Modelling and Quantifying Learner Motivation for Adaptive Systems: Current Insight and Future Perspectives

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Abstract. Adaptation and personalization of learning systems are promising approaches aiming to enhance learners' experience and achievement of learning objectives. Adaptive learning systems support and enhance learning through monitoring important learner characteristics in the learning process and making appropriate adjustments in the process and the environment. For example, intelligent tutoring systems (ITSs) provide adaptive instruction to a learner based on his/her learning needs by tailoring learning materials and teaching methods to each learner based on information available in the learner's model. However, present ITSs predominantly emphasize the role of instructional content adjustment to the modelled cognitive processes of a learner, disregarding the significance of motivation in learning processes. According to research, motivation is essential in the knowledge building process and in fostering high academic performance. This paper reviews the literature on modelling of motivational states and adaptation to motivation on ITSs, mapping research progress in terms of techniques and strategies for modelling motivational states and adapting to motivation. A new approach for adapting and increasing motivation through the use of machine learning techniques and persuasive technology is proposed. The approach addresses learner knowledge and motivational states to improve learning and sustain the learner's motivation.

Keywords: Adaptive systems · Intelligent tutoring systems · Learner model · Student model · Motivation to learn · Motivational states · Machine learning · Multimodal machine learning approach · Persuasive technology

1 Introduction

There is increasing interest and investments in using adaptive educational systems to promote learning. Over the past years, research focused on developing adaptive educational systems that automatically adjust online content delivery methods and the sequencing of learning materials to the individual needs of each learner. For instance, adaptive instruction and adaptive learning environments, adaptive hypermedia, and adaptive game-based learning systems are just a few of the many user-adaptive systems available today. Intelligent tutoring systems (ITSs), for example, are adaptive instructional systems providing

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personalized instruction to learners based on their learning needs by tailoring learning materials and teaching methods to the learner's needs based on information available in the learner model. Thus, ITSs monitor the individual learner's characteristics and context to dynamically adapt the learning processes to the inferred learning needs of the individual. Hence, appropriate modelling of the learner's characteristics and relevant knowledge representation within the systems are essential in detecting the learner's needs to adjust instructional content. Several studies conducted systematic literature reviews to identify various learner characteristics modelled in adaptive educational systems for adaptation and existing techniques that were applied [1, 2]. According to the studies, many learners' characteristics (such as age, gender, cognitive abilities, personality, emotions and affect, motivation, past learning activities, domain knowledge etc.) were employed in learner models. Adapting learning based on these characteristics helps in improving the learning experience and achievement of learning objectives for learners [3]. Popular interest in ITSs research focuses on adaptive instruction that tailors learning materials and teaching methods based on the individual learning needs of learners. Often neglected is the role of motivation in empowering learners by improving how they perceive, learn, remember concepts and master skills learnt. Due to the importance of learner motivation in learning with ITSs, there is a concern to summarize research contributions in this area to provide current insight and future perspective. The ITSs monitor learner's activities, create learner models based on different learner characteristics, determine which teaching activities should be selected for each learner, choose the type of hints and feedback to be provided, and pick the next exercise for each learner. These processes help in providing one-on-one personal tutors based on individual learner needs. The learner model quantifies current knowledge state and its variations over time based on instructional actions. The future for ITSs is thought-provoking especially when it comes to creating more efficient learner models that will enhance adaptivity and learning outcomes. Although *motivation to learn* has been mentioned among the identified learner characteristics which are modelled in adaptive educational systems, there is a need for comprehensive literature analysis to identify existing techniques applied to model and adapt learning based on motivation.

Motivation is among the learner's characteristics that influence learning processes. It is a major driver of engagement in learning, particularly in online educational systems [4–7] where the learners plan and coordinate their learning process without teachers' intervention. Lack of motivation and inability to engage learners for a reasonable period of time required to achieve the desired learning objectives are among the top and most frequently cited barriers to online education [5, 8–10] and a major reason for the high drop-out rate experienced by many online educational platforms compared to the traditional education system [11–13]. Improving and maintaining learner motivation has consequently emerged as a key challenge in both traditional and online educational systems because motivation constantly changes over time. As a result, sustaining focus to engage in learning for a continuous amount of time in online educational systems is a difficult task, even in adaptive systems.

Therefore, there is a need to include automatic detection of motivational issues into ITSs learner models. This will allow the systems to self-improve and respond with appropriate intervention without the need for direct human intervention.

Thus, in this paper, we present a review of current literature on modelling learner's motivational states and strategies for maintaining them to enhance learning processes. To achieve our research goal, we formulated research questions to help us understand and focus this study on modelling motivation to learn on ITSs. Thus, we intend to answer the following research questions:

RQ1. How can the motivational states of a learner be detected?
RQ2. What are the strategies for adapting in response to motivation?
RQ3. What features should be adapted?

Research question RQ1 helps us to understand the main techniques that are used for accessing learner's motivation in ITSs. The second and third questions intend to identify the main components of ITSs which are adapted in response to motivational states of a learner and how.

The contributions of this work to adaptive educational systems are two-fold. First, we summarize and highlight emerging trends in modelling and adapting learning processes of ITSs based on learner's motivation. Secondly, we pinpoint the challenges that remain to be solved and explore how machine learning algorithms and persuasive technology could be applied in modelling and responding to learner's motivational problems. Incorporating motivation models with algorithms for modelling and predicting the learning needs of learners will help to find the right time to adapt the system with an appropriate persuasive intervention to maintain or enhance learner motivation while at the same time adaptively addressing the current learning needs.

2 Research Background

This section provides a brief review of the existing research on the impact of motivation on learning and the current state of the art of persuasive technologies targeting learner motivation.

2.1 Motivation

Motivation has over the years been increasingly recognized as one of the factors affecting learning both in the traditional and online educational systems. As a result, many assessment scales [14–16] have been developed for determining learners' motivation during learning processes. The motivation assessment scales use a range of approaches in capturing motivation and learning variables in the context of learning environments. Several studies have adopted and used these scales for different purposes to reveal their usefulness and reliability in measuring the motivation of learners. For example, using the Students' Motivation toward Science Learning (SMTSL) questionnaire [17], a study [18] revealed that students' motivational levels affect their achievement and attitude in learning science. Other research [19] employed the Motivated Strategies for Learning Questionnaire (MSLQ) [16], which was developed for assessing academic motivation and learning strategies, in investigating motivational levels of students learning in a traditional and online educational system. The study reported that for students learning through an online educational system, motivational variables correlated stronger with their performance than the learning strategies deployed in the system. A growing number of studies have shown that motivational variables are relevant to students' success in online educational systems. For example, Barba et al. [20] revealed that the strongest predictors of students' performance in an online educational system are participation and motivation. The research indicated that participation and motivation influenced each other. Similarly, Waschull [21] investigated factors associated with success of students in an online psychology course and reported that self-discipline and motivation were the predictors of the students' success. The importance of learner motivation for online educational systems has been also shown in [22]. According to the research, motivation is a significant factor in determining learners' persistence, engagement and achievement levels.

The complexity and multifacet nature of motivation [23] have resulted in adoption of different perspectives in exploring its influence on learners using online educational systems. According to literature, motivation is viewed from three perspectives: instructional design perspective, as a form of learner's trait, and as dynamic and responsive depending on different contexts [22]. Research that explored motivation from the perspective of instructional design focuses on the design of motivational strategies that could improve students' interest in learning with online education systems [24, 25]. As a result, several instructional design frameworks such as the ARCS model [15] have been developed to be used in online educational systems to influence learners' motivation. Furthermore, some studies viewed motivation as a personal characteristic of a learner [26, 27]. Those studies based their investigation on well-established theories of motivation such as the self-efficacy [28] and self-determination theories [29]. The majority of existing studies [24, 27] are based on one of these two perspectives and are the most commonly used in assessing learner's motivation. A limited number of studies [23, 30] have tried to explore motivation to learn in terms of its dynamic and responsive nature. This approach tries to capture the mutifacet nature of motivation instead of adopting cognitive or behavioural perspective. Research using this approach emphasizes the effect of contextual factors on the relationship between a learner and their learning environment. While research has established that motivation to learn is an important factor affecting learners, the need to understand the complexity involved in its assessment in online educational systems is highlighted.

In traditional educational systems, teachers facilitate and promote learning processes through monitoring engagement and motivational states of learners [31]. Teachers recognize different behaviours of learners through interaction, questions, and facial expressions. They use various tactics and teaching strategies to motivate and encourage students to engage in more active learning. However, in online educational systems including ITSs, learners coordinate and carry out learning on their own and they rely on motivation to perform the learning activities. This creates the need for the systems to track and detect motivational issues of learners. Vicente et al. [32] expressed the need for ITSs to monitor and detect motivational states of learners in order to improve their effectiveness. Many researchers have worked on enhancing ITSs in various ways which include modelling learner motivation for adaptation of learning processes. However, detecting the motivation of learners in the systems and the factors which influence it is a complex process involving multiple dimensions such as cognitive, emotional and physiological [23].

2.2 Persuasive Technology

According to Fogg [33], technologies and techniques built into systems which help users to change their attitude, opinion, and behaviour without using coercion or deception are called Persuasive Technology (PT). The systems are usually developed to encourage users to accomplish a positive goal. Persuasive technology strategies have been shown to be effective in systems at encouraging users to achieve specific goals in various domains such as health [34], energy conservation [35] and education [36]. Persuasive technologies have the potential to be used in online educational systems to encourage and sustain learners to realize the learning objectives, as several studies show. For instance, research has shown that persuasive strategies could be incorporated into an online educational system to promote students' engagement and improve learning [37]. Similarly, persuasive technology was applied in teaching and learning through creating learning objects with embedded persuasive concepts [38].

Though research has shown that PTs can motivate users to accomplish specific goals, it has also been revealed that users differ in their susceptibility to PT strategies, and personalization can amplify the effect of PT [39]. Modelling users according to their susceptibility to persuasive strategies result in persuasion profiles that can be used to tailor or personalize the persuasive strategies to the individual user to improve its efficiency. The persuasion profile contains user features such as gender, age, cultural background or personality, as well as shown susceptibility/preference to certain persuasive strategies. The user features can be obtained through implicit or explicit measures such as questionnaires, online interactions, application logs, and sensors.

Several studies have shown that personalized PTs are more effective than the one-size-fits-all approach [40–42]. Hence, construction of user persuasion profile is important in developing personalized persuasive applications.

3 Modelling of Motivation to Learn in Intelligent Tutoring Systems

A variety of studies investigated the effect of different learner characteristics on teaching and learning on ITSs [43, 44]. However, limited studies investigated the impact of modelling motivational states of students to enhance learning experience and outcome. Modelling motivational states of learners have been recognized as an important component that could be incorporated into ITSs. The scope of motivational states modelling involves a range of measurement tools, techniques, and methodologies. An overview of studies performed in this area is provided in the following section.

3.1 Techniques for Learners' Motivational States Diagnosis in ITSs

Studies that modelled student motivation to learn in ITSs used several techniques involving explicit and/or implicit measures. For example, Vicente et al. [45] employed motivational slider technique and self-report in assessing the motivational level of university students learning with ITS called MOODS (Motivational Diagnosis Study). In detecting students' motivational states at various interaction stages with MOODS, the researchers issued short self-reports of motivation to students. McQuiggan et al. [46] modelled self-efficacy in ITS using decision tree models. The research explored how to build a dynamic self-efficacy model that will automatically update itself using an inductive approach. The dynamic model learns from pre-test data, physiological data of students captured with a biofeedback apparatus, and interaction data of students in their learning environment. The result of the research shows that the dynamic self-efficacy model predicted students' self-efficacy more accurately than a static model generated from data obtained using a validated self-efficacy instrument. The researchers suggested that the dynamic model could be used to predict student's level of self-efficacy at runtime to inform pedagogical decisions in their learning systems. Qu et al. [47] investigated the use of Bayesian model which combines focus of attention data (obtained through a combination of learner's eye gaze and interface activities) and interactions of learners in ITS in detecting learner's degree of confidence, confusion and effort. To evaluate the model the researchers performed an experimental study, which revealed that the model using human tutor's observation as baseline and the one that used learner's self-reports as baseline have recognition accuracies of above 70% for the learner's motivation. The research suggested that the model could be used in providing accurate information about learner motivation. Santos et al. [48] explored the use of convolutional networks in detecting levels of intrinsic motivation using visual cues from student's facial expressions. The research shows that the level of intrinsic motivation of students could be detected with visual input only. Johns et al. [49] investigated inferring student's motivation from a hidden Markov model (HMM) and student proficiency from an Item Response Theory (IRT) model. They generated a dynamic mixture model and used students' log data from ITS in validating the model. The researchers reveal that their model accounted for student motivation.

Monitoring and detecting motivational states of students learning with ITSs is not a common feature in many ITSs. The broader idea of motivational states modelling is concerned with trying to replicate the sort of assistance human tutors provide to students when they detect that their motivation to learn has dropped. Based on the ITSs literature surveyed only a few studies are available in this area and the techniques used for estimating the student's motivational states range from static to dynamic. An overview of studies and techniques for modelling motivational states is presented in Table 1. The studies employed different variable requirements obtained from the following: self-report data, learning interaction data, and physiological data. The techniques used for motivational states detection include self-report analysis, decision tree models, Bayesian models, and convolutional networks. Using techniques that provide more accurate evaluation of learner's states through a combination of surveys, physiological, performance, and interaction data will enhance the adaptability of ITSs.

According to [50], focus on dynamic adaptation to motivation of learners using ITSs is increasing. Existence of available techniques for automated diagnosis of learner's level of motivation is a step towards achieving the dynamic adaptation. The ability of these techniques to monitor what learners are doing, how they are feeling, and how they are managing their learning context are important in detecting when the need to adapt arise.

Table 1. An overview of research and techniques for modelling motivation

Techniques for modelling motivation	Data collection methods	Studies
Motivational slider	Self-report	[45]
Decision tree model	Mixed (self-report, biofeedback apparatus, system logs)	[46]
Motivation diagnosis rule	Mouse movement, history of interactions and performance	[51]
Natural language processing (semantic cohesion measure)	Mixed (self-report and non-intrusive Dialog) Measure	[52]
Bayesian model	Eye gaze and interface activities logs of learners	[47]
Hidden Markov model	Learning logs of learners	[49]
Convolutional network	Visual cues from facial expression	[48]

One of the notable insights about the current techniques for motivation modelling is that multiple types of data could be explored to make the models generated more robust in representing motivational states of learners. However, excluding studies that used pre-and post-surveys for motivation measures, the proportion of papers that explicitly stated how motivational states were modelled is small, and this suggests that researchers were not discussing their modelling technique or little work has been done in this area. A wider exploration of techniques for inferring motivational states of learners has the potential to advance ITSs research.

3.2 Strategies and Features for Adapting to Learner Motivation

Motivationally-intelligent tutoring systems consider the motivational states of a learner during adaptation [50]. Varying forms of adaptation such as macro-adaptation or micro-adaptation are employed. Micro-adaptation dynamically monitors and tracks changes in motivational states of a learner over time while macro-adaptation is often a one-off adaptation usually done prior to a task using existing motivational measures. Due to the complexity of motivational state and difficulty in assessing it, covering all aspects of motivation might not be feasible. Thus, researchers focus on adapting to a specific aspect of motivation. They have tried to model motivational states of learners in ITSs using validated instruments, affective states monitoring, and engagement in learning activities. For instance, Matsubara et al. [53] incorporated into ITS a motivation system that focuses on student's motivation levels in learning processes to give appropriate encouragement, praise or reproach messages. The students' motivation levels were represented as action parts and fuzzy rules were used for inferencing. The research presented that the system considered the learner model and the motivation rules in generating appropriate messages for each learner.

Research presented that main feelings associated with motivational states present a useful way to refer to the states [54]. Several studies have detected and differentiated feelings such as frustrated, excited, confident, and interested [55], states of boredom, confusion, frustration, eureka, neutral, and flow/engagement [56] that occur during learning. Equally, research has shown that emotions play important role in motivation. And that responding to affective states of learners accordingly will improve motivation and learning processes. Hence, some researchers adapt to affective states of students to improve their motivation. As such research developed a dynamic decision network for emotions based on personality theories and teachers' expertise and incorporated it to an ITS for learning mobile robotics. The research revealed that contextual adaptation based on cognitive and emotional states of learners helps to maintain motivation to learn at high level [57]. Also, D'Mello et al. [58] investigated how students can be assisted to regulate negative states such as boredom, frustration, and confusion when they arise so that positive states (flow/engagement and curiosity) can persevere. The researchers used sensors in estimating the probability value of the type of emotion a student is experiencing. They developed rules based on theories, experts' guidance, and intuition which helped them in mapping students' cognitive (dynamically assessed student ability and quality of current response) and affective states with suitable tutor actions. When the tutor detects that a student has a negative affect state, it responds with empathetic and motivational messages which will encourage the student to continue with the tutor. Thus, for the tutor to be motivationally intelligent, it needs to recognize cognitive and emotional consequences of tutorial intervention to be more efficient. Furthermore, an overview and discussion on some intelligent tutoring systems that adapted to learner's motivation dynamically or as a one-off thing were presented in research [50] to highlight progress in the area of motivationally adaptive intelligent tutoring systems.

Besides the cognitive needs of students, diagnosing their motivational states and adapting the tutor to keep them motivated will strongly impact their learning outcomes. The connection between observable learning outcomes and behavior of a learner reveals actions contributing to improving ability to engage in tutoring. According to research, regular positive emotions (affect) of students are associated with higher levels of engagement whereas negative emotions correlated with low levels of engagement. The effect of adaptivity partially mediated the correlation between positive emotions and student engagement [59].

4 Proposed Architecture for Integrating Motivation Modelling into ITSs

Over the years, surveys and interviews are the most commonly used method for assessing motivation to learn. The methods require students to report their motivation levels. Pretest and posttest surveys are often used in the methods. Using surveys in assessing motivational states of learners at different intervals in ITSs are intrusive and could negatively impact motivation to learn. In traditional learning systems, teachers can perceive the current motivational states of students and adapt the teaching strategies to increase motivation. According to research [32], the ability of ITSs to automatically detect motivational states of learners will bring numerous advantages. This leads to the need to build a tool for measuring real-time motivational states of students dynamically using their digital traces in ITSs. Current advances in technology such as cheap miniature sensors, digital cameras, and deep learning algorithms, enable unobtrusive continuous measurement of physiological and interaction data of students during learning, offering the possibility of modelling motivational states of learners over time. Recent studies are making progress in this area to create more efficient student models that will enhance adaptivity to improve students' learning.

We present a new approach that could be adopted in monitoring and improving motivation of learners in ITSs. The approach targets dynamic detection of motivational states of learners in ITSs over time. For this purpose, we rely on machine learning techniques that could use a set of behavioural indicators (objective measures) of students in ITS for measuring motivation. Our approach will involve the development of a Multimodal Machine Learning (MML) mechanism that will automatically predict motivational states of a learner at intervals during learning processes in ITS using a combination of the learner's behavioural responses on ITS. As mentioned previously, traditional methodologies for assessing learner motivation rely on data collected through questionnaires only. The MML approach will use a combination of subjective responses and unobtrusive objective measures of learner's digital traces in developing an integrated model comprising of predictive features from each measure. According to research [60], "*a deeper understanding of the learner behaviours, traits, and preferences (learner data) collected through performance, physiological and behavioural sensors and surveys will allow for more accurate evaluation of learner's states (e.g., engagement level, confusion, frustration) which will result in a better and more persistent model of the learner*" (see Fig. 1). Also, research has shown that multimodal affect detection (using a combination of data sources) yields more accurate results than the best unimodal counterparts [61]. In addition, McQuiggan et al. [46] revealed that a multimodal decision tree model predicted students' self-efficacy more accurately than the model built using students' self-reported data (unimodal). Thus, our multimodal technique will use the following data sources: data on students' motivation will be collected through self-report using the Motivated Strategies for Learning Questionnaire (MSLQ), physiological data of students are captured through eye-gaze and facial expressions, and their interaction and performance data will be provided by the ITS. Features extracted from the provided data sources through appropriate feature engineering techniques are passed to a decision tree model to predict student motivational states at intervals during learning processes with ITS, as the motivational states of learners likely change during learning interactions. Using learner's self-reports as baseline, corresponding motivational states are calibrated and mapped to any of the levels (threshold, low, and high) as a linear scale. The threshold value divides the scale into two subscales - low and high. When a low motivational state is detected the system selects an appropriate persuasive strategy that could help to increase the motivational state.

The architecture of ITS consists of four main components: domain model, learner model, tutoring model, and user-interface model. Current learner model depends more on cognitive assessments. A more efficient learner model will enhance the capability of ITSs to provide individualized help to learners when needed. Therefore, we propose to modify ITS architecture and integrate motivation detection (using MML), labelling and

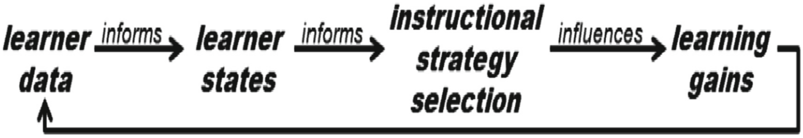

Fig. 1. Adaptive tutoring learning effect chain (Sottilare [60])

response (see Fig. 2) since motivation plays a vital part in learning. The response part takes into consideration the persuasive strategy that could motivate each learner. The learner model part of ITS architecture is modified such that modelling of motivational states during learning processes and persuasive profiles of learners are incorporated as shown in Fig. 2. The tutoring model updates the current knowledge while the module for motivational states monitoring updates learner's motivational states at intervals during learning processes. The decision model in the figure combines the cognitive (current knowledge) and motivational states of a learner in establishing appropriate pedagogical and persuasive actions that will be sent to the tutoring model and then to the interface model. Thus, the current state of a learner determines the tutoring model activities. The persuasive intervention and the pedagogical process will be delivered to a learner when the decision model diagnoses a motivational issue. The learner's persuasive profile is used in tailoring the persuasive intervention to make it more efficient. The intervention is to encourage learners to get more involved and complete the tutoring process.

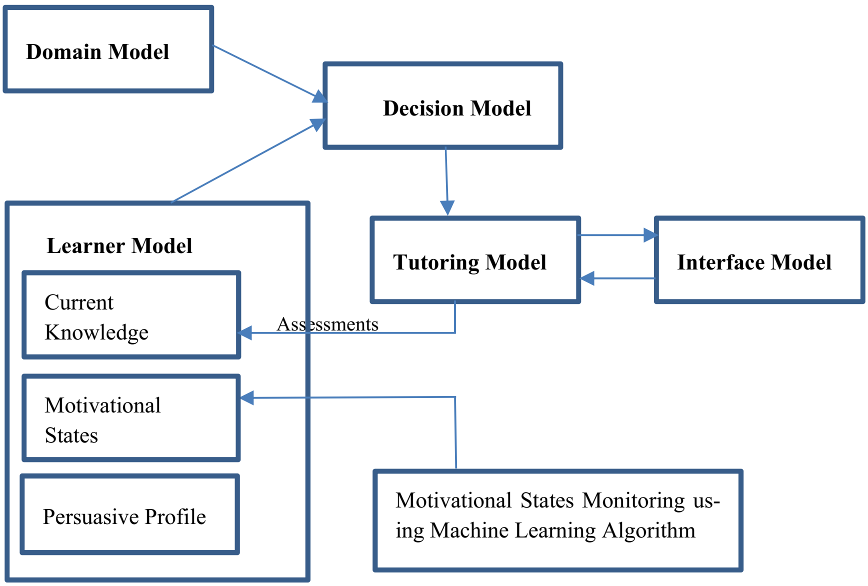

Fig. 2. Architecture of motivationally-adaptive intelligent tutoring system

Future Perspectives. Adaptive educational systems such as intelligent tutoring systems could be improved in the future through implementation of an adaptive mechanism that takes into consideration, not only the cognitive states but also the motivational states of learners. Developing a framework that will dynamically determine changes in a learner state as a guide to what will be adapted is an important area. Hence, there is need for more efficient modelling technique for determining and confirming different states to improve the effectiveness of adaptation. Existence of a more comprehensive learner model will allow adaptation to be better align to learner's needs and this will probably affect learning experience and outcome. Moreover, the type of motivational tactics that could be applied in encouraging and sustaining learners in the process of learning when negative motivational states occur is another area that needs to be explored. Research in this direction is using non-intrusive (such as physiologic sensors and interaction data) and multimodal machine learning approach for dynamic detection of learner emotional states. This category involves learner models that capture motivational/ affective states.

5 Conclusion

In view of supporting a more individualized learning experience in ITSs, this paper surveyed literature on modelling of motivational states to establish the various techniques and methods employed. Based on the current research trend in this area, we proposed an architecture for an intelligent tutoring system that will monitor and adapt learning based on the cognitive and motivational states of a learner. Thus, the architecture addresses knowledge and motivational needs and employs a dynamic technique for motivating learners using persuasive technology. Dynamic motivation is enriched with the use of persuasive strategies that a learner is susceptible to. The architecture represents an initial attempt on how motivational states of a learner could be integrated into learner model in ITS and how persuasive technology could be incorporated and adapted based on motivational states while preserving the usually ITS adaptation. The future research will involve the following: 1) implementation of ITS framework based on this approach, 2) system evaluation to determine the efficiency of the approach and its effect on students' learning. An evaluation of a system built with this architecture will be compared with similar conventional ITS that did not have motivational states modelling, persuasive technology and decision model incorporated.

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