# Using MotSaRT to Support On-Line Teachers in Student Motivation

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**Abstract.** In classrooms teachers know how to motivate their students and exploit this knowledge to adapt or optimize their instruction when a student shows signs of demotivation. In on-line learning environments it is much more difficult to assess the motivation of the student and to have adaptive intervention strategies and rules of application to help prevent attrition. We developed MotSaRT – a motivational strategies recommender tool – to support on-line teachers in motivating learners. The design is informed by Social Cognitive Theory and a survey on motivation intervention strategies carried out with sixty on-line teachers. The survey results were analysed using a data mining algorithm (J48 decision trees) which resulted in a set of decision rules for recommending motivational strategies. MotSaRT has been developed based on these decision rules. Its functionality enables the teacher to specify the learner's motivation profile. MotSaRT then recommends the most likely intervention strategies to increase motivation.

**Keywords:** on-line learning, motivation, intervention strategies, on-line teachers, self-efficacy, goal orientation, locus of control, perceived task difficulty, recommender tool.

## 1 Introduction

On-line learning is a dynamic and potentially enriching form of learning but attrition remains a serious problem, resulting in personal, occupational and financial implications for both students and academic institutions [5]. Motivation to learn is affected by the learner's self-efficacy, goal orientation, locus of control and perceived task difficulty. In the traditional classroom, teachers infer learners' levels of motivation from several cues, including speech, behaviour, attendance, body language or feedback, and offer interventional strategies aimed at increasing motivation. Intelligent Tutoring Systems (ITS) need to be able to recognize when the learner is becoming demotivated and to intervene with effective motivational strategies. Such an ITS would comprise two main components, an assessment mechanism that infers the learner's level of motivation from observing the learner's behaviour, and an adaptation component that selects the most appropriate intervention strategy to increase motivation. This paper presents the results of a survey of on-line teachers on how they motivate their learners. These results

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informed the development of the adaptation component by extracting and validating selection rules for strategies to increase motivation. The recommender tool, MotSaRT, has been developed based on these rules. Its functionality enables the teacher to specify the learner's motivation profile. MotSaRT then recommends the most likely intervention strategies to increase motivation.

# 2 Background

The focus of this research is intervention strategies which can be implemented and validated in an Intelligent Tutoring System to increase motivation and reduce attrition. Previous approaches in this field were mainly based on the ARCS model - attention, relevance, confidence, and satisfaction, which is an instructional design model ([4][14][18]). These states are inferred from behavioural cues in the interaction such as time taken, effort, confidence, and focus of attention.

## 2.1 Learner Modelling

We argue that a model of motivational states of learners should build upon a well established theory of motivation in learning. The approach being taken in this research is based on Social Cognitive Theory (SCT) [1], particularly on self-efficacy, locus of control, perceived task difficulty and goal orientation. As learners differ widely in these constructs, intervention strategies must be adapted to suit the individual and the task. The interventions may take the form of 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).. Such interventions therefore focus the attention on the learner rather than on instructional design.

## 2.2 Motivation

Motivation in general is defined as "the magnitude and direction of behaviour and the choices people make as to what experiences or goals they will approach or avoid and to the degree of effort they will exert in that respect" [6]. Students with higher levels of intrinsic motivation and self-efficacy achieve better learning outcomes [11]. Intrinsic motivation is created by three qualities: challenge, fantasy and curiosity [8].

Social cognitive theory provides a framework for understanding, predicting, and changing human behaviour. The theory identifies human behaviour as an interaction of personal factors, behaviour, and the environment.

## 2.3 Self-efficacy

Self-efficacy is an "individuals' confidence in their ability to control their thoughts, feelings, and actions, and therefore influence an outcome" [1]. 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 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. Perceptions of self-efficacy influence actual performance [7], and the amount of effort and perseverance expended on an activity [3].

### 2.4 Attribution Theory

Attribution Theory [16] 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. 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.

### 2.5 Locus of Control

Locus of control [15] 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.

### 2.6 Perceived Task Difficulty

Perception of task difficulty will affect the expectancy for success, and strongly influences both instigation of a learning activity as well as persistence [10]. The learner's sense of accomplishment, as well as their reaction to failure, if often tied to their subject beliefs about the difficulty of the goal they have undertaken.

### 2.7 Goal Orientation

One classification of motivation differentiates among achievement, power, and social factors [9]. Goals enhance self-regulation through their effects on motivation, learning, self-efficacy and self-evaluations of progress [1]. According to self-regulated learning (SRL) theorists, self-regulated learners are "metacognitively, motivationally, and behaviourally active participants in their own learning process" [19]. Individuals with a 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. 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 [13]. Individuals may have both mastery and performance goals [12]. 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" [2].

## 3 Eliciting Intervention Strategies from On-Line Teachers

In order to find out about the intervention strategies used by on-line teachers we designed questionnaires that would systematically elicit recommended strategies for given learner profiles.

A learner model was created based on the SCT constructs of Self-Efficacy, Goal Orientation, Locus of Control and Perceived Task Difficulty, as these are the four most important factors contributing to self-regulation. Research has shown that self regulatory behaviour can account for academic achievement [10]. The model contained 21 learner profiles. These were systematically developed using the above constructs (see Table 1). The profiles were selected from a possible 48 as the most likely to experience demotivation. For example, a person with the profile of Persona 1 is likely to become demotivated when not sufficiently challenged.

**Table 1.** Profile of personas

| **Persona** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** | **11** | **12** | **13** | **14** | **15** | **16** | **17** | **18** | **19** | **20** | **21** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **SE** | H | H | M | M | M | M | L | L | M | H | L | L | M | M | M | M | H | L | L | M | M |
| **GO** | M | M | M | M | M | M | M | Pa | Pa | Pa | PA | PA | PA | PA | PA | PA | PA | D | D | D | D |
| **LOC** | I | E | I | I | E | E | E | E | E | E | I | E | I | E | I | E | I | I | E | E | I |
| **PTD** | L | L | L | H | L | H | H | H | H | H | H | H | L | L | H | H | L | H | H | H | H |

Key: Self Efficacy (SE) [High (H)/Medium (M)/Low (L)]; Goal Orientation (GO) [Mastery (M)/Performance Avoidance (Pa)/Performance Approach (PA)/Disengagement (D)]; Locus of Control (LOC) [Internal (I)/External (E)]; Perceived Task Difficulty (PTD)[Low (L)/High (H)]

Based on the model, personas (i.e., short textual descriptions) were then developed, e.g. 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*)." Note that the italic profile labels were inserted here for illustration, but were not part of the instruction given to the participants.

From the literature on motivation and an initial pilot questionnaire, completed by classroom teachers, a list of intervention strategies was compiled (see Table 2). In order to identify rules to determine which intervention strategy is the most appropriate for each learner's persona, on-line teachers were surveyed. If, for example, a learner had low self-efficacy and external locus of control, teachers might indicate that reviewing progress with the student at regular intervals would be a strategy to adopt. In this way the relationship between motivational states and intervention strategies was elicited with the assistance of the on-line teachers.

**Table 2.** 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 on-line 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 |

As there were twenty-one personas to be considered, the on-line survey was divided into six parts with three or four personas in each. The personas were similar to the example above, but without the references to the theoretical constructs. Every effort was made to ensure that the personas in each of the surveys were based on different constructs. For example, in Survey No. 1, each persona had either high, medium or low self-efficacy and had different goal orientations. Participant teachers were randomly assigned to one of the six surveys. The same 14 intervention strategies were presented in the same order under each persona. The teachers were asked to select the strategies they would *Highly Recommend*, *Recommend* or considered *Not Applicable* for each persona. They were also asked to suggest any further strategies that they find particularly useful in the case of each persona type. The teachers were required to have at least two years experience teaching on-line. The survey could be completed anonymously or the participants could enter their email address if they wished to get feedback on the results. Sixty participants completed the surveys which resulted in each persona getting a minimum of six and a maximum of fourteen responses.

## 4 Survey Results

The participants varied widely in the number of years of experience they had as on-line teachers. The least experienced participants had tutored on-line for two years, and the most experienced had tutored for eighteen years. The average was five years.

For the purpose of this paper, we merged Highly Recommended and Recommended strategies into one category "Recommended".

Using the Weka data mining tool set [11], 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;

and 5) Naïve Bayes as a standard baseline. All experiments were run with a 10-fold stratified cross validation. J48 decision trees turned out to provide the best predictions (see Table 3).

**Table 3.** Correct predictions (%) of the J48 decision tree algorithm separated by the 13 intervention strategies

| | |
|---|---|
| Strategy 1 | 89.86 |
| Strategy 2 | 93.26 |
| Strategy 3 | 84.55 |
| Strategy 4 | 66.58 |
| Strategy 5 | 77.31 |
| Strategy 6 | 86.50 |
| Strategy 7 | 68.83 |
| Strategy 8 | 83.60 |
| Strategy 9 | 88.90 |
| Strategy 10 | 82.64 |
| Strategy 11 | 88.90 |
| Strategy 12 | 79.24 |
| Strategy 13 | 80.67 |

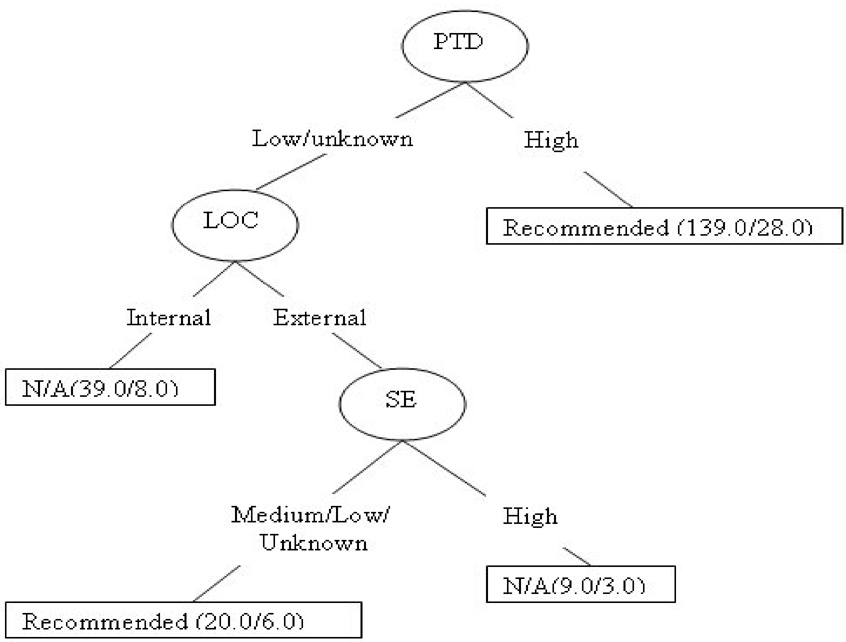


**Fig. 1.** Decision Tree for Strategy 5

The J48 analysis results in one decision tree per strategy predicting under which circumstances a certain strategy would be recommended or not. Figure 1 gives an example of such a decision tree: Strategy 5 – Remind students of the student support services. If Perceived Task Difficulty (PTD) is high, then Strategy 5 is recommended If PTD is low or unknown and Locus of Control (LOC) is internal, then Strategy 5 is not recommended. If PTD is low or unknown and LOC is external and Self-Efficacy (SE) is high, then Strategy is not recommended. If PTD is low or unknown and LOC is external and SE is medium, low or unknown, then Strategy 5 is recommended.

## 5 MotSaRT – Motivational Strategies: A Recommender Tool for On-Line Teachers

Using the recommendation rules derived from the questionnaire study, we have developed a recommender tool, MotSaRT, to support on-line teachers in motivating learners (see Figure 2). 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.

Technically, MotSaRT is a Java Applet and can thus be integrated into most L[C]MS fairly easily. Observing the activities of learners in the learning environment and possibly interacting with them synchronously or asynchronously through instant messaging, email or fora, teachers would assess learners in terms of their self-efficacy, goal-orientation, locus of control and perceived task difficulty. MotSaRT would then classify this case and sort the strategies in terms of their applicability. Teachers could then plan their interventions according to these recommendations.

### 5.1 MotSaRT Functionality

By observing the progress of the students and interacting with them either synchronously or asynchronously, an on-line teacher will become aware if a student is falling behind and not submitting assignments or making sufficient progress in the coursework. At this stage 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 thus possibly exit from the course, the teacher can utilize 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 teacher will be able to access the student's level of self-efficacy, goal orientation, locus of control and perceived task difficulty. With this information the teacher would use MotSaRT as follows:

In the Learner Profile area, the teacher would select the student profile:

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

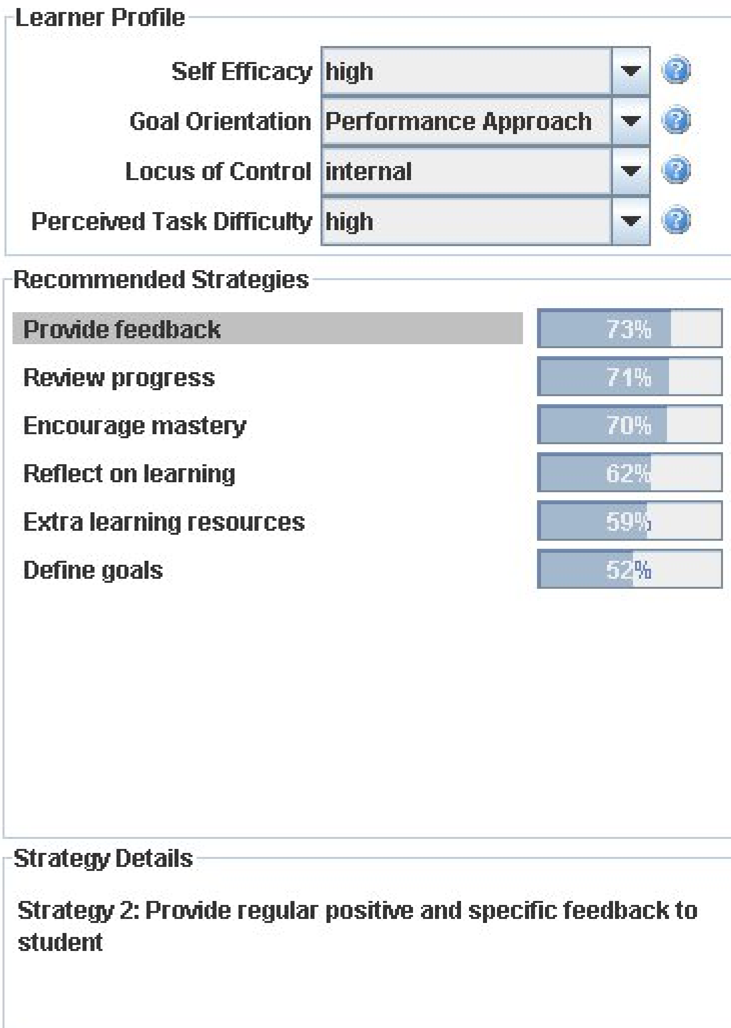


**Fig. 2.** Screenshot of MotSaRT

A question mark located beside each of the constructs enables the teacher to find out more about the construct if desired.

In the Recommended Strategies area, depending on the profile entered by the teacher, a list of strategies will appear showing the percentage recommendation according to the J48 decision tree algorithm.

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

From the suggested strategies the teacher selects the strategy that they believe is the most suitable for intervention with the particular student. The 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.

### 5.2 Testing MotSaRT

Approximately half of the on-line teachers who took part in the survey on the intervention strategies requested feedback. It is planned to make MotSaRT available to these teachers. They will be asked to comment on the usability and usefulness of the tool. They will also be asked for suggestions for improvement and recommended changes. If they actually use the tool as outlined in Section 5.1 above, they will also be asked to report on any perceived increase in the student's motivation level. In this way it is intended also to get feedback on both the quality and appropriateness of the recommendations. Preliminary results are expected soon on this part of the research.

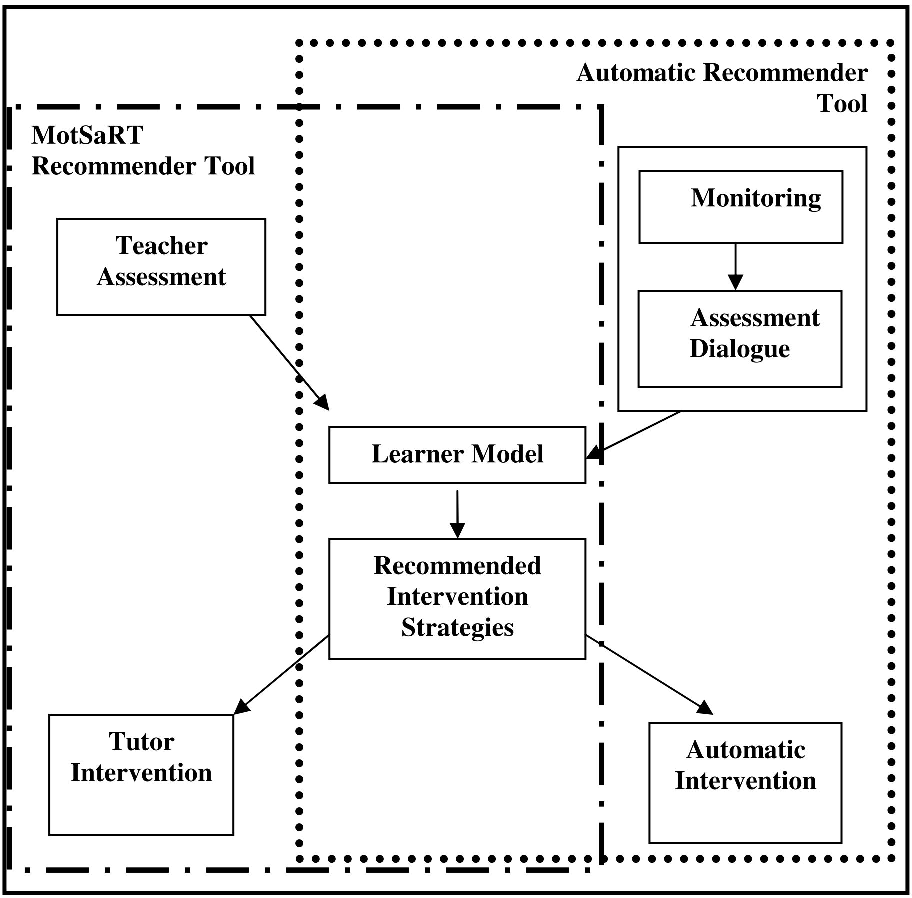


**Fig. 3.** High Level Architecture

## 6 Future Perspectives

Informed by a study with on-line teachers, we developed MotSaRT, a tool that shows appropriate intervention strategies for motivational profiles. Prompting on-line teachers with personas we were able to elicit their knowledge about suitable interventions and modelled these decisions using a decision tree algorithm. 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.

Our vision is to develop an automated tool which can be used in a fully automatic system, a semi-automatic system or in a manual system (Fig 2), to recommend motivational intervention strategies to students who are diagnosed as becoming demotivated during the course of their studies. This diagnosis may be made either by a teacher or by automatic assessment. The diagnosis will be fed into the learner model. MotSaRT can then be used to either make recommendations to the teachers or to make an automatic intervention.

As this stage MotSaRT will be used to implement the path on left hand side of Figure 3 (dashed outline). However, it is envisaged that eventually other possible uses will include either the teacher or the ITS identifying the preferred intervention strategy using MotSaRT and the selected strategy being implemented automatically by the ITS.

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