive dynamic version. Each student sat through two tutorials. All students experienced both least and most preferred presentation strategies in different tutorials. A summary of the analysis is provided in Table 7-20.

Table 7-20: Summary of analysis for Study B

Analysis	Conclusion
Independent variables: choice and presentation strategy	Higher learning performance (relative learning gain) when adaptively presented with resources not preferred
Learning Activity	High activity levels or use of MI resources correlate with higher post-test scores
Learning Activity	Students in adaptive group with low activity levels had larger increases in learning gain with the least preferred presentation strategy
Time on Task	For adaptive dynamic group, least preferred strategy increases time spent exploring MI resources
MI Profile	MI Profiles did not influence post-test scores
Resources Used	For Single group, no significant conclusions about use of MI resources For dynamic and inventory groups, some students use MR resources and nothing else, nothing conclusive to say about use of resources and post-test scores

7.3.1 Choice and presentation strategy

The results were analysed to determine the effect of different adaptive strategies on learning performance. It was expected that students would have greater learning gain when guided to resources they prefer instead of those they do not prefer. It was also expected that the groups (inventory and dynamic) with access to a range of resources would have higher learning gain than the group (single) who did not. Furthermore, it was also expected that the group (dynamic) who were guided to resources based on a dynamic model of behaviour would have higher learning gain than all other groups.

To explore the effects of the two independent variables, choice and presentation strategy, a mixed between-within ANOVA was conducted. Both the post-test and relative gain scores obtained under the two presentation strategies, least and most preferred, were compared.

With the post-test score, there was no significant difference between the different presentation strategies and the choice groups. Table 7-21 presents the means and standard deviations. However, with the relative gain scores, there was a significant within subject main effect for presentation strategy: Wilks Lambda: 0.897, $F = 4.944 (1, 43)$, $p = .031$, multivariate eta square = .103. The mean relative gain score at the least preferred sitting ($M=76.2$, $SD=99.5$) was significantly greater than the score at the most preferred sitting ($M=38.9$, $SD=51.9$). The eta square suggests a moderate to large effect size. Table 7-22 presents the means and standard deviations. Figure 7-10 plots the relative gain for the

least and most preferred strategies. It shows that for all groups, and in particular for the inventory and dynamic choice groups, that the relative gain is greater in the least preferred condition. The differences between the different choice groups were not significant.

Surprisingly, the results indicate that students learn more when first presented with their least preferred material rather than their most preferred material, in contradiction to the original hypothesis.

Table 7-21: Post-test for least/most presentation strategy

Choice	Post-test: Least Preferred		Post-test: Most Preferred		N
	Mean	Std. Dev.	Mean	Std. Dev.	
Single	69.00	20.75	71.00	19.44	20
Inventory	67.78	21.02	68.89	17.11	18
Dynamic	68.08	19.41	60.00	18.71	9
Total	68.09	19.41	68.09	18.40	47

Table 7-22 Relative Gain for least/most presentation strategy

Choice	Relative Gain: Least Preferred		Relative Gain: Most Preferred		N
	Mean	Std. Dev.	Mean	Std. Dev.	
Single	50.50	63.84	34.15	48.95	19
Inventory	97.46	135.14	45.93	62.23	18
Dynamic	87.78	70.98	35.00	36.93	9
Total	76.17	99.55	38.92	51.93	46

Presentation Strategy/Choice and Relative Gain

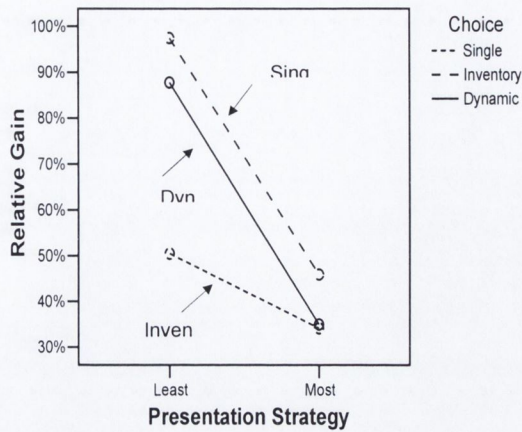


Figure 7-10: Plot of Relative Gain for least/most presentation strategy

7.3.2 Learning activity

To investigate the reasons for the difference in learning gain with the least/most preferred presentation strategies, learning activity was analysed. The purpose was to explore if students using a large variety of resources had the same learning gain as students who used only the minimum. It was expected that the activity level would increase with the least preferred presentation strategy, and that higher learning activity would result in increased learning gain for all students.

To determine the overall activity level, the average of the percentage of resources used in the least and most condition was calculated. Three categories are defined for activity: low, medium and high. The cut points for each category were determined by dividing students into three equal groups based on their activity level. Table 7-23 displays the cut points for the different groups. Typically, a student in the low activity group would look at only one resource per learning unit, a student in the high activity group would on average look at two resources per unit and in a student in the medium activity group would be somewhere in between. Only the inventory and dynamic choice groups were included in the analysis as it is irrelevant to calculate the activity level for the single choice group, having access to only one resource.

Table 7-23: Activity Groups

Activity Group	Cut-Points	Average	Resources used per learning unit
Low	≤ 28	19	One resource
Medium	> 28 and ≤ 37.5	25	Between one and two resources
High	> 37.5	31	Two resources

First, a two way mixed between-within ANOVA was conducted to explore the effect of activity level and presentation strategy on post-test score. There was no statistically significant main effect for activity level or presentation strategy. However, Figure 7-11 shows that students with high activity levels obtained the highest scores in both the least and most preferred sitting. It suggests that learners who are interested in exploring different learning options will get higher post-test scores.

Second, a two way mixed between-within ANOVA was conducted to explore the effect of activity level and presentation strategy on relative gain. The means and standard deviations of the relative gain scores are presented in Table 7-24. There was a significant within-subject main effect for presentation strategy: Wilks Lambda: 0.818, $F = 5.332$ (1, 24), $p = .03$, multivariate eta square = .182. There was also a within-subject interaction effect between presentation strategy and activity level, however it was only significant at the $p < .1$ level: Wilks Lambda: 0.808, $F = 2.851$ (2, 24), $p = .077$. This interaction effect was primarily due to the fact that low activity learners had a higher relative gain at the least preferred sitting than at the most preferred sitting. For medium and high activity learners, despite the learning gain been slightly higher at the least preferred sitting, the presentation strategy had no statistically significant impact on learning gain.

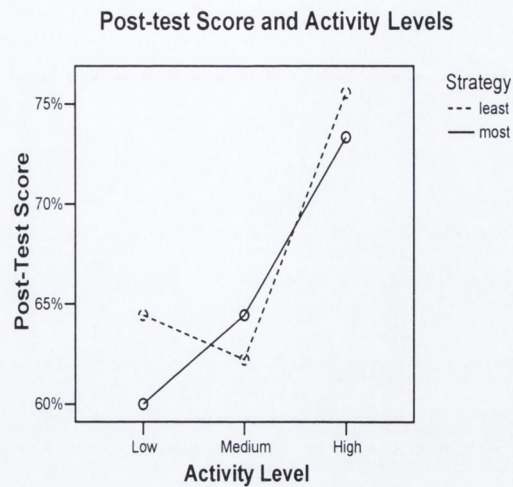


Figure 7-11: Activity Groups and Post-test Scores

Figure 7-12 plots the relative gain for the different activity groups in the least and most preferred condition. It shows how students with low activity have higher relative learning gain when given least preferred resources first. Students with medium and high activity have the same relative gain in both the least and most preferred conditions. The results indicate that students with low learning activity levels benefit most when they are encouraged to use resources not normally used.

Finally, analysis was also conducted to determine if presentation strategy had an impact on learning activity for the different activity groups. Figure 7-13 shows how activity levels remain similar in both the least and most preferred presentation conditions. This was supported by a correlation between the activity levels in both conditions ($r=.65$, $p<.01$). It suggests the presentation strategy did not influence learning activity and that the difference in learning gain for low activity learners may be dependent on the type and variety of resource provided. In addition, the relationship of prior knowledge and pre-test score with activity level was also analysed. No correlation was measured between prior knowledge and activity level, and between pre-test and activity. It seems that the activity level of the student is not related to prior knowledge, and that some other factor is determining the activity level.

Together, the results indicate that the presentation strategy had a different effect for students with different levels of activity. Students with high and medium activity levels were not influenced by presentation strategy. In contrast, the presentation strategy had a

significant impact on low activity students, who had larger increases in learning gain when encouraged to use resources not normally preferred. The implications are that students with low levels of learning activity have the most to benefit from adaptive presentation strategies.

Table 7-24: Relative gain for different activity groups

Activity	Least Relative Gain		Most Relative Gain		N
	Mean	Std. Dev.	Mean	Std. Dev.	
Low	174.07	160.75	46.30	48.42	9
Medium	48.07	69.05	30.00	40.72	9
High	60.56	49.64	50.56	73.59	9
Total	94.23	116.25	42.28	54.58	27

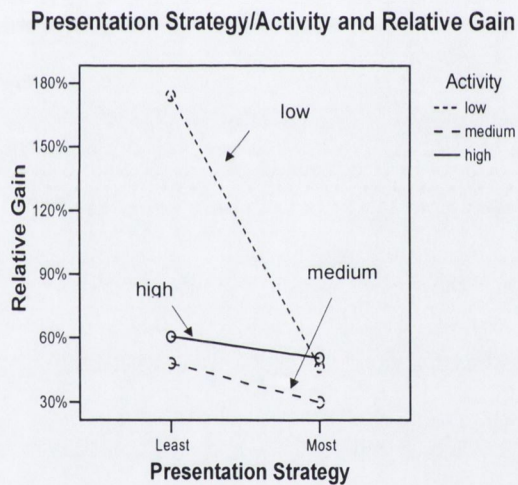


Figure 7-12: Relative gain for different groups in least/most preferred conditions

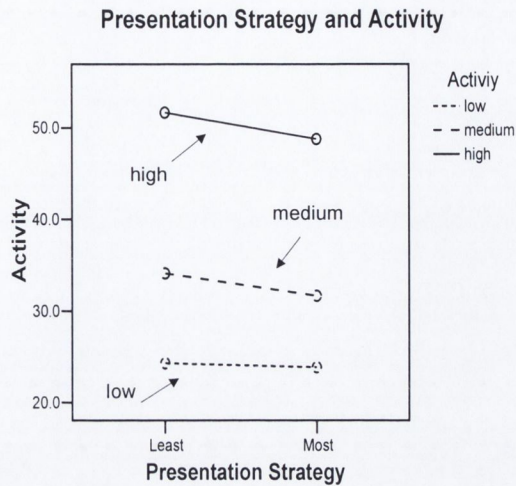


Figure 7-13: Activity and least/most presentation strategy for different activity groups

7.3.3 Time-on-Task

To determine if learning performance was related to the time spent using MI resources, analysis was conducted on both the time spent using each MI category of resources and the total time spent using all MI resources. When investigating the effect of time spent on resources, only the inventory and dynamic choice groups were included in the analysis, the reason being that students in these groups had the option to use more than one resource. For the complete tutorials, students spent an average of 17.5 minutes on each tutorial, with a total of 35 minutes over the two tutorials.

First, the time spent using each MI category was analysed. For each category, the time spent on resources was correlated with the activity level (number of resources used) at $p < 0.01$ level. As a result, the analysis of time spent on individual resource categories did not provide any additional insights proved by the analysis of activity level and learning performance.

Next, the total time spent using MI resources was analysed. A two way mixed between-within ANOVA was conducted to explore the effect of choice and presentation strategy on total time spent. The means and standard deviations of the relative gain scores are presented in Table 7-25. There was a significant within-subject main effect for

presentation strategy: Wilks Lambda: 0.851, $F = 4.379 (1, 25)$, $p = .047$, multivariate eta square = .149. There was also a within-subject interaction effect between presentation strategy and choice, however it was only significant at the $p < .1$ level: Wilks Lambda: 0.890, $F = 3.097 (1, 25)$, $p = .091$. Figure 7-14 illustrates the main effect and shows how students spent more time using MI resources with least preferred presentation strategy. It also illustrates the within-subject interaction effect and shows how students using the adaptive dynamic version spent less time using MI resources with the most preferred strategy than with the least preferred strategy.

It is interesting to note the presentation strategy did not have an effect on the adaptive inventory group. However, the result suggests that the effect of the least preferred presentation strategy on the adaptive dynamic group is to increase the time spent exploring MI resources. It appears that students spend more time learning when initially presented with resources they do not prefer. This could be explained by the fact that more time is needed to use resources not preferred and students spend more time exploring different options.

Table 7-25: Total time spent on MI resources

Choice	Least Time		Most Time		N
	Mean	Std. Dev.	Mean	Std. Dev.	
Inventory	371.2	145.0	358.9	162.5	19
Dynamic	399.3	218.2	256.6	93.7	9
Total	380.6	169.0	324.8	149.6	27

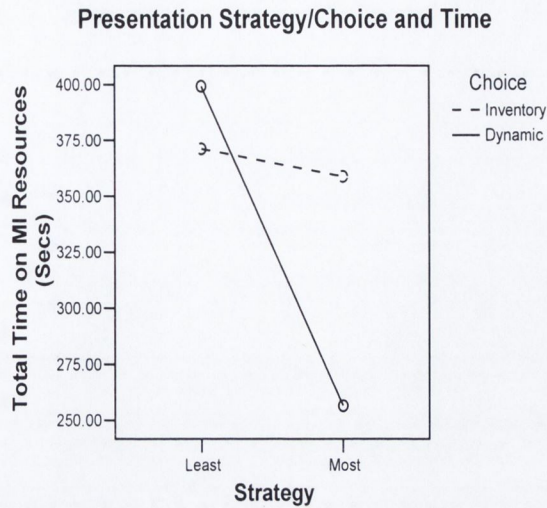


Figure 7-14: Total time spent on MI resources for choice and presentation strategy

7.3.4 Students with Low Activity Levels

On using quantitative analysis techniques, it was found that students with low activity levels had higher learning performance when guided to resources they least preferred. A deep analysis was performed on this group of students to help identify reasons for this surprising behaviour. As part of this analysis, differences between the least and most preferred strategies in the number and range of resources used were assessed. Also evaluated, was the qualitative feedback from several students in this group.

First, the number of resources used or activity level was analysed. It was found that the activity levels for both least and most preferred strategies were the same. Regardless of presentation strategy, students used the same number of resources (24 %) that is just the one resource.

Next, the range and spread of resources used was evaluated. Table 7-26 illustrates the average use of resources and indicates that this group of students used all categories of resources and not just one type. It is interesting to note the large use of the MR resource category with both presentation strategies.

Table 7-26: Average use of resources in the different MI Categories

	AvUseVL	AvUseLM	AvUseVS	AvUseMR
Most Preferred Strategy	13	21	12	49
Least Preferred Strategy	14	17	22	44

The range was found by calculating for each student the Euclidean distance between their use of resources and the average use of resources by all students. On calculating the range, it was found that the range with the least preferred strategy was greater than with the most preferred strategy. Students used a greater variety of resources with the least preferred strategy.

Qualitative feedback from the four students in this group was next explored. The four students are labelled Student A, B, C and D and all had greater relative gain with the least preferred presentation strategy. Qualitative feedback was received from the students by asking for feedback at the end of each learning unit. Students were asked which option helps them remember most and why. Also, at the end of the entire session, students were asked to reflect on a number of questions such as

- What were the differences between the options?
- After going to your favourite choice did you try other options?

Student A:

Student A was assigned to the adaptive dynamic group. He mainly used the MR resource category with the most preferred presentation strategy. Table 7-27 illustrates how he used 100 % of MR resources. The feedback indicated that MR and LV were his favorite categories, the reasons being:

- “It gives you a sound of thunder and lightning”
- “the rap music and songs”

Interestingly, the results from the MIDAS inventory indicated that VL and LM were his two most preferred intelligences, with MR a strong third.

In contrast the range of resources used with the least preferred presentation strategy increases. Table 7-27 illustrates how the MR category is used less and other categories

are used more. Despite using a wider range of resources, the student when asked which resource he preferred typically answered that MR was the preferred resource.

The results suggest that the least preferred presentation strategy encouraged the student to use a broader range of resources in addition to the preferred MR and that using a broader range of resources resulted in greater learning performance.

Table 7-27: Use of MI resource categories for Student A

	UseVL	UseLM	UseVS	UseMR
Most Preferred Strategy	0	8	0	100
Least Preferred Strategy	21	28	36	28

Student B:

Student B was also assigned to the adaptive dynamic group. With the most preferred presentation strategy, he was guided mainly to the MR resources. His responses indicated that MR was his favourite category, with the comment “because it was better”. In contrast, the feedback from the MIDAS inventory indicates he prefers LM, VS and VL resources to MR.

With the least preferred strategy, the learning activity and range of used resources increased. As illustrated in Table 7-28, more VL, LM and VS resources were used with the least preferred strategy. However, despite using a broader range of resources, the student stated that MR was his favorite resource type.

The feedback suggests that regardless of the strategy used, the student identified MR resources as the preferred resource. It appears that the effect of the least preferred presentation strategy was to encourage the student to explore a broader range of resources, which resulted in greater learning performance.

Table 7-28: Use of MI resource categories for Student B

	UseVL	UseLM	UseVS	UseMR
Most Preferred Strategy	0	0	0	100
Least Preferred Strategy	15	23	23	23

Student C:

Student C was also assigned to the adaptive dynamic group. With the most preferred presentation strategy, he was guided mainly to the VL resources. The responses indicate that he preferred a broad range of resources. At different stages throughout the tutorial he selected VL, VS, MR and LM in turn as his favourite category.

With the least preferred strategy, the range of used resources increased. As illustrated in Table 7-29, more MR, LM and VS resources were used with the least preferred strategy. The feedback during this session indicated that LM and VL were his favourite resources. This feedback matches the results from the MIDAS inventory where the two most preferred intelligences were LM and VL.

It appears that the effect of the least preferred strategy was to encourage the student to use a broader range of resources rather than just the preferred ones, the effect of which was to improve learning performance.

Table 7-29; Use of MI resource categories for Student C

	UseVL	UseLM	UseVS	UseMR
Most Preferred Strategy	36	7	7	14
Least Preferred Strategy	23	23	38	23

Student D:

Student D was assigned to the adaptive inventory group. The feedback from the MIDAS inventory revealed that VS was his most preferred intelligence and MR his least preferred intelligence. Accordingly, as the adaptive inventory group presents the initial resource based on the static MI profile, the VS resource was presented first with the most preferred presentation strategy and the MR resource first with the least preferred strategy. Table 7-30 illustrates how, as the student was a low activity learner, only one primary resource was used with the least and most preferred strategies.

With the most preferred presentation strategy, the feedback from the student was that he preferred VS but remembered more from VL resources:

- "I like art. I remember things better because I remember what I read"

In contrast with the least preferred strategy, when the student was asked what did he prefer and remember, his response was:

- “I like all those subjects”
- “I like them (all)”

It appears that the effect of the least preferred presentation strategy was to broaden the student’s perceptions of what he liked. In particular it encouraged him to explore MR resource category, an intelligence low down on his list of preferences.

Table 7-30: Use of MI resource categories for Student D

	UseVL	UseLM	UseVS	UseMR
Most Preferred Strategy	0	0	79	0
Least Preferred Strategy	0	0	8	92

Altogether, the results suggest that encouraging learners to use a broad range of resources can enhance learning. In particular, it suggests that by using the least preferred presentation strategy, it is possible to encourage students to experiment with different options. It seems that that encouraging students to step outside habitual preferences and promoting a broader range of thinking maybe a strategy for increasing learning performance.

7.3.5 MI Profile

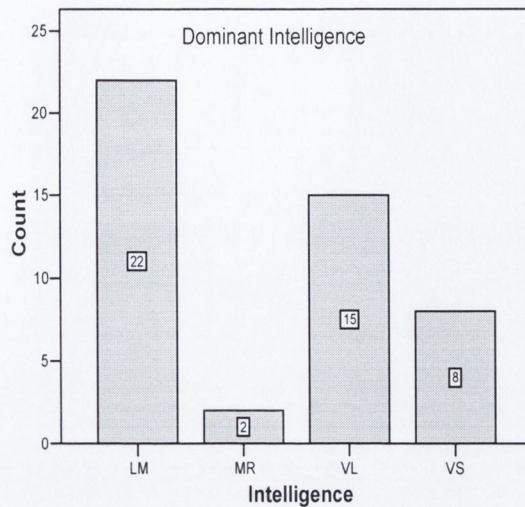


Figure 7-15: Highest ranking intelligence for students

As part of the study, all students completed the MIDAS inventory to determine their MI profile and their highest-ranking intelligence. For the 47 students in the study, the results were: Verbal/Linguistic 15, Logical/Mathematical 22, Visual/Spatial 8 and Musical/Rhythmic 2, as displayed in Figure 7-15. The results were next analysed to determine if students of a particular MI profile had greater learning performance than other MI profiles. It was expected that due to the nature of the post-test (multi-choice questions) that verbal/linguistic students would have higher scores.

A one-way ANOVA was first conducted to explore the impact of highest-ranking intelligence on prior knowledge, average post-test score and average relative gain. The two MR students were removed as the MR cell size was too small for the analysis. The results were not statistically significant, for prior knowledge: $F(2, 42) = .256, p = .776$; for post-test score: $F(2, 42) = 1.758, p = .185$; and for relative gain: $F(2, 42) = .072, p = .931$. Table 7-31 displays the prior knowledge, average post-test score and relative gain for each intelligence group. VL students had a slightly higher post-test score than all other students. The results suggest that despite VL students doing slightly better, there was no significant difference for students with different MI profiles and that no conclusions could be drawn about the performance of students with different MI profiles on standard tests.

Table 7-31: Average post-test score and relative gain for each intelligence group

Intelligence	N	Prior Know.	Std. Dev	Post-test	Std. Dev.	Relative Gain %	Std. Dev.
VL	17	58.7	16.2	73.0	16.0	60.8	65.9
LM	28	61.4	16.5	69.1	12.8	61.1	38.3
VS	8	57.3	12.6	61.3	15.1	52.6	78.8
MR	3	57.0	7.1	47.5	10.6	15.4	31.2
Total	56	59.6	15.3	68.0	15.0	57.6	55.0

The results together suggest particular MI profiles do not have higher prior knowledge or learning performance. It suggests that the post-test mechanism did not unfairly bias a particular MI category and that other factors may explain the difference in learning performance.

7.3.6 Resources Used

The type of resource predominantly used by a student may be a factor in learning performance. The following sections describe for the different adaptive groups how the use of different types of resources influence learning performance. The first section analyses the single group and the influence of using their most preferred resource with the most preferred strategy, the only resource available to this group. The second section analyses the inventory and dynamic groups, both of which had the option of using multiple resources.

7.3.6.1 Single group

First, an analysis was conducted in order to determine the effect of using just the preferred resource type. For this analysis, only students from the single choice group were selected and only the scores when given their most preferred resource were used.

A one-way ANOVA was conducted to explore the impact of favourite resource type on post-test score and relative gain. The results were not statistically significant, for post-test score: $F(2, 17) = 1.179, p = .332$ and for relative gain: $F(2, 16) = .947, p = .409$.

Table 7-32 displays the average post-test score and relative gain for each intelligence group (there was no students in the MR group). It illustrates how VL students had slightly higher post-test scores, with LM students next and finally VS.

The results suggest that VL and LM students perform slightly better than VS students. However the results were not significant and no significant conclusions can be drawn about how the use of particular resources influences performance.

Table 7-32: Average post-test score and relative gain in the single choice group (most preferred)

Intelligence	N	Total Score	Std. Dev	Relative Gain	Std. Dev.
VL	9	77.8	15.63	56.0	57.0
LM	8	67.5	22.5	28.3	31.1
VS	3	60.0	20.0	-4.8	34.3
Total	20	71.0	19.43	58.1	48.2

7.3.6.2 Inventory and Dynamic group

The adaptive inventory and dynamic groups were analysed to determine if there were patterns in the use of particular resources and learning performance. Both groups were presented with one resource based on either a static or dynamic MI profile, and subsequently had the option of using other resources.

First, analysis was conducted on the use of resources when the most preferred presentation strategy was used. Examining the relationship between how different resource categories were used, it was discovered that there was significant correlations between the use of VL/MR, LM/MR and VS/MR resources. Table 7-33 provides the details. It shows how high use of MR resources is correlated with low use of VL, LM and VS resources.

The relationship between the use of the different resources and the post-test score was next analysed. Significant correlations were found between the use of MR resources and post-test score, and LM resources and post-test score. The negative correlation between the use of MR and post-test score indicates that high use of MR resources is related to lower post-test scores. The positive correlation between LM and post-test score indicates that high use of LM resources is related to high post-test scores. The results suggest that MR students do not use other types of resources and have lower post-test scores. It should be noted that there was no significant correlations between the use of resources and relative gain.

Second, analysis was conducted on the use of resources when the least preferred presentation strategy was used. Significant correlations were found between the use of MR and VL, and MR and VS resources. This suggests that high use of MR resources was correlated with low use of VL and VS resources, which again suggests that students using MR resources are not using any other resources.

On analysing the relationships between use of resources and post-test scores, significant correlations were found between the post-test score and the use of LM and VS resources. High use of VS was related to high post-test scores. Surprisingly there was a negative correlation between the use of LM resources and post-test scores, indicating that the high use of LM resources was related to low post-test scores. This is in direct contradiction to the positive relationship between the use of LM resources and post-test score with the most preferred strategy, and suggests that other factors in addition to the use of resources are influencing the post-test score.

Table 7-33: Correlations for least and most preferred strategies

	Significant Correlations	Amount
Most Preferred Strategy	Use of VL and MR	$r=-.466, n=27, p=.014$
	Use of LM and MR	$r=-.477, n=27, p=.012$
	Use of VS and MR	$r=-.454, n=27, p=.017$
	Use of LM and Post-Test	$r=.416, n=27, p=.031$
	Use of MR and Post-Test	$r=-.442, n=27, p=.021$
Least Preferred Strategy	Use of VL and MR	$r=-.646, n=27, p=.000$
	Use of VS and MR	$r=-.759, n=27, p=.000$
	Use of LM and Post-Test	$r=-.490, n=27, p=.009$
	Use of VS and Post-Test	$r=.417, n=27, p=.031$

The results are summarised together in Table 7-33. With the most preferred strategy, high use of LM and low use of MR resources is related to high post-test scores. With the least preferred strategy, high use of VS and low use of LM resources is related to high post-test scores. With the most preferred strategy, high use of MR resources is correlated to low use of VL, LM and VS resources and with the least preferred strategy, high use of MR resources is correlated with low use of VL and VS resources.

In summary, it seems that some students use MR resources and do not bother with other types of resources. However, how the use of resources relates to learning performance is unclear. When students were presented with the most preferred resource, the results suggest that high use of MR resources is related to poor performance, but this result is not replicated with the least preferred strategy. In addition the relationship of LM resources to post-test score is completely the opposite in both the least and most preferred strategies. It appears that learning performance is not just influenced by the type of resource used.

Summarising the results for the single, inventory and dynamic groups together, there are indications that there are students who only use MR resources and nothing else. However, the relationship between the use of resources and learning performance is unclear, with contradictory results for the least and most preferred presentation strategies. There seems to be many factors influencing learning performance, one of which is the resource type.

7.3.7 Qualitative Feedback

Qualitative feedback was received from students in order to determine perceptions and preferences. Table 7-34 and Table 7-35 provides a summary of the comments students made on the different types of resources and provides insights into why students preferred different types of resources.

Some students are clearly able to articulate the differences between resource categories and provide comments such as “they teach you in different ways” and “they get you working in different ways”. As to why students tried different options after their favourite one, the main reasons seem to be “to see if the other things were as interesting” and “to get a variety”. However some students did not bother to explore other options as is revealed by the comments “I really liked my first choice” and “no because my favourite was the easiest to learn for me”. The comments suggest that one benefit in providing multiple MI resources is that it can support a learning environment that encourages curiosity and interest. However it is of note that some students are quite content to stay with their preferences and are not inclined to explore other options.

The feedback together suggests that students do have different strengths and preferences and the challenge is to find out best to adapt to this diversity. It suggests that a wide approach to learning is necessary so that all students can find something attractive and beneficial.

Table 7-34: Feedback to questions during tutorial: What do you prefer and remember?

<p>Comments on VL:</p> <ul style="list-style-type: none"> • because all information goes into your head when you read • because u learn more • because it gets stuck in yur head • BECAUSE its easy to remember • Because its the easiest to learn • When you repeat something it helps me rember so aI read over and over again. • If you read something you rember the most important bits • When you read you pick up the important bits. • i just like to read • reading it is easyer than rapping it • I like to read • all I had to do was read it of the screen • it is easier to remember 	<p>Comments on MR:</p> <ul style="list-style-type: none"> • Music has a tune that Stays in your head • its easy to remember by tune • tune stays in your head • because music is easy to remember • because it stays in my mind and I can remember it well • Because its loud and funny. • the tune got in my head. • Because it is more fun to learn • it helps you remember things when they have a tune • the music is stuck in my mind • the music keeps in your mind • The rap song was funny • because it was most exciting • i liked the sound because it holds the idea in your head.
<p>Comments on LM:</p> <ul style="list-style-type: none"> • It tell you what you need to know • It explains each thing clearly • it was easier to use • it made it easy to remember because it went in steps. • It explained better than the other ones 	<p>Comments on VS:</p> <ul style="list-style-type: none"> • i love art • Because I Like Art • Because of the pictures • the pictures stick to my mind • The one that took less time to remember • It helps you by displaying the visual side of things • You can visualize the stuff in your head • It catches your attention more than the others • because it give me more detail

Table 7-35: Feedback to questions during tutorial: What do you prefer and remember?

“What were the differences between the options?”	“After going to your favourite choice did you try other options?”
<ul style="list-style-type: none"> • some are useful some are bad • some are fun and some are not • they are put in different ways • some are better than the others • Some are easier to learn from than others • the music and the pictures more fun and easier to remember than the other two options • Some are easier to remember and some are boring • They all have different ways to remember • They have their own way of explaining • Different options cater for different learning methods • They have different ways of showing you how to do things • they show you different ways of remembering things • different things and ways of learning • They Get You working In different Ways • you use different senses • they all help in different ways. • some are easier to understand • all different types of learning • They teach you in different ways 	<ul style="list-style-type: none"> • yes to see the difference between them all • no not really, because i did not want to • yes to see if the other things were as interesting • Sometimes because i wanted to try them all out • Yes. To see if they were better • no coz i really liked my first choice • yes to see what they were like • Yes to see which was better • yes to find out more things • to see if they were funny • I tried other options to see if I could improve my understanding • Because i wanted to see what each option was like • no. i was enjoying the music category too much. • not really because i knew what i needed to know • no because my favourite was the easiest to learn for me • Yes To See If There Was Different Information On Offer • yes, to give me more information • yeah to see which one was best • yes i got bored • for a change. • Yes to get a variety

7.3.8 Summary

Study B was conducted to explore the effect of different types of adaptive control. In particular, it explored the differences in performance between students who use adaptive systems that match and mismatch resources with preferences based on both static and dynamic profiles. Most of the results presented for Study B are consistent with the results from Study A and a comparison between the two studies will be presented in the following section.

To explore the effects of choice and presentation strategy, the results of students with the least and most preferred presentation strategies were compared. Nothing conclusive could be said about the effect of level of choice as the results were not statistically significant. However, when exploring the impact of presentation strategy, the relative gain scores in the least and most preferred conditions were significantly different. Unexpectedly, the results suggest that students learn more with the least preferred strategy rather than with the most preferred strategy. Surprisingly, the results indicate that students learn more when first presented with their least preferred material rather than their most preferred material

To analyse this result, students were divided into groups defined by their learning activity or the number of resources they used during the tutorial. Examining the post-test scores, the results indicate that students with high activity levels obtain the highest scores. On exploring the relative gain for different activity groups in the least and most preferred condition, further insight was revealed. It was only students with low activity levels who demonstrated different relative learning gains, with significantly greater learning gain with the least preferred strategy. Typically, low activity learners only use the presented resource and did not explore other options. It seems such learners with low levels of learning activity can improve their performance when adaptive presentation strategies are in use

A further analysis was conducted to determine if presentation strategy had an impact on learning activity. For the different activity groups, there was no significant difference in the levels of activity in the least and most preferred conditions. The result indicates that presentation strategy may not influence learning activity, and that low activity learners will remain low activity learners regardless of the resource they use, least preferred or most preferred. Combining this with the fact that the relative learning gain is higher in the least preferred condition, it suggests that the type of resource used may make a difference.

Related to activity level is the measure of time spent using MI resources. The analysis of time spent using each MI category did not provide any further insights. On examining the total time spent using MI resources, it was revealed how students in the adaptive dynamic group spent more time using MI resources with the least preferred strategy than with the most preferred strategy. The results indicate that the effect of the least preferred strategy, for this group, is to increase the time spent learning and exploring different options.

To further investigate the difference in learning performance for low activity students, a deep analysis was performed on the qualitative feedback and the resources used. The analysis reveals that by initially presenting resources not normally used, it is possible to encourage students to move outside habitual modes of thinking. This may be the reason for increased learning performance with the least preferred presentation strategy.

Using the highest-ranking intelligence as identified by the MIDAS inventory, no significant results were found on the impact of intelligence on activity level and post-test score. Students with different highest-ranking intelligences did not score significantly higher than other students and did not have different levels of learning activity. This may be due to the fact that all students are catered for through the provision of different types of resources.

The use of different MI resources was also investigated to determine its influence on learning performance. On examining the single group when using only their most preferred resource, it was found that there was no significant difference in performance between students with different MI profiles.

On analysing the adaptive inventory and dynamic groups, no clear relationships were found between the use of resources and learning performance. The results found with the least preferred and most preferred strategies were not replicated and in some instances contradicted. The only clear conclusion that can be drawn is that some students prefer to use MR resources and nothing else. However it is not clear how this preference can be best exploited to enhance learning.

Qualitative feedback on preferences was also received from students. The responses that were received indicate the diverse nature of student preferences and inclinations. Some students comment that they prefer the verbal/linguistic approach as it gets "stuck in your head" while others prefer the visual/spatial approach because "you can visualize the stuff in your head". Some students prefer the logical/mathematical approach because "it made it easy to remember because it went in steps". Finally, some prefer the

musical/rhythmic approach because “its easy to remember by tune” and because “it is more fun to learn”.

It was also obvious that some students are clearly able to articulate the differences between resource categories and provide comments such as “they teach you in different ways” and “they get you working in different ways”. The comments also reveal that some students tried different option “to see if the other things were as interesting”, while other students did not bother because their “favourite was the easiest to learn”.

Taken together, the results suggest that using adaptive presentation strategies can enhance learning performance for learners with the certain types of characteristics. In particular the use of adaptive presentation strategies can benefit learners who use just the resource that is presented. Such learners can benefit from adaptive presentation strategies that guide them to resources not normally used. The feedback together suggests that students do have different strengths and preferences and the challenge is to find out best to adapt to this diversity.

7.4 Discussion

The two studies presented in this chapter investigate the differences on performance, between adaptive and learner control and between different types of adaptive control. Also investigated, by both studies, is the impact of adaptive strategies that match and mismatch student preferences to learning resources.

Integrating the results of the two studies together, certain conclusion can be drawn, as illustrated in Table 7-36. In both studies, only slight differences in performance were observed between students who had complete learner control and those who used adaptive systems based on both static and dynamic MI profiles. However, in both studies it was observed that the presentation strategy had an impact on relative gain. In contrast to the original hypothesis, that the most preferred presentation strategy would result in improved performance, it was found that the least preferred presentation strategy gave rise to larger increases in learning gain. The results suggest that there is higher learning gain when adaptively presenting resources that are not preferred.

To analyse this surprising result, students were divided into groups defined by their learning activity or the number of resources they used during the tutorial. For both groups, it was found that students with high activity levels obtained the highest post-test

scores. On exploring the relative gain for different activity groups in the least and most preferred condition, further insight was revealed.

For Study A, it was found that students with medium learning activity levels benefit most when they are encouraged to use resources not normally used. In contrast, for Study B, it was found that students with low activity levels had the greater improvement in performance when initially presented with resources not preferred. This difference may be explained by looking closer at how the activity level was derived. The different activity categories: high, medium and low; were determined by dividing students in three equal groups based on their activity level. For Study A the cutpoints for the medium activity learner were >22 and ≤ 26 . In this study, a learner classified with a medium activity level would on average look at one resource per learning unit. For Study B, the cutpoint for the low activity learner was < 28 . In this study a low activity learner would use on average one resource per unit. It appears that the overall activity levels were much greater in Study B than in Study A, and that a low activity learner in Study B would use approximately the same number of resources as a medium activity learner in Study A. Hence, it can be concluded that, for learners who use on average one resource per unit, adaptive strategies that present the least preferred resource result in greater learning performance.

A deep analysis on students in both these groups revealed that there was a broad range of aptitudes for different resources. It also suggests that the least preferred presentation strategy encourages students to experiment with different options. It appears that by promoting a broader range of thinking and encouraging students to transcend habitual preferences, it is possible to increase learning performance for learners who are not inclined to explore the learning environment.

In contrast, adaptive presentation strategies do not appear to have any effect on learners who explore the learning environment and who use more than one resource. It seems that learners with high activity levels have higher post-test scores regardless of presentation strategy. It may be explained by the fact that such learners will use two or three resources, and will naturally avail of the benefits of using multiple resources.

Both studies also revealed that by comparing performance using the highest-ranking intelligence, no significant differences were found in performance. Students with different highest-ranking intelligences did not score significantly higher than other students. Extensive analysis was also conducted on the use of particular resource categories and how it influenced learning performance, however no clear conclusions can be drawn.

There is some indications that the use of the VL resource category can result in higher performance, as reported in Study A. However this result was not repeated in Study B, a study in which no clear conclusions could be derived about how the use of particular resources could influence performance. In both studies, it is significant to note the popularity of MR resources. MR resources seem to excite and captivate certain students, however it is not clear how music can be best employed to enhance learning performance.

From the presented results, it is possible develop a set of guidelines for pedagogical strategies in adaptive systems. These strategies should:

- Initially present resources that are not preferred.
- Encourage a broad range of thinking and encourage students to transcend habitual preferences.
- Motivate the learner to explore more learning resources.

In summary, the most interesting result from the empirical studies is that adaptive presentation strategies can enhance performance by presenting a variety of resources that are not preferred. This, somewhat, surprising result is in contrast to the traditional MI approach of teaching to strengths and suggests that the best instructional strategy is to provide a variety of resources that challenge the learner. However this may not be as surprising when one considers the motivational aspects of games and their characteristic features. Challenge is one of the key motivational characteristics of games (Prensky, 2001) and it maybe that in education too, challenge at the appropriate level is also needed.

Table 7-36: Comparison of results for Study A and Study B

Analysis	Study A: Adaptive Dynamic vs. Free Learner Control	Study B: Adaptive Single, Inventory and Dynamic	Similar Result?
Independent variables: choice and presentation strategy	Higher learning performance (relative learning gain) when adaptively presented with resources not preferred	Higher learning performance (relative learning gain) when adaptively presented with resources not preferred	Yes
Learning Activity	High activity levels relate to higher post-test scores	High activity levels relate to higher post-test scores	Yes
Learning Activity	Students in adaptive group with medium activity levels had larger increases in learning gain with the least preferred presentation strategy	Students in adaptive inventory and dynamic groups with low activity levels had larger increases in learning gain with the least preferred presentation strategy	Yes but different category of learner
Time on Task	Time-on task correlated with activity level and no additional insights provided	For adaptive dynamic group, least preferred strategy increases time spent exploring MI resources	No
MI Profile	MI Profiles did not influence post-test scores	MI Profiles did not influence post-test scores	Yes
MIDAS Results vs. Behaviour	For LM, VS, MR students preferred resource matches results of MIDAS inventory	N/A	N/A
Resources Used	For Free group, high use of VL and low use of MR result in greater post-test scores. For adaptive group, high use of VL results in greater post-test scores, nothing conclusive to say about use of MR resources.	For Single group, no significant conclusions about use of resources For dynamic and inventory groups, some students use MR resources and nothing else, nothing conclusive to say about use of resources and post-test scores	No

8 Conclusions

8.1 Introduction

Adaptive educational systems attempt to enhance learning by identifying individual trait differences and customising the learning environment to support these differences. However, in the design and development of such systems, several research challenges exist. Outstanding research questions include: what is the relevant educational theory with which to model individual traits, how are the relevant learning characteristics identified and in what way should the learning environment change for users with different learning characteristics?

This thesis has described how the adaptive educational system, EDUCE, addresses these challenges to create an environment that enhances learning through the dynamic identification of learning characteristics and adaptive presentation of content. First, it described how EDUCE uses Gardner's theory of Multiple Intelligences as the basis for modelling learning characteristics and for designing instructional material. Second, it described how EDUCE's novel predictive engine dynamically identifies the learner's Multiple Intelligence profile from interaction with the system and makes predictions on what Multiple Intelligence informed resource the learner prefers. Last, it described empirical studies conducted with EDUCE, that explored how the learning environment, and in particular the presentation of content, should change for users with different characteristics.

The following sections summarise the main research findings, the limitations of the research work and some directions for future research.

8.2 Summary of Research Findings

During the course of the research work, several research findings were discovered when addressing the following three research questions:

- Which learning theory could effectively categorise and model individual trait differences in learning?

- How is it possible to identify learning characteristics from observations of the learner's behaviour?
- How should the learning environment change for users with different learning characteristics?

The following three sections present the main conclusion to each of these questions.

8.2.1 Multiple Intelligences

Gardner's theory of Multiple Intelligences was chosen as the basis for modelling learning characteristics and for designing instructional material for several reasons. It is a rich concept that offers a framework for developing adaptive educational systems that supports creative, multimodal teaching and in the past 20 years since its inception its use in the classroom has been significant. Furthermore, Gardner himself predicted when he published his theory in 1983, that computers have the potential to be a vital facilitator in the process of instruction. However, despite this prediction very little research has been undertaken to explore how the theory of MI can be used in adaptive educational systems. As a result of the research undertaken as part of this thesis, it is possible to draw several conclusions that may guide the application of MI to adaptive systems in its early stages of research:

- MI is a theory from which it is possible to derive an established set of principles for instructional design. The different intelligences are easily recognizable from experience and it is possible to create a rich set of content which reflects the principles of the different intelligences.
- The MI theory supports the development of content outside the traditional verbal/linguistic and logical/mathematical approaches. For example, it supports the development of musical/rhythmic content which was found to be of great appeal to students.
- The development of content using the MI theory requires the teacher to think in different ways. This may be difficult for people who do not appreciate or who do not have strengths in different intelligences. For example, a teacher strong in logical/mathematical intelligence may find it very difficult to create content that appeals to the musical/rhythmic intelligence.

- Developing different representations of the same content using different intelligences can be difficult. However, developing a range of content seems to be important in order to spark interest and motivation.
- As content can be developed to reflect the principles of the different intelligences, it becomes possible to dynamically build a MI profile by observing the behaviour of the learner. From the interaction with the learning environment, from the selection of different resources and from observation of the navigation path, the learner's preferences for different MI resources can be inferred.
- Despite tools being available, assessing the MI profile is a time-consuming and difficult task. The static MI profile identified by the MIDAS inventory requires substantial self-reflection and awareness. The dynamic MI profile identified by EDUCE's predictive engine is based on preferences which may not reflect the student's actual strengths.

In summary, despite some of the reservations outlined, it can be concluded that MI provides a rich educational model with which to model individual learning traits and develop content.

8.2.2 Dynamic Diagnosis

Machine-learning algorithms have been used in many applications but to date, research has not been conclusive about how best to apply machine-learning techniques in the dynamic identification of learning characteristics. As part of this research, a predictive engine was developed in order to dynamically diagnose the MI profile from the student's behaviour. Using this profile it was possible to make predictions on what MI informed resource the learner prefers and does not prefer. From the development of EDUCE's predictive engine, several conclusions can be drawn about the use of machine learning techniques to identify learning characteristics:

- The real challenge with all machine-learning applications is the identification of a useful set of input features. In order to infer learning characteristics, it is necessary to identify a set of features that act as behavioural indicators of the student's learning characteristics. This research proposed a novel set of navigational and temporal features based on real data coming from the learner's interaction with the system. The predictive engine using these features as input was able to dynamically

detect patterns in the learning behaviour and determine the learner's preferences for different MI resources with reasonable success.

- EDUCE's predictive engine uses the Naïve Bayes algorithm for inference. The algorithm was found to be an effective statistical approach for diagnosing preferences. The algorithm can operate on input datasets that are continuously updated based on the student's interaction with the learning environment and hence can dynamically make predictions online.
- The prediction task of the predictive engine was to identify the most preferred resource to use. On entry to a learning unit the predictive engine predicts which resource the student will use first. During the studies conducted to evaluate the engine's performance, predictions made were compared against the real behaviour of the student. The results suggest that strong predictions can be made about the student's preferred resource and that it can be determined, with a relatively high degree of probability, that the student will use the predicted preferred resource within a learning unit. The results also suggest that predictions about the preferred resource are relatively stable, that students only use a subset of resources and that different students use different subsets. The results together suggest that different groups have different learning characteristics and that it is possible to model these learning characteristics. However it should also be noted that certain students do not have distinct preferences and consequently it is not possible to model their learning characteristics.
- Another considerable challenge with machine-learning applications is the need for prior data on which to base classification and predictions. One of the main reasons for choosing the Naïve Bayes algorithm was its ability to work well with sparse datasets. When a student enters EDUCE for the first time, there is no information on the dynamic profile available. To overcome this problem, the student was allowed, during the first learning unit, to express their preferences and freely choose any resource. Subsequently, from analysis of the behaviour in the first learning unit, it was possible from the second learning unit forward to make dynamic predictions on preferred resources. In effect, students were making the initial adaptation and the predictive engine, by monitoring the user's actions was further enhancing this initial adaptation. This approach, used to overcome the lack of prior data, worked well and suggests that to identify learning characteristics, it is

necessary to have an environment over which both the student and the system have the ability to change.

In summary, the Naïve Bayes algorithm is an effective method for identifying learning preferences online when there is not much prior data available. This research also proposed a novel set of input features that are indicative of learning characteristics and which can be used in dynamic diagnosis techniques.

8.2.3 Pedagogical Strategies

Empirical studies were conducted with EDUCE to explore how the learning environment should change for users with different characteristics. In particular it explored: 1) the effect of using different adaptive presentation strategies in contrast to giving the learner complete control over the learning environment and 2) the impact on learning performance when material is matched and mismatched with learning preferences. The following points summarise the main results of these studies:

- Disappointingly, no significant difference in learning outcomes was observed between students who had complete control over the learning environment and students using different adaptive versions of EDUCE. Thus, no conclusions could be made when comparing adaptive presentation strategies based on static and dynamic profiles. Some reasons could be that the sample size was too small, between-subject rather than within-subject differences were compared and that the primary method of assessing differences, the relative gain, was not sensitive enough. The experimental design could also be improved by adding another treatment where students would only use one random resource per learning unit, thus allowing comparisons between adaptive strategies and a random selection.
- The adaptive presentation strategy had an impact on relative gain. It was found that the least preferred presentation strategy gave rise to larger increases in relative learning gain than the most preferred strategy. In particular, it was found that learners who use on average one resource (out of a maximum of four) per learning unit benefit the most when encouraged to use resources not normally used or preferred. It can be concluded that one method for improving learning gain is to adaptively present resources that are not preferred. This result has implications for the role of personalisation in learning. It indicates that there is a difference between the needs and preferences of the student. A preferred resource may not necessarily be the most appropriate resource for the student. Resources that are not preferred

may lead to more challenging learning activities and it maybe that challenging students is one of the paths to better learning. Challenging students may stimulate flexibility in thinking and lead to a broader range of competencies.

- Through a deep analysis of quantitative and qualitative data, it was found that there was a broad range of preferences for different types of resources. It also revealed that the effect of the least preferred presentation strategy was to encourage students to experiment with different options. It can be concluded that adaptive presentation strategies can improve learning performance by promoting a broader range of thinking and encouraging students to transcend habitual preferences.
- It was found that students with high learning activity levels or who use a high proportion of the resources available obtain the highest post-test scores. This suggests that learning strategies that motivate the learner to explore more learning resources can improve learning performance.
- There was no significant difference found when comparing performance using the highest-ranking intelligence. Students with different highest-ranking intelligences did not score significantly higher than other students. In addition, no clear conclusions could be made on how the use of particular resource categories influenced learning performance. There are some indications that the use of the VL resource category can result in higher performance, but this is not consistent across the different studies. However it is significant to note the popularity of MR resources. MR resources seem to excite and captivate certain students, however it is not clear how music can be best employed to enhance learning performance.

The most interesting empirical result is that adaptive presentation strategies can enhance the performance of low activity learners by presenting a variety of resources which are not preferred. This, somewhat, surprising result is in contrast to the traditional MI approach of teaching to strengths and suggests that the best instructional strategy is to provide a variety of resources that challenge the learner.

8.3 Limitations of work

In the light of some interesting research findings, it must be recognised that there are limitations to the significance of the research. When considering these limitations, it must also be remembered that the issues involved in the developing adaptive educational system to support individual trait differences are very complex.

- Some critics argue there that there is no empirical basis for the theory of MI. However Gardner disagrees and argues that the theory of MI is grounded in the disciplines of biological sciences, logical analysis, developmental psychology and traditional psychological research.
- Despite the existence of the MIDAS questionnaire, Gardner does not support the concept of MI assessment instruments or the labelling of students into particular categories. This raises question about the best method for identifying MI preferences and for supporting students with different strengths. Gardner argues that intelligence is the capacity to solve problems or fashion products that are of value, that one intelligence is not better than any other and that everybody has the potential to develop all the different intelligences.
- Currently content has only been created for four of the eight intelligences. Hence, for the concept of MI to be fully explored either content or features need to be developed to support the other four intelligences.
- Different representations of content were created using the principles of four intelligences. In the process of developing resources one specific intelligence was utilised more than any other. Hence, it was possible to clearly identify MI preferences. For example, a student selecting a verbal/linguistic resource would be identified as having a preference for using the verbal/linguistic intelligence. In reality, the different intelligences work together and it is more natural for resources to use two or three intelligences with one being more dominant than the others.
- Content was only developed for one domain, Science, and for one age group, 12 to 15. To generalise the empirical results, particularly the result that presenting resources students do not prefer can enhance learning, it would be necessary to develop content for different age groups and for different domains by different content authors.
- In the original design of EDUCE, there is a rich set of links to support non-linear learning. However, the purpose of the experimental design was to evaluate presentation strategy with different learner and adaptive controlled environments. Thus, links were disabled to ensure that students progressed in a linear manner through the content. Students could only navigate to different MI resources and go back or forward. This restricted navigation path made it possible to observe students as they made decisions about which MI resource to use and to examine the

effect in isolation. However in reality, some students prefer non-linear learning and the linear learning model may have influenced the learning performance. Further studies may need to allow for non-linear learning and to support students with different learning strategies.

- The Naïve Bayes algorithm was chosen as the basis of the predictive engine. For the task of predicting learning preferences it works reasonably well. However, for this prediction task it may be too complex and it may be simpler to base predictions on the last choice a student makes. In addition, the predictive engine is also of questionable value for students who change their preferences frequently, and these students may benefit by having the option to turn adaptivity off.
- This research proposed a novel set of input features based on navigational and temporal measures. However to assess the validity of these measures, further research would need to determine how indicative they are of learning characteristics. This could be achieved by comparing the performance of different sets of input features using different machine-learning algorithms.
- The duration of the experiment was short. Each student spent an average of 35 minutes over both tutorials. To observe student preferences with greater accuracy, it would be necessary to extend the duration of the experiment and develop more content.
- The sample population was small with only 117 students participating in the experiments. To generalise the results it would be necessary to conduct experiments with larger groups. In addition, the range of schools in the studies was limited. One study was conducted in just one school. The other study was conducted with students from academically disadvantaged backgrounds. A sample consisting of a broader range of schools and students would allow the results to be generalised.
- The pre-test and post-test consist of the same factual multi-choice questions. Conceptual based questions would allow for a deeper assessment of student learning. Similar but different questions in the post-test would also determine if facts have just been remembered or have been understood at a deeper level.

Recognising the limitations of the research provides the directions for future research. Such future work outlined in the following section may provide the empirical basis for consistent and valid results that can be generalised.

8.4 Directions for Future Research

The work presented in this dissertation does not represent the definitive solution for developing adaptive systems that support individual trait differences. Rather it is a stepping-stone from which further research can be undertaken. This section outlines a small list of suggestions for future work that could be carried out based on this research.

8.4.1 Multiple Intelligence

To further develop MI as the relevant educational theory with which to model learning trait characteristics and develop content, several suggestions are outlined:

- The static MI profile is based on the MIDAS inventory. Gardner argues that intelligence is the capacity to solve problems or fashion products of value. An interesting method for assessing MI profiles would be to use interactive games and exercises. Using this approach the student's behaviour could be observed and MI strengths inferred while problems are being solved.
- It is clear that musical/rhythmic based resources are extremely popular. Musical/rhythmic resources seem to captivate students, maybe because of the novelty effect or because music conveys an emotional power that traditional text-based learning does not. Further research is required to understand how the power of music can be tapped into for education purposes and understand how music can be best employed to enhance learning performance.
- Currently content has been developed for four of the eight intelligences. To fully explore the concept of MI, content and features would need to be developed in order to support the other four intelligences: intrapersonal, interpersonal, naturalistic and bodily/kinesthetic.
- The current experimental design assumes that students have a strength in one intelligence greater than all others. In reality most students have strengths in two or three intelligences. It would be of interest to experiment with an interface that displays two or three intelligences concurrently.
- Content has only been created for one domain. To generalise the application of MI, it would be useful to develop content for multiple domains and age groups by different content authors.

- It is quite demanding and time consuming to develop content using the principles of MI, particularly if multiple representations of the same content need to be developed. To help speed up the process, templates or authoring tools for creating MI informed content would be very beneficial.
- Different MI representations have different amounts of information and this may influence learning behaviour. It would be of interest to derive a framework for measuring the amount of information in each representation. Subsequently, it would be possible to examine patterns in how people use high or low information representations and determine their impact on learning performance.
- Different MI representations have different computational properties and will require greater or less effort by the student. This may influence decisions a student makes, who may switch to different MI resource if too much effort is required. Students may choose resources they prefer rather than resources that exploit their strengths and subsequently, learning performance may be affected. It would be of interest to measure how the computational properties of different resources impact on learning performance.

8.4.2 Dynamic Diagnosis

Future work to help in the dynamic diagnosis of learning characteristics from observation of learner's behaviour is outlined in the following suggestions:

- This research has proposed a novel set of temporal and navigational features that can be used as input to a machine-learning algorithm such as Naïve Bayes. Future analysis could identify the relevance of these features and identify other features that may be indicative of learning characteristics.
- The current prediction task of the predictive engine is to identify the order of preference for different MI resources. There may be other prediction tasks that are of interest, such as predicting the order in which resources are used or the relationship between questions answered correctly and resources used.
- Other machine-learning algorithms could be investigated to determine if prediction accuracy could be improved. These learning algorithms could include rule based learning, neural networks, probability learning, instance-based learning and content-based/collaborative filtering.

- The predictive engine currently operates with very little prior data about the student's preferences. One approach to overcome this problem would be to develop a student model combining the dynamic and static MI profiles. Such a model might be a more accurate reflection of both a student's preferences and strengths, and provide the basis for more appropriate pedagogical strategies.
- It should be possible to generalise the predictive engine for use with different learning style models. This research categorises resources based on the theory of MI. It should be possible to use different categorisation frameworks based on different learning theories. Thus, the extent to which the predictive engine can be generalised could be evaluated.

8.4.3 Pedagogical Strategies

This research reports some interesting results regarding the pedagogical strategies adaptive educational systems should use. To determine if these results can be generalised the following suggestions are outlined:

- The results suggest that challenging students with learning resources may lead to greater learning. They suggest that adaptively presenting resources that are not preferred, rather than resources that are preferred, can result in greater learning gain. This is particularly the case with low activity learners who only use the resource presented and are not inclined to explore other resources available. Further empirical studies are needed with more content and a broader sample population to determine if this result can be repeated and to determine the role of challenge in learning environments.
- The results indicate that adaptive presentation strategies have different effects for students with different activity levels and that learning activity is correlated with learning performance. An interesting research direction would be to explore the influences on learning activity and to determine strategies that increase learning activity.
- Systems using different variations of adaptive control and personalisation were compared, but no significant differences in learning were found when comparing relative gain. It would be interesting to measure the effectiveness of these systems not only by relative gain, but also by qualitative measures such as motivation levels

and enjoyment. Personalisation may bring other benefits such as raising motivation levels, making learning more enjoyable or accelerating the learning process.

- This research could not conclusively report on how the use of different types of resources impacts on learning performance. It may be that certain MI representations have a greater measure of information. Future work, involving different experimental designs, could determine if students using a particular type of resource have greater performance levels.
- The method for assessing learning gain was based on the use of a pre-test and post-test consisting of the same factual multi-choice questions. It would be interesting to assess learning gain using different methods. Different questions examining conceptual understanding in the post-test would allow for a deeper assessment of the student's knowledge. In addition, it would be interesting to have different modes of assessment for different MI categories rather than using multi-choice questions which are orientated towards the verbal/linguistic intelligence.
- The quantitative analysis techniques used were grounded in correlational and experimental research methodology and produced some valuable information in understanding the factors influencing learning performance. However, it would be interesting to analyse the data using a multivariate approach such as structural equation modelling (SEM) (Tabachnick & Fidell, 2001) in order to develop a more theoretically robust and clinically meaningful description of individual differences.
- This research uses an experimental design that compares different adaptive systems with a non-adaptive system. An additional variation in the experimental design would be to have another system that randomly presents one resource per learning unit and disable the option to view other resources. This would allow comparisons between specific adaptive strategies and an adaptive strategy based on random selection.
- The version of EDUCE used in experiments was based on a linear model of learning where each concept is presented in a fixed sequence. The reason for this was to isolate and explore the effect of the adaptive presentation strategy. In reality, some students prefer to learn following a different sequence of concepts. Further studies may need to allow for non-linear learning and to support students with different learning strategies.

- The influence of other personalisation factors such as learning context, goals and motivation needs to be investigated. Students choose different MI representations for different reasons, for example to do well in the post-test, for stimulus and fun or because they think it is what they are good at. It would be useful to develop a model for measuring motivation. This model needs to identify the constructs to measure and the inputs, such as navigation data and questionnaires, to measure these constructs.

8.5 Conclusions

In summary, the main contributions of this research are:

- The development of an original framework for using Multiple Intelligences to model learning characteristics and develop educational resources in an adaptive educational system.
- A novel online predictive engine that dynamically determines a learner's preference for different MI resources.
- Results from empirical studies that support the effectiveness of adaptive presentation strategies for learners with low levels of learning activity.

This research presents interesting insights into the broader question of how personalisation and adaptivity can be used to enhance learning performance. It seems that dynamic personalisation is a challenging task and it is not always clear on how best to adapt the learning environment. In fact, personalisation may need to be supported by adaptable systems that allow learners to select their preferences and update their individual learner models.

The results of this study may be significant for researchers and practitioners. For researchers, it demonstrates that adaptive presentation strategies are important for learners who are not inclined to explore different learning options. For practitioners, it demonstrates how teaching in different ways can affect learning. It is hoped that the results of the research will help in the development of technology enhanced learning environments that support individual trait differences and enable all learners to fulfil their true potential.

Appendix

A. Naïve Bayes Algorithm

The Naive Bayes algorithm is a statistical modeling technique that can be used as the basis for making predictions and decisions. It uses all input attributes and allows them to make contributions to the decision that are equally important and independent of one another.

This algorithm is based on Baye's rule of conditional probability. Bayes rule provides a way to calculate the probability of a hypothesis based on its prior probability, the probabilities of observing various data given the hypothesis, and the observed data itself.

Baye's rule says that if you have a hypothesis h , and evidence E (training data) which bears on that hypothesis, then

$$P[E | h] = \frac{P[E | h] P[h]}{P[E]}$$

The notation $P[A]$ denotes the probability of an event A , and $P[A | B]$ denotes the probability of A conditional on another event B . Thus:

- $P[h]$ is the probability of the event happening before any evidence has been seen. It is called the prior probability and may reflect any background knowledge about the chance h is a correct hypothesis.
- $P[E]$ is the denotes the prior probability that evidence E will be observed, i.e. the probability of E given no knowledge about which hypothesis holds.
- $P[E | h]$ is denotes the probability of observing evidence E give some world in which hypothesis h holds.
- $P[h | E]$ is the probability of the event after evidence has been seen. It is called the posteriori probability of h , because it reflects the confidence that h holds after the evidence E has been seen. The posterior probability $P[h | E]$ reflects the influence of the evidence E , in contrast to the prior probability $P[h]$, which is independent of E .

In learning scenarios, a set of candidate hypotheses H is considered and the most probable hypothesis $h \in H$ given the observed evidence. Any such maximally probable hypothesis is called a maximum a posteriori (MAP) hypothesis. The MAP hypothesis can be determined by using Bayes theorem to calculate the posterior probability for each candidate hypothesis. More precisely

$$h_{MAP} = \operatorname{argmax}_{h \in H} P[h | E]$$

$$h_{MAP} = \operatorname{argmax}_{h \in H} \frac{P[E | h] P[h]}{P[E]}$$

$$h_{MAP} = \operatorname{argmax}_{h \in H} P[E | h] P[h]$$

The final step drops the term $P[E]$ because it is constant independent of h .

The Bayesian approach to classifying new instances and making predictions is to assign the most probable target value, v_{MAP} , given the attribute values $(a_1, a_2 \dots a_n)$ that describes the instance.

$$v_{MAP} = \operatorname{argmax}_{v_j \in V} P[a_1, a_2 \dots a_n | v_j] P[v_j]$$

The naive Bayes Classifier is based on the assumption that the attribute values are conditionally independent given the target value. In other words, the assumption is that given the target value of an instance, the probability of observing the conjunction $a_1, a_2 \dots a_n$ is just the product of the probabilities for the individual attributes

$$P[a_1, a_2 \dots a_n] = \operatorname{argmax}_{v_j \in V} Pr[v_j] \prod_i P[a_i | v_j]$$

The algorithm goes by the name of Naive Bayes because it is based on the Bayes's rule and "naively" assumes independence – it is only valid to multiply probabilities when the events are independent.

B. Questionnaires

B.1 Pre- and Post-Tests

B.1.1 Static Electricity

1. What is everything in the universe made up of ?

Space

Stars

Atoms

Galaxy

2. Which particle goes around the nucleus ?

Proton

Neutron

Electron

Atom

3. Electrons have what sort of charge ?

Positive (+)

Negative (-1)

Neutral (0)

No Charge

4. Protons have what sort of charge ?

Positive (+)

Negative (-1)

Neutral (0)

No Charge

5. What is the charge on an atom that loses electrons ?

- Positive
- Negative
- Neutral
- Balance

6. Two positive charges _____ each other

- Attract
- Repel
- Move
- Stop

7. A ballon rubbed in your hair picks up extra _____ and becomes charged

- Protons
- Neutrons
- Electrons
- Atoms

8. Lightning in the sky is caused by the build up of what?

- Storms
- Electricity
- Thunder
- Static Electricity

9. The negative charge on the bottom of the cloud causes a _____ charge on the ground underneath

- No Charge
- Negative

Neutral

Positive

10. Where is the safest place to be when lightning strikes above ?

Tree

Car

Umbrella

House

B.1.2 Electricity in the Home

1. Electric current is the _____ of electrons in a closed circuit.
 - Measure
 - Number
 - Size
 - Flow
2. What is the unit of electricity ?
 - Watt
 - Volt
 - Ohm
 - Amp
3. A battery pumps _____ from a region of high electrical pressure to a region of low electrical pressure ?
 - Circuits
 - Air
 - Electricity
 - Electrons
4. What instrument is used to measure voltage ?
 - Voltmeter
 - Ammeter
 - Wattmeter
 - No device
5. What unit is a measure of how quickly an appliance converts electrical energy to other forms of energy ?
 - Volt

- Watt
 - Amp
 - Secs
6. Before an electric circuit can conduct electricity it must be
- Complete
 - Open
 - Large
 - Small
7. When the current is too big the fuse
- does nothing
 - goes blue
 - keeps circuit working
 - blows
8. Circuit breakers protect a circuit against too large a
- Breaker
 - Switch
 - Current
 - Circuit
9. The brown wire is connected to which terminal ?
- Earth
 - Live
 - Neutral
 - None

10. A 5 kW electric fire is on for five hours. How many cents does it cost when each unit costs 10 cent ?

25

50

250

500

B.2 Reflection during tutorial

1. Which learning mode did you prefer ?



All

None

2. Which helps you remember best ?



All

None

3. Why ?

B.3 Reflection after tutorial

1. Which option do you prefer the most?



All

None

Why ?

2. Which option do you remember the most?



All

None

3. Do you have favourite choice ? Which one is it ?



All

None

4. What are the differences between the options ?

5. After going to your favourite choice did you try other options? Why ?

6. Describe one thing you remember from studying on the computer.

7. Would you like to study more science with the computer? Why?

8. What was the highlight in using the computer today ?

B.4 MIDAS Questionnaire

B.4.1 What is it ?

The purpose of the Multiple Intelligence Development Assessment Scales (MIDAS) profile is to provide information that you can use to gain a deeper understanding your skills, abilities and preferred teaching style. It is not a test. It is an “untest” that allows you to talk about yourself. The scores are not absolute and it is up to you to decide if these scores are a good description of your intellectual and creative life. The profile can be described as the general overall intellectual disposition that includes your skill, involvement and enthusiasm for different areas.

The MIDAS questionnaire was developed by C. Branton Shearer, Ph.D. In 1996 Howard Gardner made comments on the MIDAS. These included:

“I think that it (MIDAS) has the potential to be very useful to students and teachers alike and has much to offer the educational enterprise.

Branton Shearer is to be congratulated for the careful and cautious way in which he has created his instrument and continues to offer guidance for its use and interpretation”

B.4.2 How is it used ?

4. The inventory will be first filled out. It consists of 93 questions. For some sample questions see page 196
5. A MIDAS Brief Learning Summary will be returned to you, listing your two highest, your four middle and your two lowest areas. See page 199 for a sample.
6. Complete the Brief Learning summary by describing actual activities you do the most or best. For example “played the piano for 5 years”.
7. Reflect on and validate the summary of your skills to determine if it accurately describes you. You can evaluate this description by discussing it with people who know you well.
8. If necessary, revise the Brief Learning Summary to better represent your actual range of skills and abilities

B.4.3 Samples Questions from MIDAS Inventory

Musical/Rhythmic

Q. Did you ever learn to play an instrument or take music lessons ?

A = Once or twice

B = Three or four times maybe

C = For a couple of months

D = Less than a year

E = More than a year

F = I never had the chance

Bodily/Kinesthetic

How well can you run, jump, skip, hop or gallop ?

A = Fairly well

B = Well

C = Very well

D = Excellent

E = The best

F = I don't know

Mathematical/Logical

When you were young, how easily did you learn your numbers and counting ?

A = It was hard

B = It was fairly easy

C = It was easy

D = It was very easy

E = I learned much quicker than most kids

F = I don't know

Visual/Spatial

Do you like to decorate your room with pictures or posters, drawings etc ?

A = Not very much

B = Sometimes

C = Many Times

D = Almost all the time

E = All the time

F = I don't know or I have'nt had the chance

Verbal/Linguistic

How hard was it for you to learn the alphabet or learn how to read ?

A = It was hard

B = It was fairly easy

C = It was easy

D = It was very easy

E = I learned much quicker than all the kids

F = I don't know

Interpersonal

How well can you help other people to settle an argument between two friends?

- A = Not very well
- B = Fairly well
- C = Well
- D = Very well
- E = Excellent
- F = I don't know

Intrapersonal

Do you choose activities that are challenging for you to do ?

- A = Once in a while
- B = Sometimes
- C = Many times
- D = Almost all the time
- E = All the time
- F = I don't know

Naturalist

Have you ever been good at helping to train a pet to obey or do tricks ?

- A = No
- B = Maybe a little
- C = Fairly good
- D = Good
- E = Excellent
- F = I don't know

B.4.4 The MIDAS Brief Learning Summary - Sample

Name: _____ Terry _____ Date: _____ 2004 _____

The following profile was compared from data provided by you. It represents areas of strengths and limitations as described by you. This is preliminary information to be confirmed by way of discussion and further exploration.

	Main	Specific
High	Visual/Spatial Musical	Artistic Construction Reading Musical Appreciation Leadership
Moderate	Interpersonal Intrapersonal Bodily/Kinesthetic Verbal/Linguistic	
Low	Naturalist Mathematical / Logical	Calculations Understanding others Animal Care Working with Hands Dancing/Acting
Preferred Activities	Drawing Listening to music Art class if favourite	

B.4.5 Reflection on Brief Learning Summary– Student Sample

The areas of the summary I think are too high or low are:

	Hig h	O K	Lo w		Hig h	O K	Lo w
Verbal/Linguistic			X		Musical	X	
Visual/Spatial		?			Kinestheti c		X
Logical/Mathemat ical	?				Interperso nal	X	
Intrapersonal		X			Naturalist	?	

Overall I think the profile is:

OK X Too High _____ Too Low _____ Mixed up _____

What supprises me is ...

I did not know I was so strong in Maths and Music

What puzzles me is ..

I wonder why my results in maths class do not reflect my strong ability in this area

What I have learned about myself by completeing this assessment is ..

I have good understanding of other people and I am good when working with pictures _____

Other comments:

I know that I like pictures, I will now try and use this ability in other classes besides art classes

C. Educe Implementation

C.1 Domain Knowledge Representation

Tutorial content is stored in XML format. The following is a sample of the XML file which stores the content for section one of the Static Electricity Tutorial. Note that the panels make extensive use of multimedia developed using Flash Macromedia.

```
<?xml version="1.0"?>
<tutorial img="../media/images/electricity.jpg" alt="Learning Applets" feedback-link="feedback-
panel" help-link="help-panel" points-link="points-panel" end-link="end-panel"
filename="EleSta">
  <title>Static Electricity</title>
  <section id="1">
    <title>Static Electricity</title>
    <unit id="11">
      <title>Static Electricity</title>
      <panel id="111" type="Anchor">
        <learningStyle intelligence="All">
          <body>
            <table align="center">
              <tr>
                <td>
                  <p align="center">
                    <animation title="Jumper" type="Flash" src="jumper.swf" width="250"
height="250"/>
                  </p>
                </td>
              </tr>
            </table>
          </body>
        </learningStyle>
      </panel>
      <panel id="112" type="Content">
        <learningStyle intelligence="Word">
          <body>
            <table align="center">
              <tr valign="middle">
                <td width="505">
                  About 600 BC, a Greek philosopher, Thales de Miletus,
                  noticed a mysterious property of a hard dry yellow substance called amber.
                  <br/>
                  When he rubbed it with wool or fur, it attracted light materials
                  such as hair and bits of dry leaves.
                  This attraction is caused by static electricity.
                  <br/>
                  <br/>
                </td>
              </tr>
            </table>
          </body>
        </learningStyle>
        <learningStyle intelligence="Math">
          <body>
            <table align="center">
              <tr>
                <td>
                  <animation type="Flash" src="staticintro_flowchart.swf" width="340" height="320"/>
                </td>
              </tr>
            </table>
          </body>
        </learningStyle>
      </panel>
    </unit>
  </section>
</tutorial>
```

```

        </tr>
      </table>
    </body>
  </learningStyle>

<learningStyle intelligence="Music">
  <body>
    <table align="center">
      <tr valign="top">
        <td width="300" align="right">
          <animation type="Flash" src="sound_thunder.swf" width="175" height="50"/>
        </td>
        <td width="40">
          <nbsp;/>
        </td>
        <td>
          An electrical storm.
          <br/><br/>
        </td>
      </tr>
    </table>
    <br/><br/><br/>
  </body>
</learningStyle>
<learningStyle intelligence="Art">
  <body>
    <table width="" align="center">
      <tr>
        <td align="center">
          <animation type="Flash" src="doorknob.swf" width="250" height="250"/>
        </td>
        <td width="20">
          <nbsp;/>
        </td>
      </tr>
    </table>
  </body>
</learningStyle>
</panel>
<panel id="113" type="Content">
  <learningStyle intelligence="All">
    <body>
      <table align="center" border = "1">
        <tr>
          <td>
            <textformat color="3">Static Electricity</textformat> can give a shock when
            you touch<br/> a door handle or sparks when taking off a jumper.
          </td>
        </tr>
      </table>
    </body>
  </learningStyle>
</panel>
<panel id="114" type="Question">
  <learningStyle intelligence="All">
    <body>
      <p>
        What causes your hair to stand up when you take your jumper off ?
        <br/>
        <br/>
        <multichoice-button qnum="111" label=" Storm " id="mc1" answer=" Electricity "
        message="Try again"/>
      </p>
    </body>
  </learningStyle>
</panel>

```

```
        <multichoice-button qnum="111" label="    Shock    " id="mc2" answer=" "
message="Try Again"/>
        <multichoice-button qnum="111" label="    Energy    " id="mc3" answer=" "
message="Try Again"/>
        <multichoice-button qnum="111" label="Static Electricity" id="mc4"
answer="Static Electricity" message="Well done"/>
        <br/> <br/>
    </p>
</body>
</learningStyle>
</panel>
<panel id="115" type="Feedback">
    <learningStyle intelligence="All">
        <body>
            <feedback-intra/>
        </body>
    </learningStyle>
</panel>
</unit>
</section>
```

C.2 Presentation Model

The presentation model consists of XSLT style sheets. Parameters are passed in from the pedagogical model and transformations are performed on the XML files. The following sample is an extract of the style sheet which generates the page that contains the tutorial content.

```
<xsl:template match="tutorial" mode="build-individual-panels">
  <xsl:param name="outputSectionPosition" select="1"/>
  <xsl:param name="outputUnitPosition" select="1"/>
  <xsl:param name="outputPanelPosition" select="1"/>
  <xsl:for-each select="section">

    <xsl:variable name="sectionNumber" select="position()"/>

    <xsl:for-each select="unit">
      <xsl:variable name="unitNumber" select="position()"/>
      <xsl:variable name="lastUnit">
        <xsl:choose>
          <xsl:when test="$unitNumber=last()">
            <xsl:text>true</xsl:text>
          </xsl:when>
          <xsl:otherwise>
            <xsl:text>false</xsl:text>
          </xsl:otherwise>
        </xsl:choose>
      </xsl:variable>

      <xsl:for-each select="panel">
        <xsl:variable name="panelNumber" select="position()"/>
        <xsl:variable name="lastPanel">
          <xsl:choose>
            <xsl:when test="$panelNumber=last()">
              <xsl:text>true</xsl:text>
            </xsl:when>
            <xsl:otherwise>
              <xsl:text>false</xsl:text>
            </xsl:otherwise>
          </xsl:choose>
        </xsl:variable>

        <xsl:if test="$sectionNumber=$outputSectionPosition">
          <xsl:if test="$unitNumber=$outputUnitPosition">
            <xsl:if test="$panelNumber=$outputPanelPosition">

.....

      <html>
        </xsl:text>
        <head>
          <title>
            <xsl:value-of select="./title"/><xsl:text>-</xsl:text>
            <xsl:value-of select="$sectionNumber"/><xsl:text>-</xsl:text>
            <xsl:value-of select="$unitNumber"/><xsl:text>-</xsl:text>
            <xsl:value-of select="$panelNumber"/><xsl:text>-</xsl:text>
            <xsl:value-of select="$titleInfo"/><xsl:text>-</xsl:text>
            <xsl:value-of select="$studentName"/>
          </title>

          <style type="text/css">
            <xsl:value-of select="$css-settings"/>
```

```

</style>
</head>

<body bgcolor="#FFFFFF" ONLOAD = "startTimer()">

  <script language="javascript">
    <xsl:value-of select="$mouse-effects"/>
  </script>
  <script language="javascript">
    <xsl:value-of select="$dk-javascript"/>
  </script>

  <xsl:call-template name="dk-top-bar">
    <xsl:with-param name="sectionNum" select="$sectionNumber"/>
    <xsl:with-param name="unitNum" select="$unitNumber"/>
    <xsl:with-param name="panelNum" select="$panelNumber"/>
    <xsl:with-param name="unitTitle" select="./title"/>
    <xsl:with-param name="feedbackLink" select="$feedbackLink"/>
    <xsl:with-param name="pointsLink" select="$pointsLink"/>
    <xsl:with-param name="helpLink" select="$helpLink"/>
  </xsl:call-template>

  <table width="750" border="0" cellspacing="0" cellpadding="5" align="center">
    <tr background="../nav_images/squares_bg.gif">
      <td height="300" background="../nav_images/squares_bg.gif">
        <xsl:apply-templates
          select="learningStyle[@intelligence=$pageIntelligence]/body"
          mode="build-individual-panels">
          </xsl:apply-templates>
        </td>
      </tr>
    </table>

    <xsl:call-template name="dk-move-bar">
      <xsl:with-param name="sectionNum" select="$sectionNumber"/>
      <xsl:with-param name="unitNum" select="$unitNumber"/>
      <xsl:with-param name="panelNum" select="$panelNumber"/>
      <xsl:with-param name="lastUnit" select="$lastUnit"/>
      <xsl:with-param name="lastPanel" select="$lastPanel"/>
      <xsl:with-param name="nextPrev" select="$nextPrev"/>
      <xsl:with-param name="goBack" select="$goBack"/>
      <xsl:with-param name="wordGo" select="$wordGo"/>
      <xsl:with-param name="mathGo" select="$mathGo"/>
      <xsl:with-param name="artGo" select="$artGo"/>
      <xsl:with-param name="bodyGo" select="$bodyGo"/>
      <xsl:with-param name="musicGo" select="$musicGo"/>
    </xsl:call-template>
  </body>
</html>

</xsl:if>
</xsl:if>
</xsl:if>
</xsl:for-each>
</xsl:for-each>
</xsl:for-each>

</xsl:template>

```

C.3 Pedagogical Model

The pedagogical model is implemented using Java servlets running on a Apache Tomcat Web server. The servlets passes parameters to the style sheet and performs the transformation on the XML file storing the domain knowledge when generating the specific page requested by the user. The following sample from the Dispatcher servlet illustrates how the parameters holding the values of the next page and preferred intelligence option are retrieved.

```
public void processRequest(HttpServletRequest request,
                          HttpServletResponse response) throws ServletException, IOException
{
    .....

    //*****
    // determine output mode, panel & section position
    //*****

    String outputMode = "";
    String outputSectionPosition = "";
    String outputUnitPosition = "";
    String outputPanelPosition = "";

    if ( nextPageID.length() >= 12)
    {
        outputSectionPosition = nextPageID.substring(7, 8);
        outputUnitPosition = nextPageID.substring(9, 10);
        outputPanelPosition = nextPageID.substring(11, 12);
    }

    if ( outputSectionPosition.compareTo("0") == 0 )
        outputMode = "build-main-index";
    else if ( outputUnitPosition.compareTo("0") == 0 )
        outputMode = "build-section-indexes";
    else
        outputMode = "build-individual-panels";

    //*****
    // get and set prefIntelligence - intelligence to go to
    // get current page Intelligence
    //*****
    String prefIntelligence;
    boolean bUserSpecifiedIntelligence;

    prefIntelligence = request.getParameter("prefIntelligence");

    if ( prefIntelligence != null ) { //from web page
        // store in session
        session.setAttribute("prefIntelligence", prefIntelligence);
        bUserSpecifiedIntelligence = true;
    }
    else {
        // get parameter from session
        prefIntelligence = (String)session.getAttribute("prefIntelligence");
        if ( prefIntelligence == null ) { // default first value
            prefIntelligence = "Word";
        }
        bUserSpecifiedIntelligence = false;
    }
}
```

```

String pageIntelligence;
pageIntelligence = request.getParameter("pageIntelligence");
if ( pageIntelligence == null ) { // default first value
    pageIntelligence = ""; // no intelligence for page
}

// anchorchoice - choice made from anchor page
boolean bAnchorChoice = false;
// set firstTimeAnchor when come into anchor page on different section/unit
int nCurSection = 0;
int nNextSection = 0;
int nCurUnit = 0;
int nNextUnit = 0 ;
int nCurPanel = 0;
int nNextPanel = 0;

if ( ( curPageID.length() > 6 ) )
{
    nCurSection = Integer.parseInt(curPageID.substring( 7 , 8));
    nCurUnit = Integer.parseInt(curPageID.substring( 9 , 10));
    nCurPanel = Integer.parseInt(curPageID.substring( 11 , 12));
}
if ( ( nextPageID.length() > 6 ) )
{
    nNextSection = Integer.parseInt(nextPageID.substring( 7 , 8));
    nNextUnit = Integer.parseInt(nextPageID.substring( 9 , 10));
    nNextPanel = Integer.parseInt(nextPageID.substring( 11 , 12));
}
}
}

```

C.4 Predictive Engine

The Predictive engine is implemented using a number of classes interacting with the WEKA class library. The following is an extract from the MIBayesPred, the class which interfaces with the WEKA class library and calculates the probability that a particular MI resource is preferred.

```
/**
 * Java Class implementing Naive Bayes Classifier
 */

import weka.core.*;
import weka.classifiers.*;
//import weka.filters.*;
import java.io.*;
import java.util.Enumeration;

// How to use from another class
//      MIBayesPred aMIBayesPred = new MIBayesPred();
// aMIBayesPred.updateDataModel2 (attResSel,attFirstChoice,
//                                attLongTime, attRepeat, attOneOnly,
//                                attMotivateQuest, attMotivateQuestRight,
//                                attAppropriate);
//      aMIBayesPred.calculatePred();
//      predRes=aMIBayesPred.getMaxRes();
//      predRes2= aMIBayesPred.getMaxRes2();
//

public class MIBayesPred implements Serializable {
    /* The training data. */
    private Instances m_Data = null;
    /* The classifier. */
    private DistributionClassifier m_Classifier = new NaiveBayes();
    private String[] m_Keywords = {"learningres, longtime"};
    private final int SMARTTOTAL = 4;
    private String[] smartNames = {"Word", "Math", "Art", "Music"};
    private SmartNumber[] smartPred = new SmartNumber[SMARTTOTAL];
    private FastVector attributes = null;
    public String maxRes = "";
    public String maxRes2 = "";
    public String minRes = "";
    public int type = 0; // sets the attribute list
    public int numKeywords; // number of attributes

    /**
     * Constructs empty training dataset.
     */

    public MIBayesPred()
    {
        try {
            String[] args;
            String[] attNames = {"ressel1", "ressel2", "firstchoice1", "firstchoice2",
"firstchoice3", "longtime", "repeat", "oneonly", "motivatequest", "motivatequestright"};
            buildMIBayesPred(attNames);
        } catch (Exception e)
        {
            System.err.println(e.getMessage());
        }
    }
}
```



```

public void buildMIBayesPred(String[] keywords) throws Exception
{
    int i,j;
    String nameOfDataset = "MIPrediction";

    m_Keywords = keywords;
    // Create numeric attributes.
    attributes = new FastVector(m_Keywords.length + 1);
    FastVector classValues;

    for (j=0; j< m_Keywords.length; j++)
    {
        classValues = new FastVector(2);
        classValues.addElement("Yes");
        classValues.addElement("No");
        attributes.addElement(new Attribute(m_Keywords[j], classValues));
    }

    // Add class attribute.
    classValues = new FastVector(4);
    for (i=0; i<smartNames.length; i++)
        classValues.addElement(smartNames[i]);
    attributes.addElement(new Attribute("appropriate", classValues));

    // Create dataset with initial capacity of 100, and set index of class.
    m_Data = new Instances(nameOfDataset, attributes, 1);
    m_Data.setClassIndex(m_Data.numAttributes() - 1);
}

/**
 * Updates model using the given training message.
 */
public void updateDataModel2(String ressel, String firstChoice,
                             String longtime, String repeat, String oneonly,
                             String motivatequest, String motivatequestright,
                             String appropriate) throws Exception
{
    String[] atts = {""];
    if (type==0)
    {
        String[] temp = {ressel, ressel, firstChoice, firstChoice, firstChoice, longtime,
repeat, oneonly, motivatequest, motivatequestright, appropriate };
        atts = temp;
    }
    updateDataSet(atts);
}

public void calculatePred() throws Exception
{
    if ( !emptyDataSet() )
    {
        rebuildClassifier();
        getPredictions();
        sortPredictions();
        maxRes = smartPred[0].smartName;
        maxRes2 = smartPred[1].smartName;
        minRes = smartPred[3].smartName;
    }
}
}

```

D. Predictive Engine – Sample Output

At the beginning of each learning unit, the preference for different MI resources is calculated. The prediction is based on past behaviour up to that point the prediction is made. The following sample illustrates how for one student the predictions are calculated. Note that as the student progresses through the tutorial there is a greater amount of training data upon which the prediction is made.

TIMESTAMP: Wed Mar 24 13:45:16 GMT 2004 --> SessionID =
4D633A348B5BA817749257AD94D88AED

--> StudentID = 96

--> Dataset

Yes, Yes, No, Yes, No, No, Yes, Yes, Music

Yes, Yes, No, Yes, No, No, Yes, Yes, Art

No, No, No, No, No, No, No, No, Word

No, No, No, No, No, No, No, No, Math

--> End Dataset

--> SmartPred=

Art == 0.4848484848484848

Music == 0.4848484848484848

Word == 0.01515151515151515

Math == 0.01515151515151515

--> Predicted Bayes MIRes is = Math

--> -----

TIMESTAMP: Wed Mar 24 13:46:14 GMT 2004 --> SessionID =

4D633A348B5BA817749257AD94D88AED

--> StudentID = 96

--> Dataset

Yes, Yes, No, Yes, No, No, Yes, Yes, Music

Yes, Yes, No, Yes, No, No, Yes, Yes, Art

No, No, No, No, No, No, No, No, Word

No, No, No, No, No, No, No, No, Math

Yes, Yes, No, Yes, No, Yes, Yes, Yes, Math

No, No, No, No, No, No, No, No, Word

No, No, No, No, No, No, No, No, Art

No, No, No, No, No, No, No, No, Music

--> End Dataset

--> SmartPred=

Math == 0.49612403100775193

Art == 0.24806201550387597

Music == 0.24806201550387597

Word == 0.007751937984496124

--> Predicted Bayes MIRes is = Word

--> -----

TIMESTAMP: Wed Mar 24 13:47:26 GMT 2004 --> SessionID =

4D633A348B5BA817749257AD94D88AED

--> StudentID = 96

--> Dataset

Yes, Yes, No, Yes, No, No, Yes, Yes, Music

Yes, Yes, No, Yes, No, No, Yes, Yes, Art

No, No, No, No, No, No, No, No, Word

No, No, No, No, No, No, No, No, Math

Yes, Yes, No, Yes, No, Yes, Yes, Yes, Math

No, No, No, No, No, No, No, No, Word

No, No, No, No, No, No, No, No, Art

No, No, No, No, No, No, No, No, Music

Yes, Yes, No, Yes, No, Yes, Yes, Yes, Word
No, No, No, No, No, No, No, No, Math
No, No, No, No, No, No, No, No, Art
No, No, No, No, No, No, No, No, Music

--> End Dataset
--> SmartPred=
Word == 0.3333333333333333
Math == 0.3333333333333333
Art == 0.1666666666666666
Music == 0.1666666666666666

--> Predicted Bayes MIREs is = Music
--> -----

TIMESTAMP: Wed Mar 24 13:48:46 GMT 2004 --> SessionID =
4D633A348B5BA817749257AD94D88AED

--> StudentID = 96

--> Dataset

Yes, Yes, No, Yes, No, No, Yes, Yes, Music
Yes, Yes, No, Yes, No, No, Yes, Yes, Art
No, No, No, No, No, No, No, No, Word
No, No, No, No, No, No, No, No, Math
Yes, Yes, No, Yes, No, Yes, Yes, Yes, Math
No, No, No, No, No, No, No, No, Word
No, No, No, No, No, No, No, No, Art
No, No, No, No, No, No, No, No, Music
Yes, Yes, No, Yes, No, Yes, Yes, Yes, Word
No, No, No, No, No, No, No, No, Math
No, No, No, No, No, No, No, No, Art
No, No, No, No, No, No, No, No, Music
Yes, Yes, No, Yes, No, Yes, Yes, Yes, Music
No, No, No, No, No, No, No, No, Word
No, No, No, No, No, No, No, No, Math
No, No, No, No, No, No, No, No, Art

--> End Dataset
--> SmartPred=
Music == 0.7523219814241486
Math == 0.09907120743034054
Word == 0.09907120743034054
Art == 0.04953560371517027

--> Predicted Bayes MIREs is = Art
--> -----

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