“MotSaRT”- Motivation Strategies: A Recommender Tool for On-line Learning Facilitators

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Abstract: On-line education is one of the most dynamic and potentially enriching forms of learning that exists today. However, attrition is a serious problem resulting in personal, occupational and financial implications for both students and academic institutions. Motivation to learn is affected by a student’s self-efficacy, goal orientation, locus of control and perceived task difficulty. In the classroom teachers know how to motivate their students and how to exploit this knowledge to adapt or optimize their instruction when a student shows signs of demotivation. In online learning environments it is much more difficult to assess the level of motivation of the student and to have adaptive intervention strategies and rules of application to help prevent attrition. We have developed MotSaRT to support online facilitators in motivating learners. The design is informed by the Social Cognitive Theory constructs outlined above and a survey on motivation intervention strategies carried out with sixty on-line facilitators (lecturers/tutors). 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. For example: where a learner has low self efficacy, is disengaged motivationally, has an external locus of control and perceives the task as being very difficult, the most frequently recommended intervention strategies are (a) to review progress with the student at regular intervals, (b) explain the importance of and encourage student to maintain contact with facilitator, and (c) encourage peer-to-peer contact. The recommender tool, MotSaRT, has been developed based on these decision rules. Its functionality enables the facilitator to specify the learner’s motivation profile. MotSaRT then recommends the most likely intervention strategies to increase motivation. A pilot study is currently being carried out using the MotSaRT tool.

Keywords: online learning, motivation, intervention strategies, online facilitators, self-efficacy, goal orientation, locus of control, perceived task difficulty, recommender tool.

1 Introduction

On-line learning is a dynamic and potentially enriching forms of learning but attrition remains a serious problem [4]. Motivation to learn is affected by the learner’s self-efficacy, goal orientation, locus of control and perceived task difficulty. In the traditional classroom tutors infer learners’ levels of motivation from several cues, including speech, behavior, 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 behavior, 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 facilitators on how they motivate their learners. These results will inform 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 facilitator to specify the learner's motivation profile. MotSaRT then recommends the most likely intervention strategies to increase motivation.

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, which is an instructional design model ([3][9][12]). In contrast, 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. Self-efficacy is the individuals' confidence in their ability to control their thoughts, feelings, and actions, and therefore influence an outcome. Individuals with an external locus of control believe that factors such as luck, task difficulty, or other people's actions, cause success or failure [10]. Individuals with an internal locus of control believe that success is due to their own efforts. Perception of task difficulty will affect the expectancy for success, and it has a strong influence on both instigation of a learning activity as well as persistence. Goals enhance self-regulation through their effects on motivation, learning, self-efficacy and self-evaluations of progress [1]. Individuals with a learning goal orientation strive to master the task and are more 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 and not appear incompetent and so may avoid challenging tasks, or exhibit low persistence, when encountering difficulties [8]. Individuals may have both mastery and performance goals [7]. 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]. As learners differ widely, intervention strategies must be adapted to suit the individual and the task, thereby focusing the attention on the learner rather than on instructional design.

2 Eliciting Intervention Strategies from On-Line Facilitators

In order to find out about intervention strategies of on-line facilitators 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 behavior can account for academic achievement [8]. The model contained 21 learner profiles which 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.
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)*."

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)]

From the literature on motivation and an initial pilot questionnaire, completed by classroom tutors, 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 facilitators were surveyed. If, for example, a learner had low self-efficacy and external locus of control, facilitators 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 facilitators.

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

Participants were randomly assigned to one of six online surveys containing either three or four personas (similar to the example above, but without the reference to the theoretical constructs). The same 14 intervention strategies were presented in the same order under each persona. The facilitators 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 facilitators 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.

3 Survey Results

The participants varied widely in the number of years' of experience they had as on-line facilitators. 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 facilitators 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. 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

4 MotSaRT – Motivational Strategies: A Recommender Tool for On-line Learning Facilitators

Using the recommendation rules derived from the questionnaire study, we have developed a recommender tool, MotSaRT, (see Fig 1) to support online facilitators in motivating learners. 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 (See Fig 2). Observing the activities of learners in the learning environment and possibly interacting with them synchronously or asynchronously through instant massaging, email or fora, facilitators 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. Facilitators could then plan their interventions according to these recommendations.

Currently MotSaRT is being used to validate the facilitator recommendations for each profile. Students are asked to complete an on-line motivational survey instrument in order to obtain their profile. By observing their progress throughout their course, and monitoring the email and chat fora, the researcher hopes to be in a position to recognize when a student is becoming demotivated and to intervene with a recommended strategy. The researcher will use MotSaRT, as described above, to select the most suitable intervention and will suggest it to the student. The researcher will then monitor the student's progress to try to gauge the effect of the intervention on the student's motivation. The student will be asked to complete the survey instrument once more during their course to compare their profile following the intervention. At the end of the on-line course (12 weeks duration), it is planned to qualitatively evaluate the impact of intervention on each student by means of interview. Preliminary results for this part of the study are expected shortly.

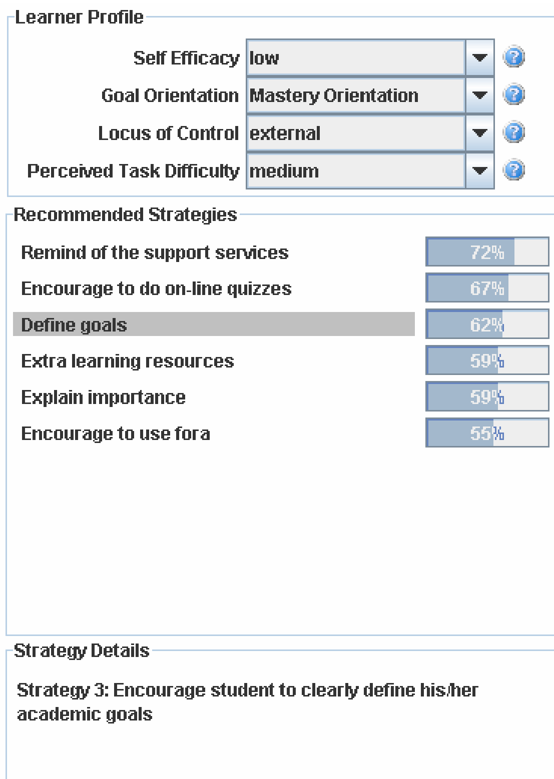

Figure 1: Screenshot of MotSaRT

5 Future Perspectives

Informed by a study with on-line facilitators, we developed MotSaRT, a tool that shows appropriate intervention strategies for motivational profiles. Prompting on-line facilitators with personas we were able to elicit their knowledge about suitable interventions and modeled these decisions using a decision tree algorithm. Predictions are accurate. Future work will focus on an empirical validation of the predictions in a real 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, 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 facilitator or by automatic assessment. The diagnosis will be fed into the motivation learner model. MotSaRT can then be used to either make recommendations to the facilitator or to make an automatic intervention.

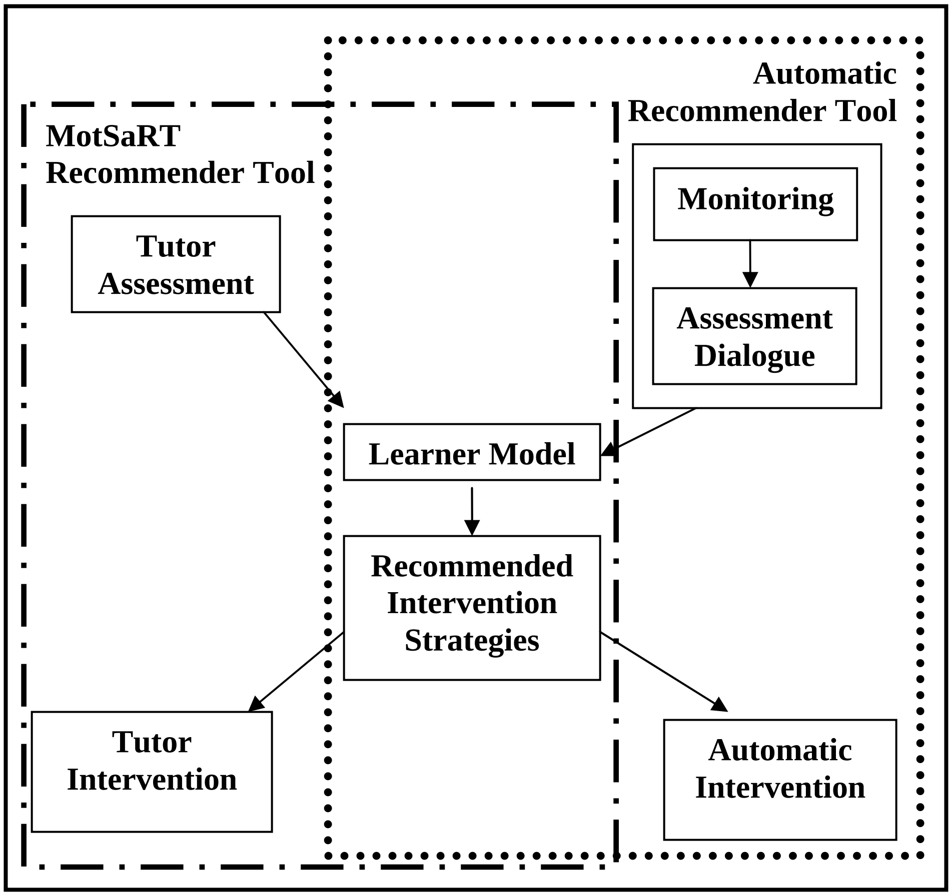

Figure 2. High Level Architecture

As can be seen from Fig 2, MotSaRT will implement the path on left hand side of the figure. Other possible paths include the facilitator identifying the preferred intervention strategy using MotSaRT and, based on the facilitator's knowledge of the individual student, the selected strategy being implemented automatically by the ITS.

Note: "Facilitator" is a generic term chosen to represent lecturer, teacher or tutor.

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