Intervention strategies to increase motivation in adaptive online learning

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Declaration

I, Teresa Hurley, declare that this thesis is submitted by me in partial fulfilment of the requirement for the degree of Masters of Science by Research, and that it is entirely my own work unless otherwise accredited. It has not at any time, either whole or in part, been submitted for any other educational award.

Teresa Hurley
August 2008

"If I have the belief that I can do it,
I shall surely acquire the capacity to do it
even if I may not have it at the beginning"

~ Mahatma Gandhi ~
(1869-1948)

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ABSTRACT

One of the most difficult challenges within online learning is keeping the learner motivated so as to prevent attrition or dropout. Motivation is considered to be of primary importance in determining success in online learning. Currently little research exists on intervention strategies, based on the individual learner's profile, which increase motivation in an adaptive online learning environment, so automatic intervention is not possible.

The research outlined in this thesis is based on Social Cognitive Theory and the motivational constructs of self-efficacy, goal orientation, locus of control and perceived task difficulty, all of which affect the learner's self-regulation. Using systematically constructed personas, surveys were conducted with experienced classroom and online teachers to extract and validate selection rules for intervention strategies to increase learners' motivation. The results were modelled using a decision tree algorithm with correct prediction rates showing 66% to 93% accuracy. A comparison between two algorithms was carried out to predict the level of trust in the rules and in the analysis. Based on the decision rules, a motivational strategies recommender tool, MotSaRT, was designed and evaluated. The recommender tool will be incorporated into the learner model of an adaptive Intelligent Tutoring System, enabling the system to automatically select the most suitable intervention strategy to use depending on the particular student's motivational profile.

This study extends the existing body of knowledge on motivational strategies by first targeting the intervention strategies to specific profiles and then by designing an automated component for the learner model of an adaptive Intelligent Tutoring System. The adaptation component will enable the system to directly intervene when a student shows signs of becoming demotivated by delivering motivation messages to the student. It is anticipated that these messages will reduce the level of attrition currently experienced in online learning.

Keywords: Online learning, adaptive systems, adaptation component, motivation, intervention strategies, self-efficacy, goal orientation, locus of control, perceived task difficulty, recommender tool, data mining algorithms, motivational messages.

1 Introduction

Information Communication Technology (ICT) offers the potential to enrich and empower learning in the 21st century. ICT and broadband telecommunications are expanding rapidly into many areas of learning, work and life (Wolpers and Grohmann, 2005). With this expansion of broadband the internet has become the technology of choice for online learning and teaching (Dabbagh and Bannan-Ritland, 2005). Educational institutions are now offering more and more online courses to attract students who might not otherwise be able to participate in educational programmes. According to a report issued by the Sloan Consortium (2007), in autumn 2006 nearly 20% of all U.S. higher education students were taking at least one online course. This report shows that for several years online enrolments have been growing substantially faster than overall higher education enrolments. Their statistics show that almost 3.5 million students were taking at least one online course during the autumn of 2006; a nearly 10 percent increase over the number reported the previous year (Sloan Consortium, 2007). Business and military organisations, attracted by the potential for computer-mediated learning to provide "anytime, anywhere" access to education and training, are adopting online learning as the main delivery method to train employees and personnel (Fletcher, Tobias, and Wisher, 2007).

However, attrition or drop out is a serious problem for many of these providers (Frankola, 2001; O'Connor, Sceiford, Wang, Foucar-Szocki, and Griffin, 2004; Carr 2000). Frankola (2001) states that while there are no national statistics, a recent report in the Chronicle for Higher Education found that institutions report drop out rates ranging from 20 to 50 percent for online learners. In 2004, O'Connor et al. claimed that the dropout rate for e-learning is approximately 26 percent after surveying e-learners and e-learning managers from various organisations and industries.

One of the most important and difficult challenges for online learning is keeping the learner motivated, particularly when, due to geographical separation of teacher and student, the learner has no opportunity to meet face to face with either the teacher or his or her peers on the course. These challenges are even greater when only asynchronous contact can be made with either the teacher or peers, for example, through the use of email or message boards. This often causes delays in getting a response. This lack of direct contact with the teacher and peers may result in online learners facing such challenges as lack of motivation, time management problems, isolation, frustration, and technical problems.

Learning orientation includes a comprehensive set of psychological factors (beliefs, values, emotions and intentions) that influence how individuals approach learning. Motivation is generally considered to be one of the primary determining factors of student success in online learning. Fundamental to motivation is the concept of self-efficacy. "Perceived self-efficacy refers to beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments" (Bandura, 1997, p.3). Thus, self-efficacy beliefs influence students' behaviour by influencing the decisions regarding which tasks to engage in, what level of effort to expend, and how long to persevere in the face of difficulty.

Lepper, Woolverton, Mumme, and Gurtner (1993) state that in a traditional classroom, experienced teachers infer the level of motivation of a student from several cues, including the student's facial expressions, body language and intonation. These teachers then use interventional strategies aimed at increasing self-efficacy and self-regulation. In online learning these cues are mostly absent and the motivational problems of students can remain undetected, which results in the student receiving no outside help to increase their motivation. The demotivated learner is therefore in danger of dropping out of a course. One way to promote and maintain online learners' motivation is to design and structure

the learning materials so as to make them more intrinsically motivational. Keller's (1987) ARCS model is a method for systematically designing motivation strategies into instructional materials; it focuses on several strategies for sustaining attention, relevance, and instilling confidence to help learners feel satisfied with their accomplishments. However, it is not always feasible to build motivational strategies into the design of the learning materials, especially if it involves updating and revising the material for the course, which can be very costly.

Another possibility to help with learner motivation is to extend existing student support as part of an Intelligent Tutoring System (ITS). Oppermann et al. (1997) describes two kinds of systems that have been developed to support the user. The first of these systems allows the user to change certain parameters and adapt their behaviour accordingly and is called *adaptable*. The second type of system adapts to the user automatically, based on the system's assumptions about the user, and is known as an *adaptive* system. Adaptive Intelligent Tutoring Systems tailor their behaviour to the individual learner by assessing and modelling learner needs, goals and preferences (Brusilovsky, 2001). The most frequent learner characteristic used for adaptation in online learning is knowledge. The adaptive model takes the current state of the learner's knowledge into account when performing adaptation and updates the learner model accordingly. Other characteristics often used include goals, interest and preferences. In some of these systems the learner has to input this type of data manually.

Intelligent Tutoring Systems are personalised adaptive systems which typically have three components (De Bra, Houben, and Wu, 1999):

(1) a *domain model* that comprises the structure of the domain (the concepts and the relations between them);

(2) a *learner model* that stores the learner's characteristics, including knowledge, goals, and learning needs; and

(3) an *adaptation* model that contains a set of rules that combine the information from the learner model with the information from the domain model and decides whether and how the information in the learner model is to be changed, what content should be presented to the learner and how it should be presented.

Thus, adaptive ITS use the knowledge about the domain, the student, and adaptation mechanisms, including teaching strategies, to support flexible individualised learning and tutoring.

For a long time, motivational considerations were largely ignored in the area of online learning. A number of factors have contributed to this: motivation, like all affective issues is hard to perceive, structure and formalise, all of which are pre-requisites for system implementation. There is also a theoretical separation between cognitive and affective processes which led to the influence of affectivity on cognition being largely ignored.

More recently attempts have been made to integrate motivation into the online learning process and now the influence of motivation on cognition is acknowledged and taken into consideration. Depending on the focus of the research, these integration attempts fall into several categories: (1) design: mostly based on Keller's ARCS Model (1987); (2) learners' actions: based on information provided by log files and learner management systems (Beck, 2004; Johns and Woolf, 2006; Arroyo and Woolf, 2005; Baker et al. 2004); and, (3) learners' self-assessment (Arroyo and Woolf, 2005; Beal et al. 2006; Beal and Lee, 2005).

Research efforts have also focussed on motivating learners through the use of motivational messages, using either the postal system or email (Visser, Plomp and Kuiper, 1999; Chyung, 2001; Miller, 2001; Jackson, 2002; Frey, Yangelov, and Faul, 2003; and Hodges, 2005).

1.1 Research Goals

Currently very little research exists on intervention strategies based on the individual learner's profile to increase motivation in an adaptive online learning environment, so automatic intervention is not yet possible. This study aims to inform the development of the adaptation component of an Intelligent Tutoring System (ITS), so that it can intervene automatically when the assessment model detects that the learner is becoming demotivated. In particular the focus of this study is learners in third level education. Automatic intervention is especially important to those students who have enrolled in online courses where they have no opportunity to meet face to face at any stage during their studies with either their teachers or their peers. Online learners face major challenges with motivation including a sense of isolation, frustration with delays in getting responses to email queries, problems in utilising the technology and lack of social support. They may not yet have developed the self-regulation that would enable them to cope with these challenges of online learning. Despite these challenges, online learning is often the only means learners have to pursue higher education because of geographical location or lack of local availability of suitable courses.

The first steps of the proposed approach involves (a) creating a learner model which identifies the learners most likely to become demotivated based on the individual learners' profiles; and (b) extracting and validating selection rules for intervention strategies to increase such learners' motivation. Finally it is planned to design an intervention recommender tool which can be incorporated into the adaptation component of the adaptive ITS (see chapter 4 for full details). When the assessment model detects disengagement, the recommender tool will be utilised by the adaptive system to profile the student according to his or her levels of self-efficacy, goal orientation, locus of control and perceived task difficulty – (see chapter 2 for full details) - which will have been assessed through the dialogue system in the assessment model. The recommender tool will then

automatically implement the recommended intervention strategies for that particular profile by delivering a message (or messages) directly to the student. It is anticipated that these strategies will help the learner to increase their self-regulation and also increase their motivation by giving the student the sense that they are being monitored and that feedback is immediately available when they are encountering problems. This in turn should help to alleviate the sense of isolation and lack of support which are two of the most common problems faced by a distance online learner, particularly those who are relying on asynchronous communication.

In summary, the focus of this study is (a) to develop motivational intervention strategies based on the individual learner's profile, and (b) to design the prototype of a recommender tool for the implementation of these strategies into a learning system for tertiary education. By incorporating a motivational strategies recommender tool into the adaptation model of the ITS, motivational messages aimed at increasing the motivation and self-regulation of the learner would be delivered by the ITS when demotivation of the learner is detected by the system.

1.1.1 Research Question

The hypotheses of this research study is that when the characteristics of the individual learner's motivational profile are determined (i) suitable motivational intervention strategies can be developed and (ii) such interventions can be implemented in an Intelligent Tutoring System. It is anticipated that the interventions will increase the learner's motivation which will (iii) help to reduce attrition or drop out from online learning courses.

The research goal of this study, therefore, is to answer the following question: "What needs to be considered when designing a recommender tool which can be incorporated into an adaptive Intelligent Tutoring System to

automatically deliver motivation intervention strategy messages to learners?" This question leads to a number of sub-questions, including:

1. How to develop a learner model which will recognise the students most likely to become demotivated?
2. How to identify suitable motivation intervention strategies to improve the motivation and self-regulation of online learners?
3. How to design a motivation intervention strategy recommender tool suitable for incorporation into the learner model of an adaptive Intelligent Tutoring System?

1.2 Structure of the Dissertation

This dissertation is structured as follows:

Chapter 1 introduces the problem, the context and the proposed solution. Chapter 2 presents the background theory and related work. Particular emphasis is placed on Social Cognitive Theory on which this research work is based. The research question is also identified here.

Chapter 3 covers the methodology used in this research and describes both the pilot study and the main study. It also reports the results of the two studies.

Chapter 4 outlines the design of the recommender tool, MotSaRT, for the adaptation component of an Intelligent Tutoring System.

Chapter 5 summarises the main findings of the research, discusses some methodological issues and outlines future research.

2 Literature Review

Emerging technologies such as the World Wide Web and online communication tools have led to major changes in how education is delivered throughout the world. These technologies offer an opportunity for anywhere-and-anytime learning, as courses can be delivered asynchronously, synchronously or in a combination of the two. Increasingly, colleges and business organizations are adopting online learning as their main delivery method (Dabbagh and Bannan-Ritland, 2005; Simmons, 2002). Online learning offers a more convenient access to learning for students who, for whatever reason, are unable to attend more traditional colleges which offer face to face instruction. It also helps the meet the needs of the increasingly high numbers of non-traditional or lifelong learners (Kearsley, 2000).

2.1 Attrition from Online Courses

Online learning is potentially one of the most dynamic and enriching forms of learning that exists today. However, attrition, or drop out, which is defined as the number of students who enrol in a course but do not fulfil all the course requirements nor complete the course, is a serious problem (Frankola, 2001; Diaz, 2002; O'Connor, Sceiford, Wang, Foucar-Szocki, and Griffin, 2004; Carr 2000). Parker (1999) found that with the growth of online learning came the problem of exceedingly high attrition rates. Estimates vary, but attrition from online learning is reported to be as high as 70 - 80% (Flood 2002, Forrester 2000, in Dagger and Wade, 2004). Frankola (2001) and Diaz (2002) put it at between 20-50%, while Carr (2000) estimated it to be 10-20% higher than for traditional on-campus education.

It is important to find ways to decrease attrition in online learning both from an economical and quality viewpoint. High attrition rates have a negative economic impact on universities and companies. Attrition from online learning

courses results in personal, occupational and financial implications for learners and academic institutions and for companies which have invested in online training for their staff (Atman, Egan, Sebastian, Welch, and Page, 1991). Moody (2004) found that the costs for development, delivery, and assessment, as well as lost tuition revenue, resulted in wasted expenditures for the institution. Reducing student attrition is, therefore, one of the most important challenges facing education institutions which offer online courses (Rovai, 2002; Tresman, 2002; Woodley, 2004; Guri-Rosenblit, 2005). Researchers acknowledge that the reasons for attrition are many and complex and that there are no simple solutions (Berge and Huang, 2004).

2.1.1 Is Attrition Really a Problem?

Much has been written about attrition and retention rates in online learning courses. Researchers have attributed attrition to several causes. Some of the issues include lack of instructor training, poor course design, lack of student interaction, and personal commitments, as well as characteristics such as age, gender, ethnicity and learning style.

However, there may be other reasons for the high attrition rate which are not always considered in the literature. Some learners may drop out because their needs have been satisfied and they feel ready to meet their performance expectations. Furthermore, some argue that dropping out is not a sign of failure and that the learners should be encouraged to drop in and out (Diaz 2002). From this viewpoint, flexibility and access are seen as virtues and not vices. The psychology of learning points towards spaced learning, rather than the traditional model of completion and time-based courses, as being more effective (Clark, 2002). The constructivist approach to learning states that learners learn through incremental steps and the adaptation of the mental models of the learner. Online learning offers this opportunity through repositories of learning resources. Also, comparisons with the traditional classroom may be unreliable. The student may

continue to attend the classroom because of the social element, but be disengaged from the learning experience because they have become bored or frustrated (Clark, 2002).

In the workplace, the motivation for many employees to take part in training courses may relate more to the opportunity to take some time away from the workplace rather than improvement of their work activities (Clark, 2002). When online training courses are offered in-house, workers may feel that they cannot take time during the working day for their study and so must sacrifice personal time for it which can be detrimental to family life (Thalheimer, 2004). Alternatively, they may have to contend with constant interruptions by those working around them as there is a perception that online learning can be interrupted, without much consequence. In reality once a learner is interrupted several times, motivation falls and this may result in the learner dropping out of the course (Clark, 2002).

Although the foregoing arguments have some credence, clearly, for colleges and workplaces that have invested heavily in online learning, it is important to anticipate issues that contribute to learner attrition, and to deal with those issues effectively. From the learner's point of view, failure to complete a course could have major consequences both personally and financially.

2.1.2 Learners' Perspectives on Attrition

Motivating the learner to start, persist with, and complete an online learning course is of great importance if online learning is to reach its full potential. Tinto (1975) developed a model, based on classroom teaching, which is frequently cited to explain student retention. This model attributes an individual's decision of retention/dropout to pre-entry attributes, the student's goals and commitments, and academic and social institutional experiences and integration. Online learning researchers, however, tend to place more emphasis on external

environmental factors such as the students' occupation and family responsibilities (Kember, 1995). Online learners are typically older, attend school part-time, and often juggle a full-time job along with family responsibilities (Holmberg, 1995; McGivney, 2004). Figure 1 shows some of the research that has been undertaken and the reasons given for attrition by students.

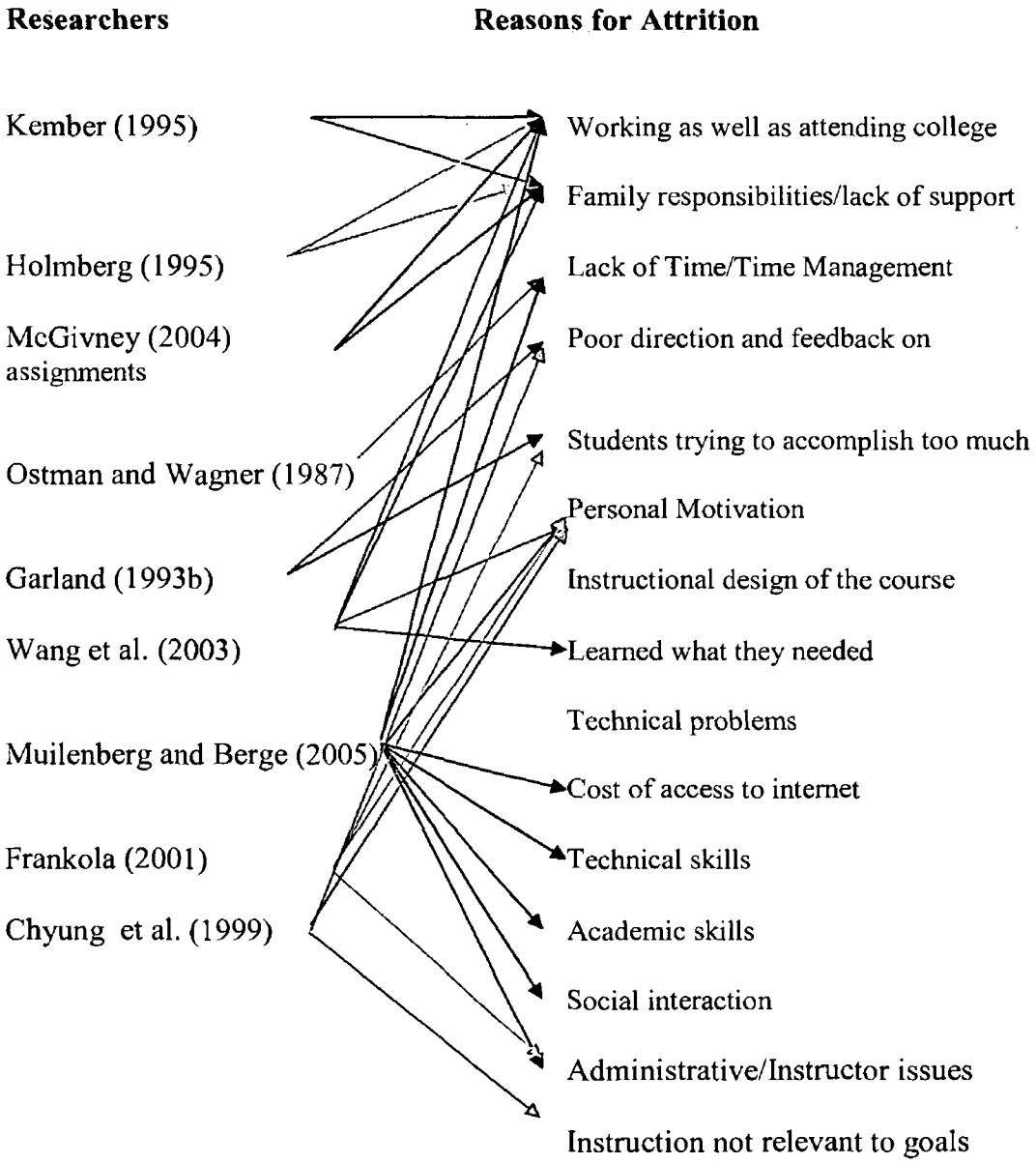

Figure 1: Reasons for attrition

As can be seen from Figure 1, Ostman and Wagner (1987) found "lack of time" to be the reason most often cited for dropping out by online learners.

Garland (1993b), interviewed students who had dropped out and found reasons such as poor direction and feedback on assignments, time management, and students trying to accomplish too much.

Chyung, Winiecki, and Fenner, (1999) found that learners lose motivation due to dissatisfaction with the learning environment or when they no longer perceive the instruction to be relevant to their goal.

Frankola (2001) found that that adult learners drop out of online courses due to the lack of time, lack of motivation, poorly designed courses, and lack of satisfaction with instructors.

Wang, Foucar-Szocki, Griffen, O'Connor, and Sceiford (2003) attempted to identify students' perception of the reasons for their attrition. They identified four main factors which contributed to the decision to drop out from courses: (1) personal motivation; (2) instructional design of the course; (3) conflicts between study, and work and family; and (4) the feeling that they had learned what they needed.

Muilenberg and Berge (2005) found the eight factors out of forty-three possible factors to be significant barriers to online learning: (1) technical problems; (2) cost of access to the internet; (3) time and support for studies; (4) personal motivation; (5) technical skills; (6) academic skills; (7) social interactions; and (8) administrative/instructor issues.

Although there is not complete agreement between these researchers as to which factors contribute to attrition, two factors frequently arise. These are: lack of time, especially when juggling college with full or part-time work, and personal

motivation, especially where family responsibilities/lack of support is a factor. These two factors are closely linked.

When a learner is highly motivated they are much more likely to employ greater effort to participate in their course. However, when a learner lacks personal motivation, finding the time to study becomes more problematic. This is especially true if the learner is also trying to hold down a job while attending college and if family responsibilities place demands on time (Thalheimer, 2004). Finally, a sense of being isolated through lack of support and a perceived lack of control may lead to frustration and demotivation. This is particularly so if feedback from course instructors is slow or inadequate (Takiya, Archbold and Berge, 2005). This occurs particularly in asynchronous online courses where the learner may be left waiting for a reply to an email or a message placed on a bulletin board. These learners may drop out from the course even if they were performing well in their studies (Ozga and Sukhnandan, 1998).

Although there is little that can be done for students who are forced to drop out due to time constraints and lack of family support, the fact that personal motivation is also a recurring theme relating to attrition raises the question as to how intervention strategies might be used to increase motivation.

2.2 Theoretical Background

A model of motivational states of learners should build upon a well established theory of motivation. Social Cognitive Theory (SCT) (Bandura, 1986, 1997) views motivation as a function of the learner's thoughts, beliefs, attributions, and goals. This theory differs from other theories of motivation such as those of Freud (1915), Hull (1943) or Maslow (1954) which focus on instincts, needs, drives or incentives. SCT was selected as the most suitable theory on which to base this research as it offers a framework for enhancing human learning through the use of both motivational and social intervention strategies. Such

interventions may include verbal persuasion, vicarious experience (someone else models a skill), mastery experience (repetitive successes instil a strong sense of self-efficacy which becomes quite resistant to occasional failures) or scaffolding (help from a more able peer or mentor). Verbal persuasion, vicarious experience and scaffolding are all examples of the social element of SCT, whilst mastery experience reflects the motivational element of this theory. Thus SCT provides clear guidelines and techniques that can be used to develop intervention strategies that can be used to motivate learners.

SCT has been shown to have good application in many different learning situations, including classroom learning (Schraw and Brooks, 2000; Tuckman, 1993; Zimmerman and Martinez-Pons, 1992; Pintrich and De Groot, 1990), online learning ((Hodges, 2004; Irizarry, 2002 and blended learning (Wang and Newlin, 2002).

2.2.1 Social Cognitive Theory

SCT focuses on how children and adults operate cognitively on their social experiences and how these cognitions influence behaviour, development and learning. Bandura's Social Cognitive Theory was the first to incorporate the notion of modelling, or vicarious learning, as a form of social learning. In addition, Bandura also introduced several other important concepts, including reciprocal determinism, self-efficacy, and the idea that there can be a significant temporal variation in time lapse between cause and effect. In 1986, Bandura renamed his social learning theory, Social Cognitive Theory (SCT), to better describe what he had been advocating in his work since the 1960's (Bandura, 1986).

SCT thus explains how people acquire and maintain certain behavioural patterns, and also provides a solid theoretical basis for developing intervention strategies (Bandura, 1997). SCT is based on several key assumptions: (a)

reciprocal interactions among personal, behavioural, and environmental factors; (b) the relation of learning to motivation; and (c) enactive and vicarious learning.

As this research is concerned with developing intervention strategies to increase motivation in adaptive online learning, its focus will draw primarily on the motivational aspects of SCT. Within SCT, six motivational constructs can be divided in three general groups. The first group refers to individuals' perceptions about their ability to accomplish a task. This group includes the constructs of self-efficacy, locus of control and attributions. The second group relates to individuals' reasons for engaging in a task. It encompasses constructs such as goal orientation and intrinsic versus extrinsic motivation. The final group refers to individuals' techniques and strategies for accomplishing a task and includes self-regulation, which occurs through the interplay of self-produced and external sources of influence.

In this research the interventions being developed will take the form of verbal persuasion, vicarious experience, mastery experience or scaffolding. In SCT the behavioural-personal interaction involves the bi-directional influences of one's thoughts, emotions, and biological properties and one's actions (Bandura, 1986; 1989). For example, a person's expectations, beliefs, self-perceptions, goals, and intentions give shape and direction to behaviour. However, the behaviour that is carried out will then affect one's thoughts and emotions. This behavioural-personal factor interaction can be shown using self-efficacy. Research shows that self-efficacy (a personal factor) influences such achievement behaviours as choice of task, persistence and effort (Schunk, 1995). In turn, students' behaviours modify self-efficacy. As learners differ widely in self-efficacy, locus of control, perceived task difficulty and goal orientation, intervention strategies must be adapted to suit the individual and the task. A bi-directional interaction also occurs between the environment and personal characteristics (Bandura, 1986; 1989). In this process, human expectations, beliefs, and cognitive competencies are

developed and modified by social influences and physical structures within the environment. These social influences can convey information and activate emotional reactions through such factors as modelling, instruction, and social persuasion (Bandura, 1986).

2.2.1.1 Motivation

Although motivation is a key component to instruction and learning, no standard definition for the hypothetical construct of motivation seems to exist. Since the 5th century BC Greek philosophers such as Plato and Aristotle have questioned why learners engage in, pursue, and accomplish particular goals or tasks, and why they avoid others. Motivation increases individuals' energy and activity levels (Maehr, 1984). It propels the initiation of certain activities and persistence in those activities (Stipek, 1988). In Bandura's (1986, 1997) Social Cognitive Theory, motivation is described as goal directed behaviour instigated and sustained by expectations concerning the anticipated outcomes of actions and self-efficacy for performing those actions. Outcome expectations are the expected results of one's actions (Bandura, 1986; Locke and Latham, 1990; Weiner, 1974). From a motivational perspective, outcome expectations are important because learners think about potential results and act in ways they believe will attain the outcomes they value. Academically motivated learners believe if they study diligently, they will make good grades. Given that they value high grades, it is to be expected that they will study hard and therefore validate their expectations.

As motivation affects the learning strategies and cognitive processes individuals employ when studying (Eccles & Wigfield, 1985) it is important in determining self-regulated strategy use (Pintrich and De Groot, 1990; Ames and Archer, 1988). Students who are motivated perceive themselves as self-efficacious and goal-directed (Zimmerman, 1989). It is generally accepted by teachers that students with higher levels of intrinsic motivation and self-efficacy achieve better learning outcomes (Pintrich and De Groot 1990). Intrinsic motivation refers to a

learner's internal desire to perform a task for no reward other than the personal satisfaction or enjoyment. Clearly, the most desirable form of motivation is intrinsic. External rewards may be useful initially but care must be taken with the use of them. Over time learners who are intrinsically motivated, but rewarded extrinsically, can devalue their intrinsic interest in learning in favour of the extrinsic rewards (Husen and Postlethwaite, 1994).

2.2.1.2 Self-Efficacy

Self-efficacy is grounded in the larger theoretical framework of Social Cognitive Theory, which postulates that human achievement depends on interactions between one's behaviours, personal factors (e.g., thoughts, beliefs), and environmental conditions (Bandura, 1986, 1997). Self-efficacy is defined as "people's judgements of their capabilities to organise and execute courses of action required to attain designated types of performances" (Bandura, 1986). Self-efficacy beliefs influence task choice, effort, persistence, resilience, and achievement (Bandura, 1997; Schunk, 1995). Individuals with high self-efficacy beliefs are likely to exert effort when facing difficulties and persist at a task when they have the requisite skills. On the other hand, learners with low self-efficacy for accomplishing a task may avoid it.

Bandura's Social Cognitive Theory (1986, 1997) postulates that individuals acquire information to help them assess self-efficacy from (a) actual experiences, where the individual's own performance, especially past successes and failures, are the most reliable indicator of efficacy; (b) vicarious experiences, where observation of similar others performing a task conveys to the observer that they too are capable of accomplishing that task; (c) verbal persuasion, where individuals are encouraged to believe that they possess the capabilities to perform a task; and (d) physiological indicators, where individuals may interpret bodily symptoms, such as increased heart rate or sweating, as anxiety or fear indicating a lack of skill.

Pajares (1996) and Schunk (1995) found that self-efficacy influences academic motivation, learning, and achievement. Locke, Frederick, Lee, and Bobko (1984) state that perceptions of self-efficacy influence actual performance, while Brown and Inouye (1978) state that self-efficacy determines the amount of effort and perseverance expended on an activity.

2.2.1.3 Locus of Control

Self-efficacy is also linked to Locus of Control (LOC) (Rotter, 1966). LOC is a relatively stable trait and is a belief about the extent to which behaviours influence successes or failures. Individuals with an internal locus of control believe that success or failure is due to their own efforts or abilities. Individuals with an external locus of control believe that factors such as luck, task difficulty, or other people's actions, cause success or failure. Perceived control is one aspect of self-efficacy. People who believe they can control what they learn and perform are more apt to initiate and sustain behaviours directed toward those ends than are individuals who hold a low sense of control over their capabilities (Bandura, 1997).

Intervention strategies can be used to motivate the learner to develop an internal locus of control. Liu, Lavelle and Andris (2002) found that locus of control evolved over the course of a semester with students scoring higher (becoming more internal) at the end of a semester of online instruction. Liu et al. also found that online instruction can improve students' sense of personal competence, self-responsibilities, and beliefs about their own learning.

2.2.1.4 Attribution Theory

Attribution Theory (Weiner, 1974) expands the Theory of Locus of Control and has been used to explain the difference in motivation between high and low achievers. Ability, effort, task difficulty and luck have been identified as

the most important factors affecting attributions for achievement. Research shows that learners tend to believe either that intelligence is a fluid quality that can be enhanced through practice and effort, or that it is a fixed quantity (Dweck and Leggett, 1988). High achievers approach rather than avoid tasks relating to achievement as they believe success is due to ability and effort. Failure is attributed to external causes such as bad luck or a poor exam. Thus, failure does not affect self-esteem but success builds pride and confidence. Low achievers avoid success-related tasks because they doubt their ability and believe success is due to luck or other factors beyond their control. Success is not rewarding to a low achiever because he/she does not feel responsible, i.e. it does not increase his/her pride or confidence. Thus, attributions are causal interpretations by students to explain academic success and failure.

Attributional responses vary along three causal dimensions: *locus of control,* i.e. internal vs. external causes; *stability*, i.e. short vs. longstanding effects; and, *controllability*, i.e. controllable vs. uncontrollable (Table 1).

Table 1: Attribution Theory

	Internal	**External**
Control	Effort	Task difficulty
Non-control	Ability	Luck

Different attributions elicit different emotions in learners. The attributions of effort and ability are both classified as internal causes, whereas task difficulty and luck are classified as external causes. So, for example, attributing failure to a teacher, i.e. an uncontrollable, external, unstable cause, is less personally threatening than attributing failure to low ability, i.e. an uncontrollable, internal, stable cause.

2.2.1.5 Perceived Task Difficulty

Pajares and Schunk (2001) state that perception of task difficulty will affect the expectancy for success, and strongly influences both instigation of a learning activity as well as persistence. The learner's sense of accomplishment, as well as his/her reaction to failure, is often tied to beliefs about the difficulty of the goal they have undertaken. At the outset of an activity, students differ in their self-efficacy for learning due to their prior experiences, personal qualities, and social supports. As they engage in activities, students are affected by personal (e.g. goal setting, information processing) and situational influences (e.g. rewards, teacher feedback) that provide students with cues about how well they are learning.

Self-efficacy, however, is not simply a reflection of prior performance. Task difficulty and the context in which the prior performances were accomplished are evaluated in the cognitive process of forming self-efficacy beliefs. Tasks which are perceived as being too easy will not increase self-efficacy. Neither will tasks which are perceived as being too difficult due to the uncertainty of being able to achieve success in the future. In fact, research shows that successful completion of a task which required enormous effort can actually reduce self-efficacy (Bandura and Cervone, 1986). Self-efficacy is enhanced, however, when students perceive they are performing well or becoming more skilful. Lack of success or slow progress will not necessarily lower self-efficacy if learners believe they can perform better by expending more effort or using more effective strategies (Schunk, 1995).

2.2.1.6 Goal Orientation

Self-efficacy affects achievement directly and indirectly through its influence on goals (Zimmerman and Bandura, 1994). Goals enhance self-regulation through their effects on motivation, learning, self-efficacy and self-evaluations of progress (Bandura, 1986, 1977). According to self-regulated

learning (SRL) theorists, self-regulated learners are "metacognitively, motivationally, and behaviourally active participants in their own learning process" (Zimmerman, Bandura, and Martinez-Pons, 1992).

Individuals with a mastery learning goal orientation strive to master the task and are likely to engage in self-regulatory activities such as monitoring, planning, and deep-level cognitive strategies. They focus on learning, skill development, creativity and understanding. This in turn leads to a variety of desirable outcomes including: enhanced interest in and more positive attitudes towards learning; attribution of failure to lack of effort rather than lack of ability; academic engagement and effort including perseverance when facing challenging material, and asking for assistance when needed (Printrich and Schunk, 2002).

Individuals may have both mastery and performance goals (Pintrich and Garcia, 1991). Individuals orientated towards performance approach goals are concerned with positive evaluations of their abilities in comparison to others and focus on how they are judged by parents, teachers or peers.

Individuals with performance avoidance goals want to look smart, not appear incompetent and so may avoid challenging tasks, or exhibit low persistence, when encountering difficulties (Pintrich and Schunk, 1996). Students with these goals are concerned with protecting their self-worth at all costs. Consequently, they are more likely to engage in self-sabotaging behaviours such as cheating, avoiding help when needed, and withdrawing effort (Urdan, Ryan, Anderman, Gheen, 2002). Furthermore, students with performance avoidance goals are more likely to view errors as indicating a lack of ability, experience high anxiety levels, give up in the face of difficulty, exert less effort, place less value on tasks, and demonstrate lower levels of achievement (Pintrich and Schunk, 2002).

Disengaged orientation is displayed by students who do not really care about doing well in school or learning the material; their goal is simply to get through the activity (Beal and Lee, 2005).

Self-efficacy is one of the most important positive influences on personal goal setting. Learners with higher self-efficacy set higher goals. Self-efficacy also has a positive relationship to goal commitment, i.e. how determined a learner is to achieving his/her goal. Causal attributions can also play a role in goal setting; for example, attributing failure to unstable causes (bad luck, low effort) leads to setting higher goals on subsequent tasks.

Goal difficulty does not bear a linear relationship to performance. Overly easy goals do not motivate; neither are people motivated to attempt what they believe are impossible goals (Schunk, 1995). Assuming that people have the requisite skills, goals that are moderately difficult – viewed by learners as challenging but attainable - seem to have the best effects on motivation and self-regulated performance (Locke and Latham, 1990).

In addition, goals may be proximal or distal. Proximal goals are those that can be achieved in a reasonably short time period, whereas distal goals are those that will be met far into the future. Typically, proximal goals are associated with maintaining motivation. According to Driscoll (2000), performance goals foster the implicit belief that intelligence is fixed, while learning goals are associated with the belief that intelligence is malleable and can be developed. Hence, proximal learning goals are desired to maintain motivation.

Because goal orientation influences academic outcomes, it is important that the learner's motivation is monitored and that adaptive motivational beliefs are cultivated in students. Feedback plays a very important role in this cultivation. Most important is the provision of positive self-efficacy information which stresses mastery, self-improvement, and achievement. The intervention strategies

developed in this research are designed to provide such feedback to learners to enable them to self-regulate.

2.2.1.7 Self-Regulation

Self-regulation concerns how the learner can control his/her own motivation, cognition and behaviour (Printrich, 2000d). Self-regulation in the context of academic learning refers to the degree that the learner is metacognitively, motivationally and behaviourally an active participant in his/her own learning process (Zimmerman, 1989). Research has found that students with higher levels of self-efficacy are more likely to demonstrate self-regulated learning (Tuckman and Sexton, 1991; Zimmerman and Martinez-Pons, 1992). Pintrich and De Groot (1990) found that cognitive and self-regulation strategies were more important than self-efficacy beliefs for academic performance, but that increased self-efficacy beliefs may result in more use of cognitive and self-regulatory strategies.

Social Cognitive Theory views self-regulation as comprising three processes: self-observation (monitoring), self-judgement and self-reaction (Bandura, 1986; Schunk, 1994; Zimmerman, 1990). Self-observation is critical to determine progress at an activity. For example, students who have difficulty studying should keep a written record of their activities to enable them to explore how their time could be used more effectively. They can then react to this knowledge and alter their behaviour. Self-judgement refers to comparing current performance levels to one's goals so that the learner can maintain or alter self-regulatory strategies depending on the judgement of progress. Self-reactions are behavioural, cognitive, and affective responses to self-judgements. Negative evaluations do not decrease motivation if the learner believes s/he can improve. However, motivation will not improve if the learner believes s/he lacks ability and will not succeed no matter how hard s/he works or which strategy is employed.

Thus, effective self-regulation requires having goals and the motivation to attain them (Bandura, 1986; Pintrich, 2000d). Learners must regulate not only their actions, but also their underlying achievement-related cognitions, behaviours, intentions, and affects. An increasing body of research shows that self-monitoring of achievement beliefs sustains learning efforts and promotes achievement (Schunk and Zimmerman, 1998: Zimmerman and Martinez-Pons, 1992).

In their learning environment learners have exposure to peer models, verbal persuasion, and assistance from peers or teachers (Zimmerman and Schunk, 1989). Schunk and Hanson (1985, 1989) found that learners who observed models verbalising their methods of solving problems had increased self-efficacy and achievement in arithmetic tasks. They also found that verbal persuasion was valuable in the development of self-efficacy and academic achievement.

Cennamo and Ross (2000), in a review of self-regulation literature, found that the most effective strategies to support self-directed learning included reviewing notes, keeping records, and self-evaluating. They also found that many learners do not seek information from social sources or teacher assistance and believe this may be due to the solitary nature of web-based learning environments.

Shih and Gamon (2001) studied the relationships of student motivation, learning styles, and achievement in web-based courses and found that motivation was the only factor that was significantly related to achievement. Their motivation survey indicated that their participants (a) wanted to get better grades than their classmates (performance approach goal); (b) believed they could do well in class (high self-efficacy); and (c) that they could do better if they studied hard (internal locus of control). These statements have both self-efficacy and self-regulation components.

Whipp and Chiarelli (2004) affirm that self-regulation is helpful in facilitating learning in online environments. They state that more research is needed in online learning so that effective self-regulation models can be developed for this type of learning.

Azevedo, Guthrie and Seibert (2004) investigated college students' abilities to regulate their learning in a hypermedia environment. They found that those who regulated their learning with specific strategies such as goal setting, planning and monitoring their learning showed an increase in knowledge.

The evidence therefore demonstrates that there is a positive relationship between success in web-based learning and the learners' ability to self-regulate. The research indicates that building self-regulatory scaffolding into web-based courses can be effective. Such scaffolding should ideally be aimed directly at the learner as well as being designed into the learning material of the course.

2.3 Identifying Intervention Strategies to Increase Self-Regulation

Social Cognitive Theory emphasises the interaction of personal, behavioural, and environmental factors (Bandura, 1986, 1997; Zimmerman, 1990). Self-regulation is a cyclical process because these factors typically change during learning and must be monitored. Such monitoring leads to changes in an individual's strategies, cognitions, affects and behaviours. This cyclical process is divided into three phases: the *forethought phase* precedes actual performance and refers to processes that set the stage for action; the *performance control phase* involves processes that occur during learning and affect attention and action, while the *self-reflection phase* occurs after performance when learners respond to their efforts. Effective self-regulation depends on students developing a sense of self-efficacy for self-regulating their learning and for performing well (Zimmerman, Bandura and Matinez-Pons, 1992). The intervention strategies

selected for this study were targeted at improving the learner's self-regulation at each phase of the learning.

Additional factors which must be taken into consideration when selecting intervention strategies include the differences between face to face classes and online learning as regards the role of the teacher and peers. Knowlton (2000) states that the instructor must take on the role of facilitator or coach rather than the sole source of knowledge. Shrivastava (1999) proposed the creation of online learning communities, to include class peers and teachers, among others, operating as a network of information. Such a networked learning community extends the role of the instructor as expert to that of facilitator of resources, knowledge, and student learning. Chickering and Gamson's (1987) seminal work, Seven Principles of Good Practice in Undergraduate Education, also provides guidelines on intervention strategies. These Principles rose out of faculty concern over student apathy and incompetent teaching. A summary of the Seven Principles (Chickering and Gamson 1987) is given in Table 2 below.

Perhaps because the principles are fairly simple and therefore obvious to those concerned with effective teaching, attention has mainly been given to them in educational journals and in practitioner literature, but has largely been lacking in instructional research. Furthermore, Worley (2000) found that teachers of online courses are really faced with the same questions that have always plagued the classroom, technically enhanced or otherwise.

Several other studies on how to motivate learners support the principles of Chickering and Gamson (1987). These include: Cashin (1979) who recommends that teachers should be specific when giving negative feedback. Because negative feedback is very powerful it is important to make it clear that comments relate to a particular task or performance, not to the student as a person. Cashin also recommends the "sandwich method:" trying to cushion negative comments with a compliment about aspects of the task in which the student succeeded. He also

recommends that teachers help students set achievable goals for themselves and to encourage students to focus on their continued improvement, not just on their grade on any one test or assignment.

Table 2: Seven Principles of Good Practice in Undergraduate Education (Chickering and Gamson 1987)

1	Encourage contact between students and faculty: Frequent student-faculty contact both in and outside of class is an important factor in student motivation and involvement.
2	Develop reciprocity and cooperation among students: Faculty should create and encourage opportunities for collaborative learning among students.
3	Encourage active learning: Faculty should require students to apply their learning in oral and written forms.
4	Give prompt feedback: Faculty should provide appropriate and prompt feedback on performance. Students need help assessing their current competence and performance, and need frequent opportunities to perform and receive suggestion for improvement. Such feedback should be an ongoing process.
5	Emphasise time on task: Faculty should create opportunities for students to practice good time management. This includes setting realistic time for students to complete assignments as well as using class time for learning opportunities.
6	Communicate high expectations: Faculty should set and communicate high expectations for students. Such expectations become a self-fulfilling prophecy for students and they often will rise to meet the challenge.
7	Respect diverse talents and ways of learning: Faculty should create learning opportunities that appeal to the different ways students will process and attend to information. Varying presentation style and assignment requirement will allow students to showcase their unique talents and learn in ways that work for them.

Ames and Ames (1990) also emphasise mastery and learning rather than grades and recommend assigning un-graded written work, stressing the personal satisfaction of doing assignments, and helping students measure their progress. Students can be helped to evaluate their progress by encouraging them to critique their own work, analyse their strengths, and work on their weaknesses (Cashin, 1979; Forsyth and McMillan, 1991). By giving students feedback as quickly as possible, students get both an indication of how well they have done and how to improve. Both positive and negative comments influence motivation, but research

consistently indicates that students are more affected by positive feedback and success. However, if a student's performance is weak, it is important that the student knows that the teacher believes he or she can improve and succeed over time (Cashin, 1979; Lucas, 1990). The principles of effort-based learning show that effort feedback is also critical. Effort feedback may change a learner's attributional style from a belief in native ability to the value of effort (Dweck and Legget, 1988).

2.4 Motivation in Online Learning

Several approaches have been taken to addressing the question of motivation in online learning. These include studies on the assessment of motivation including those by Del Soldato (1994), de Vicente and Pain (2002; 2003), Qu, Wang and Johnson (2005) and Zhang, Cheng and He (2003). These studies primarily focus on motivational states such as *attention, relevance, confidence*, and *satisfaction*, mainly derived from the ARCS model (Keller, 1987a, 1987b). These states are inferred from behavioural cues in the interaction taken from an analysis of the log files in the Learner Management System, such as *time taken, effort, confidence,* and *focus of attention.*

Studies which address the question of how to intervene to increase motivation have mainly focused on improving the instructional design of the content to make it more motivating. These studies are mainly based on the work in Wlodkowski's (1985) Time Continuum Model of Motivation and Keller's (1987) ARCS model. Both of these models outline methods for systematically designing motivation strategies into instructional materials including strategies for sustaining attention, relevance, confidence and increasing learner satisfaction with their accomplishments.

More recently a small number of studies have attempted to motivate the online learner directly. These studies have studied the effect of motivational

messages, sent through the postal system, via email or by direct phone contact, on the learner.

Visser, Plomp and Kuiper (1999) devised a 'Motivational Messaging System' (MMS) of short postal messages to students. Their goal was to send motivational messages but they mainly addressed learner confidence. Confidence is, of course, a central concept of self-confidence. They claimed that such a system had significant retention effects. They found that short messages were as effective as long ones and that the source of the messages – tutor or institution - did not seem to make a significant difference to their effects.

Chyung (2001), in a US study, used a system of phone calls based on the ARCS model used phone contacts and found that between two to five contacts seemed to be the most effective in motivating learners.

Miller (2001) examined the effect that computer mediated communication (CMC) has on learner activity levels in a self-regulated online learning environment, to determine whether or not CMC, in the form of email messages, could be used to positively influence the learning experience. Each time the student logged into an online course module, their activity level was automatically measured and recorded into a central database. Students were informed that this was happening. An activity report was generated for the student every five days. A total of nine activity reports were generated for each student during the eight-week course. When an activity report was generated the student was assigned to one of five categories based on their activity during the corresponding reporting period. A coded e-mail message was assigned to each category. The positive or negative tone of the coded e-mail message was directly related to the activity level of the category to which it was assigned. So students who spent none or relatively little time in the modules received an email with a negative tone. Students who spent a fair amount of time in the modules received a slightly negative email.

Students who spent a great deal of time in the modules received a positive email whilst those who spent a significant amount of time in the modules received a very positive email. The results indicted that the negative e-mail messages had a positive effect on activity levels, while the positive e-mail messages did not seem to have either a positive or negative effect. This does not indicate that a positive e-mail message has a detrimental effect on activity levels. Instead it showed that some students are ideally suited for a self-directed learning environment and do not necessarily require feedback to facilitate their success as they are able to effectively manage their time and activity levels.

This study had some limitations in that the researcher did not measure all the variance that accounted for increases in activity levels. Such factors might include demographic differences, attitudes toward online learning and computers, and self-efficacy with the subject matter. In addition, the timing of activity reports delivered via e-mail could have been a limitation. For example, a student who scheduled most of their work on the weekend would have regular activity on a seven-day cycle. Activity in a seven-day cycle may be recorded as irregular in the activity level reports that were generated every five days.

In another study by Jackson (2002), an increase in student self-efficacy and performance was observed in an experiment using emails to students in a traditional introductory psychology course. He asked the participants to email him to earn extra credits for their course. He responded to the experimental group with an email designed to enhance self-efficacy. Each of these students got one email which contained information based on the four traditional sources of self-efficacy, i.e. verbal persuasion, vicarious experience (someone else models a skill), mastery experience (repetitive successes instill a strong sense of self efficacy which becomes quite resistant to occasional failures), and scaffolding (help from a more able peer or mentor). Each student in the control group also received one email, but this email was just an acknowledgement in which they were informed that

they had received the extra credit points. Jackson did not conduct a further study to validate if in fact it was the emails that enhanced the students' self-efficacy, rather than other possible external sources which may have led to the increased self-efficacy of these students.

In a traditional face-to-face course which had a web-based component, Frey, Yankelov, and Faul (2003) found that email communication with the instructor was perceived by students as being very valuable.

Finally, a study by Hodges (2005) investigated the effects of motivational email messages on learner self-efficacy and achievement in an asynchronous college algebra and trigonometry course. 125 participants with an average age of 18.21 years completed the study. Email messages designed to enhance efficacy were sent to the experimental group weekly for four weeks. The control group was sent email messages designed to be neutral with respect to self-efficacy weekly for four weeks. Self-efficacy to learn mathematics asynchronously (SELMA) and math achievement were measured after the email messages were sent in week four. The results showed that both the control and the experimental groups revealed a significant increase in self-efficacy to learn mathematics asynchronously.

In summary, these studies show that direct intervention in the form of verbal persuasion positively affects self-efficacy for learning. Visser, Plomp and Kuiper (1999) found that the source of the messages – tutor or institution - did not seem to make a significant difference to their effects. This finding is interesting from the point of view of the current research study in that it will be the system, rather than the instructor, that will intervene with the motivational message. They also found that short messages were as effective as long ones, whilst Chyung (2001) found that between two to five contacts seemed to be the most effective.

The study by Miller (2001) which examined whether or not CMC, in the form of email messages, could be used to positively influence the learning

experience also provides useful information for our research. First, there is no suggestion that the students were bothered by the fact that their activity level was automatically being measured and recorded into a central database even when informed about this. It also provides guidelines about the type of messages, positive or negative, and the impact of these messages on learners. The results indicted that the negative e-mail messages had a positive effect on activity levels, while the positive e-mail messages did not seem to have either a positive or negative effect. This finding lends support to our hypothesis that motivational interventional strategies in the form of feedback to students who are demotivated may help to prevent attrition from online courses.

Finally, the studies by Jackson (2002), Frey, Yankelov, and Faul (2003) and Hodges (2005) all show that self-efficacy and performance were increased as a result of the emails sent to the learners. Furthermore, most of the studies claim to have demonstrated positive retention effects and that the messages were perceived by students as being very valuable.

The research outlined in this thesis builds on the findings of these previous works but differs in a number of ways. First, none of the previous studies attempted to develop intervention motivational strategies that were specific to the individual learner's profile. In this study, the learner's motivational profile in terms of self-efficacy, goal orientation, locus of control and perceived task difficulty will form the basis for the selection of the most suitable intervention strategies. Second, by designing a recommender tool which can be incorporated into the learner model of an adaptive Intelligent Tutoring System, the system will automatically be able to select the most suitable intervention strategy to use depending on the particular student's motivational profile. The ITS will be able to monitor the effect of the strategy on the student's motivation through its assessment component, and will, if deemed necessary, issue further motivational strategy messages as appropriate.

3 Method

From the studies outlined in the Literature Review, it is clear that lack of motivation is a constantly recurring theme relating to attrition from online courses. It follows therefore that motivating the learner is very important to prevent drop out.

As previously mentioned, the aim of this study was to design a recommender tool which could be incorporated into an adaptive Intelligent Tutoring System to automatically deliver motivation intervention strategy messages to learners. Figure 2 below illustrates the high level architecture for two possible uses of the recommender tool. The left side of the figure (dashed outline) illustrates how the recommender tool would be used manually by an online teacher where an automatic assessment component was not available. The Method Section of this thesis is based on the left side of Figure 2. On the right side of the figure, outlined by the dotted lines, is the path which would be utilised by an adaptive Intelligent Tutoring System with an automatic assessment component. This will be dealt with in the Discussion and Conclusion Section of this thesis.

To address the research goal, a number of studies were undertaken and will be described in detail in this section, including:

(a) A learner model was developed based on the constructs of self-efficacy, goal orientation, locus of control and perceived task difficulty. This resulted in twenty one learner profiles being identified as the most likely learners to become demotivated while studying online.

(b) A study to identify which intervention strategies would be most useful to motivate the twenty one learner profiles was undertaken. The views of both classroom and online teachers were elicited for this study.

(c) Based on the results of the above studies, a motivation intervention strategies recommender tool, MotSaRT, was designed. This tool can be incorporated into an Intelligent Tutoring System. Utilising this tool, learners can be profiled and a list of suitable intervention strategies obtained. An evaluation of MotSaRT was carried out and the results are reported.

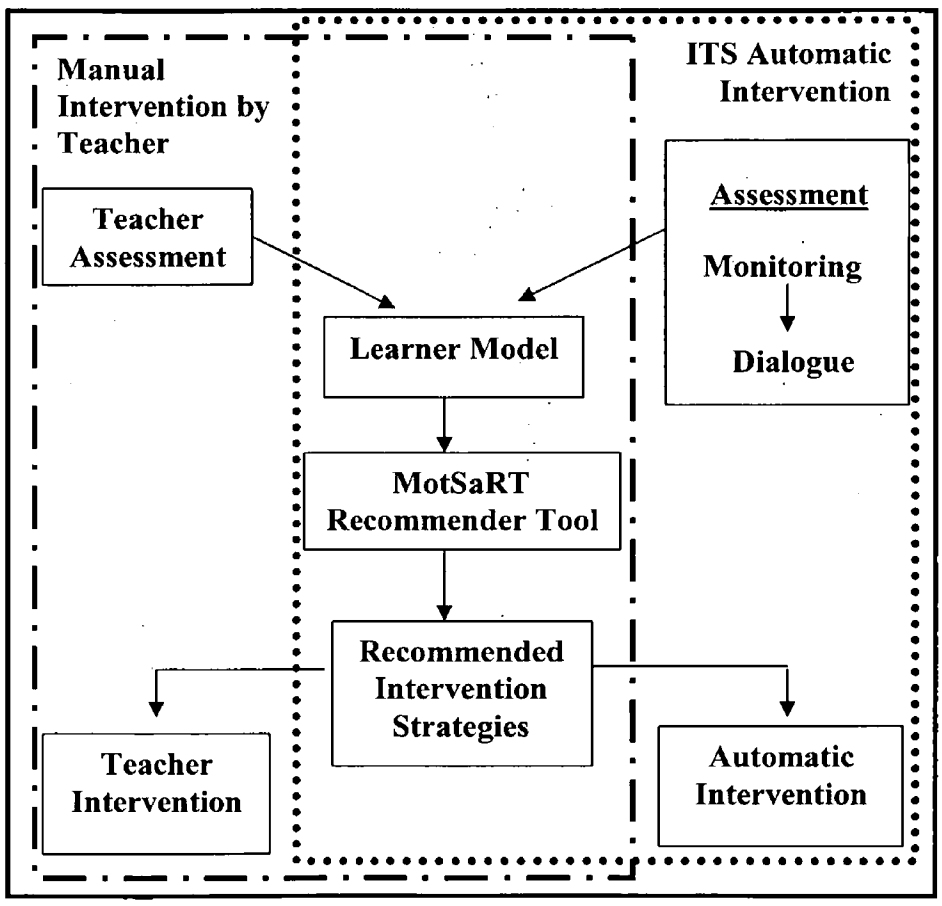

Figure 2: High Level Architecture

3.1 Developing the Learner Model

As previously indicated, Intelligent Tutoring Systems are personalised adaptive systems which typically have three components: (1) a *domain model* that comprises the structure of the domain (the concepts and the relations between them); (2) a *learner model* that stores the learner's characteristics; and (3) an

adaptation model decides whether and how the information in the learner model is to be changed, what content should be presented to the learner and how it should be presented.

As the automatic motivational assessment component is not currently available, the first step was to develop a generic learner model.

The research questions associated with developing a learner model based on motivation levels include: Is it possible to identify the students most likely to become demotivated? Which factors should be taken into account when identifying those who may drop out of online courses?

Our model is based on the constructs of Social Cognitive Theory, including self-efficacy, goal orientation, locus of control and perceived task difficulty.

By systematically examining each of these constructs, every possible profile was elicited. First, self-efficacy was split into three parameters - high, medium and low. Then goal orientation was split into four parameters - mastery, performance approach, performance avoidance and disengagement. Next locus of control was divided into internal or external. Lastly, perceived task difficulty was split into two groups – high and low. From this 3 x 4 x 2 x 2 matrix, a possible 48 different learner profiles emerged (Table 3).

Table 3: Learner model construct parameters

Self-Efficacy	High	Medium	Low	
Goal Orientation	Mastery	Performance Approach	Performance Avoidance	Disengagement
Locus of Control	Internal	External		
Perceived Task Difficulty	High	Low		

However, not all 48 profiles are equally at risk of becoming demotivated. As shown in the literature review, learners with high self-efficacy, who have a mastery goal orientation or a performance approach orientation, an internal locus of control and who perceive the task as being challenging but attainable are the least likely to become demotivated. They are also more likely to have the necessary self-regulation skills to be successful online learners. Therefore, it was necessary to systematically examine each of the forty-eight profiles with a view to deciding which of the motivational constructs represented a risk factor which might indicate that a learner was in danger of becoming demotivated.

For example, a learner with high self-efficacy, mastery goal orientation, an internal locus of control and who perceives the task difficulty level to be high, is much more likely to approach the task with a sense of anticipation towards the learning, rather than with a lack of motivation. For this reason this persona was not included in the list of personas used in the study.

On the other hand, a learner with the profile outlined in the previous paragraph, but who perceives the task difficulty as being low, might be bored. This could result in that learner becoming demotivated as they would not be challenged in their efforts. For this reason they are included in the list of learners likely to become demotivated.

Through this systematic examination process, twenty-one profiles were judged most likely to become demotivated. Table 4 below outlines each of these profiles. The risk factors for each profile are shown in italics. As can be seen from this table, depending on the persona profile, the number of risk factors ranges from one to four. The personas numbered 1 and 4 have only one risk factor each. In the case of Persona No. 1, the risk factor here is when the Perceived Task Difficulty is Low. This is because this learner is likely to be bored. In the case of Persona No. 4 the risk factor is that Self-Efficacy is medium and should the task difficulty prove too challenging, this weakness in self-efficacy may prove to be a

stumbling block. At the other extreme, Personas numbered 8, 9, 19 and 20 have four risk factors. In the case of Persona No. 8, for example, the four risk factors indicate that this learner has a high risk of becoming demotivated: Self-efficacy is low; Goal Orientation is performance avoidance; Locus of Control is external; and, Perceived Task Difficulty is high.

Table 4: Learner Model Profiles *

Profile	Self-Efficacy	Goal Orientation	Locus of Control	Perceived Task Difficulty
1	High	Mastery	Internal	*Low*
2	High	Mastery	*External*	*Low*
3	*Medium*	Mastery	Internal	*Low*
4	*Medium*	Mastery	Internal	High
5	*Medium*	Mastery	*External*	*Low*
6	*Medium*	Mastery	*External*	*High*
7	*Low*	Mastery	*External*	*High*
8	*Low*	*Performance Avoidance*	*External*	*High*
9	*Medium*	*Performance Avoidance*	*External*	*High*
10	High	*Performance Avoidance*	*External*	*High*
11	*Low*	Performance Approach	Internal	*High*
12	*Low*	Performance Approach	*External*	*High*
13	*Medium*	Performance Approach	Internal	*Low*
14	*Medium*	Performance Approach	*External*	Low
15	*Medium*	Performance Approach	Internal	High
16	*Medium*	Performance Approach	*External*	*High*
17	High	Performance Approach	Internal	*Low*
18	*Low*	*Disengagement*	Internal	*High*
19	*Low*	*Disengagement*	*External*	*High*
20	*Medium*	*Disengagement*	*External*	*High*
21	*Medium*	*Disengagement*	Internal	*High*

* Risk factor(s) in italics

3.2 Developing the Personas

The idea of personas was popularised by Alan Cooper in his book "*The inmates are running the asylum,*" (Cooper 1999). A *persona* is a model of a user that focuses on the individual's goals. The persona model resembles classical user profiles, but with some important distinctions. It is an archetypical representation

of real or potential users. It is not a description of a real, single user or an average user. The persona represents patterns of users' behaviour, goals and motives, compiled in a fictional description of a single individual. It also contains made-up personal details, in order to make the persona more "tangible and alive".

Based on the learner model, personas were developed for each profile. These personas were used in the studies which were conducted with the classroom and the online teachers as part of this research and will be explained further in the studies section.

In an attempt to avoid bias arising from the wording of the personas, a similar sentence structure was used in each case to describe the learner. Each persona description began by giving a name to the learner. This was followed by a sentence in which the learner's goal orientation was described in words. The next sentence indicated the learner's self-efficacy level and whether this person had an internal or external locus of control. Finally, the most likely problems which would lead to demotivation for that particular learner were described.

> Example Persona 1: "Chris is an intelligent student who enjoys learning for its own sake. She is motivated to learn new things and enjoys being challenged (*GO: Mastery*). She believes she can do very well in her studies as she has a very good understanding of her subject (*SE: High*). Chris believes hard work will conquer almost any problem and lead to success (*LOC: Internal*). However, she finds that she becomes bored when she has to work on a concept which she already understands well (*PTD: Low*)."

Labels for the Social Cognitive Theory (SCT) constructs of self-efficacy, goal orientation, locus of control or perceived task difficulty were not used. In the example above they are entered in italics for illustration purposes only. Full details of the personas can be found in Appendix 1.

3.3 Identifying Suitable Intervention Strategies

As a first step in eliciting suitable intervention strategies from experienced teachers a generic list of intervention strategies was drawn up. This list was based on the findings and recommendations already discussed in the literature review, particularly on the work of Chickering and Gamson (1987). The initial list included strategies that could be used either in an online situation or in a face to face classroom (Table 5).

Table 5: Intervention strategies to increase motivations

1	Review progress with student at regular intervals
2	Provide regular positive and specific feedback to student
3	Provide information in an interesting manner
4	Set clear learning objectives and targets
5	Encourage student to clearly define academic goals
6	Use small group discussion forums
7	Use online quizzes with immediate feedback
8	Send regular individual emails to students
9	Remind student of the student support services
10	Encourage use of chat room/discussion forums
11	Use continuous assessment towards final marks
12	Use a rubric of motivational keywords
13	Make assignments moderately challenging, varied and relevant
14	Help student to develop a study plan/timetable
15	Explain importance of and encourage student to maintain contact with tutor
16	Encourage peer to peer contact
17	Base evaluation on personal improvement/mastery when possible, rather than grades
18	Encourage the learner to reflect on and evaluate the learning
19	Provide pre and post assessments
20	Provide positive and constructive feedback
21	Explain why learning a particular content is important
22	Relate the learning to the student's needs
23	Provide guidance to extra learning resources
24	No intervention required

When the list of strategies was compiled, a pilot study was conducted in which experienced classroom teachers participated in order to identify which of

the intervention strategies they used to motivate their learners. There were two reasons for seeking the views of experienced teachers:

(a) To elicit from teachers which strategies they considered were best suited to the different profiles outlined in the personas; and

(b) To validate the strategies contained in the list.

In the pilot study, the teachers were given the list of strategies, together with the personas, and were asked to select which of the strategies they would use to motivate each persona. The teachers were asked to suggest any further strategies that they would use with any particular profile. This question was asked in order to elicit any strategy that may have been overlooked when the list was being compiled. The next section describes the pilot study which was conducted with classroom teachers. It also details the main study which was conducted with online teachers and which was developed based on the results of the pilot study.

3.3.1 Eliciting and Validating the Intervention Strategies

As mentioned in the previous section, experienced teachers were consulted in order to identify the intervention strategies they use to motivate their learners. In this way the list of strategies developed for this study could be refined and verified. Each teacher was required to have a minimum of two years' teaching experience. Two studies were carried out for this purpose. Firstly, a pilot study was conducted with classroom teachers. When the results of this study were analysed, a further study was conducted with online teachers to identify if there were any differences between how classroom teachers and online teachers motivate students that needed to be considered.

3.3.2 Pilot Study

Convenience sampling was used for this study. Twenty classroom teachers from the researcher's college were asked to participate in the study. This group of

teachers were chosen as they were easily accessible, promised a good response rate, and fulfilled the basic selection criteria of having a minimum of two years' teaching experience. Teachers were asked to indicate their subject area and any online teaching experience (Table 6). Ten responses were received to the Pilot Study.

Table 6: Classroom Teachers

Participant	2 years Teaching Exp	Online Teaching Exp	Subject area
1	Yes	No	Informatics
2	Yes	Yes	E-learning
3	Yes	Yes	IT
4	Yes	No	Software Eng.
5	Yes	No	Software Dev.
6	Yes	No	Informatics
7	Yes	No	Finance
8	Yes	No	Informatics/Bus.
9	Yes	No	Community Dev.
10	Yes	No	Industrial Relations

The instructions given to the classroom teachers regarding the learners were: (1) that all learners were first year undergraduate students; (2) all learners were enrolled in an online course with asynchronous facilities only; (3) all learners had acquired the necessary computer skills to undertake their online course; and (4) it was the first time that any of the learners had enrolled in an online course.

In the pilot study, the teachers were given a pack which outlined the 23 personas and had a list of 24 intervention strategies under each persona (Appendix 2). The list of strategies was always presented in the same order concluding with the option of "No intervention required". They were asked to read each persona and then to tick the intervention strategies which they would use to motivate the

student profiled, first as a classroom teacher and then as an online teacher (two separate columns). As can be seen from Table 6 above, only two of the teachers had online teaching experience. A decision was made therefore to disregard the online results for this study. As a final question, the teachers were asked if there was any strategy which they would use with the type of student profiled and which was not included in the list provided. In response to this question, the majority of the teachers validated the strategies by indicating that they felt the strategies listed were appropriate and included all the ways that they would attempt to motivate students. No new strategies were indicated that could be used in an online situation.

3.3.3 Results of the Pilot Study

A radar chart (Figure 3) is used to visualise the results of the pilot study with the classroom teachers. In this chart the legend shows the name given to each persona which was presented to the classroom teachers. The numbers 1 -23, on the outside of the graph, represent the 23 strategies that were listed (Section 3.3 – Identifying Suitable Intervention Strategies). The numbers 0 – 8 (bold font), radiating from the centre of the graph, indicate the number of respondents who selected each strategy.

As can be seen from this radar chart, hardly any of the strategies seem to be specifically selected. Thus the graph stays clustered in the middle of the radar. This results in a generalised picture of how teachers motivate students in the classroom. However, it yields no clear insight in how exactly classroom teachers differentiate between students with different motivational profiles. It seems unlikely that experienced classroom teachers do not take into account these differences between students. This is particularly so as the teachers are normally in a position to get to know their students quite well as individuals. The clustering effect may be the result of the common problem that often arises when people are

asked to fill in a questionnaire, i.e. respondents tend to answer what they think they should do, rather than what they actually do in real life.

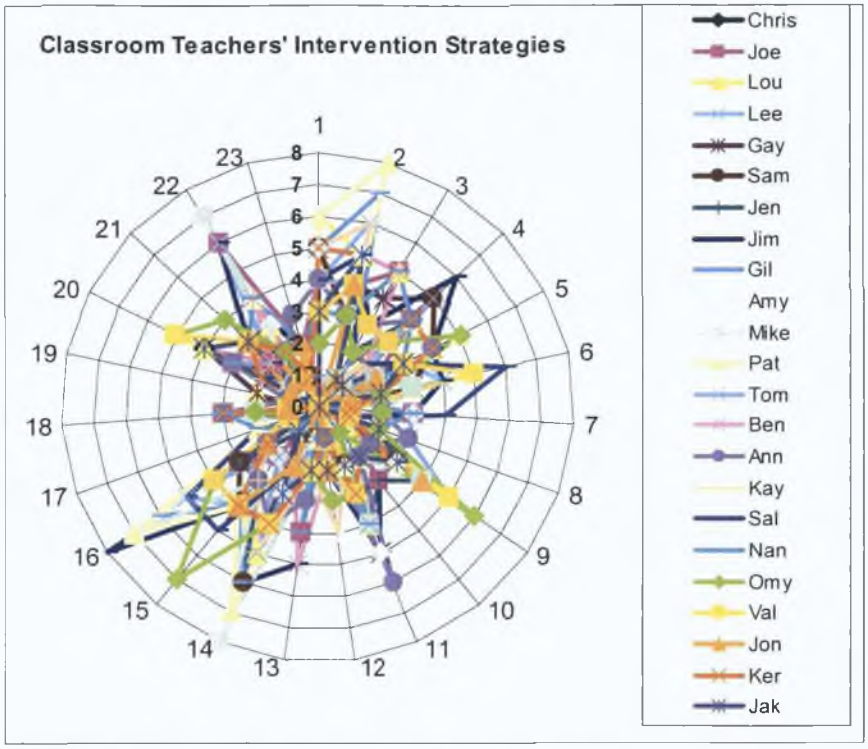

Figure 3 Classroom Teachers' Intervention Strategies

The only strategies that were selected by at least 60% of the participants are numbers: 1, 2, 4, 6, 9, 11, 14 and 16. These strategies were looked at in more detail to see if there was any particular reason they were selected more often than the others by the classroom teachers (Table 7).

Strategy 1, "Review progress with student at regular intervals," was selected for the Persona "Lou" and "Pat". In the Learner Model the persona "Lou" relates to a learner who has the following characteristics: SE –Medium; GO – Mastery; LOC – Internal: and PTD – Low. In the case of "Pat" the persona relates to a person who has the characteristics of: SE – Low; GO – P Approach; LOC – Internal; PTD – High. Therefore the only motivational attribute that they both share is the fact that their LOC is internal. It would appear, therefore, that this

strategy has been chosen by the classroom teachers more because it is a good general motivational strategy than because they considered it to be especially relevant to the particular profile outlined in the persona.

Table 7: Strategies selected by at least 60% of classroom teachers

No.	Strategy	Lou	Pat	Gil	Sal	Omy	Ann	Kay	Jim	Sam	Mike
1	Review progress with student at regular intervals	x	x								
2	Provide regular positive and specific feedback to student		x	x				x			
4	Set clear learning objectives and targets								x		
6	Use small group discussion forums				x						
9	Remind student of the student support services					x					
11	Use continuous assessment towards final marks						x				
14	Help student to develop study plan/timetable		x	x					x	x	x
16	Encourage peer to peer contact		x	x					x		x

Strategy 2, "Provide regular positive and specific feedback to student," is again a good general motivational strategy that most teachers would routinely apply in their classrooms. However, in this case, each of the three personas who got the highest selections on this strategy did share a common motivational attribute – PTD was high and in two out of the three personas self-efficacy was low, while the third persona had medium self-efficacy. These learners would very definitely benefit from receiving regular positive and specific feedback to prevent

them giving up when struggling with a difficult task and also to increase their self-efficacy as they work through the task.

Strategy 4, "Set clear learning objectives and targets": In this case the persona has the following characteristics: SE –Low; GO – Mastery; LOC – External; PTD – High. It is interesting that this is the only persona for which this strategy got a high selection rating. It is relatively unusual to find a learner with mastery orientation having low self-efficacy. When these attributes are combined with an external LOC, this type of learner would really benefit from having clear objectives and targets set out for them.

Strategy 6, "Use small group discussion forums": This strategy may have been selected as the persona has an external locus of control and would therefore be likely to value input from others. However, it is unclear why only one persona got a high selection rating.

Strategy 9, "Remind student of the student support services": This strategy got a high selection rating for a persona which had SE – Low; GO – Disengagement; LOC – Internal; PTD – High. It is a very appropriate strategy to select for a disengaged student. However, there were three other disengaged students in the learner model but it was only in this particular case more than 50% of the classroom teachers selected it.

Strategy 11, "Use continuous assessment towards final marks": This strategy was selected by more than 60% of the classroom teachers for one persona: SE – Medium; GO – P Approach; LOC – External; PTD – Low. There is no obvious reason why this strategy got a higher selection rate for this particular persona.

Strategy 14, "Help student to develop a study plan/timetable" and Strategy 16, "Encourage peer to peer contact": The personas who had the highest rating

with these strategies did not share any common motivational attributes across all personas.

In contrast, some of the strategies were selected by less than 25% of the classroom teachers. These include strategies 8, 10, 12, 17, 18, 19 and 23 as shown in Table 8 below. While strategies numbered 8 and 10 might possibly be explained by the fact that most of the classroom teachers had no online experience, there is no obvious reason why the other strategies were not popular with these teachers.

Table 8: Strategies selected by less than 25% of the classroom teachers

8	Send regular individual emails to students
10	Encourage use of chat room/discussion forums
12	Use a rubric of motivational keywords
17	Base evaluation on personal improvement/mastery when possible, rather than grades
18	Encourage the learner to reflect on and evaluate the learning
19	Provide pre and post assessments
23	Provide guidance to extra learning resources

Conclusion: As the number of responses to the survey with the classroom teachers was small, ten in total, it is difficult to draw any definite conclusions from the fact that some of the strategies were selected more than the others. Although no obvious pattern emerged as to why teachers choose a particular strategy, a number of lessons were learned from this study that should enable the main study with the online teachers to yield more useful results. These lessons are discussed next.

3.3.4 Lessons Learned from the Pilot Study

First, it was an enormous task for teachers to respond to twenty-three personas. This was indicated by many of the teachers resorting to write "same for this student", or "as before" on successive pages after the first few personas had been dealt with. For this reason, it was decided that a maximum of four personas

would be presented to each of the online teachers in their study, which will be reported on in the next section.

Second, it was clear from the responses that some of the teachers had difficulty distinguishing between some of the profiles and they stated that many of the personas were too similar. For example, some teachers had difficulty differentiating between learners with medium or low self-efficacy, despite the fact that the wording used to describe each learner type was different. This may have resulted in the same strategies being selected for almost every student regardless of the persona. Another possible explanation for this happening is that the teachers were asked to consider too many personas. Alternatively, it could have arisen because the persona types were too closely grouped and therefore appeared to be very similar. In response to this problem, when the personas were being sent to the online teachers a number of changes were made. It was decided that the online teacher survey would be split into six different surveys and to bring all the results together at the end. In this way no online teacher would have to deal with more than three or four personas. It was felt that it would be easier to achieve a good mix of persona types in each smaller survey. For example, if the persona types were chosen on the basis of goal orientation, a survey could contain personas with mastery, performance approach, performance avoidance and disengagement goal orientations.

The list of strategies was also reviewed as the feedback from the classroom teachers suggested that the list was too long. A number of the strategies were deemed more suitable for implementation at the design of the learning material stage rather than for direct intervention with the learner. These strategies included: provide information in an interesting manner; set clear learning objectives and targets; use online quizzes with immediate feedback; provide pre and post assessments- relate the learning to the student's needs; make assignments moderately challenging, varied and relevant; use a rubric of motivational keywords; and use continuous assessment towards final marks. This pruning

resulted in a revised list of fourteen strategies, including "no intervention required" as shown in Table 9 below.

Table 9: Revised list of intervention strategies

1	Review progress with student at regular intervals
2	Provide regular positive and specific feedback to student
3	Encourage student to clearly define his/her academic goals
4	Encourage the student to use online quizzes
5	Remind student of the student support services
6	Encourage student to use the chat room/discussion forums
7	Help student to develop a study plan/timetable
8	Explain importance of and encourage student to maintain contact with tutor
9	Encourage peer to peer contact
10	Encourage student to base self-evaluation on personal improvement/mastery when possible, rather than grades
11	Encourage the student to reflect on and evaluate his/her learning
12	Explain why learning a particular content is important
13	Provide guidance to extra learning resources
14	No intervention required

Finally, two of the personas, Jen and Jak, were removed from the learner model as it was discovered that an error had been made and that they were in fact duplicates of other persona types. This meant that the classroom teachers were given twenty-three personas when in fact they should only have been given twenty-one. The results of these changes were then implemented in the main online teacher study which will be discussed in the next section.

3.4 Main Study

The purpose of this study was to identify which intervention strategies could be used to help motivate the learner directly in an online learning situation. A survey was conducted with online teachers to determine if there are interventional strategies which can be used to motivate students. If so, are different strategies required depending on the profile of the student? Finally, are the interventional motivational strategies used by online teachers the same as those used in face-to-face teaching?

3.4.1 Eliciting Intervention Strategies from Online Teachers

Based on the first lesson learned from the pilot study, each participant teacher was asked to concentrate on a maximum of four very different personas. Therefore the twenty-one personas were divided into six different surveys, with each survey containing either three or four personas. Systematic efforts were made to ensure that the personas contained in each survey were as different to each other as possible. The study was conducted using Surveymonkey, a web-based tool that enables surveys to be created online. To ensure that each survey had an equal opportunity of being selected, a random link was set up in Surveymonkey. In this way, when a teacher clicked on the survey link, any one of the six individual surveys was randomly presented to this teacher. When the results were collated, all the survey responses were brought together to once again form one large survey.

Snowball sampling was used to recruit participants. Snowball sampling is a technique for developing a research sample where existing study subjects recruit future subjects from among their acquaintances. Thus participants were contacted through personal contacts and listserves - such as EDTECH and DEOS. In addition, colleges posting details of online courses and the names of teachers on the internet were contacted and were requested to post information about the

survey on their internal mailing lists. In all, just over 1,200 potential participants were contacted directly. It is not possible to quantify how many teachers were reached through the listserves or by means of internal mailing lists. A copy of the email sent to the teachers, requesting them to participate and giving them the link to the survey, can be found in Appendix 3.

To participate in the survey, teachers were required to have at least two years' online teaching experience. The instructions given to the participants were:

> "You are being asked to read through the persona descriptions for each of the students outlined below. Under the persona description, a list of 14 intervention strategies (same for each persona) that could be implemented in online learning environments is provided. Having read through the persona, for each intervention strategy listed, please choose "Highly Recommended", "Recommended", or "Not Applicable", as you believe appropriate for this persona. Alternatively, if your choice is "Not Applicable" you can choose to ignore the options completely. For each persona, if you would use any other motivation strategy not listed, or would like to add any further comments, please fill in the details in the box provided".

In the online survey the teachers were presented with a persona description followed by the common list of fourteen strategies (Figure 4). This procedure was repeated for either three or four personas depending on which survey they had randomly selected.

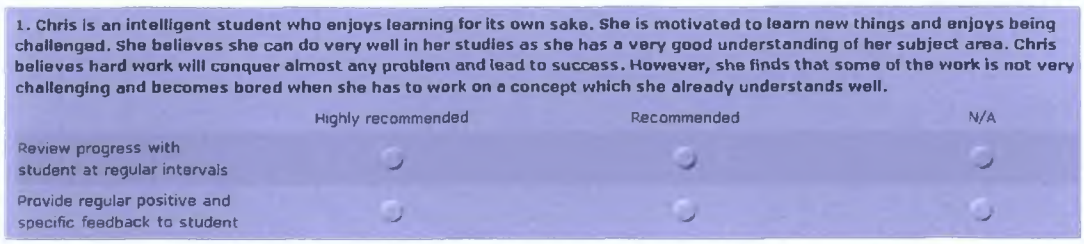

Figure 4: Survey Screenshot 1

When the teachers completed their strategy selections, the next question they were asked was if they had any other interventions or comments that they would like to add (Figure 5).

Figure 5: Survey Screenshot 2

The penultimate question in the survey concerned the level of online teaching experience of the participant (Figure 6).

Finally, each participant was invited to enter his/her email address to enable feedback to be given on the results. Alternatively, the survey could be completed anonymously (Figure 6).

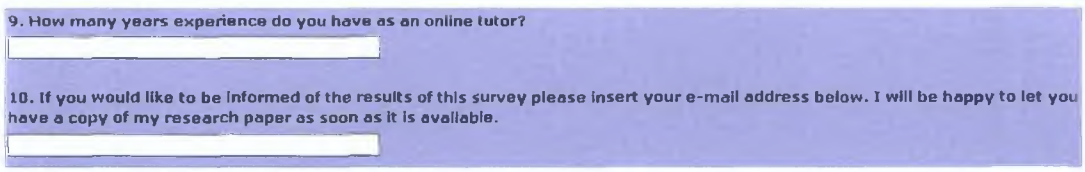

Figure 6: Survey Screenshot 3

3.4.2 Survey Results

Seventy teachers responded to the online survey. Ten responses were eliminated as they either did not meet the criteria of the teacher having at least two years' online teaching experience or the survey was not completed as required. In this way sixty valid responses were obtained (Figure 7).

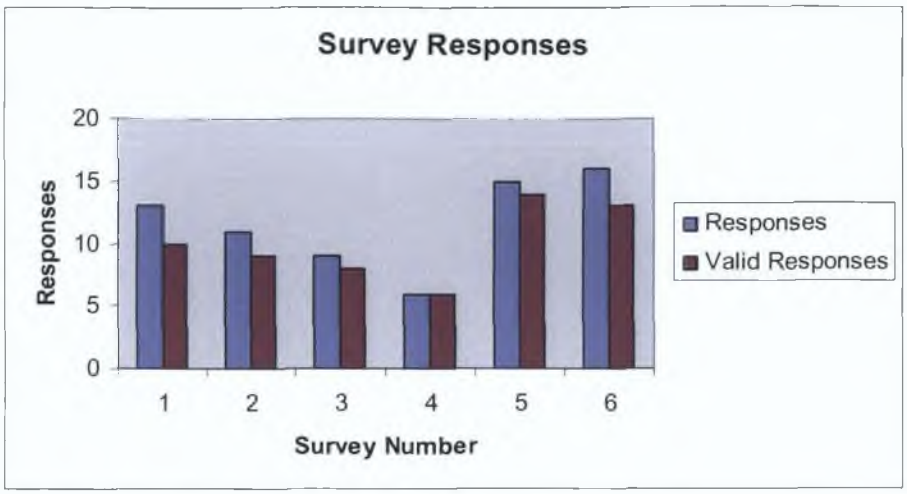

Figure 7: On-line Survey Responses

Forty of the participant teachers requested feedback by inserting their email addresses at the end of the survey. It was from this information that the geographical spread of the responses was noted. The responses were received from Ireland, America, Sweden, Australia, Austria, and the United Kingdom. The participants' teaching experience varied between the required two years and fifteen years, with an average of five and a half years' experience (Figure 8).

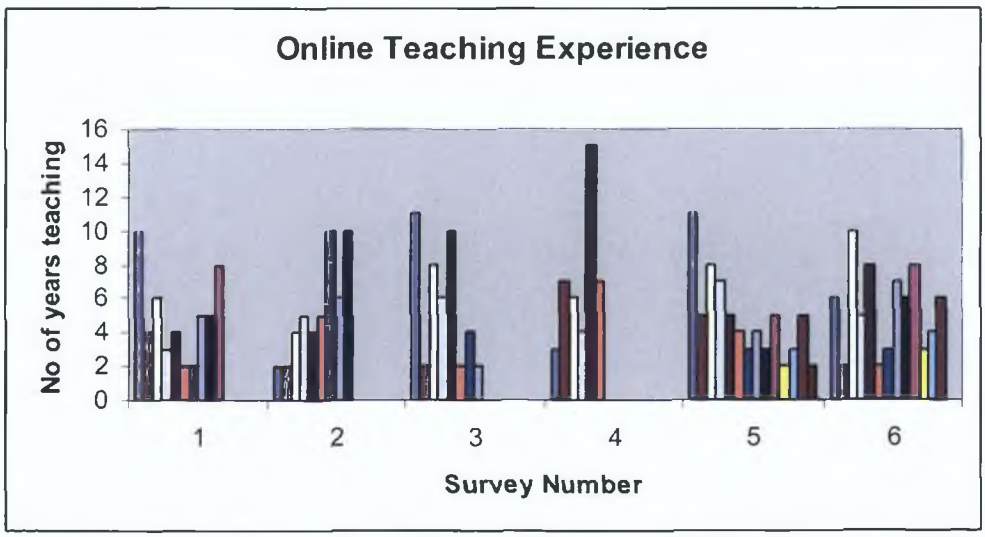

Figure 8: Number of years' online teaching experience

The number of responses to the surveys varied from six to fourteen. To make the results for the different personas comparable, it was necessary to get the percentage response rate for each strategy for each persona. Radar charts are again being used to visualize the results. These charts display the response rate from 0% to 100%.

On these charts, the legend on the right of the figure shows a list of the persona names, followed by two numbers. The first of these numbers indicates in which of the six surveys the persona appeared, and the second number indicates the number of valid responses to that survey. The numbers 1 – 13 which appear on the perimeter of the radar itself indicate the thirteen strategies which were selected by the participants from the revised Intervention Strategies list (Table 9). No participant selected strategy 14 "No intervention required" for any persona. Therefore this strategy does not appear on the chart. The strength of agreement on the use of a particular strategy for different personas is indicated by the dispersal of the nodes for each persona on each of the radial axes. For example, on the radial axes for strategies 1, 8, 12 and 13 the persona nodes are closely clustered between 50% and 80% indicating high agreement between the participants on the use of these strategies for several personas. On the other hand, on the radial axis of strategy 5 the persona nodes are much more widely dispersed between 10% and 80% indicating less agreement between the participants on the use of this strategy for the various personas.

The combined results of all the surveys are shown in Figure 9. It can be seen from this figure that between 50% and 80% of the online teachers would use almost every strategy when attempting to keep any of the personas motivated. Two personas, Joe and Chris, show an even higher response rate, up to 100% for strategies 2, 3 and 9. A possible explanation for this may be that these were the first personas which appeared in Survey 1 and Survey 2. Accordingly,

the higher response rate may be due to the fact that more attention was being paid to these personas as they were the first ones that the participant teachers considered.

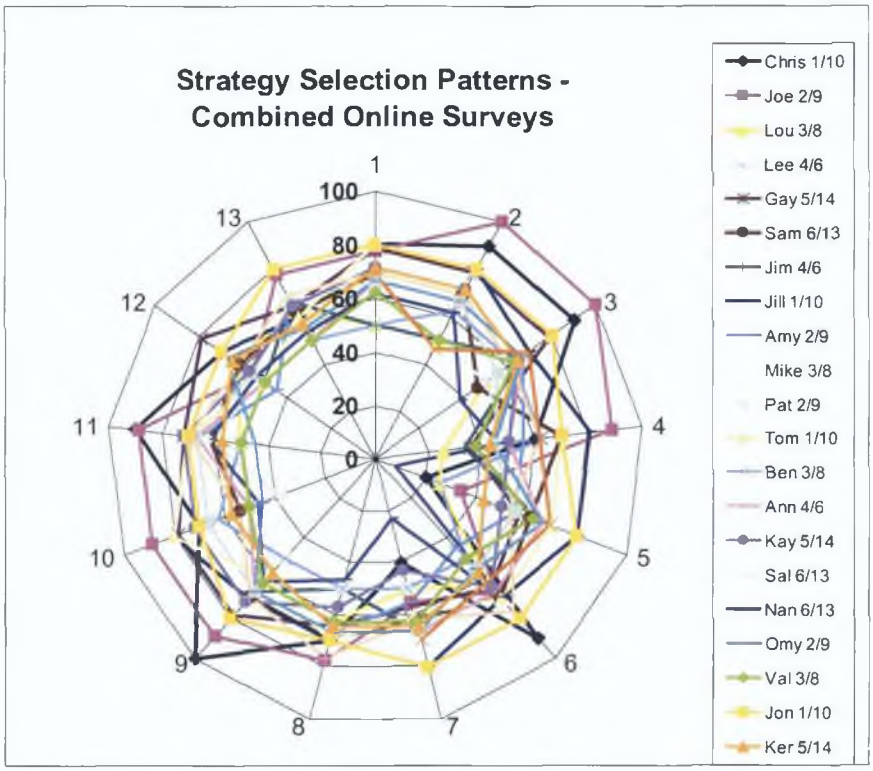

Figure 9: Online Teacher Survey Results

In order to compare the online teachers' results with the classroom teachers' results, a decision was made to disregard the strategies that were eliminated from the questionnaire presented to the online teachers from the results of the pilot study. The result of this change is visualised in the radar chart below (Figure 10).

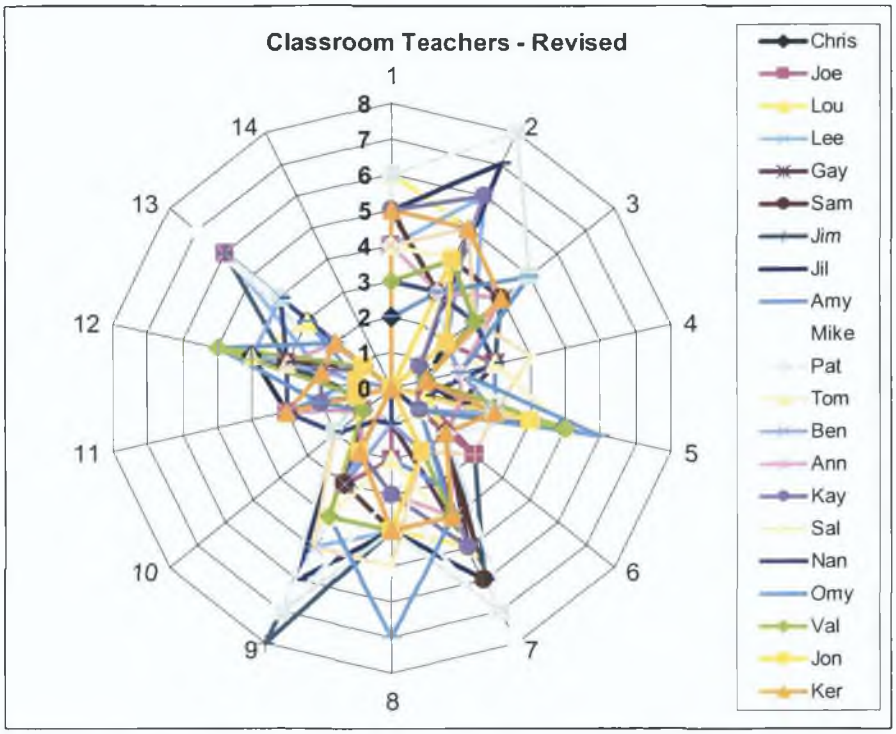

Figure 10: Revised strategy selection for classroom teachers

It is obvious from even a cursory inspection of Figures 9 and 10 that the online teachers and the classroom teachers had a very different approach to how they would motivate students. The selection pattern for the online teachers is circular shaped, showing a level of agreement amongst the on-line teachers on how to motivate students. The selection pattern for the classroom teachers is star shaped, showing that these teachers display much less agreement as to how to motivate students. In the case of the classroom teachers, between 0% and 50% of the teachers were prepared to use most of the strategies to keep most of the persona types motivated. This is in sharp comparison to the 50% and 80% of the online teachers who would use almost every strategy when attempting to keep any of the personas motivated. The average number of strategies selected across all personas by both the classroom teachers (based on the revised data) and the online teachers is shown in Figure 11.

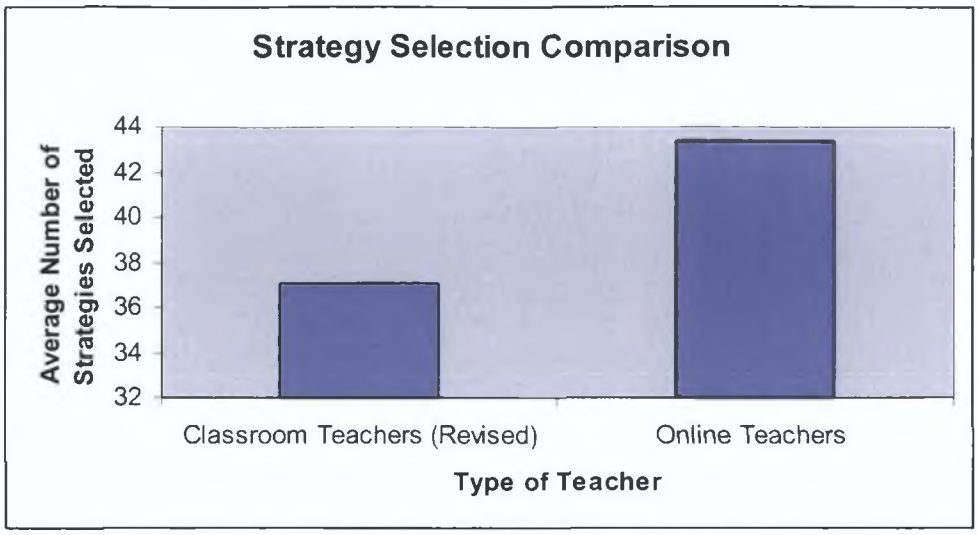

Figure 11: Average strategy selection across personas

Indeed, a closer study of these two radar charts reveals several significant differences in strategy selection. As can be seen from Figure 9, strategy No. 5, "Remind students of the student support services," is the only strategy that was selected by less than 40% of the online teachers for a number of the personas. This may be because such services are not widely available to those who are studying online in asynchronous courses. However, as can be seen from Figure 9, several strategies were selected by less than 40% the classroom teachers, for example, strategies numbered 4, 6, 10, 11 for all of the personas. The reason for the disparity between online teachers and classroom teachers is obvious in the case of strategies 4 and 6, as Strategy No. 4, "Encourage the student to use on-line quizzes," and Strategy No. 6, "Encourage the student to use the chat room/discussion forums," are less likely to be relevant to a classroom situation. However, Strategy No. 10, "Encourage the student to base self-evaluation on personal improvement/mastery when possible, rather than grades," and Strategy No. 11, "Encourage the student to reflect on and evaluate his/her learning," are equally useful in both a classroom and in an online situation. It is very difficult, therefore, to account for the different selection choices in these two cases.

Although from Figure 9 it may appear at first glance that the online teachers selected almost every strategy for every persona, a correlation of the number of risk factors for each persona in the Learner Model (see Table 4) with the number of strategies recommended shows a weak positive correlation of .18. This confirms that the online teachers saw the differences between the personas and identified those that required "more" intervention.

Table 10 below is a sub-section of Table 4 which can be found in Section 3.1 which shows the profiles of the personas, Omy, Val, Jon and Ker. This next section discusses the results for these four students in particular, as they were identified in the personas as being motivationally disengaged.

Table 10: Learner Model of Disengaged Students

Persona	Self-Efficacy	Goal Orientation	Locus of Control	Perceived Task Difficulty	Name of student
18	*Low*	*Disengagement*	Internal	*High*	*Omy*
19	*Low*	*Disengagement*	*External*	*High*	*Val*
20	*Medium*	*Disengagement*	*External*	*High*	*Jon*
21	*Medium*	*Disengagement*	Internal	*High*	*Ker*

A study of the pattern which emerges when only the disengaged personas are considered supports the argument the online teachers saw the differences between the personas and identified those that required "more" intervention (Figure 12).

As can be seen, all the strategies with the exception of Strategies 4, 10 and 11 have been selected by at least 60% of the respondents for each of the disengaged students. This shows that disengagement seems to trigger online teachers to try virtually every strategy when attempting to re-engage these learners. Despite this, among this group there are clear differences in the strategies selected for the personas with low and medium self-efficacy, when this construct is combined with an external locus of control.

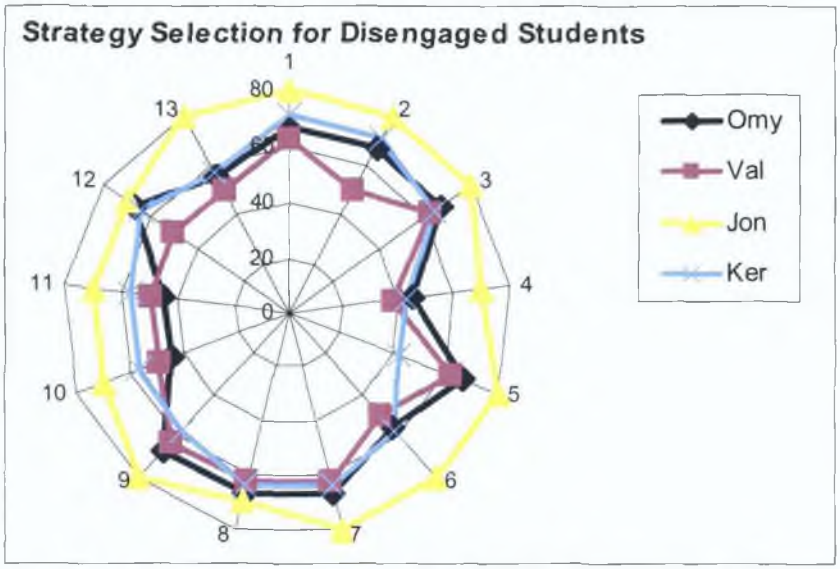

Figure 12: Online Teachers' Strategy Selection for Disengaged Students

Although there is a high agreement in the selection of all the strategies, the personas with external locus of control, i.e. Val and Jon, show a difference in the strength of the selections, whereas those with an internal locus of control, i.e. Omy and Ker, show an almost identical pattern.

With regard to the personas that have external locus of control, the differences may be explained by the fact that Val has low self-efficacy whereas Jon has medium self-efficacy. In the case of Jon, medium self-efficacy seems to trigger very definite views on how to motivate such as learner, whereas in the case of Val, who has low self-efficacy, the online teachers seem less certain about the strategies.

It was also of interest to this study to compare the online teachers' "Highly Recommended" strategy (Figure 13) selection with their "Recommended" strategy (Figure 14) selection.

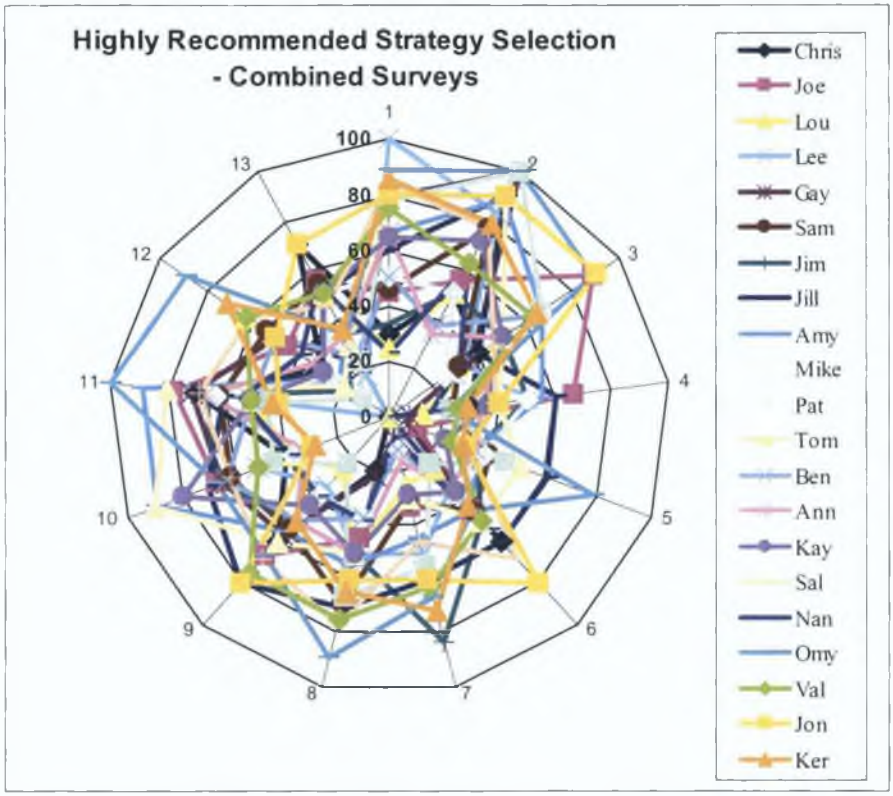

Figure 13: Online Teachers' Highly Recommended Strategies

The radar chart for the Highly Recommended strategies (Figure 13) shows that nine out of the fourteen strategies were highly recommended for most of the personas by over 60% of online teachers. These strategies were numbers 1, 2, 3, 6, 7, 8, 9, 10 and 11. Strategy 4, "Encourage the student to use online quizzes," and Strategy 5, "Remind student of the student support services," received the least number of highly recommended selections. Despite this, even these strategies were selected as being highly recommended by between 20% and 40% of the online teachers for most of the personas. It could be suggested that due to their position in the list of strategies, the first three strategies would be selected

most often by the participants. On the other hand, Strategy 12, "Explain why learning a particular content is important," and Strategy 13, "Provide guidance to extra learning resources," are both strategies that are important in motivating learners. In addition, they are strategies that would be likely to be used frequently by any teacher, but clearly the online teachers did not feel as strongly that they merited a "highly recommended" selection. This suggests that the online teachers were indeed considering each strategy on its own merits.

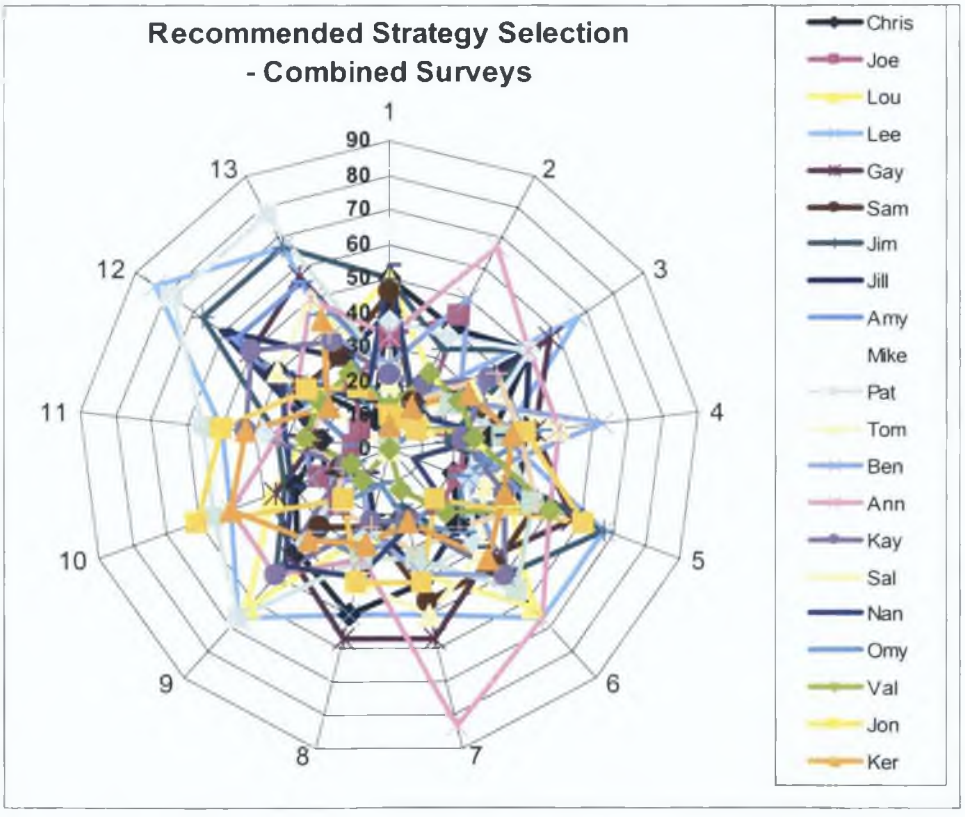

Figure 14: Online teachers' recommended strategy selection

There is a sharp contrast between the "highly recommended" strategy selection and the "recommended" strategies selection (Figure 14). Only a very small number of personas had strategies marked as recommended by more than 60% of the online teachers. As can be seen from this figure, the majority of the

strategies selected as "recommended" were chosen by between 0% and 40% of the online teachers. Furthermore, Figure 14 shows that many of the strategies were not selected as "recommended" for any of the personas while several of the strategies were only selected as "recommended" by up to 20% of the participants. This shows that the online teachers had very definite views regarding how strongly they would recommend the use of the various strategies for each persona type.

In conclusion, the results of the study with the online teachers show different intervention strategies are recommended for different personas. Even when students are clearly disengaged, online teachers will use almost every strategy available to them in an attempt to re-engage the student. The study also revealed that online teachers are prepared to try many more interventions than classroom teachers to keep students motivated. The results of this study also show that it is possible to elicit adaptation knowledge from experienced teachers through the use of personas for use in an Intelligent Tutoring System.

3.5 Automatic Strategy Selection

Data mining was used in an effort to predict which strategies online tutors would select for a certain motivational profile.

WEKA (Waikato Environment for Knowledge Analysis), (Witten et al., 1999), is a collection of machine learning algorithms for data mining tasks. The algorithms can either be applied directly to a dataset, as is the case with this study, or called from your own Java code. Weka contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. It is also well-suited for developing new machine learning schemes.

For the purposes of the WEKA classification a decision was made to merge the *Highly Recommended* and *Recommended* strategies into one category, hereinafter referred to as "Recommended strategies".

Using the WEKA data mining tool set, five different algorithms were applied to predict whether a strategy was marked as recommended by the teachers or not. These algorithms included the following classifiers: 1) Bayesian Networks. 2) IBk, an instance-based k-nearest neighbours classifier. 3) J48, generating pruned C4.5 decision trees. 4) PART, a classifier based on partial C4.5 decision trees and rules. 5) Naïve Bayes as a standard baseline. All experiments were run with a 10-fold cross validation. The quality of the predictions can be examined in order to see if the comparison between the responses of the teachers and the WEKA results show a high level of agreement.

To enable decision tree learning to occur, values for the motivational constructs of each of the twenty one personas were applied. These values were: self-efficacy – high, medium and low; goal orientation – mastery, performance approach, performance avoidance and disengagement; locus of control – internal and external; and perceived task difficulty – high and low (Table 11).

Table 11: Persona Motivation Constructs

Self-Efficacy	Low	Medium	High	
Goal Orientation	Mastery	Performance Approach	Performance Avoidance	Disengagement
Locus of Control	Internal	External		
Perceived Task Difficulty	High	Low		

An overview of the percentage of strategy recommendation predictions of the five algorithms for the first thirteen intervention strategies is provided in Table 12. The fourteenth strategy, "No intervention required," is not included as it was not selected by any of the teachers who responded to the surveys for any persona.

Table 12: Percentage of strategy recommendation predictions of the five algorithms

	BayNet	IBk	J48	PART	NaïveBayes
Strategy 1	89.86	89.86	**89.86**	89.86	89.86
Strategy 2	93.26	93.26	**93.26**	93.26	93.26
Strategy 3	84.55	80.78	**84.55**	82.03	84.55
Strategy 4	66.09	58.88	**66.58**	63.11	65.23
Strategy 5	74.04	74.80	**77.31**	77.12	74.33
Strategy 6	86.50	85.71	**86.50**	86.50	86.50
Strategy 7	**70.92**	67.59	68.83	70.23	69.81
Strategy 8	83.60	82.64	**83.60**	83.60	83.50
Strategy 9	88.90	88.22	**88.90**	88.90	88.90
Strategy 10	82.64	80.66	**82.64**	82.25	82.64
Strategy 11	88.90	88.90	**88.90**	88.90	88.90
Strategy 12	79.24	74.86	**79.24**	78.57	78.47
Strategy 13	80.67	79.66	**80.67**	80.67	80.67

Both Bayesian Networks and J48 were able to predict the recommendations very well, with correct prediction rates from at least 66% and up to 93%. Strategy 4, "Encourage the student to use online quizzes," seems to be harder to predict. This strategy has also been recommended less often than most other strategies. The fact that results across methods are similar means that the pattern in the data is fairly obvious. J48 decision trees provided the best predictions for all strategies except No. 7 (figures in bold format).

3.5.1 J48 Decision Trees compared to PART Decision Lists

The J48 analysis results in one decision tree per strategy predicting under which circumstances a certain strategy would be recommended or not.

In this section a comparison between the J48 Decision Trees and the PART Decision Lists will be made on strategies 3, 4, 5, 7, 10 and 12. These strategies were selected as they have the lowest percentage of strategy recommendation predictions for the J48 Decision Tree. The purpose of the comparison is to answer the question "Does this prediction increase our trust in

the rule and in the analysis?" If the decisions made are reasonable then it is possible to say that this is a valid interpretation of the strategy that has been gleaned from the teachers' online survey.

Table 13 hereunder shows how the J48 Decision Tree predicts Strategy 5 "Remind student of the student support services".

Table 13: Strategy 5 "Remind student of the student support services"

If PTD = High	Strategy 5 is recommended
If PTD = Low/Unknown and LOC = internal	Strategy 5 is not recommended
If PTD = Low/Unknown and LOC = external and SE = Medium/Low/Unknown	Strategy 5 is recommended
If PTD = Low/Unknown and LOC = external and SE = High	Strategy 5 is not recommended

If the student is finding the task difficult it makes sense to remind the student about the support services available. On the other hand, if the student finds the task easy and has an internal locus of control, s/he is unlikely to need student support services. However, even if the task is easy, if the student has an external locus of control and medium/low or unknown self-efficacy as regards this domain, again it would make sense to recommend the student support services to such a student. Finally, if the student does not find the task difficult and has high self-efficacy in that domain, even if s/he has an external locus of control, they are less likely to need support from student services. Therefore, this predication does increase our trust in the rule and in the analysis.

Figure 15 shows the J48 Decision Tree for Strategy 5 "Remind student of the student support services" in graphical format.

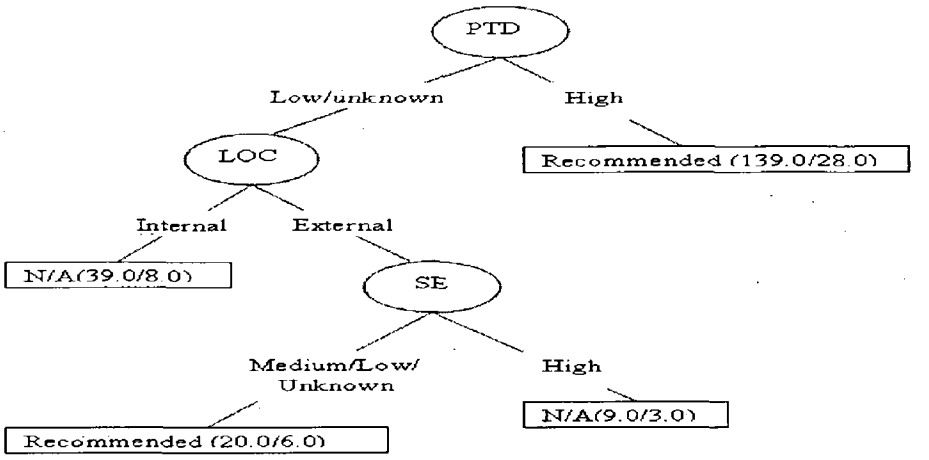

Figure 15: Decision Tree for Strategy 5

The validation for Strategy 5 is further supported by the four rules in the PART Decision List (Table 14).

Table 14: Strategy 5 PART Decision List

If PTD > 1 (i.e. High)	Strategy is recommended (139.0/28.0)
If PTD is Low And LOC is internal	Strategy is N/A (39.0/8.0)
If PTD is low And LOC is external And SE is <=2 (Medium/Low/Unknown)	Strategy is Recommended (20.0/6.0)
If PTD is low And LOC is external And SE =>1 (High)	Strategy is N/A (9.0/3.0)

Comparisons were made for strategies 3, 4, 10 and 12 between the J48 Decision Tree and the PART Decision List. Each of these strategies yielded the same result: A J48 tree with one leaf and a PART Decision List simply showing "Recommended" in one rule. This implies that the tutors seem to recommend these strategies regardless of the motivational profile of the learner.

The final strategy that is compared is Strategy 7, "Help student to develop a study plan/timetable". It can be seen from Table 12 that this is the only strategy to get a higher percentage of strategy recommendation prediction in an algorithm

other than J48. Table 15 hereunder shows how the J48 Decision Tree predicted this strategy.

Table 15: Strategy 7 "Help student to develop a study plan/timetable"

If PTD = >1 (i.e.) High	Strategy is Recommended
If PTD = <=1 (i.e.)Low/Unknown And LOC = Internal	Strategy is not Recommended
If PTD = <=1 (i.e.) Low/Unknown And LOC = External	Strategy is Recommended

In the case of Strategy 7, when the student perceives the task as being difficult, the strategy is recommended. When the student perceives the task difficulty as being either low or unknown, but has an internal locus of control, it is very likely that the student already uses a study plan/timetable. However, even if the task difficulty is low, but the student has an external locus of control, it is recommended to help the student to develop the study plan/timetable. It is usual for students with an external locus of control to rely on outside help and therefore this predication validates the rule and increases our trust in the analysis.

The J48 Decision Tree for Strategy 7 "Help student to develop a study plan/timetable" in graphical format is shown in Figure 16.

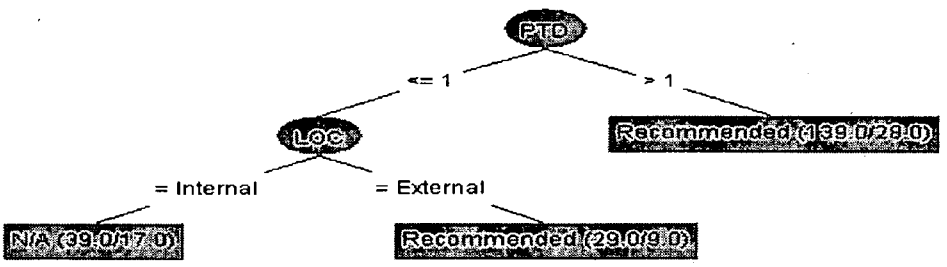

Figure 16: Strategy 7 Decision Tree

The validation for Strategy 7 is further supported by the five rules in the PART Decision List (Table 16).

As both the J8 Decision Tree and the PART Decision List agree when Strategy 7 should be recommended or not, this prediction is validated and again increases our trust in the rule and in the analysis.

Table 16: Strategy 7 "Help student develop a study plan/timetable"

If PTD > 1 (i.e. High)	Strategy is Recommended (139.0/28.0)
If PTD <= (i.e. Low/Unknown) And LOC = External	Strategy is Recommended (29.0/9.0)
If PTD <= (i.e. Low/Unknown) And LOC = External And GO = PApproach	Strategy is not Recommended (21.0/8.0)
If PTD <= (i.e. Low/Unknown) And LOC = External And GO = PApproach And SE >2 (i.e. High)	Strategy is not Recommended (10.0/4.0)
If PTD <= (i.e. Low/Unknown) And LOC = External And GO = PApproach And SE = <2 (i.e. Medium/Low/Unknown)	Strategy is Recommended (8.0/3.0)

4 MotSaRT – Motivational Strategies: A Recommender Tool for Online Teachers

Using the recommendation rules derived from the questionnaire study, the author designed a recommender tool, MotSaRT, to support online teachers in motivating learners (Figure 17). Its functionality enables the facilitator to specify the learner's motivation profile. MotSaRT then recommends the most likely intervention strategies to increase motivation for any particular profile. Thus, MotSaRT not only selects strategies for personas, but for any combination of the four motivational constructs of self-efficacy, goal orientation, locus of control and perceived task difficulty.

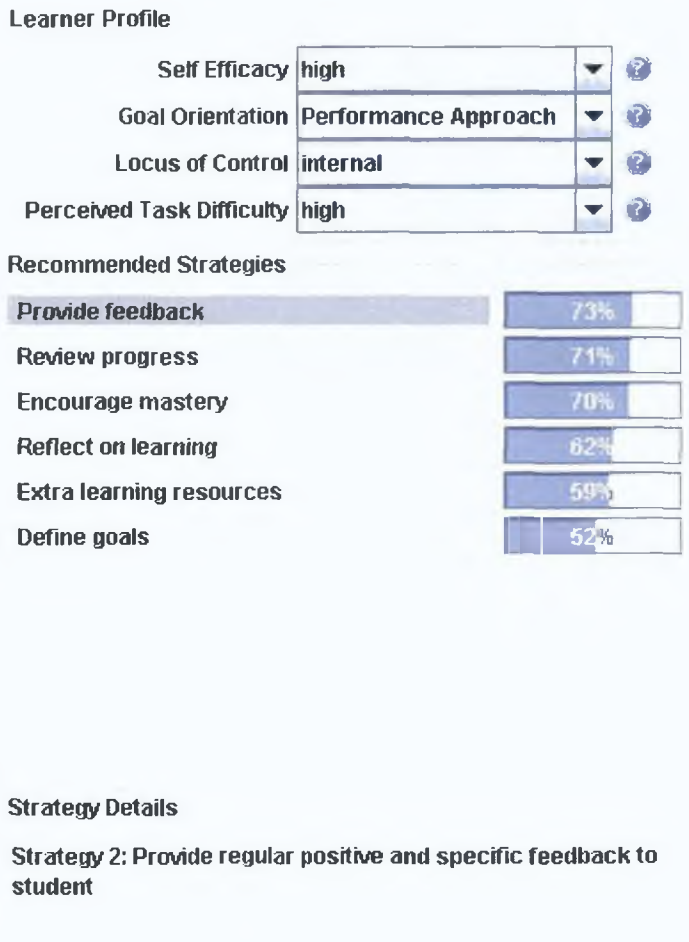

Figure 17: Screenshot of MotSaRT

Technically, MotSaRT is a Java Applet and can thus be integrated into most L[C]MS fairly easily. By observing the activities of learners in the learning environment and possibly interacting with them synchronously or asynchronously through instant messaging, email or fora, an adaptive ITS, or a teacher, can assess a learner in terms of his/her self-efficacy, goal-orientation, locus of control and perceived task difficulty. MotSaRT then classifies this case and sorts the strategies in terms of their applicability. Either the ITS or the teacher can implement the interventions according to the recommendations displayed by MotSaRT.

A graphical representation of how MotSaRT can be used as either a manual system or, alternatively, as part of an ITS when combined with an automatic assessment component, is shown in Figure 18.

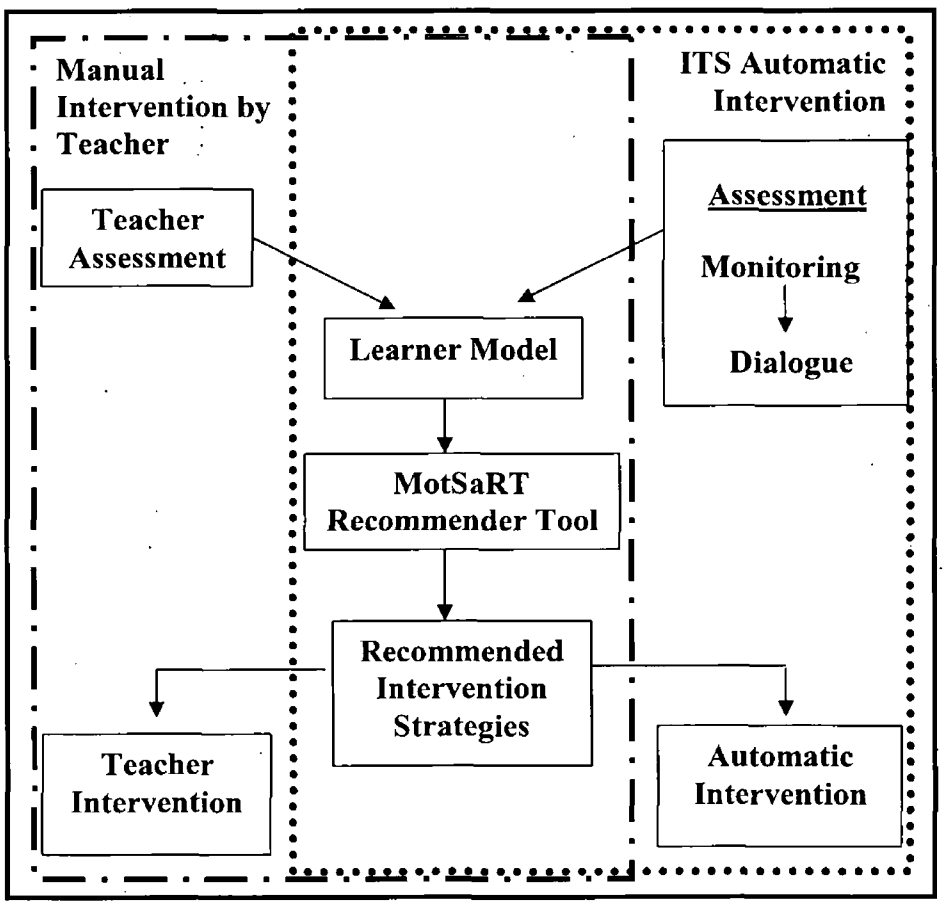

Figure 18: MotSaRT High Level Architecture

On the left of Figure 18, and enclosed by the dashed line, is the representation of how MotSaRT can be used by an online teacher who would be responsible for monitoring the students and conducting the dialogue with the student when demotivation is suspected. Alternatively, on the right side of this figure, and enclosed by the dotted line, is the representation of how MotSaRT would combine with an automatic assessment component in an adaptive ITS. In this scenario the system would be responsible for monitoring the student's progress and engaging the student in a dialogue when demotivation is suspected. As can be seen from the graphic, either the teacher or the system enters the details regarding the student into the learner model. Based on the information entered into the learner model, MotSaRT recommends the appropriate intervention strategy. The recommended strategy can then be implemented either by the online teacher or by the ITS.

4.1 MotSaRT Functionality

By observing the progress of the students and interacting with them either synchronously or asynchronously, an adaptive Intelligent Tutoring System or an online teacher would become aware if a student was falling behind and not submitting assignments or making sufficient progress in the coursework. At this stage the ITS or the teacher can contact the student and through dialogue and/or the use of a reliable and validated motivation survey instrument assess the motivation level of the student. If it becomes obvious that the student is demotivated and may possibly exit from the course, the ITS or the teacher can utilise the functionality of MotSaRT to select suitable intervention strategies to attempt to motivate the student and thus prevent attrition. From the dialogue and the motivation survey, the ITS or teacher would be able to access the student's level of self-efficacy, goal orientation, locus of control and perceived task difficulty. With this information, the ITS or the online teacher would use

MotSaRT as follows: In the Learner Profile area, the student profile would be entered as follows (Figure 19):

Self-Efficacy	–	High, Medium, Low or Unknown
Goal Orientation	–	Mastery, Performance Approach, Performance Avoidance, Disengagement or Unknown
Locus of Control	–	Internal, External or Unknown
Perceived Task Difficulty	–	Low, Medium, High or Unknown

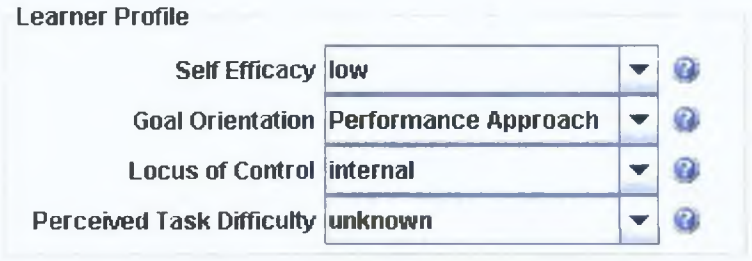

Figure 19: Screenshot of Learner Profiles in MotSaRT

In the Recommended Strategies area, depending on the profile entered by the ITS or the teacher, a list of strategies showing the percentage recommendation according to the J48 decision tree algorithm is displayed (Figure 20). By clicking on a strategy, an elaboration of the strategy will appear in the Strategy Details area.

Figure 20: Recommended Strategies in MotSaRT

By clicking on a strategy, an elaboration of the strategy will appear in the Strategy Details area (Figure 21).

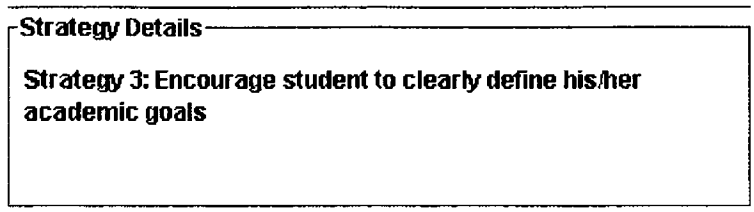

Figure 21: Strategy Details on MotSaRT

From the suggested strategies, the ITS or the teacher selects and implements the strategy that is considered the most suitable intervention for the particular student. The ITS or the online teacher can then monitor the student's progress to see if the motivation level of the student increases and the student begins to make progress in the coursework again.

4.1.1 Evaluating MotSaRT

With MotSaRT at prototype stage, a questionnaire was designed to elicit the views of teachers on the usability and functionality of MotSaRT (Appendix 4). The questionnaire was initially sent to the forty online teachers who had requested feedback on the results of the survey outlined in the main study. Unfortunately no feedback was received from this source. In order to progress the evaluation, it became necessary to use snowball sampling once more. The evaluation questionnaire was therefore sent out to twenty teachers whom the researcher knows personally and to another twelve who had expressed interest in the tool at two conferences where papers on it were presented. These teachers agreed to publish the evaluation request on their internal mailing lists. In addition, the questionnaire was sent out to fifteen colleges who offered online courses who were not contacted as part of the online survey study and these colleges agreed to add the evaluation request to their internal mailing list. Finally, the questionnaire was sent to a further twenty people who had completed a taught Masters in

eLearning technologies and who were therefore familiar with the concepts, although it was not known if they are now teachers. Despite this, the response rate was very poor and resulted in only seven evaluation forms being completed and returned to the researcher. However, these responses yielded very useful information on how the tool was perceived and how it could be developed further. The results from the seven responses are reported hereunder.

4.1.1.1 Using the Recommender Tool

Questions 1 and 2 were concerned with whether the respondents had used MotSaRT to get recommendations for students and if they would use it again in the future. Four respondents replied that they had used MotSaRT to profile their students and would do so again. Three stated that they did not use MotSaRT to profile students (Figure 22). Two of these respondents stated that this was due to lack of opportunity to do so but indicated that they would use it in the future to profile students.

When asked about using MotSaRT while teaching online, one respondent suggested that it might be better as an offline tool, as when online "...even anonymous information can be related to a source e.g. a college".

Of the four respondents who would use MotSaRT again, one stated that they would use it again but that it required a "better introduction to the concept of student profiling". Two said they would not use MotSaRT again in its current format. These respondents felt that the tool was "too simplified and a little mechanical in its current format" and "...they would consider using it....if some sort of profiling tool was available". Four respondents stated that they would use MotSaRT when teaching online and three stated that they would not, drawing attention to the comments made in response to the previous question.

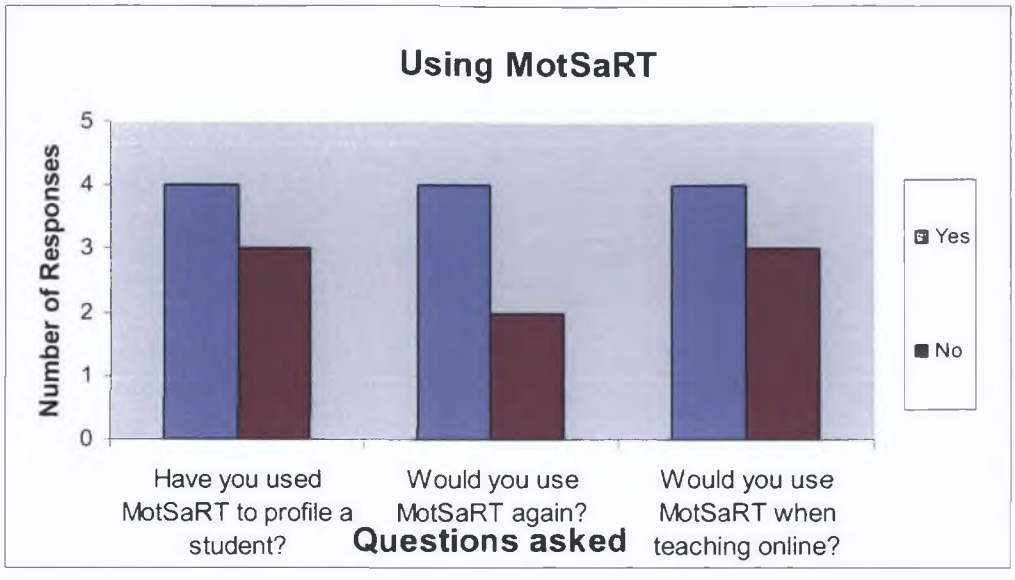

Figure 22: Use of MotSaRT

4.1.1.2 Features and information offered on MotSaRT

Questions 3 and 4 concerned the usefulness of the features and information offered by MotSaRT. All seven of the respondents found the availability of the drop-down menus where they could input the student characteristics useful (Figure 23). Six of the respondents found the explanation feature useful, while one found it somewhat useful. Finally, four of the respondents stated that they found the dynamic presentation of the recommended strategies useful, and the other three found this feature somewhat useful.

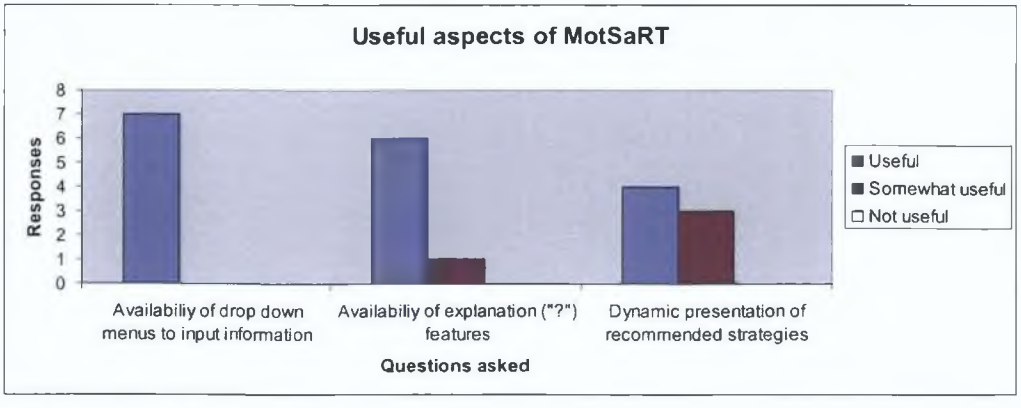

Figure 23: Useful Aspects of MotSaRT

Clicking on the question mark in the learner profile area opens a message box that gives a short explanation of the various profiling characteristics, such as self-efficacy or locus of control (Figure 24). Six of the respondents found the explanation features useful while one stated they were "somewhat useful," stating that "it is difficult to assess all the information required in the learner profile".

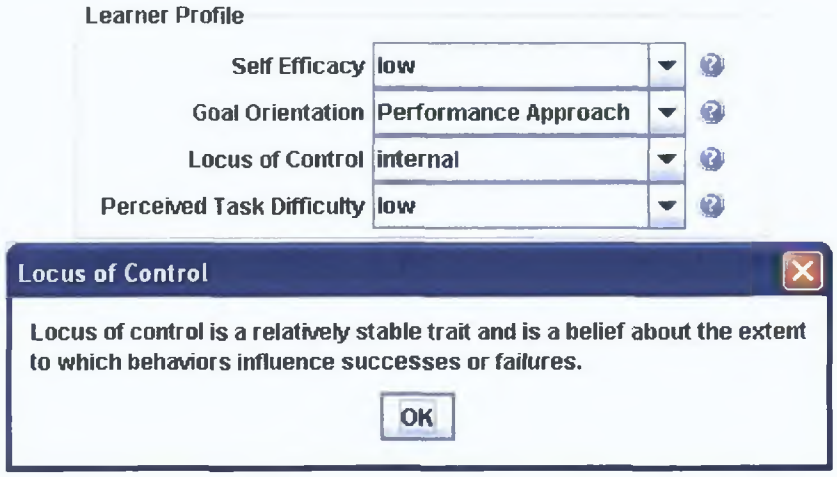

Figure 24: Explanation of Goal Orientation

The dynamic presentation of the recommended strategies comprises a colour coded box which also includes the percentage agreement on the strategy across the teachers surveyed (Figure 25). Four of the respondents found this feature useful while three found it somewhat useful. This may be because the meaning of the percentage figure was not fully understood and so an explanation might be a useful addition to the tool.

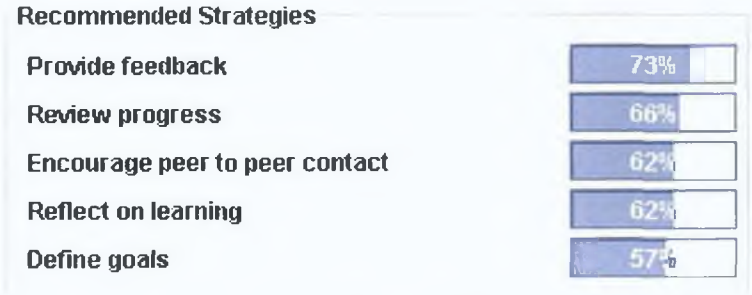

Figure 25: Dynamic Presentation of Recommended Strategies

In question 4, the evaluators were also asked to rate the information provided on MotSaRT on a scale of 1-5, where 1 = not informative and 5 = very informative. Figure 26 below shows that five out of the seven respondents rated the numerical percentage information, the strategy detail and the coloured percentage recommendation indicators informative, while one further respondent rated the coloured percentage recommendation indicators as very informative. One respondent stated that s/he did not find the numerical percentage recommendation values informative and one respondent stated that s/he did not find the strategy details informative.

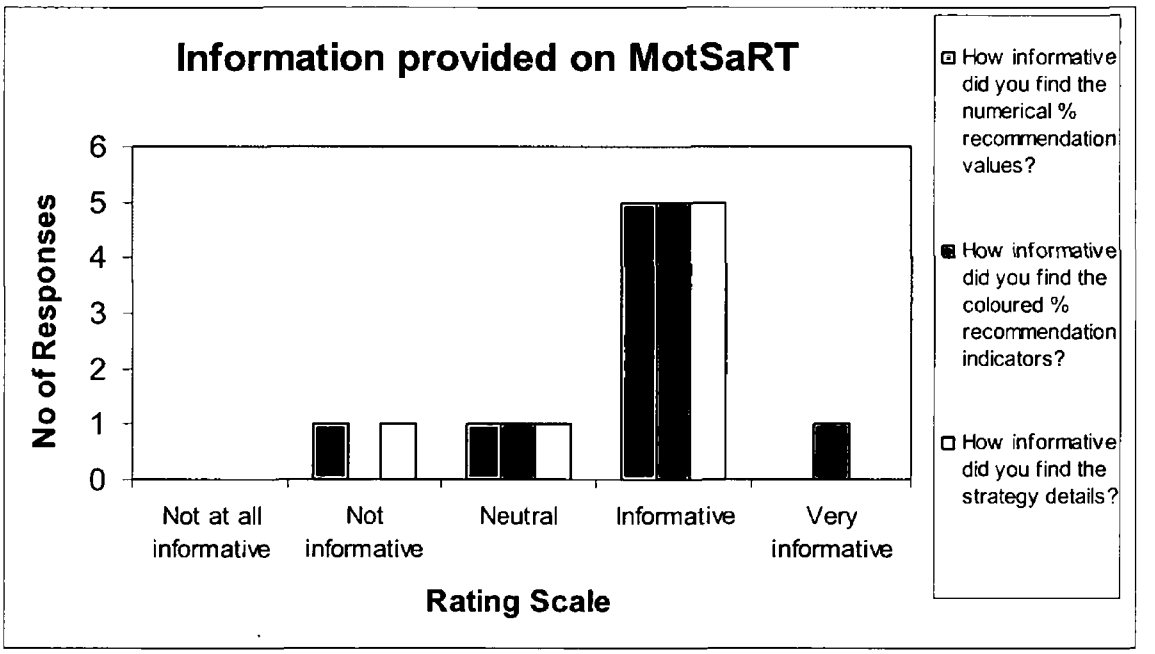

Figure 26: Information Provided on MotSaRT

Further suggestions by the respondents in relation to the strategies included "a means of adding new strategies and rating the recommendations for profiles" and a request for suggestions on "how to follow up using the strategies advised". Requests for "real world examples of how to apply the suggested strategies" were also made by two of the participants.

4.1.1.3 Strategy Elaboration

In question 5, the evaluators were asked, "Should the strategies detail be elaborated further?" Five respondents answered "Yes", one said "No" and one did not answer the question. They were then asked for suggestions on how this could be done. Suggestions received from four of the participants included: "Give more concrete examples", e.g. use mind maps, give explanations of strategies; provide feedback on strategies that were not recommended; give explanations as to why the strategy is suggested.

4.1.1.4 User Friendliness of MotSaRT

Question 6 asked the evaluators to rate how user friendly they found MotSaRT on a scale of 1 – 5 (with 1 = Strongly Disagree and 5 = Strongly Agree). Figure 27 below sets out the results for this question. Six out of the seven respondents agreed or strongly agreed that MotSaRT was easy to use. The respondent who disagreed (gave a rating of 2) was the same respondent who stated that s/he did not understand the profiling parameters and so this probably explains the low rating for this question. Four of the respondents agreed or strongly agreed that the interface was pleasant, and five agreed or strongly agreed that the information provided was clear. Finally, all seven respondents either agreed or agreed strongly that they found the dynamic presentation of the information on MotSaRT helpful.

Some suggestions made by the respondents regarding the help information include: "could be better organised to directly relate to the options in the drop-down menus", "break up paragraphs into bullets points" (two respondents suggested this), and "explanation of profile parameters quite brief".

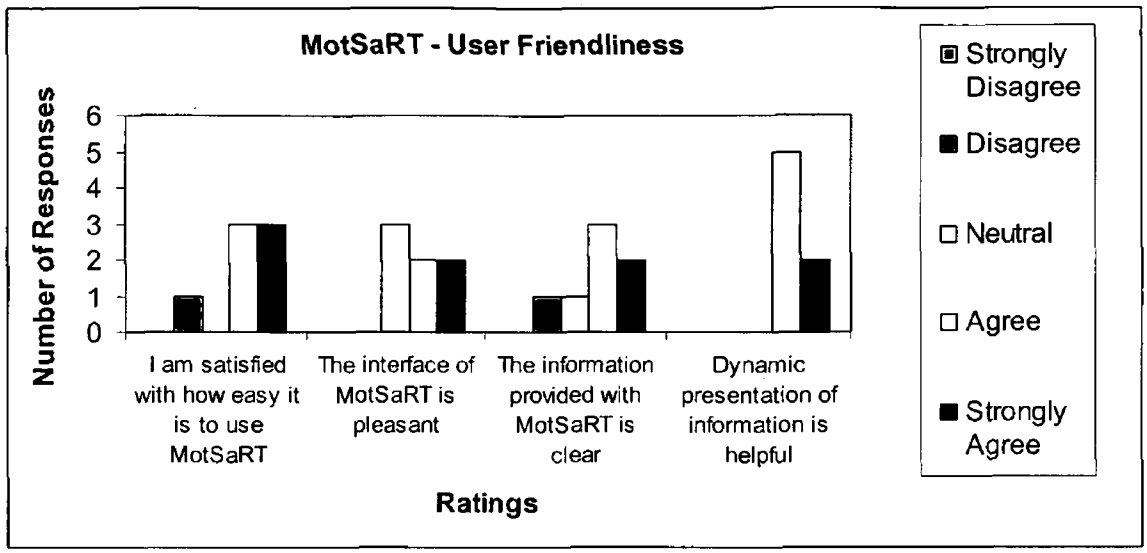

Figure 27: MotSaRT - User Friendliness

4.1.1.5 Problems, Comments, Criticisms and Suggestions

In question 7, the evaluators were asked if they experienced any problems using MotSaRT. One respondent mentioned that the profiles did not load initially and suggested that a "submit" button would help indicate that new data had been submitted and a new profile generated. Three of the respondents indicated slight problems with the profile parameters including "understanding the categories for each drop down list"; find the explanations of the profile parameters "quite brief"; and, understanding the language used, e.g. "Locus of Control".

Question 8 invited comments, criticisms and suggestions relating to the usability of MotSaRT. Six responses were received. The tool was positively perceived by the evaluators but four of them felt that they would need more guidance on how to profile the students for self-efficacy, goal orientation, locus of control and perceived task difficulty. For example, questions such as "how are you advising the teachers to determine the learner profile?" and suggestions such as "provide a survey instrument or profiling tool" were made on these responses. Two of the respondents suggested that an introductory text, coupled with an

explanation of the categories for the profiles and reformatting of the text in the message boxes would "provide the finishing touches".

The recommender tool was also perceived to be a "bit basic or bare". This was not unexpected as it is an initial prototype with a lot of potential further development (this will be dealt with further in the future work section).

In Question 13, suggestions were invited for additional functionality. Several suggestions were received as to how the tool could be developed further. Figure 28 shows the suggestions received: giving explanations as to why a strategy is or is not recommended (4); providing some introductory text to the tool (3); giving more detail to explain the motivational constructs (6); facilitating ability to add other dimensions (2); expansion of the strategies into more concrete examples (4); allow both the teacher and the student to have access to the profile (2); providing suggestions for how the teachers could use the information gained from the tool (1); and, finally, to provide a print feature so that the profile and the suggested strategies could be printed out (2).

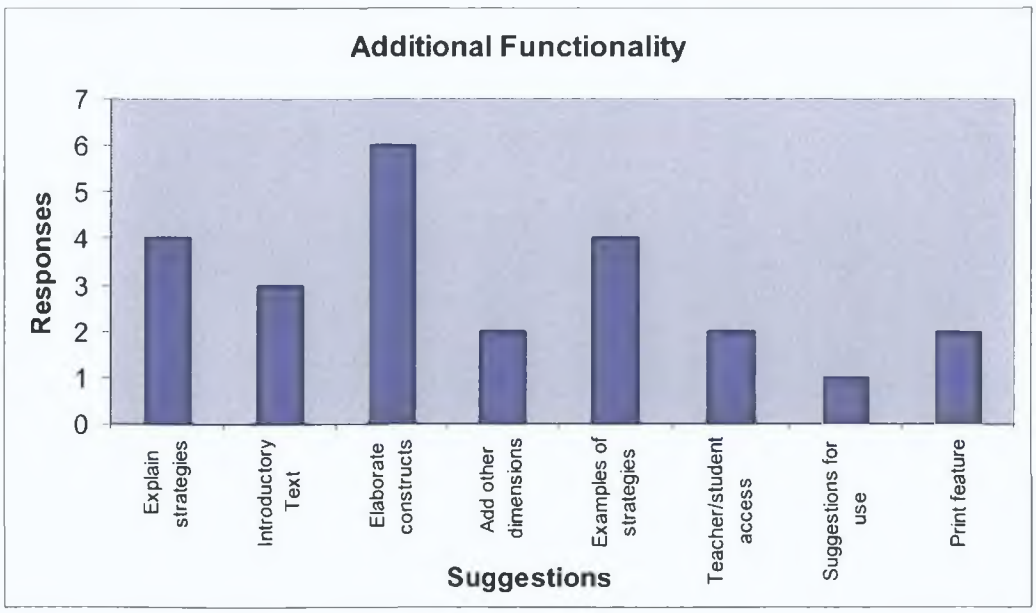

Figure 28: Additional functionality features

4.1.1.6 Student Profiling

Question 9 dealt with the evaluators' understanding of the meaning of the four profile parameters: self-efficacy, goal orientation, locus of control and perceived task difficulty (Figure 29). The results show that all but one of the respondents clearly understood all of the parameters and this respondent had difficulty only with the parameter "Locus of Control".

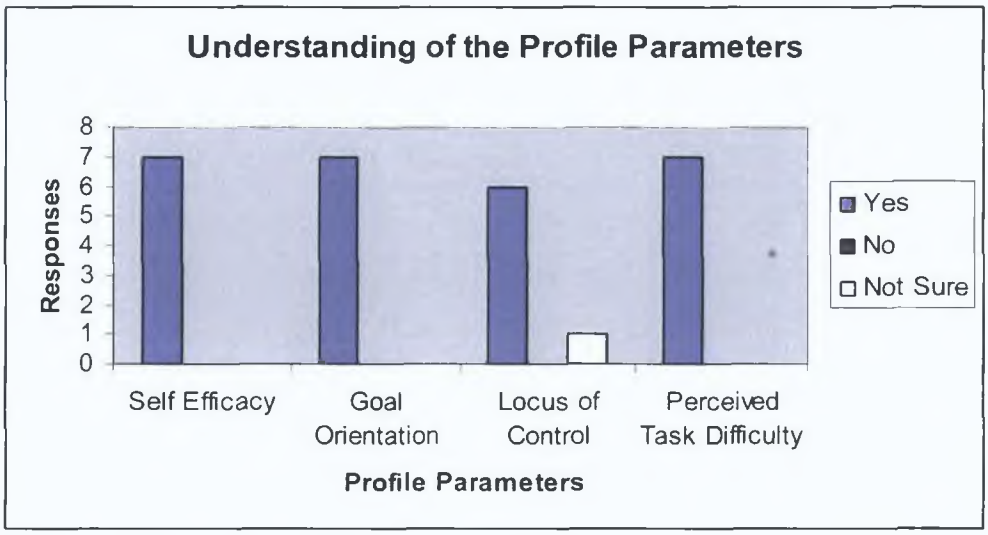

Figure 29: Understanding Profile Parameters

In Question 10, the respondents were asked if they believed that they had sufficient knowledge of their students to profile them. As can be seen from Figure 30 below, the responses to this question were varied. With regard to self-efficacy three respondents believed that they would have sufficient knowledge to profile their students while three were unsure and one said that s/he would not have this knowledge. With regard to goal orientation, four of the respondents believed they would have sufficient knowledge of their students to profile them for this construct, one disagreed and two were not sure. With regard to Locus of Control, three believed they could profile a student for this construct, while two were unsure and two believed they would not have the necessary knowledge to do so. Only with perceived task difficulty were five of the respondents comfortable that

they would have this knowledge about their students. These results may reflect the fact that some of the respondents were not teachers. They also highlighted the necessity of providing some sort of profiling tool or instrument as part of MotSaRT to enable teachers to get the full benefit from the tool. As has already been mentioned, this was one of the recommendations made by many of the respondents and will form part of the future work on this project.

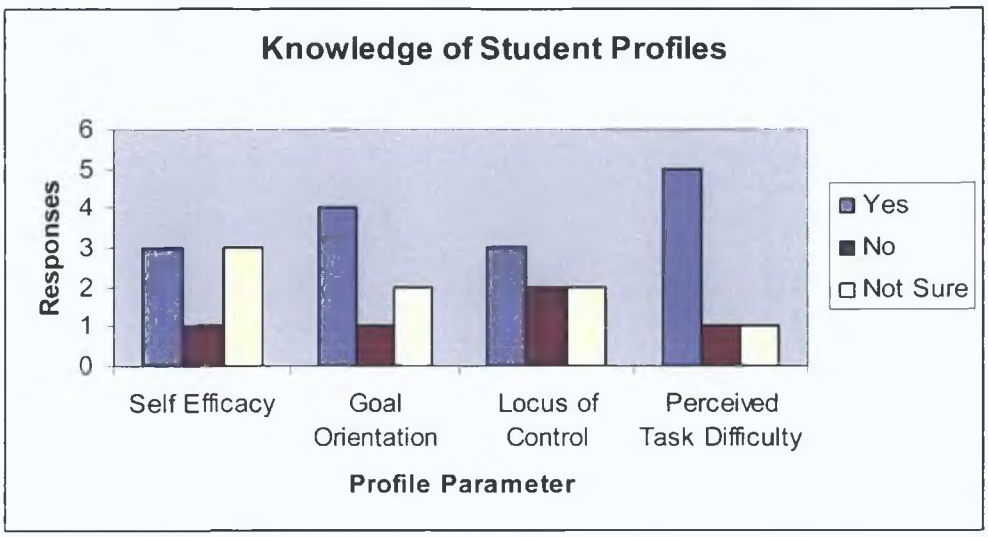

Figure 30: Sufficient knowledge to profile students

4.1.1.7 Contact Methods

The aim of Question 11 was to investigate which methods teachers felt would enable them to get the knowledge they needed to profile students. This is very important, particularly in an online teaching situation, where the student and teacher might never meet face to face. Six of the respondents answered this question. The respondents were free to make as many choices as they wished from the list provided (Figure 31). As can be seen, only one respondent would use the chat function, while four would make a direct telephone call. None would be comfortable using a conference call for this purpose, while two would use either a personal email or a survey instrument.

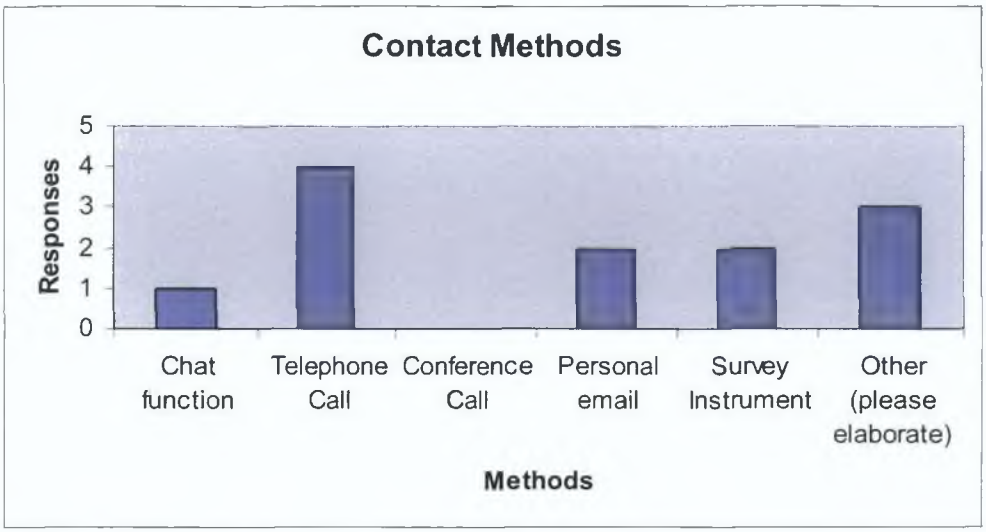

Figure 31: Making contact with students

The suggestions given under the heading "Other" included: observation of interaction with others "in-class" and on tasks such as project work and assignments; and face to face meetings (3). Face to face meetings, of course, may not be an option for some online teachers and learners. With regard to using email, two of the respondents said that they would not "trust this method" but neither elaborated on their response as to why they would not trust emails. One respondent also stated, "I doubt that I would have the time resources to profile students". This is particularly true in large classes and it highlights the necessity of having a reliable assessment mechanism built into an adaptive intelligent tutoring system.

4.1.1.8 Appropriateness of Strategies

The purpose of Question 12 was to get an overview of how appropriate the respondents believed the recommended strategies to be for the particular profiles. The respondents were asked to use a 5-point Likert scale, where 1 = not appropriate and 5 = very appropriate. This question was added as the respondents were not the original group who took part in the online survey and the researcher was interested in their views on the strategies. As can be seen in Figure 32 below,

none of the respondents believed that any of the strategies were either not at all appropriate or not appropriate. Three of the seven respondents rated the appropriateness of the strategies neutrally, two found them appropriate and two found them to be very appropriate.

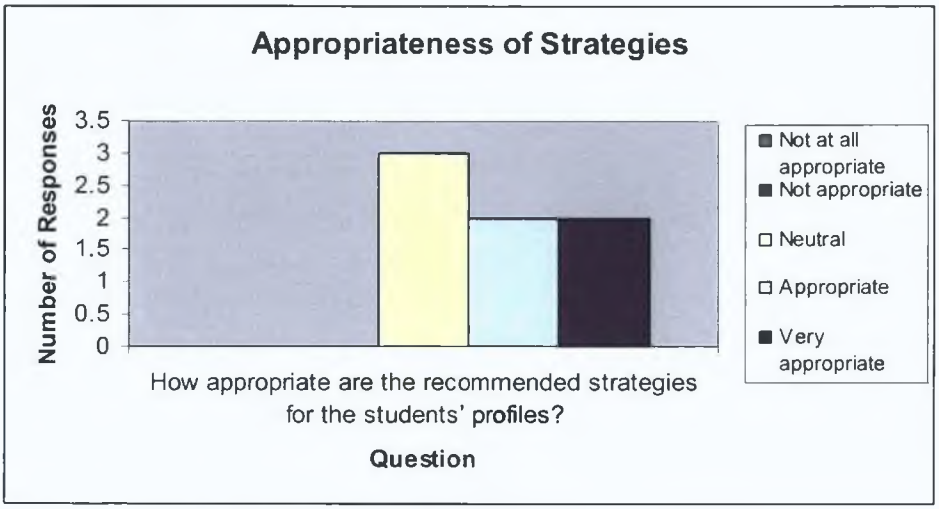

Figure 32: Appropriateness of Strategies

Amongst the comments received from the respondents in relation to this question were "none of the recommendations clash with my understanding of how to deal with students with these profiles", and several requests for "profiling help".

4.1.2 Evaluation Summary

Overall MotSaRT received positive recommendation from the respondents who completed the evaluation survey, but the feedback indicated that several improvements were necessary. This was not surprising given that MotSaRT was only at the prototype stage and that the purpose of the evaluation was to elicit feedback in order to enhance its design. The main issues signposted by the respondents are:

(a) Provide a profiling tool to enable teachers to profile students accurately.

(b) Provide explanations of the strategies with more concrete examples and a means of adding new strategies, with information on how to follow up in a "real-world" situation.

(c) Provide some introductory text to the tool.

(d) Give explanations as to why a strategy is or is not recommended.

(e) Allow both teacher and the student to have access to the profile.

5 Discussion, Future Work and Conclusion

This chapter summarises the research findings of the work presented in this thesis on intervention strategies to increase motivation in online learning. Some methodological issues from the research are also discussed and future research directions are outlined.

5.1 Summary of Research and Findings

As more and more educational institutions and training companies utilise online learning, the problem of attrition from these online courses is attracting attention. Research shows that high among the reasons for attrition from online courses are challenges which the learners face, such as lack of personal motivation, time management problems, isolation, frustration, and technical problems. As outlined in the literature review of this thesis, the research to date has focused attention on several aspects of motivation. The focus of the research presented in this thesis is also on motivation – more particularly on identifying strategies that could be used to motivate individual learners based on specific motivational constructs including self-efficacy, goal orientation, locus of control and perceived task difficulty. Thus, while this research builds on the existing body of research that has been undertaken on the use of motivational messages, it extends the research by targeting the intervention strategies to specific profiles. It further extends the existing research by developing an automated component for adaptive Intelligent Tutoring Systems which, when eventually combined with an assessment component, will enable the system to directly intervene when a student shows signs of becoming demotivated. In this way it is hoped that early recognition and intervention will help to reduce the level of attrition that is currently experienced from online learning courses.

Specifically, this research has demonstrated that knowledge about appropriate motivation intervention strategies can be elicited from experienced teachers by prompting them with systematically constructed personas. While the relationship between parameters of the personas and intervention strategies are not obvious and cannot be explained directly by the teachers, the research has demonstrated that standard machine learning algorithms can learn to predict this relationship well.

The research has also shown that the recommended interventions for different personas vary. Even where two personas have very similar profiles and differ on only one dimension, the recommended intervention strategies vary, e.g. Val and Jon, two of the disengaged personas who differed only in the strength of their self-efficacy.

The method of eliciting adaptation knowledge from experienced or more "expert" teachers through the use of personas has been used for the first time in this research.

In the course of this research a prototype recommender tool, MotSaRT, was designed. This tool displays appropriate intervention strategies for different motivational profiles. It could be used by teachers in a classroom, in a blended learning situation and it could also be incorporated into an adaptive Intelligent Tutoring System as a component of the Learner Model.

Finally, this research will aid the development of the intervention component of an adaptive Intelligent Tutoring System. When combined with an assessment component that can create an accurate model of the motivational states of the learner, appropriate intervention strategies can then be inferred enabling the adaptive Intelligent Tutoring System to deliver the intervention strategies to the individual online learner in the form of messages.

5.2 Methodological Issues

Some methodological issues arose that, in hindsight, could have been approached differently.

In the first instance it might have been more appropriate to ask the teachers to select their top three interventions only. In this way, instead of almost every intervention being selected as either "Highly Recommended" or "Recommended", a clearer picture, and a more positive correlation (as against a weak positive of .18) between risk factors and strategy selection, might have emerged for the various personas.

Secondly, the intervention strategies themselves are very generic in nature. If the strategies were more detailed and specific, e.g. if instead of "Review progress with student at regular intervals," the strategy read "You have completed a, b and c, but have not yet attempted d and e which most of your fellow students have now completed...." teachers might have made different selections. Again, however, no teachers raised this issue when invited to make further comments or add other interventions.

It was assumed that teachers would have a good understanding of the concepts of self-efficacy, goal orientation, locus of control and perceived task difficulty. For this reason, no information was provided to the teachers in the survey regarding these concepts, except what was outlined in each persona. It might have been better to supply some information on these constructs to enable the teachers to make more informed decisions on each persona, although in fact no participant requested any further information before completing the questionnaire. However, it is not known if the lack of this information influenced some teachers who might have participated in the survey from doing so.

Finally, there is no way to absolutely guarantee that the participants were actually teachers and had the requisite experience to complete the surveys. The

survey was available online and so, in theory, could have been completed by anyone. However, as 40 out of the 60 valid participants did in fact supply their email addresses in order to get feedback, it can be inferred that in fact they were genuine teachers with the requisite experience of a minimum of two years, as these details can be easily verified. Ten other participants did take part in the survey but were eliminated as they either did not fulfil the experience requirement or did not satisfactorily complete the survey. It would also have been interesting to get more information on the area of expertise of the various teachers.

5.3 Future Work

The research presented in this thesis focuses on building a generic intervention strategy component for an adaptive Intelligent Tutoring System. It has yet to be tested in a real system and with real students and before this can be done several aspects will require further development. A list of further developments which are possible is presented hereunder:

1. By prompting online teachers with personas it was possible to elicit their knowledge about suitable interventions. The decisions were then modelled using a decision tree algorithm and the predictions are accurate. Future work will focus on an empirical validation of the predictions in a real e-Learning environment to see if the intervention strategies adopted actually increase the motivation of the learner.

2. The list of intervention strategies is too generic to be fully useful. It will be necessary to "flesh out the strategies" so that they are much more explicit and to enable them to be applied in different situations. It will also be necessary to consider when and how any strategy should be applied. Decisions regarding the timing of the use of the strategies, how to evaluate if the strategy employed has resulted in a shift in motivation and whether a further strategy should be

used will all need further development before they can be implemented in an adaptive Intelligent Tutoring System.

3. Informed by the study with online teachers, a prototype for a recommender tool, MotSaRT, was designed. This tool will need further development before it will be fully functional for use in an adaptive ITS or manually by teachers. This work would take into account the recommendations of the evaluation study outlined in Chapter 4.

5.4 Conclusion

The vision guiding this research is to develop an automated tool which can be used in a fully adaptive Intelligent Tutoring System, a semi-automatic system or in a manual system. This tool will recommend motivational intervention strategies to students who are diagnosed as becoming demotivated during the course of their studies and therefore help to prevent attrition from the course. Before the intervention strategies component can be incorporated into an adaptive Intelligent Tutoring System, an assessment component that can reliably assess the motivational profile of the students in an online learning environment will need to be developed. Although the assessment component is not yet available, this research on intervention strategies, while in need of further refinement, represents a first step in the direction of achieving a fully automated Learner Model within an adaptive Intelligent Tutoring System.

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Appendices

Survey Monkey 1

Chris: SE – High; GO – Mastery; LOC – Internal; PTD – Low;

Chris is an intelligent student who enjoys learning for its own sake. She is motivated to learn new things and enjoys being challenged. She believes she can do very well in her studies as she has a very good understanding of her subject area. Chris believes hard work will conquer almost any problem and lead to success. However, she finds that some of the work is not very challenging and becomes very frustrated when a concept of which she already has a good understanding is being worked on in the course.

Jill: SE –Low; GO – P Avoid; LOC –External; PTD - High

Jill does not believe that she will perform well in her course as she finds her subjects difficult but she does not want her teacher/peers to think she is the worst pupil in the class. Even when she performs well, she feels that she was lucky or that task was easy. Jill never believes that her success derives from her own efforts. When she finds the work challenging she works lackadaisically and gives up easily when she does not understand a concept.

Tom: SE – Low; GO – P Approach; LOC – External; PTD – High

Tom fears that he will not perform well in his course as he finds his subjects difficult. He is not content to be second best and so works tirelessly to try to do better than everyone else in his class. He compares his work with that of other students to determine how well he is performing. He continues to work hard on tasks even when they are not well understood rather than ask for assistance. Even when Tom performs well, he feels that he was lucky or that task was easy. When he finds the work very challenging and struggles with the concepts he becomes frustrated and often has difficulty completing his assignments.

Jon: SE – Medium; GO – Disengagement; LOC – External; PTD – High

Jon is an intelligent student. However, he would rather be playing his electric guitar or hanging out with friends than working on his course material. He believes that he will have difficulty with some modules but does not think that working hard on these subjects is worthwhile as, at the end of the day, it will all come down to whether he is lucky with what comes up on the exam papers. When he finds the work challenging and has to struggle with the concepts he becomes frustrated and just gives up.

Survey Monkey 2

Joe: SE –High; GO – Mastery; LOC – External; PTD - Low

Joe is an intelligent student who enjoys learning for its own sake. He is motivated to learn new things and enjoys being challenged. He believes he can do very well in his studies as he has a very good understanding of his subject area. Although Joe is a good student who works hard and makes good grades he takes little credit for his success. When he performs well, he feels lucky or that task was easy. He seldom believes that his success derives from his own efforts. Furthermore, he finds that some of the work is not very challenging and he becomes very frustrated when a concept of which he already has a good understanding is being worked on in the course.

Amy: SE –Medium; GO – P Avoid; LOC –External; PTD - High

Amy has doubts about her own performance as she finds some aspects of the course difficult. She does not want her teacher/peers to think she is the worst pupil on the course. She compares her work with that of others to make sure she is doing better than at least one other student. Even when she performs well, she feels that she was lucky or that task was easy. Amy never believes that her success derives from her own efforts. When she finds the work challenging she works lackadaisically and gives up easily when she does not understand a concept.

Pat: SE – Low; GO – P Approach; LOC – Internal; PTD – High

Pat fears that he will not perform well in his course as he finds his subjects difficult. However, it is important to him to be seen to be doing very well in his class and he likes to come out in first place. He knows that if he is to do well he has to work hard. However, when he finds the work very challenging and struggles with the concepts he becomes frustrated and often has difficulty completing his assignments.

Omy: SE – Low; GO – Disengagement; LOC – Internal; PTD – High

Omy is an intelligent student but has little interest in his course as he does not feel that he can do well in it. He would rather be playing his electric guitar or hanging out with friends. He knows that it is important for him to put effort into his work if he wants to succeed but he fails to do this. He finds the work very challenging and struggles with the concepts. As a result he becomes frustrated and seldom completes assignments.

Survey Monkey 3

Lou: SE –Medium; GO – Mastery; LOC – Internal; PTD - Low

Lou is an intelligent student who enjoys learning for its own sake. She is interested in her work but has doubts about her own performance as she finds some aspects of the subject difficult. She believes that hard work will conquer almost any problem and lead to a successful outcome. However, she finds that some of the work is not very challenging and becomes very frustrated when a concept of which she already has a good understanding is being worked on in the course.

Mike: SE –High; GO – P Avoid; LOC –External; PTD – Very High

Mike believes he can do very well in his studies as he has a very good understanding of his subject area. However, when he encounters very difficult problems he prefers not to ask for help from his tutor or peers as he finds it hard to admit that he cannot do something himself and fears that his tutor or peers might consider him to be stupid. For the same reason, he would rather not submit an assignment than risk getting lower marks than less able students. He mainly attributes his successes to luck rather than effort.

Ben: SE – Medium; GO – P Approach; LOC – Internal; PTD – Low

Ben has doubts about his own performance as he finds some aspects of his course difficult. He is not content to be second best and so works tirelessly to try to do better than everyone else in his class. He compares his work with that of other students to determine how well he is performing. He continues to work hard on tasks even when they are not well understood rather than ask for assistance. Ben believes hard work will conquer almost any problem and lead to success. However, when he finds that some of the work is not very challenging or is already familiar to him, he becomes bored and frustrated with having to do this work.

Val: SE – Low; GO – Disengagement; LOC – External; PTD – High

Val is an intelligent student but has little interest in her course as she does not feel that she can do well in it. She would rather be listening to her music or hanging out with friends. Val understands that if she works hard work on almost any problem, this will lead to success. However, she finds the work very challenging and struggles with the concepts so she becomes frustrated and seldom completes her assignments.

Survey Monkey 4

Lee: SE –Medium; GO – Mastery; LOC – Internal; PTD - High

Lee is an intelligent student who enjoys learning for its own sake. He is interested in his work but has doubts about his own performance as he finds some aspects of the subject difficult. He believes that hard work will conquer almost any problem and lead to a successful outcome. However, when he finds the work very challenging and struggles with the concepts he becomes frustrated. For this reason, he often has difficulty completing his assignments and does not always submit them.

Jim: SE –Low; GO – Mastery; LOC –External; PTD - High

Jim is an intelligent student who enjoys learning for its own sake. He is interested in the work but has doubts about performing well as he finds the subjects very difficult. Even when he performs well, he feels that he was lucky or that task was easy. Jim never believes that his success derives from his own efforts. When he finds the work very challenging and struggles with the concepts he becomes frustrated and often has difficulty with his assignments.

Ann: SE – Medium; GO – P Approach; LOC – External; PTD – Low

Ann has doubts about her own performance as she finds some aspects of her course difficult. She is not content to be second best and so works tirelessly to try to do better than everyone else in her class. She compares her work with that of other students to determine how well she is performing. She continues to work hard on tasks even when they are not well understood rather than ask for assistance. Even when Ann performs well, she feels that she was lucky or that task was easy. Ann never believes that her success derives from her own efforts. Furthermore, when she finds that some of the work is not very challenging or is already familiar to her, she becomes bored and frustrated with having to do this work.

Survey Monkey 5

Gay: SE –Medium; GO – Mastery; LOC – External; PTD - Low

Gay is an intelligent student who enjoys learning for its own sake. She is interested in her work but has doubts about her own performance as she finds some aspects of the subject difficult. When she performs well, she feels that she was lucky or that task was easy. Gay never believes that her success derives from her own efforts. However, when she finds that some of the work is not very challenging or is already familiar to her, she becomes bored and frustrated with having to do this work.

Kay: SE – Medium; GO – P Approach; LOC – Internal; PTD – High

Kay has doubts about her own performance as she finds some aspects of her course difficult. She is not content to be second best and so works tirelessly to try to do better than everyone else in her class. She compares her work with that of other students to determine how well she is performing. She continues to work hard on tasks even when they are not well understood rather than ask for assistance. When Kay finds the work very challenging and struggles with the concepts, she becomes frustrated and often has difficulty completing her assignments.

Ker: SE – Medium; GO – Disengagement; LOC – Internal; PTD – High

Ker is an intelligent student but has little interest in her course. She would rather be listening to her music or hanging out with friends. She believes that she will have difficulty with some aspects of the course and knows that it is important for her to put effort into her work if she wants to succeed. She often fails to do this. When she finds the work very challenging and struggles with the concepts she becomes frustrated and seldom completes her assignments.

Survey Monkey 6

Sam: SE –Medium; GO – Mastery; LOC – External; PTD - High

Sam is an intelligent student who enjoys learning for its own sake. He is interested in his work but has doubts about his own performance as he finds some aspects of the subject difficult. When he performs well, he feels that he was lucky or that task was easy. Sam never believes that his success derives from his own efforts. When he finds the work very challenging and struggles with the concepts he becomes frustrated and often has difficulty with his assignments.

Sal: SE – Medium; GO – P Approach; LOC – External; PTD – High

Sal has doubts about her own performance as she finds some aspects of her course difficult. She is not content to be second best and so works tirelessly to try to do better than everyone else in her class. She compares her work with that of other students to determine how well she is performing. She continues to work hard on tasks even when they are not well understood rather than ask for assistance. Even when Sal performs well, she feels that she was lucky or that task was easy. She never believes that her success derives from her own efforts. Furthermore, when she finds the work very challenging and struggles with the concepts she becomes frustrated and often has difficulty completing her assignments.

Nan: SE – High; GO – P Approach; LOC – Internal; PTD – High

Nan believes she can do very well in her studies as she has a very good understanding of her subject area. She is determined to be at the top of her class when she graduates and works very hard to achieve this goal. She works tirelessly to try to do better than everyone else in her class. She compares her work with that of other students to determine how well she is performing. Nan believes hard work will conquer almost any problem and lead to success. However, when she finds the work very challenging and struggles with the concepts she becomes frustrated and often has difficulty completing her assignments.

INTERVENTIONAL STRATEGIES OF EXPERINENCED TEACHERS

Thank you.

I really appreciate you taking the time and trouble to complete this questionnaire. It will greatly assist me in my research.

To ensure confidentiality, I do not need to know your identity. This questionnaire should be left in Stephan Weibelzahl's pigeonhole for collection by Wednesday, 12/04/06.

For the purposes of my research I will need the following information:

What is your subject area?.....

Do you have at least two years experience as a qualified teacher? Yes ☐ No ☐

Do you have experience as an on-line tutor? Yes ☐ No ☐

Once gain, thank you so much for your co-operation.

Teresa Hurley,
Learn3K

Notes:
For the purposes of this exercise, please make the following assumptions:

For the classroom situation:
1. All learners are 1st year undergraduate students.

For the on-line course:
1. All learners are enrolled in on-line courses with asynchronous facilities only, i.e. not in real time.
2. All learners are 1st year undergraduate students.
2. All learners have acquired the necessary level of computer skills to undertake their course.
3. This is the first time a learner has enrolled in an on-line course.

Chris **Code 0100**

Chris is enrolled on a mathematics course, a subject she thoroughly enjoys. She is confident that she will do very well on her course as she likes learning and is prepared to work hard to increase her knowledge of mathematics. She has organised herself well for her course and has made out a study plan which includes plans for time management. She is working to this plan very successfully. She is prepared to seek help from both her tutor and her peers on the course when she cannot complete a task on her own. Chris finds herself becoming very frustrated when a concept which she already has a good understanding of is being worked on in the course.

1. **How would you recognize that this learner is becoming demotivated in (a) a classroom situation and (b) in an on-line situation?**

2. **When and why would you consider it appropriate to offer interventional motivational strategies (see examples in list below) to this learner?**

3. **Tick the strategy or strategies you would use to motivate this student (a) in the classroom and (b) in an online course**

	Classroom	***Online Course (asynchronous)**
Review progress with learner at regular intervals		
Provide regular positive and specific feedback		
Provide information in an interesting manner		
Set clear learning objectives and targets		
Encourage student to clearly define academic goals		
Use small group discussion forums		
Use on-line quizzes with immediate feedback		
Send regular individual e-mails to students		
Remind student of the student support services		

Encourage use of the chat room/discussion forums		
Use continuous assessment towards final marks		
Use a rubric of motivational keywords		
Make assignments moderately challenging, varied and relevant		
Help learner develop a study plan/timetable		
Explain importance of and encourage learner to maintain contact with tutor		
Encourage peer to peer contact		
Base evaluation on personal improvement/mastery when possible, rather than grades		
Encourage the learner to reflect on and evaluate the learning		
Provide pre and post assessments		
Provide positive and constructive feedback		
Explain why learning a particular content is important		
Relate the learning to the student's needs		
Provide guidance to extra learning resources		
No intervention required		

4. Are there other strategies which you would use which are not listed above?

Strategy	Classroom Situation	On-line Course (asynchronous)

* You may not have experience as an on-line tutor but, if possible, please answer this section hypothetically based on your experience as a teacher.

Note:
This format was replicated exactly for all 23 personas in the classroom teachers' survey.

Research Project Title: "Intervention Strategies to increase motivation in adaptive online learning"

Dear Teacher,

I am a Masters Research student at the National College of Ireland in Dublin. My research topic is "Intervention Strategies to increase motivation in adaptive online learning". I am conducting an online survey in order to investigate how expert lecturers/ teachers/tutors, who have at least two years experience teaching online, motivate their online students. The survey will take no more than 15 minutes to complete. The survey is completed anonymously but if you would like feedback on the results please insert your email address in the box provided in the survey.

The online survey is available via the following link:
http://www.ncirl.ie/Research%20&%20Innovation/REALT/Projects/Motivation%20in%20On-Line%20Learning

This link will bring you to my project page within the Research Department of the National College of Ireland. Here you will find a brief description of my research and the survey link which will bring you directly to the survey.

Should you have any queries please do not hesitate to contact me at thurley@ncirl.ie. Alternatively, you can contact my supervisor, Dr. Stephan Weibelzahl at sweibelzahl @ ncirl.ie

Thanking you in anticipation.

Teresa Hurley
thurley@ncirl.ie
Masters Research Student

Evaluation of MotSaRT

Instructions:
Please familiarise yourself with the Motivational Strategies Recommender Tool, MotSaRT.
Complete the questionnaire by inserting x in the appropriate box or boxes for each question.

1. Have you used MotSaRT to profile a student? Yes ☐ No ☐

   a. *If yes, would you use it again in the future?* *Yes* ☐ *No* ☐

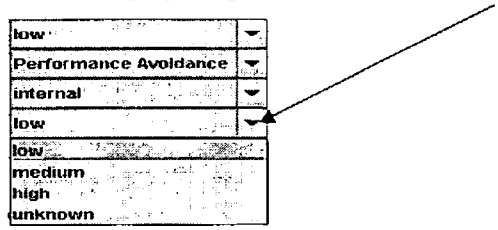
   b. *If no, why not?*

2. Would you use MotSaRT when teaching if it was available online?

   Yes ☐ No ☐ Don't know ☐

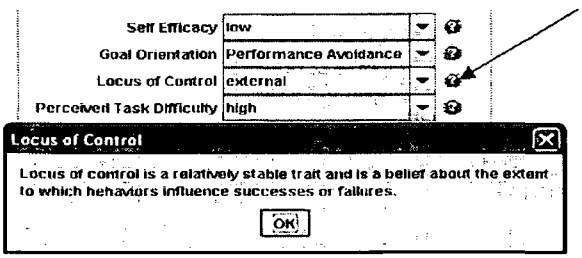
3. Which aspect(s) of MotSaRT did you find useful:

Availability of drop down menus to input information



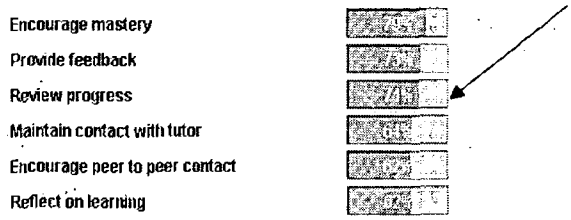
Useful ☐ Somewhat useful ☐ Not useful ☐

Availability of explanation ("?") features



Useful ☐ Somewhat useful ☐ Not useful ☐

Dynamic presentation of the recommended strategies



Useful ☐ Somewhat useful ☐ Not useful ☐

4. On a scale of 1 to 5, (1 = not informative, 5 = very informative) please rate

How informative did you find the numerical % recommendation values?

Not at all informative 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ Very Informative

How informative did you find the colored % recommendation indicators?

Not at all informative 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ Very Informative

How informative did you find the strategy details on the recommendations?

Not at all informative 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ Very Informative

5. Should the "Strategies Details" feature be elaborated further? Yes ☐ No ☐

If yes, please suggest how?

6. How user friendly did you find MotSaRT?

Overall, I am satisfied with how easy it is to use MotSaRT

Strongly Disagree 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ Strongly Agree

The interface of MotSaRT is pleasant

Strongly Disagree 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ Strongly Agree

The information (such as on-screen messages) provided with MotSaRT is clear

Strongly Disagree 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ Strongly Agree

Dynamic presentation of feedback information is helpful

Strongly Disagree 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ Strongly Agree

7. What problems did you experience using MotSaRT, if any

8. Do you have any other comments, criticisms, or suggestions relating to the usability – ease of use – of MotSaRT?

9. I understand what each of the four profile parameters mean:

Self-Efficacy	Yes ☐	No ☐	Not Sure ☐
Goal Orientation	Yes ☐	No ☐	Not Sure ☐
Locus of Control	Yes ☐	No ☐	Not Sure ☐
Perceived Task Difficulty	Yes ☐	No ☐	Not Sure ☐

10. I believe that I have sufficient knowledge of my students to profile them:

Self-Efficacy	Yes ☐	No ☐	Not Sure ☐
Goal Orientation	Yes ☐	No ☐	Not Sure ☐
Locus of Control	Yes ☐	No ☐	Not Sure ☐
Perceived Task Difficulty	Yes ☐	No ☐	Not Sure ☐

11. If you answered "No" or "Not Sure" to Question 10, which method(s) would you use to obtain this information from a student?

Chat function ☐
Telephone call ☐
Conference call ☐
Personal email ☐
Survey instrument ☐
Other (please elaborate) ☐

12. On a scale of 1 – 5 (1 = Not appropriate, 5 = very appropriate) please rate

How appropriate are the recommended strategies for the student profiles?

1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 ☐ Don't know ☐

13. What other functionality do you think MotSaRT should offer?

Please check that you have answered all the questions

Thank you for taking the time to complete this questionnaire

Please return to: thurley@ncirl.ie