Adapting to Intelligence Profile in an Adaptive Educational System

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Abstract: Learning characteristics, as informed by research, vary for each individual learner. Research suggests that knowledge is processed and represented in different ways and that students prefer to use different types of resources in distinct ways. However, building Adaptive Educational systems that adapt to different learning characteristics is not easy. Major research questions exist such as: how are the relevant learning characteristics identified, how does modelling of the learner take place and in what way should the learning environment change for users with different learning characteristics?

EDUCE is one system that addresses these challenges by using Gardner’s theory of Multiple Intelligences (MI) as the basis for dynamically modelling learning characteristics and for designing instructional material. This paper describes a research study, using EDUCE, that explores the effect of using different adaptive presentation strategies and the impact on learning performance when material is matched and mismatched with learning preferences. The results suggest that students with low levels of learning activity, and who use only a limited number of the resources available, have the most to benefit from adaptive presentation strategies and that surprisingly learning gain increases when they are provided with resources not normally preferred.

Keywords: Student Modelling, Learning Characteristics, Learning Styles, Instructional Design, Multiple Intelligences

1. Introduction

Educational research tells us that “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 learn differently, they process and represent knowledge in different ways, and they prefer to use different type of resources (Riding & Rayner, 1997). Research also suggests that it is possible to diagnose a student’s learning style 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 need of different students. Such systems build a model of the student’s knowledge, goals and preferences, and use the generated model to dynamically adapt the learning environment for each student in a manner that best
supports learning (Brusilovsky, 2001). Strategies that have been used to adapt to these learner characteristics include annotating links, hiding links, changing the sequence of material and hiding or tailoring the content (Brusilovsky, 2001). Several adaptive educational systems that adapt to different learning characteristics have been developed (Specht & Oppermann, 1998; Gilbert & Han, 1999; Stern & Woolf, 2000; Panpankololou et al, 2003). However building such systems is not easy and major research questions include: how are the relevant learning characteristics identified, how modelling of the learner take place and in what way shall the learning environment change for users with different learning characteristics (Papanikolaou & Grigoriadou, 2004).

EDUCE (Kelly & Tangney, 2004) is an adaptive intelligent educational system that addresses these challenges by using Gardner’s theory of Multiple Intelligences (MI) as the basis for dynamically modelling learning characteristics and for designing instructional material (Gardner, 1983). The theory of Multiple Intelligences reflects an effort to rethink the theory of measurable intelligence embodied in intelligence testing. It is compatible with the motivation behind EDUCE: that intelligence is not a fixed static entity, but something that resides inside a person, and can be enhanced significantly through education and awareness. It is also a rich concept that offers a framework and a language for developing adaptive educational systems that supports creative, multimodal teaching (Lazaer, 1999). In the past 20 years since its inception, its use in the classroom has been significant (Campbell & Campbell, 2000) but, surprisingly, its application to online learning and adaptive educational systems is still at the early stages of research (Kelly & Tangney, 2002).

This paper describes the results of an empirical study that explores the following research questions.

• What is the effect of using different adaptive presentation strategies instead of giving the learner complete control over the learning environment?
• What is the impact on learning performance when resources are matched and mismatched with learning preferences?

In particular, the study examines, using different versions of EDUCE, the relationship between the adaptive presentation strategy, the choice of resources available and the learning performance of science school students aged 12 to 14. The adaptive presentation strategy involves matching and mismatching students with resources they prefer and do not prefer to use. The level of choice determines the number of resources a student has access to and the manner in which EDUCE adaptively guides the student to view a particular resource first. Learning performance is defined by learning gain, learning activity and engagement. Learning gain is measured by a pre and post-test, learning activity is determined by the navigation profile and engagement by the attempts to answer questions during a tutorial.

The results suggest that teaching strategies that encourage students to use a broad range of resources are the most effective. 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.

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.

2. Multiple Intelligences

Research has provided a wealth of insight into how individual differences and orientations to learning could be applied to technology enhanced learning environments (Dunn & Dunn 1978, Gardner 1983). It informs that students exhibit differences in the way they process and organise information, in the way they behave while learning, in their predispositions towards particular learning modes and in the conscious actions they make to deal with the demands of specific learning situations (Riding & Rayner, 1997; Sadler-Smith & Smith, 2004). But the educational promise of developing adaptive educational systems that accommodate individual differences is only sporadically realised in practice (Brusilovsky, 2001). Some outstanding research challenges
include: which models of individual differences can be used to model learning characteristics, what are the relevant behavioural features that are indicative of learning characteristics, how can learners be supported through different forms of adaptivity, and how can intelligent techniques be developed to dynamically adapt the system and to diagnose learning preferences (Papanikolaou & Grigoriadou, 2004).

Two main theories attempt to interpret individual differences and to design educational models around these differences: learning style theory (Riding & Rayner 97) and Multiple Intelligences (Gardner1983, 1993, 2000).

Learning style theory has its roots in the psychoanalytic community. It deals with the way people perceive, the way they make decisions, and how active and reflective they are while interacting with educational material. It is defined as the habitual patterns or preferred ways of doing something, such as thinking, learning or teaching, that are consistent over long periods of time and across many areas of activity (Grigorenko & Sternberg, 1997). They entail mechanisms for the organisation and control of processes that are common to different domains of ability.

Gardner’s theory of Multiple Intelligences has its root in cognitive science, and reflects an effort to rethink the theory of measurable intelligence embodied in intelligence testing. 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 states 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. Gardner suggests (Gardner, 1983) that everybody possesses the different types of intelligences to different degrees and that they operate together in an orchestrated way. The theory 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 styles to intelligences, intelligences refer to things one can do, such as to execute skills or strategies, whereas styles refer to preferences in the use of abilities. Intelligences are concerned with how much, styles with how. Unlike intelligences, which are unipolar and value directional, styles are bipolar and value differentiated. That is, high amounts of intelligence are always preferable to low amounts, whereas each pole of a style dimension indicates different characteristics. Moreover, intelligence is usually limited to a particular domain of content or function, such as verbal or musical ability, whereas style cuts across domains of ability.

3. Previous research

Several systems adapting to the individual’s learning style have been developed (Carver et al 1999; Triantafillou et al, 2003; Panpanikolaou et al, 2003). For example, CS383 (Carver et al, 1999) modifies the presentation of content for each student using the Felder & Silverman learning style model. Before using the system, learners submit a questionnaire. Subsequently this information is used to adaptively present media elements in a sorted list ranked from the most to least conducive based on their effectiveness to each student’s learning style. In AES-CS (Triantafillou et al, 2003) the field-dependence/field-independence cognitive learning theory is used as the basis for adaptively providing learner control, contextual organisers and lesson structure support. INSPIRE (Panpanikolaou et al, 2003) also uses a questionnaire to classify students as activists, pragmatists, reflectors or theorists according to Honey & Mumford’s theory (Honey & Mumford, 1986). This system adapts the order of presentation of different types of resources according to the learning style of the student. However, despite the development of such systems and attempts to determine dependencies between learning styles and technology preferences (Klicek & Susac, 2003), it is still unclear what is the best way to model learning characteristics and how it is possible to accommodate different learners.

Machine learning techniques offer a solution in the quest to develop and refine a model of learning characteristics (Specht & Oppermann 1998, Gilbert & Han 1999, Stern & Wolf, 2000).
These systems build a model of learning characteristics using feedback from the student using questionnaires, navigation paths, answers to questions, directly requesting feedback, allowing the user to update their own student model and to make specific adaptations such as sorting links or viewing stretch text. Typically the systems contain a variety of instructional types such as explanations, examples or fragments of different media types representing the same content. Based on information in the learner model, the tutoring system chooses the most suitable instructional type from the range available. For example, ACE (Specht & Oppermann, 1998) adapts the sequence of material based on the success of the currently used teaching 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. ARTHUR (Gilbert & Han 1999) is another system that illustrates how to dynamically adapt instructional style to learner’s performance in tests. It uses multiple versions of the same resource created using different instructional styles such as: visual-interactive, auditory-text, auditory-lecture, and text style. To determine the instructional style an inference engine, based on case-based reasoning, compares the student’s performance in tests to that of other students and matches students with instructors who can work successfully with that type of student. In contrast, iMANIC (Stern & Wolf, 2000) adapts the presentation of content based on the learner’s selection of different types of resources. When presenting the concepts, the student interaction data is analysed using the Naïve Bayes algorithm to determine which resources are wanted and should be presented first. Developing systems that use intelligent techniques for diagnosing learning characteristics offers a promising research direction, however such systems in addition to validating the effectiveness of the adaptation strategies, also need to identify appropriate behavioural indicators and validate the accuracy of the inference techniques that analyse the interaction data.

Differences in style and intelligences have been well documented and 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 in the application of research in 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).

EDUCE attempts to address some of the challenges in adapting to individual differences using the MI theory as its pedagogical framework. In the past 20 years, research has suggested that the impact of the Multiple Intelligence theory in the classroom has been significant (Campbell & Campbell 2000). However, its application to online learning and intelligent tutoring systems is still very limited and in the early stages of research (Dara-Abrams, 2002). Moreover, the different intelligences are not abstract concepts, but are 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. For these reasons, and the fact that the research on learning styles is inconclusive, EDUCE uses the MI theory as its model of individual differences. In addition EDUCE also addresses the challenge of dynamically diagnosing MI profile by using a predictive engine. This predictive engine, developed using artificial intelligence techniques, dynamically determines the learner’s preference for different Multiple Intelligence resources and informs the pedagogical strategy.

4. EDUCE

Figure 1 illustrates the architecture of EDUCE (Kelly & Tangney, 2002, 2004). 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 student model represents the knowledge, characteristics and preferences of the user, and in particular the Multiple Intelligence profile. It is constructed online using the navigation
profile and by observing the students behaviour. It also stores a static model of MI profile that is completed using a MI inventory.

- The domain model is a representation of an expert’s knowledge and the material to be learnt. It includes principles, facts, lessons and problems. The principles of Multiple Intelligences are used to structure the domain model and develop different versions of the same content.
- The presentation module handles the flow of information and monitors the interactions between the user and the system.
- The predictive engine, using artificial intelligence techniques, dynamically determines the learner’s preference for different Multiple Intelligence resources and informs 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 Multiple Intelligences 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.

The MI theory identifies eight intelligences that are involved in solving problems, in producing material such as compositions, music or poetry and other educational activities. Currently EDUCE uses four intelligences in modelling the student:

- Logical/Mathematical intelligence (LM) - This consists of the ability to detect patterns, reason deductively and think logically.
- Verbal/Linguistic intelligence (VL) - This involves having a mastery of the language and includes the ability to manipulate language to express oneself.
- Visual/Spatial intelligence (VS) - This is the ability to manipulate and create mental images in order to solve problems.
- Musical/Rhythmic intelligence (MR) - This encompasses the capability to recognise and compose musical pitches, tones and rhythms.

The three intelligences, LM, VL and VS were chosen as they reflect the abilities that are historically designated as intelligences (Gottfredson, 1997). The musical/rhythmic intelligence was chosen because it is not considered as an intelligence that can be used to deliver and inform the design of content yet the emotive power of music is widely acknowledged (Carroll, 1999).
4.1 Modelling the Student

The student model is the source of information for an adaptive educational system to adapt to individual differences. 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.

In EDUCE, the Multiple Intelligence concept provides the basis for modelling student learning characteristics. It 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 describes how a student uses different resources using the following criteria:

- Did the student spend a minimum amount of time using the resources? The assumption made is that the student has not engaged with a resource when only a brief amount of time is spent using it. It is more likely that the student was just glancing 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 his 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 an MI inventory before entering EDUCE (Shearer, 1996).

The student model also represents other information such as: the navigation history, a record of the navigation path the student has taken through the educational material, the time spend on each learning unit, answers in response to interactive questions, and reflective feedback provided by student on navigation choices.

4.2 Domain Model

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 14. 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.

Multiple Intelligences is a theory with a set of principles that structures and suggests but does not prescribe a particular pedagogical model or set of instructional strategies. Moving from a theory of
intelligence to actual implementation is an act of interpretation and 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). 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 2 illustrates EDUCE’s pedagogical taxonomy for developing MI material (Kelly & Tangney, 03). It describes the range of instructional approaches that will cultivate each of the intelligences.

For example, 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 visually 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. Figure 3 gives an example of how these instructional strategies were used.

Using this taxonomy, a set of educational material has been developed, with the help of a subject expert. For each tutorial, there are 5 sections, 15 learning units and 4 MI resources per unit, 60 in total. All resources developed were validated and identified as compatible with the principles of MI theory by expert practitioners.

![Pedagogical Taxonomy for developing MI material](image)

**Figure 2.** Pedagogical Taxonomy for developing MI material
4.3 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 4.

- **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 5 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.

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

Figure 5. The Awaken stage of “Opposites Attract”

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:
1. **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.
2. **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** options, 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 to a particular MI resource using information in the student model.

### 4.4 Predictive Engine

In EDUCE predictions are made about which resource a student prefers. 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, which is referred to as the predicted preferred resource.

Figure 6 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.
4.5 Pedagogical Module

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 in different ways. Such strategies include: providing students with a broad choice of resource, 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 in order to broaden their understanding. These strategies are implemented by dynamically tailoring the environment content 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 (Brusilovsky, 2001). With adaptive presentation, the content of a page is adapted to learning characteristics. 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 possible Multiple Intelligence. When presenting a page, EDUCE selects the page variant according to the 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.

4.6 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 modes 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.
5. Experiment

Using EDUCE, an experiment was designed 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, it was set up to explore the impact of the two independent variables, presentation strategy and level of choice, on the dependent variable, learning performance.

5.1 Design

Different configurations of EDUCE were used to support the different values of the independent variables. The effect of other variables such as MI Profile and prior ability on learning performance was also examined.

The independent variable presentation strategy encompasses two main strategies for delivery material.

1. Most preferred: showing resources the student prefers to use
2. Least preferred: showing resources the student least prefers to use

For each learning unit, there are four MI based learning resources. The MI profile and the presentation strategy determine which resource is shown first.

The second independent variable is the level of choice. There are three different levels of choice provided to different groups corresponding to the different adaptive versions of EDUCE:

1. Single – student is only able to view one resource. This is adaptively determined by EDUCE based on an analysis of the static MI profile.
2. 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.
3. 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.

Learning performance is defined by learning gain, learning activity, and engagement. To calculate the learning gain each student before and after a tutorial sits a pre-test and post test. The test for the pre-test and post-test is the same and consists of questions that appear during the tutorial. Learning activity is determined by the navigation profile. It is a measure of the different panels visited, the number of different resources used, the reuse of particular resources and the direction of navigation. Learning engagement is a measure of the student’s progression within the tutorial and the attempts made to answer questions. The questions are multi-choice question with four options. Both learning activity and engagement are analysed to provide informed explanations on learning gain. Table 1 displays the variables used in the study and their values.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Presentation Strategy</td>
<td>Least Preferred, Most Preferred</td>
</tr>
<tr>
<td>Choice Level</td>
<td>Single, Inventory, Dynamic</td>
</tr>
<tr>
<td>Relative Learning Gain</td>
<td>(Post test score-pre test score)/pre test score</td>
</tr>
<tr>
<td>Activity Level</td>
<td>% of resources used</td>
</tr>
<tr>
<td>Activity Groups</td>
<td>Low, Medium and High Activity</td>
</tr>
<tr>
<td>Engagement</td>
<td>Function of the number questions attempted and correct</td>
</tr>
<tr>
<td>Prior Knowledge</td>
<td>Score from previous class test</td>
</tr>
<tr>
<td>Dominant Intelligence</td>
<td>Highest ranking intelligence as recorded by MIDAS Inventory</td>
</tr>
</tbody>
</table>

Table 1. Variables used and their values

Students have been randomly assigned to one of the four groups defined by the levels of choice. Each student sits through two tutorials. They will experience both presentation strategies of least
preferred and most preferred. To ensure order effects are balanced out, students are randomly assigned to systematically varying sequence of conditions. The design of the experiment can be described as a mixed between/within subject design with counterbalance.

5.2 Procedure

The experiment was conducted over three days. On Day-1, students completed the MIDAS MI Inventory. On Day-2, each student spent on average 25 minutes exploring one tutorial. The session was preceded by a pre-test and followed by a post-test. Each test had 10 multi-choice questions with questions being the same for the pre-test and post-test. The questions were taken from the set of online questions that appeared throughout the tutorials. Day-3 repeated the same format as Day-2, except that the student explored a different tutorial. On different days, the most preferred and least preferred presentation strategies were used. Students were randomly assigned to one of the three groups defined by the levels of choice.

6. Results

47 boys from one mixed ability school participated in the study. The average age was 13 and the study was conducted as part of normal class time and integrated into the daily school curriculum. 20 used the single choice version, 18 the inventory choice version and 9 the dynamic choice version. The results were analysed from different perspectives:

- The effect of the experimental conditions on learning gain
- The relationship of learning activity and gain
- The relationship between engagement and gain
- The relationship between prior knowledge and gain
- The dominant intelligence, as determined by the MIDAS inventory, and gain

6.1 Effect of choice and presentation strategy

The results were first 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. The relative gain score obtained under the two presentation strategies, least and most preferred, were compared.

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 2 presents the means and standard deviations. Figure 7 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>
<thead>
<tr>
<th>Choice</th>
<th>Least Relative Gain</th>
<th>Most Relative Gain</th>
<th></th>
<th></th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>Mean</td>
<td>Std. Dev.</td>
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<td>48.95</td>
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<td>97.46</td>
<td>135.14</td>
<td>45.93</td>
<td>62.23</td>
<td>18</td>
</tr>
<tr>
<td>Dynamic</td>
<td>87.78</td>
<td>70.98</td>
<td>35.00</td>
<td>36.93</td>
<td>9</td>
</tr>
<tr>
<td>Total</td>
<td>76.17</td>
<td>99.55</td>
<td>38.92</td>
<td>51.93</td>
<td>46</td>
</tr>
</tbody>
</table>

Table 2. Descriptive Statistics for Relative Gain for least/most presentation strategy

![Presentation Strategy/Choice and Relative Gain](image)

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

### 6.2 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. 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.
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 8 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 3. 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 relative gain score 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 9 plots the relative gain for the different activity groups in the least and most preferred condition. Its 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 10 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.
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.

6.3 Engagement

Further analysis was conducted to determine if the student’s interaction with online questions could shed further light on the differences in learning gain between the least/most preferred presentation strategies. The purpose was to explore the relationship between the engagement with online questions and learning performance. It was also the aim to explore the effect of presentation strategy on engagement, and to determine if student’s interest and ability in answering questions was affected by the presentation strategy. It was expected that students displaying high levels of engagement would have the highest learning performance.

The engagement score is calculated as a function of the number of online questions attempted during the tutorial and the number of questions correct. For each online question, a score is given if the question is answered correctly, with the score deducted by one for each wrong attempt. The average engagement and post-test score were calculated over both the least and most preferred sittings.

The relationship between the engagement score and average post-test score was measured using the Pearson product-moment correlation coefficient. There was a strong positive correlation between the variables \[r=.527, n=47, p<.01\]. The results indicate that overall performance can be predicted from the level of engagement and performance in online questions.

In addition, to explore the impact of presentation strategy and level of choice on engagement, a 2-way mixed-between ANOVA was conducted. However, this not yield significant results, but is somewhat explained by the high correlation between engagement at the least and most preferred sittings \[r=.45, n=47, p<.01\]. It indicates similar scores in both the least and most preferred sittings and that the presentation strategy did not have an impact on engagement.

The results together suggest that engagement with online questions is correlated with learning performance but it is not clear what role, if any, presentation strategy and level of choice play in influencing engagement.
6.4 Prior knowledge

Analysis was also conducted to determine the role of prior knowledge on performance and to determine if presentation strategy had different effects for students with different levels of prior knowledge. It was expected that students with high prior knowledge would have the higher pre-test and post-test scores.

The prior knowledge was identified using the score obtained in the Christmas test taken halfway through the academic year. Using the Pearson product-moment correlation coefficient, relationships were measured between prior knowledge and the average pre-test, post-test, and engagement scores. Strong positive correlations were recorded for:

- Prior Knowledge and average pre-test \[r=.425, n=47, p<.01\]
- Prior Knowledge and average post-test \[r=.595, n=47, p<.01\]
- Prior Knowledge and average engagement \[r=.482, n=47, p<.01\]

The results suggest the pre-test, post-test and engagement scores are strongly related to prior knowledge.

The pre-test score relationship with post-test score and relative gain was also measured. There was also a strong correlation between the pre-test and post-test score \[r=.422, n=47, p<.01\] indicating that high pre-test scores are related to high post-test score. There was also a strong relationship between the pre-test score and the relative gain \[r=.485 n=47, p<.01\]. However, the correlation was negative, indicating that the students with the lowest pre-test scores, despite not having the highest post-test scores, had the highest relative learning gain. The same observation was recorded when examining the relative gain at both the least and most preferred sittings.

The relationship of prior knowledge and pre-test score with activity level was also analyzed. 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.

The results together suggest that students with high prior knowledge are also likely to have high pre-test and post-test scores. They also suggest that students with lower pre-test scores have greater relative increases in learning gain, indicating that they benefit more from the learning environment. However, no relationships were observed between activity level and prior knowledge, suggesting that prior knowledge alone is not the best indicator for how a student avails of different learning options.

6.5 MI Profile

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 highest-ranking intelligence was Verbal/Linguistic for 15 students, Logical/Mathematical for 22, Visual/Spatial for 8 and Musical/Rhythmic for 2 students. The results were next analyzed 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 4 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.
Next, 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 5 displays the average post-test score and relative gain for each intelligence group (there was no students in the MR group). Again VL students had slightly the higher post test scores:

<table>
<thead>
<tr>
<th>Intelligence</th>
<th>N</th>
<th>Total Score</th>
<th>Std. Dev</th>
<th>Relative Gain</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>VL</td>
<td>9</td>
<td>77.8</td>
<td>15.63</td>
<td>56.0</td>
<td>57.0</td>
</tr>
<tr>
<td>LM</td>
<td>8</td>
<td>67.5</td>
<td>22.5</td>
<td>28.3</td>
<td>31.1</td>
</tr>
<tr>
<td>VS</td>
<td>3</td>
<td>60.0</td>
<td>20.0</td>
<td>-4.8</td>
<td>34.3</td>
</tr>
<tr>
<td>Total</td>
<td>20</td>
<td>71.0</td>
<td>19.43</td>
<td>58.1</td>
<td>48.2</td>
</tr>
</tbody>
</table>

Table 5. Average post-test score and relative gain in the single choice group (most preferred)

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. Discussion

The experiment was conducted to explore the effect of presentation strategy and level of choice on learning performance. 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 in the least preferred condition rather than in the most preferred condition.

To further analyse this surprising 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 with the least and most preferred strategies, further insight was revealed. It was only students with low activity levels who demonstrated different relative learning gains, with significantly greater learning gain in the least preferred condition. A subsequently analysis of these students also revealed that they had different MI profiles and used a wide variety of resources with the least preferred strategy. The result suggests that students with low levels of learning activity can improve their performance when adaptive presentation strategies are in use. This suggests 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. It is interesting to note that the presentation strategy had no impact on medium and high activity learners who automatically involve themselves in alternative modes of thinking by exploring a number of different resources.
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.

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 that 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.

Two important indicators of learning performance were engagement and prior ability. The results indicate that engagement with online questions and prior ability correlate with learning performance. This is not surprising as much research has shown that educational systems should adapt to prior ability (Hölscher & Strube, 2000) and that engagement in learning activities is directly related to learning gain (Martens et al, 2004).

Personalisation can bring different benefits such as increased learning performance, greater enjoyment, enhanced motivation and reduced learning time. In the context of learning performance, the results presented in this study suggest that using adaptive presentation strategies to provide students with a variety of resources that are not preferred enhances the performance of low activity learners. 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.

8. Conclusion

Building Adaptive Educational Systems that acknowledge different learning characteristics can be challenging. This paper described how the EDUCE system dynamically tailors the learning environment using the theory of MI.

It also described an experimental study using EDUCE that explored the impact of presentation strategy and level of choice on learning performance. The results suggest that students with low levels of learning activity can improve their performance when adaptive presentation strategies are in use. They suggest that challenging students may be a key aspect of learning environments.

Future work will involve exploring further the role of challenge in learning environments. It will involve determining the influence of different types of resources on individual learners and their effect on learning performance. More research will be conducted to explore what influences learning activity, and to determine if strategies that increase learning activity also increase learning gain. Research will also be conducted to determine the influence of other personalisation factors such as learning context, goals and motivation.

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9. References


