Technologies for Inclusive Education:

Beyond Traditional Integration Approaches

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Chapter 9
An Emotional Student Model for Game-Based Learning

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ABSTRACT

Students' performance and motivation are influenced by their emotions. Game-based learning (GBL) environments comprise elements that facilitate learning and the creation of an emotional connection with students. GBL environments include Intelligent Tutoring Systems (ITSs) to ensure personalized learning. ITSs reason about students' needs and characteristics (student modeling) to provide suitable instruction (tutor modeling). The authors' research is focused on the design and implementation of an emotional student model for GBL environments based on the Control-Value Theory of achievement emotions by Pekrun et al. (2007). The model reasons about answers to questions in game dialogues and contextual variables related to student behavior acquired through students' interaction with PlayPhysics. The authors' model is implemented using Dynamic Bayesian Networks (DBNs), which are derived using Probabilistic Relational Models (PRMs), machine learning techniques, and statistical methods. This work compares an earlier approach that uses Multinomial Logistic Regression (MLR) and cross-tabulation for learning the structure and conditional probability tables with an approach that employs Necessary Path Condition and Expectation Maximization algorithms. Results showed that the latter approach is more effective at classifying the control of outcome-prospective emotions. Future work will focus on applying this approach to classification of activity and outcome-retrospective emotions.

INTRODUCTION

Information technologies for supporting education have evolved into increasingly sophisticated environments. Virtual environments, tele-presence, video games, intelligent tutoring, haptic devices and social environments are only some of the technologies that have been applied successfully. However, challenges are still present in the area of personalized emotional learning. Emotion is considered an essential component of human experience and from a Human-Computer Interaction (HCI) viewpoint, Graphical-User Interfaces (GUIs) that do not address emotion appropriately are perceived as socially-impaired and can limit users' performance (Brave & Nass, 2008). As a result, two research areas, Edutainment and Computer Tutoring, i.e. Intelligent Tutoring Systems (ITSs), have concentrated efforts on recognizing or showing emotion (Picard et al., 2004). Incorporation of affective modeling promises enhanced student motivation, learning and understanding. The topic of "emotion in education" is also gaining popularity in the field of Cognitive Psychology. Theories that aim to provide an enhanced explanation of the origin of emotion in an educational context are important (Schutz & Pekrun, 2007).

Whilst attempting to reason about or understand emotion, common questions appear, such as how emotion arises and the emotions most relevant for the teaching-learning experience. As part of the endeavor in finding the most suitable answers to these questions, this chapter reviews related work in the areas of ITSs and Edutainment, which aims to identify emotion. In addition, approaches, such as recognizing the physical effects of emotion (D'Mello et al., 2008), which have been derived and used to recognize and reason about emotion are examined and discussed by outlining their advantages and disadvantages. This chapter also focuses on examining cognitive psychology theories, such as the Ortony, Clore and Collins (OCC) model (Ortony, Clore & Collins, 1990), which have previously been used as a basis to implement emotional student models and other theories that have not been previously employed, such as the Control-Value theory of achievement emotions by Pekrun, Frenzel, Goetz and Perry (2007).

We have developed PlayPhysics, an emotional game-based learning environment for teaching Physics at undergraduate level. It was designed to derive and evaluate our emotional student model and facilitate students' in self-reporting their emotions. PlayPhysics is a space adventure, where the student, an astronaut, has to overcome challenges using his/her Physics knowledge of vectors, circular and linear kinematics and Newton's laws for particles and rigid bodies. The first challenge involves piloting the Alpha Centauri spaceship in order to arrive at the Athena space station before the ship's fuel is exhausted. PlayPhysics is implemented with the Unity Game Engine, Hugin Lite, MySQL and Java. The design and implementation of PlayPhysics are also discussed in this chapter.

This chapter focuses mainly on the analysis, design and implementation of an emotional student model using contextual and feasible variables related to students' observable behavior for game-based learning. The approach employed is Cognitive-Based Affective User Modeling (CB-AUM), which involves employing the Control-Value Theory (Pekrun et al., 2007) as a basis. Control-Value Theory has not been employed previously for implementing an emotional and computational student model. As part of our research methodology, we employ Probabilistic Relational Models (PRMs) to facilitate the derivation of Dynamic Bayesian Networks (DBNs) (Sucar & Noguez, 2008).

DBNs enable us to handle uncertainty and incorporate previous domain knowledge (Jensen & Nielsen, 2007). Multinomial Logistic Regression (MLR) was employed to select the most significant regressors (Kinnear & Gray, 2010) and cross-tabulation was employed for setting the probabilities in the Conditional Probability Tables (CPTs) in previous work, where we ob-

tained promising results for classifying *outcome prospective emotions* into positive and negative-neutral categories (Muñoz, Mc Kevitt, Lunney, Noguez & Neri, 2011). MLR is a method used to predict category membership using categorical variables as factors and it has the advantage of knowing the contribution of each regressor to the prediction. However, here we compare the previous approach with one using the Necessary Path Condition (NPC) algorithm for structural learning and the Expectation Maximization (EM) algorithm for learning the probabilities in the CPTs (Bashar, Parr, McClean, Scotney & Nauck, 2010; Hugin Lite, 2012). Results from our tests with high school and undergraduate students at Tecnológico de Monterrey (ITESM-CCM) are presented comparing the effectiveness of both approaches. We also compare our results to related work and discuss future research directions.

BACKGROUND AND RELATED WORK

Emotion is a component of human experience that has been shown to influence cognition, perception, learning and performance (Brave & Nass, 2008; Westerinck, Ouwerkerk, Overbeek, Pasveer, & De Ruyter, 2008). As a result, computer tutoring aims to react suitably to emotion, which requires highly responsive systems, capable of adapting to the rich behavior patterns exhibited by interacting humans. However, to know if the desired effects will be achieved, it is necessary to enable these systems to identify and model the learner's affective or motivational states.

Affective Computing is a research area focused on enabling computers to recognise and show emotion (Picard, 1995). It is an interdisciplinary field comprising Computer Science, Psychology, and Cognitive Science (Tao & Tan, 2005). When a computer tutor recognizes the student's affective state, it can respond accordingly to it, e.g. motivating students and improving the learning process. As a result, computers are able to provide suitable support to improve users' experiences, facilitate performance and encourage the creation of meaningful relationships with users by promoting their trust and give a sensation of competence (Brave & Nass, 2008). Intelligent Tutoring Systems (ITS) and serious games have been influenced by Affective Computing, and have adopted the goals of understanding and expressing emotions. Simultaneously, educational games or GBL environments incorporate ITSs to ensure personalised instruction, i.e. be aware of students' characteristics and needs, and the achievement of learning goals.

Edutainment

Edutainment is a concept that combines aspects of teaching and learning with the characteristics of video games in order to provide attractive learning environments for students. These systems combine specific teaching methods and characteristics of video games to engage students in familiar ways and make it easy to support their learning (Qianping, Wei & Bo, 2007; Rapeepisarn, Wong, Fung, & Depickere, 2006). Their main goal is to enhance the educational value of games though the addition of pedagogical techniques in order to convey educational content in a less stressful way. As a result, students can enjoy this process and increase their interest in the content that is taught. This may enhance the quality and efficiency of the teaching-learning process between professors and students.

Game Based Learning (GBL) enables learning through experiencing the effects of the students' own actions in situated contexts and facilitates the connection between learning and real-world experiences (Van Eck, 2006). GBL environments are comprised of specific elements, e.g. narrative, characters, sounds, actions, challenges and goals, which interact creating a unique experience, known as "game play" (Rollings & Adams, 2003). GBL is effective, since playing

has been considered and employed as a primary instructional strategy and a form of socialization. Therefore, Edutainment environments are effective at focusing students' attention and enabling students to play in order to learn and enjoy the experience of learning (Qianping et al., 2007). According to Lazzaro (2004), it is for this emotional experience that people play games. In addition, GBL environments comprise elements that have an emotional character, e.g. narrative, sounds or music and graphics or animations. As a result, they are capable of establishing an emotional bond with the learner (Sykes, 2006).

Educative computer games are also being adapted to be affective learning tools. These provide immediate feedback and reward learning and mastering through different modalities, e.g. heroic music, new characters, power-ups, progression of story and high scores (Sykes, 2006). Malone (1981) signalled that the characteristics of video games, e.g. challenge, fantasy and curiosity, can also encourage learning in these environments. Learners need clear goals that must be uncertain and relevant not only from an educational perspective, but also from the game fantasy viewpoint. It is important to remember that not all fantasies appeal to all users, as personal preferences and gender influence users' choices. However, fantasy or storytelling is important because users have contact with other contexts that assist them in achieving an enhanced understanding of the specific problem that they want to solve.

Overcoming Design Problems in Edutainment

Developing Edutainment systems is not a simple endeavor as these kinds of systems require balancing of entertainment and educational strategies. Some common problems encountered in GBL environment design are balancing game and learning content, supporting the curriculum and ensuring that learning actually happened (Carpenter & Windsor, 2006; Conati, 2002; Sykes, 2006; Van Eck, 2006).

In addition, research in the Edutainment field is also pursuing personalization (Paireekreng, Rapeepisarn & Wong, 2009), Therefore, ITSs are also used in combination with GBL environments in order to achieve personalized instruction and ensure the achievement of the learning goals (Conati, 2002; McQuiggan, Mott & Lester, 2008). Since emotional and cognitive capabilities have been demonstrated to be deeply intertwined (Norman, Ortony & Russell, 2003), the field of Affective Computing merged with the field of ITSs. Researchers began to focus on the creation of a new generation of ITSs, which are capable of recognizing or predicting the learner's emotional state and showing affect (Picard et al., 2004).

Towards a New Generation of ITSs

The rise of ITSs is due to several facts such as the transformation of educational and teaching methods that evolved in order to achieve an enhanced awareness of cognitive processes, learning styles and interaction methods. Another important event is the information technology (IT) revolution that has encouraged novel ideas for processing and saving information, software development and the creation of networks. The advance in AI techniques has also been meaningful in achieving adaptable instruction, managing suitably resources, evaluating students' learning or encouraging collaboration. Additionally, student data is easily accumulable and can be employed to achieve enhanced understanding about students' behaviour, i.e. Educational Data Mining (EDM). Furthermore, novel interaction techniques have arisen in order to follow and record students' progress.

ITSs keep track of the student's performance over time, provide targeted feedback when necessary, select the most suitable pedagogical action and adapt to each student's preferences and pace of learning. ITSs take a student centred approach, where AI techniques are used to model or reason about students' characteristics, skills, behaviour

or needs over time and respond accordingly to them (Woolf, 2009). These models attempt to infer what students should know and understand together with their misconceptions and learning preferences. Sometimes this entails using psychological and cognitive theories that explain how students acquire knowledge and how lecturers diagnose learning as a basis.

The new generation of ITSs attempts to address the integration of the emotional dimension in addition to addressing students' knowledge, learning and understanding successfully. The ultimate goal is to manage and hold students' motivation whilst learning (Du Boulay & Luckin, 2001), since emotional, motivational and cognitive processes have proved to be deeply interrelated and play different but equally important roles (Norman et al., 2003; Pekrun et al., 2007). Cognitive processes manage the semantic meaning, analysis, memorisation and understanding of the world. Additionally, affective processes focus on performing judgements and evaluations.

From the student modelling viewpoint, handling students motivation has comprised efforts in (1) identifying students' preferred learning styles (Kelly & Tangney, 2002), (2) diagnosing students' motivation (De Vicente & Pain, 2002; Del Soldato & Du Boulay, 1995), (3) recognising students' attitudes (Arroyo & Woolf, 2005), inferring students' level of self-efficacy (McQuiggan et al., 2008) and more recently inferring students' affective or emotional state (Conati & Maclaren, 2009; D'Mello et al., 2008; Porayska-Pomsta, Mavrikis & Pain, 2008). The latter has received increased attention due to recent research that has shown that emotional or affective states influence students' motivation, decisions and performance (Picard, 1995; Picard et al., 2004). Two approaches are employed to provide this new generation of tutors with the capabilities of understanding and reasoning about affect: (1) observing how human tutors reason about the learners' affective states as in Sarrafzadeh, Alexander, Dadgostar, Fan and Bigdeli (2008) and observing how learners experience emotion as in Conati and Maclaren (2009).

Student Modeling

A student model is an important element of an ITS, as it is useful for reasoning about how people learn, specifically how new knowledge is filtered and integrated into a person's existing cognitive structure. Several representations have been deployed in implementing student models. Student models based on Bayesian networks (BN) have been deployed in diagnosis, the task being to infer the cognitive state of the student from observable data. A proposed classification of Bayesian student models is given in Mayo and Mitrovic (2001): (1) expert-centric student models is the product of domain analysis, in which an expert specifies either directly or indirectly the complete structure and conditional probabilities of the Bayesian student model; (2) efficiency-centric models that involves partial specification or restriction of the model and fitting domain knowledge to it, and (3) data-centric models, in which the structure and conditional probabilities of the network are learned from data. However, the effort required to define the network structure, the difficulty to obtain the parameters and the computational complexity of the inference algorithms, have to be considered when implementing these types of models. The main problem is the cost and time spent on building and refining a model for each domain. Therefore, a representation that simplifies this process is very important.

The student model is a representation of knowledge with the purpose of classification or prediction (Han & Kamber, 2006). ITSs perform continuous observations of student behavior linked to student performance in order to adapt feedback to encourage student interest and learning (Woolf, 2009). Cognitive student models are derived from domain models or expert knowledge models, since these are composed of the concepts that students have to grasp and comprehend or techniques that

students may use for solving a specific problem or case study. Therefore, domain models represent these facts and methods, which are signaled by expert lecturers as those required to solve successfully domain problems or issues related to the instructional technique employed by these experts to provide feedback. The level of difficulty and time involved in the process of representing the domain is influenced by the domain complexity or structure.

Emotion in Computing and Education

Predicting emotion from its origin or CB-AUM is a computational approach for affective student modeling that uses cognitive psychology theory as a basis for reasoning about emotion. The most commonly employed is the OCC (Ortony, Clore and Collins) model (Ortony et al., 1990), which defines different types of emotions according to the sources that originate them. This theory suggests that events, agents and objects can elicit an emotion. To ensure that an individual is experiencing an emotion, it is necessary to have knowledge of their goals, social standards, attitudes, cultural context and personality traits, since this theory states that a threshold level has to be reached to experience an emotion. This approach has advantages such as it can be employed for online learning and uses feasible and low-bandwidth contextual variables, but has not yet demonstrated reasonable success (Jaques, Vicari, Pesty & Martin, 2011; Sabourin, Mott & Lester, 2011).

Identifying the physical and physiological effects of emotion is an approach that requires hardware. As a result, these kinds of ITSs are only available with full capabilities for reasonably recognizing emotion only in laboratory settings (D'Mello et al., 2008), are prone to failure (Burleson & Picard, 2007) and are considerably expensive to bring to classroom settings (Arroyo et al., 2009). This approach involves using self-reports or the opinions of expert judges to map patterns

of behavior to affective states and has shown the most successful to date. The 'hybrid approach' to reasoning about and indentifying emotion, which combines both approaches, inherits the strengths and weaknesses of both approaches and is expected to be the most successful way forward. However, it has still not shown significantly accurate results (Conati & Maclaren, 2009).

Once the computer tutor is able to predict or recognise the learner's affective, emotional or motivational state with certain accuracy, the new generation of interactive tutors focus on changing the learner's state to one optimal to attaining knowledge and understanding, i.e. encouraging the learner's motivation. Until now, there is no consensus about what is the learner's optimal state. D'Mello et al. (2008) focus on promoting flow during interaction, which was related to affective state engagement. Therefore the research was focused on changing negative affective states, e.g. boredom, frustration and confusion. Also, Conati & Maclaren (2009) focus on changing negative emotional states, distress and reproach, for joy and admiration respectively. Pekrun (2006) suggests that positive and negative achievement emotions, i.e. highly related to achievement activities and outcomes, do not necessarily produce a corresponding positive or negative effect on learning. This phenomenon is due to a complex pattern, which is the result of the interplay of task demands and different mechanisms, e.g. learning strategies, interest and motivation to learn, cognitive resources, social and cultural antecedents, personality antecedents and achievement goals.

In order to reason about emotion, it is meaningful to understand the origin of emotions and their characteristics. Two challenges are how to predict or recognize the learner's motivational and emotional states and how to suitably respond to them. Emotion is dynamic, short lasting and intentional. Self-reports are considered evidence of emotions, since they are subjective and only the person has access to them. Emotion influences students' motivation, learning and performance and plays a

main role in the students' physiology process and behavior, the employed learning strategies and the use of the available cognitive resources.

Finally, to create an emotional student model it is important to relate the relevant emotions to the educational experiences. Achievement emotions are emotions that occur in educational settings when students want to achieve relevant activities and outcomes, e.g. boredom and frustration. The Control-Value Theory of achievement emotions by Pekrun et al. (2007) defines that control and value appraisals are the most relevant when determining these emotions. This theory has not been employed previously in work to create a computational and emotional student model. Therefore, our research focuses on this goal. In addition, this section discussed that reasoning about and addressing emotion in computer tutoring is meaningful to enable students' to focus and enjoy the experience of learning. Also, GBL environments facilitate the creation of this emotional bond and include ITSs to enhance their understanding of students' needs and capability to adapt instruction. The following section describes the adaptation of the Control-Value theory to a GBL environment setting.

FORMALISATION OF THE EMOTIONAL STUDENT MODEL

The work here focuses on using the Control-Value Theory of Achievement emotions by Pekrun et al. (2007) to create an emotional student model which can reason about students' emotions from answers to questions in game dialogues and observable and contextual variables, which are of low-bandwidth and feasible. Therefore, our hypothesis is that Control-Value Theory can be adapted to online Game-based learning environments settings and can reason about emotion accurately, i.e. approximately the precision of humans recognizing emotion (Keltner & Lerner, 2010). Hence, this is done by following a Cognitive-Based Affective-User Modeling (CB-AUM) approach, which reasons

about emotion from its origin using a psychological and cognitive theory of emotion. We decided to employ Dynamic Bayesian Networks (DBNs) to characterize our emotional student model, since they are proven to handle domain uncertainty effectively, enable us to include previous information from the domain and to represent the evolution of students' behavior over time. The latter is key, since as mentioned earlier emotion is dynamic, short lasting and intentional (Brave & Nass, 2008). Therefore, we require a knowledge representation that can fulfill these characteristics and DBNs are currently shown to be suitable in recognizing or reasoning about emotion (Conati & Maclaren, 2009; Sabourin et al., 2011).

In order to facilitate the derivation of DBNs, i.e. identifying the relevant observable variables to derive its structure and Conditional Probability Tables (CPTs), we have employed a combination of Probabilistic Relational Models (PRMs) and Multinomial Logistic Regression (MLR) (Muñoz et al., 2011). MLR is one of the preferred methods in Psychology for classifying category membership, since it requires fewer assumptions than discriminant analysis, such as multivariate normality or homogeneity of variance-covariance matrices. Also, it can handle categorical regressors effectively. As mentioned earlier, we employed this technique previously and it proved to be effective in predicting negative-neutral emotions, achieving an accuracy of 75%. In that research *control* was predicted by the student's attitude towards Physics and *value* was predicted successfully by the student's confidence in achieving a successful outcome. However, it was observed that this approach comprising analysis of correlation, MLR and cross-tabulation, conducted mainly manually, is highly time consuming. Therefore, in addition to the PRMs approach, here we use specific machine learning techniques, which involve less effort and require investing less time.

PRMs have been employed previously in research to facilitate the derivation of Bayesian Belief Networks (BBNs) and create student models

that comprise the domain knowledge and concepts that students have to understand and learn (Sucar & Noguez, 2008). The PRMs approach assumes that a domain can be characterized as a series of objects with properties and relationships between them (Koller, 1999). In our research, this technique is employed to derive three PRMs, one corresponding to each type of *achievement emotion*, i.e. emotions originated from the achievement of relevant activities or outcomes, defined by Pekrun et al. (2007): (1) *prospective outcome*, (2) *activity* and (3) *retrospective outcome emotions*. These three types of emotions arise depending on the time frame and the object focus, e.g. outcome or activity. It is important to underline that achievement emotions are domain dependent. People that experiences specific emotions studying Physics do not experience the same emotions learning English. Here, we focus specifically on the creation and evaluation of the DBN corresponding to the *prospective outcome* emotions.

Adapting the Control-Value Theory to a GBL Environment Setting

As mentioned earlier, the Control-Value Theory assumes that control and value appraisals are the most relevant determining emotion. The subjective *control* over an activity and its outcomes is assumed to be related to causal expectancies and attributions, e.g. that the activity can be initiated and successfully performed or performing the activity will enable students to achieve their objectives. As a result, we inferred that control is related to students' self-efficacy, i.e. beliefs of performing in specific ways and attaining specific goals. *Value* is related to the relevant outcome or activity per se, or for its utility to contribute to later outcomes. Table 1 shows categorization of control and value and its relationship to the *prospective outcome* emotions.

It is observed that Pekrun et al. (2007) relate value and control to different factors according to the time frame, focus and educational setting

in their Achievement Emotions Questionnaire (AEQ) (Pekrun, Goetz & Perry, 2005). The AEQ is a self-report tool with statements and a scale from 1 to 5, where 1 corresponds to "strongly disagree" and 5 to "strongly agree", designed through Structural Equation Modeling (SEM) in order to determine if a student experience an emotion in classroom, tests and learning settings. The AEQ is comprised of affective, cognitive, physiological and motivational factors. We employed the factors in the AEQ to identify the employed constructs and derive our own questions in order to introduce and adapt them in game dialogues. For example: "I feel confident that I will be able to master the material". From this statement, it is observed that the student confidence is related to control or value.

Prospective outcome achievement emotions are emotions experienced by students before performing an activity and attempting to achieve its outcome. The value in this time frame is related to the students' expectancy of being able to perform an activity effectively with a successful outcome or the possibility of failing to take into account the control that they have over the outcome, i.e. if they believe that they have or can acquire the knowledge, skills and capabilities in order to achieve a successful or failed outcome or if they feel that the outcome will be achieved anyway due to the characteristics of the situation. We identified some factors from the AEQ, such as "perceived level of difficulty", "confidence towards achieving a successful outcome" or "source of motivation", but

Table 1. Prospective outcome emotions

Prospective outcome emotion	Value	Control
Anticipatory joy	Positive (achieving a successful outcome)	High
Hope		Medium
Hopelessness	Positive/Negative	Low
Anxiety	Negative (possibility of failing)	Medium
Hopelessness		High

Figure 1. Prospective outcome emotions PRM
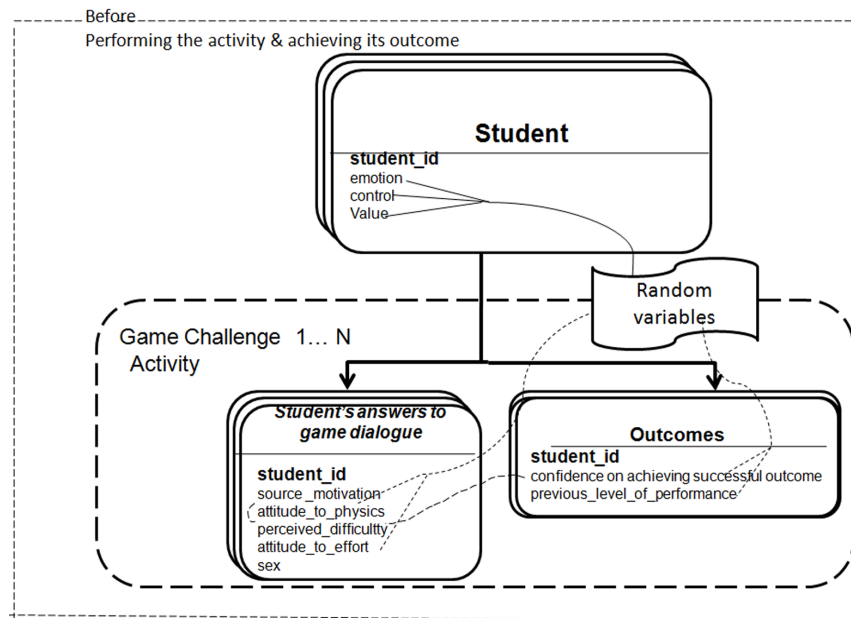
we do not know how these variables are related, if at all, to control and value. Furthermore, we do not know if these variables are related to each other. Figure 1 shows the PRM derived for the *prospective outcome emotions*. The dashed lines between properties indicate relationships, which are not certain and are necessary to verify. To select the contextual variables relevant to the online learning experience in the GBL environment, we considered a subset of the contextual variables employed by McQuiggan, Mott and Lester (2008) and Del Soldato and Du Boulay (1995), which were previously employed to diagnose students' level of self-efficacy and motivation respectively. These works were selected, since motivation and self-efficacy are deeply interrelated to emotion and are mentioned in the Control-Value Theory and the AEQ.

To know how these variables are related, it was observed that we need data from students' interaction in game dialogues and game challenges; since the ultimate goal is that our emotional student model can reason about emotion in online game-based learning (GBL) environment

settings. Also, this GBL environment should enable and encourage students to self-report their emotional state, since as Ortony et al. (1990) mentioned that self-reports are taken as evidence of emotions, as the experience of emotion is subjective and students are the only ones that have access to it. For example we cannot be sure that a person sees a green car as green with 100% certainty. However, if the person says that the car is green, we believe that the person is seen it in a green color. Also, we decided that the GBL environment setting would not have full capabilities of intelligent tutoring, since we want to study the emotions that arise when tutoring is not fully adaptable and intelligent in order to have a base to compare with when adaptable instructional strategies are implemented. Additionally, as mentioned earlier, deciding which affective and cognitive strategies are suitable to apply and how these should be conveyed are considered other challenges of the personalized and adaptable computer tutoring field.

Research Methodology

From the ideas discussed in the "Background and Related work" section, we decided that our methodology will comprise creating a GBL environment that allow students to learn and self-reporting their emotions, and then ask students to interact with the GBL environment in order to acquire data. We selected a GBL environment instead of a VLE, since GBL environments facilitate the establishment of an emotional link for inherent affective characteristics, e.g. narrative, sounds, color. Data mining and machine learning techniques are applied, specifically Necessary Path Condition (NPC) algorithm for structural learning and Expectation Maximization (EM) algorithm (Bashar et al., 2010; Hugin Lite, 2012) for parametric learning. The latter entails computing the log-likelihood in respect of the parameter values. The NPC algorithm enables us to incorporate domain knowledge about the relationships or conditional dependencies between variables when relationships are uncertain owing to scarce data. In addition NPC learning has an enhanced performance on small data sets when compared with the Peter-Clarkson (PC) algorithm. The PRMs originated from the Control-Value Theory are employed to clarify the relations according to the theory. Instead of using cross-tabulation and the observations to obtain the Conditional Probability Tables (CPTs) as in our previous work (Muñoz et al., 2011) we employed the EM algorithm, which makes the process of derivation faster and easier. The accuracy of classification of this model is compared with the accuracy of classification achieved by the model derived in previous work (Muñoz et al., 2011).

PLAYPHYSICS DESIGN AND IMPLEMENTATION

This section discusses our case study, the design and implementation of PlayPhysics, an affec-tive GBL environment for teaching Physics at undergraduate and high school levels. Our case study focuses on collecting data from students' self-reporting of emotion and answers to questions in game dialogue and interaction.

Analysis

We decided to focus on creating a GBL environment for teaching Physics, since students have been shown to find it difficult to comprehend underlying theories of Physics and hence find it difficult to stay engaged (Er & Dag, 2009). To create an application that addresses lecturers' and students' needs, an online survey was conducted. Fifty three students and four lecturers of an introductory Physics course from Tecnológico de Monterrey (ITESM-CCM) and Trinity College Dublin participated in the survey. From this survey, students' background as game players, personality traits and preferred feedback were examined. Also, it was noted that some topics were considered the most difficult, specifically the application of Newton's laws for particles and rigid bodies and principles of linear and circular kinematics. Therefore, PlayPhysics focused on these topics.

Design

PlayPhysics is a GBL environment that enables students to perform a pre-test on these topics to make them aware of their current level of understanding and knowledge. Then it enables them to play a Role Playing Game (RPG) implemented with Java, MySQL, 3D Studio Max, Poser, Hugin Lite, Jakarta Tomcat and the Unity Game Engine. The Unity Game Engine was selected to implement PlayPhysics, since it supports online gaming through the installation of the Unity Web Player in the web-browser (Unity Technologies, 2011). In the RPG, the student is an astronaut contacted by NASA with the purpose of performing a rescue mission by travelling to the Athena space station. The super computer, which was affected by a virus,

Figure 2. PlayPhysics game dialogue
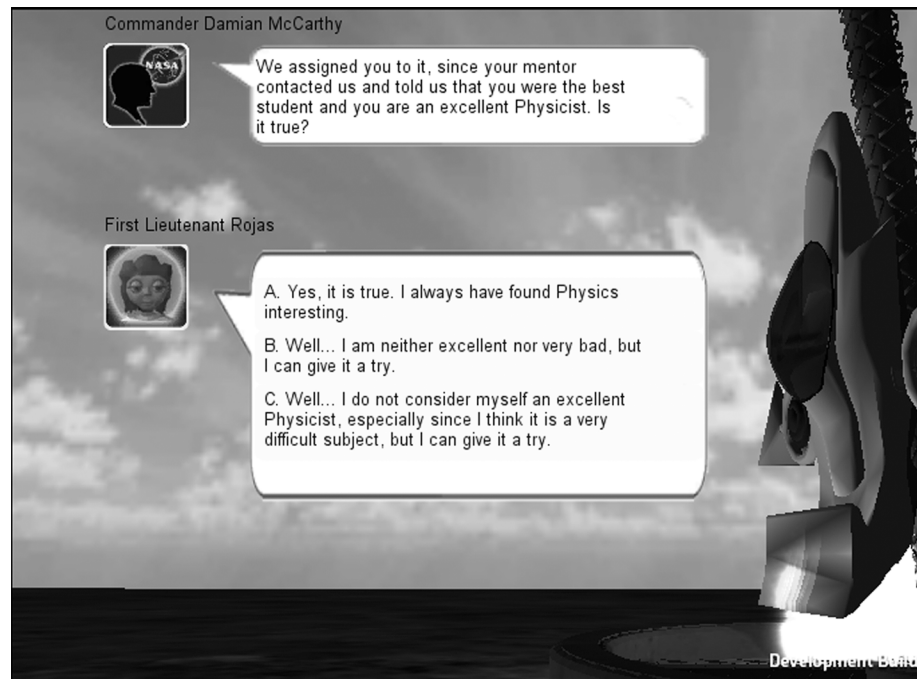
attacked the crew and the captain, Captain Foster is trapped. The first challenge comprises docking the Alpha Centauri spaceship with Athena. When the student is first contacted by NASA they are asked questions about their attitude to Physics, the level of difficulty of the mission according to the students' perspective, the source of motivation to take the mission, the effort that they are willing to spend and how confident they are in achieving a successful outcome. Figure 2 shows a screenshot depicting the PlayPhysics game dialogue. In this specific case, it illustrates the question enquiring about students' attitude towards Physics.

In addition, PlayPhysics includes a learning companion, the M8 robot, which provides hints to students if required. It was designed in this manner, since we did not want to interfere with students' independence. The M8 robot is not a highly effective instructor and companion, since we wanted to know what emotions happen in GBL environments that do not have highly adaptable instructional capabilities. Figure 3 presents the GUI corresponding to the first challenge. A con-

trol panel is displayed if the student chooses the cockpit view or internal spaceship view. The student can then interact in first person and employ the arrows and buttons in the control panel to set the required parameters to operate the spaceship and achieve the main goal corresponding to the first challenge, which involves arriving at the Athena station. The student also can switch to the outside view and watch how the spaceship is moving towards the space station from a third person perspective. The M8 robot appears in the screen on the right if it needs to convey a message, or ask the student to self-report his or her emotional state. The affective feedback provided by the M8 robot is limited to mimicking the emotions that the student self-reports, since knowing how to address and respond to students' emotions is still an ongoing question. For example, if the student reports that he or she is enjoying the learning experience M8 smiles, does a small dance with the upper part of its body and says "I am also having fun". Students can self-report their emotional state anytime using the *EmoReport* wheel.

Figure 3. PlayPhysics first challenge GUI

Game Challenge Design and Domain Knowledge Representation

PlayPhysics scenarios were designed with the assistance of an expert in Astrophysics. In the first challenge or Physics scenario of PlayPhysics, the Alpha Centauri spaceship, is heading at a constant speed towards the space station Athena. The purpose of this challenge is that the student selects appropriate values for Physics variables in order to stop Alpha Centauri precisely at Athena's rotational axis, in order to facilitate docking and entering it before the remaining fuel is exhausted (see Figure 3). The theme addressed in this phase is one-dimensional rectilinear motion with constant deceleration, one of the core topics of an introductory Physics course at undergraduate level. The complete scenario is introduced by M8 as follows:

"The objective of this challenge is to position the Alpha Centauri spaceship just below Athena station. You will have to move the spaceship in a linear path by setting the initial velocity and ac-

celeration (use the mouse to click arrows). Pay attention to the distance to the space station, the time and the available fuel. You need to arrive close to Athena station, so you can dock before the fuel runs out."

The condition variables, assigned randomly by PlayPhysics, are the initial distance from Alpha Centauri to Athena, D, and the remaining time to exhaust Alpha Centauri's fuel, T. The value ranges corresponding to these variables were defined as $D \in [15, 70]$ km and $T \in [80, 120]$ s. On the other hand, the exploration variables, variables for which the student has to select appropriate values, are: i) the direction of Alpha Centauri's acceleration (towards Athena Station '←', or away from it '→'), ii) the magnitude of this acceleration "a", which must be in the range $a = [0, 100]$ m/s², and iii) the initial speed "v_i" of Alpha Centauri, which must be in the range $v_i = [1000, 2000]$ m/s.

The first parameter that the student has to choose is the direction of the acceleration (towards the station '←', or away from it '→'). This is very important, since the chosen direction has to be '→'; otherwise, the spaceship will never stop at Athena's position, but will continue increasing its speed until the fuel is exhausted and then will continue moving at constant speed in interplanetary space forever. As a result, the astronaut will die. In this case PlayPhysics displays the player character with a sad and worried face saying that "he or she is lost in infinity". The student has to try the challenge again. However, M8 asks for the emotion of the student before restarting the game challenge. If the student decides to require a hint from M8, M8 will try to clarify the student misconception by saying: "Oops…Alpha Centauri didn't stop at Athena's axis. Its speed continued increasing".

Once Alpha Centauri's acceleration direction is correctly set, the student can focus on selecting the values corresponding to Alpha Centauri's deceleration magnitude "*a*" and initial speed "v_i" in order to precisely stop at Athena's rotation axis. The corresponding values ranges ($a \in [0, 100]$ m/s² and $v_i \in [1000, 2000]$ m/s²) were defined in order to make the solution non-trivial. For example, the student may be tempted to select a very large value for the deceleration magnitude (*a* > 40 m/s²), which causes Alpha Centauri to stop very quickly, as a result not using all the remaining fuel.

However, humans cannot stand accelerations that are greater than 4g, where g represents the gravitational acceleration on Earth (g = 9.8 m/s²). Therefore, in this case, PlayPhysics displays the player character in a purple color, i.e. blood entered the brain showing that he or she passed out, with an accompanying thinking bubble saying "Too much acceleration". The student may restart the game challenge in order to try again and asks for a hint from the M8 in order to clarify what happened. M8 says: "It seems that the magnitude of

the acceleration is too large (more than 4g)…the astronaut blacked out". Therefore, the student will have to select a smaller value for the deceleration $\left(a \geq 40 m / s^2 \right)$ in order to continue and try to overcome the challenge. On the other hand, if the student selects a very small value for *a,* there is a risk of exceeding the time limit, T, which is required to complete the challenge.

In order to evaluate how effective the student selections for *a* and v_i, PlayPhysics calculates the breaking distance, d_S, and the time used to stop, t_S, for Alpha Centauri. These quantities are calculated using Equations 1 and 2.

$$d_s = \frac{v_i^2}{2a} \quad (1)$$

$$t_s = \frac{v_i}{a} \quad (2)$$

PlayPhysics compares t_S with *T*. If $t_S > T$ PlayPhysics assigns a low grade to the student, because the fuel ran out before Alpha Centauri arrived at Athena and as a result the astronaut is not saved.

If $t_S <= T$, PlayPhysics calculates the relative error, e_d, of the distance, defined by Equation 3.

$$e_d = \frac{d_s - D}{D} \quad (3)$$

This relative error will be small, if the calculations accordingly by the student are accurate. For small values of e_d, the grade or score assigned to the student is higher. A very high grade is obtained when the absolute value of e_d is smaller than 0.02 (a relative error of 2%), and a low grade is obtained when the relative error is larger than 0.10. PlayPhysics also evaluates the student selection according to the resulting breaking time t_S. For each set of randomly assigned condition values, D and T, PlayPhysics calculates the corresponding time

interval, Δt, for all possible values of t_s that are consistent with valid values of a and v_i. Higher grades or scores are assigned for smaller values of t_s, because less fuel was consumed.

As can be seen, the student's selection of values for a and v_i is not trivial because they have to satisfy all the conditions imposed by the scenario, achieving the least value for the breaking time, not surpassing the maximum acceleration limit (40 m/s²), not exceeding the fuel exhaustion time and achieving the smallest relative error in the breaking distance. The solution to the scenario is relatively simple when D and T are large, since the combinations of a and v_i that fulfill all the requirements are greater. On the contrary, if T and/or D are too small, the valid combinations become scarce.

EVALUATION

In the winter of 2011, eighty-four high school and undergraduate students undertaking a Physics course at Tecnológico de Monterrey, Mexico City campus (ITESM-CCM), interacted with PlayPhysics. Students solved a pre-test, afterwards they interacted with the first challenge of PlayPhysics and finally solved a post-test and qualitative questionnaire. Students self-reported their emotional state before, during and after performing the game activity.

This work centres on the emotions reported before interacting with the game challenge. As a result, the data collected and recorded in the database was employed to validate and compare the performance of the emotional student model derived and presented for the *prospective outcome emotions* in Muñoz et al. (2011) with the one derived using NPC structural learning and EM learning algorithms in this work. The former DBN model was created using cross-tabulation and MLR using the data collected from a sample of sixty-six undergraduate students of Physics in September 2010 (Muñoz et al., 2011). This same data was reused in this work to derive the DBN model applying NPC structural learning and EM learning, which are implemented in Hugin Lite (Hugin Expert A/S, 2011), which also has a Java API, e.g. HAPI. The motivation for this investigation arose from observing that the derivation of

Figure 4. Prospective outcome emotions DBN derived using cross-tabulation and MLR
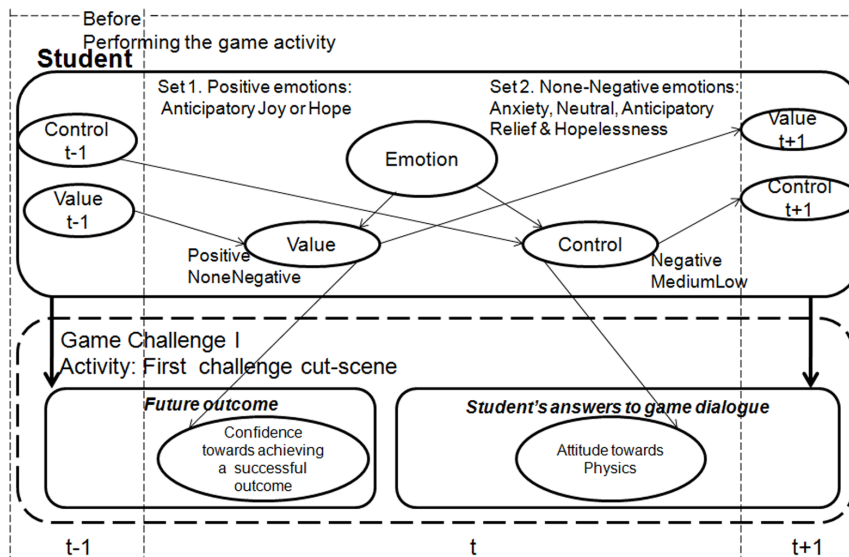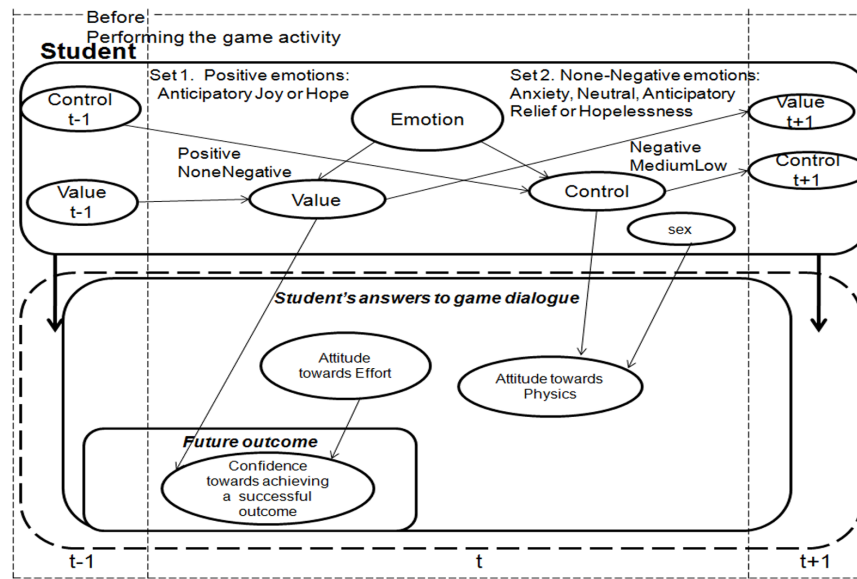
Figure 5. Prospective outcome emotions DBN derived using NPC and EM algorithms

the previous DBN was time consuming and the classification accuracy needed to be improved. Figures 4 and 5 show the comparable DBNs:

The data corresponding to sixty-six students on September 2010 was employed for deriving the network structure in Figure 5 using the NPC algorithm. Hugin Lite required us to address the links that were identified as uncertain. Confidence was linked to the node Value only and Control was linked to Emotion. The data corresponding to the eighty-four students was employed to evaluate this model and the model in Figure 4, derived in previous research (Muñoz et al., 2011). We decide to employ the same sets of data to perform a fair comparison of their performance. As can be seen the DBN structure in Figure 5 includes two additional nodes, *gender* and *attitude towards effort*, in contrast to the DBN in Figure 4. What this indicates is that in this specific population, students' sex, male or female, is associated to their attitude towards Physics. There were 40 males and 26 females in this sample, 27 males corresponding to 57.5% from the male sample reported to have a neutral or negative attitude towards Physics, while 22 females corre-

sponding to 84.6% from the female sample reported to have a neutral or negative attitude towards Physics. When analyzing the Pearson correlation between the *attitude towards physics* and *students' sex*, this resulted to be negative and equal to 0.284 and significant at 0.05 level where there are 66 pairs of values, i.e. $r(66) = -0.284$. The square of the correlation (r^2) or coefficient of determination is usually employed to analyze the effect size. In this case r^2 is equal to 0.0806, since it is less than 0.09 and larger than 0.01 the effect is small and 1% or 8% of the variance between these variables is shared. Whilst analyzing the Pearson correlation between the students' attitude towards effort and the students' confidence, this was found to be significant at 0.05 level, positive and equals to 0.281, which is related to observing that 71.9% of the students on this specific sample have a positive attitude towards effort and reported to have a high level of confidence and 55.9% of students that do not have or have a negative attitude towards effort reported to have a low or medium level of confidence, i.e. $r(66) = 0.281$ and $r^2=0.079$. This correlation has a small effect over student confidence.

Results of the performance of both models classifying emotions, control and value are summarized and presented in Tables 2, 3 and 4 respectively. As can be observed, both models classify emotion significantly with approximately 70% accuracy. This is due to being capable of classifying the categorical variable value with the same accuracy (also 70%). In this case the valence of the defined set of emotions agrees with their value. This can be understood as students that evaluate as positive (positive emotion) the probable outcome of the task expect to succeed (positive value), whilst students that evaluate as negative (negative emotion) the probable outcome of the task expect to fail (negative value). Also, it is not clear if positive emotions are classified with 58.1% accuracy, or they are classified with this percentage only by chance, since the p-value is not significant. However, it is clear that negative and neutral emotions are classified with 80.5% accuracy by both models. In addition, control is classified with an accuracy of 63% by both models. However, in the model attained using NPC and EM algorithms, it can be affirmed that high control is classified with 6.3% accuracy, while low and medium control are classified

with 98.1% accuracy. It is clear that to achieve an enhanced discrimination and reasoning of emotion, other variables that classify control more accurately should be identified. In comparison to Control-Value Theory, we are including the neutral or no-emotion, since Pekrun et al. (2007) state that if there is no control or value, there is no emotion, which we interpret as the student not having any interest in the outcome or the task, i.e. the outcome or the task is irrelevant, the student does not focus on failure or success and does not feel the motivation to compel himself or herself to manage and accomplish the task. As a result, we decided to locate the neutral emotion in the set of negative emotions, since they are emotions that we would like to address using adaptive instructions.

Focusing on the 33 cases (80.5%) that were classified accurately and correspond to the negative-none emotion set, it was observed that 13 cases corresponded to a neutral emotion, 11 cases to anticipatory relief, 6 cases to anxiety and 3 cases to hopelessness.

The emotional student model derived for reasoning about *prospective outcome emotions* using MLR revealed that the value of emotion is influenced by students' confidence and con-

Table 2. Comparison of performance classifying emotion

Prospective outcome emotions DBN model	Emotion set	Cases correctly classified	Cases incorrectly classified	Binomial test result (Bernoulli trials)
MLR & cross-tabulation derived (Muñoz et al., 2011) Accuracy ≈ 70% p =0.001, g =0.38 Large size effect	Positive emotions (anticipatory joy and hope) 43 out of 84 students	25 (58.1%)	18 (41.9%)	p = 0.360 is not significant Medium size effect g = 0.16
	None-negative emotions (neutral, anxiety, anticipatory relief and hopelessness) 41 out of 84 students	33 (80.5%)	8 (19.5%)	$p = 1.1222 \times 10^{-4}$, $p<0.05$ is significant Large size effect g = 0.61
NPC structural learning & EM learning derived Accuracy ≈ 70% p =0.001, g =0.38 Large size effect	Positive emotions (anticipatory joy and hope) 43 out of 84 students	25 (58.1%)	18 (41.9%)	p = 0.360 is not significant. Medium size effect g = 0.16
	None-negative emotions (neutral, anxiety, anticipatory relief and hopelessness) 41 out of 84 students	33 (80.5%)	8 (19.5%)	$p = 1.1222 \times 10^{-4}$, $p<0.05$ is significant Large size effect g = 0.61

Table 3. Comparison of performance classifying control

Prospective outcome emotions DBN model	Control	Cases correctly classified	Cases incorrectly classified	Binomial test result (Bernoulli trials)
MLR & cross-tabulation derived (Muñoz et al., 2011) Accuracy = 63% p=0.021, g = 0.26 Large size effect	High 32 out of 84 cases corresponded to high control	14 (43.8%)	18 (56.3%)	$p = 0.597$ is not significant Small size effect $g = 0.12$
	Medium-low 52 out of 84 cases corresponded to medium-low control	39 (75%)	13 (25%)	$p = 4.0954 \times 10^{-4}$ is significant Large size effect $g = 0.5$
NPC structural learning & EM learning derived Accuracy = 63% p=0.021, g = 0.26 Large size effect	High 32 out of 84 cases corresponded to high control	2 (6.3%)	30 (93.8%)	$p = 2.4633 \times 10^{-7}$ is significant Large size effect $g = 0.875$
	Medium-low 52 out of 84 cases corresponded to medium-low control	51 (98.1%)	1 (1.9%)	$p = 2.3537 \times 10^{-14}$ is significant Large size effect $g = 0.962$

trol is influenced by students' attitude towards Physics. However, when we derived this model using the NPC algorithm, this was confirmed, but also revealed that for this specific population, students' gender has a small influence over the attitude towards Physics and frequently females have a more negative attitude towards Physics than males. Additionally, it was also revealed that students' attitudes towards effort has a small influence over students' confidence, which is directly proportional, i.e. students' confidence decreases if the student has a negative attitude towards effort.

RELATION TO OTHER WORK

Students' attitudes towards the subject, confidence and effort are three constructs evaluated by Pekrun et al. (2007) using the AEQ questionnaire (Pekrun et al., 2005). It is also observed that approximately 70% of achievements emotions value is accurately

Table 4. Comparison of performance classifying value

Prospective outcome emotions DBN model	Value	Cases correctly classified	Cases incorrectly classified	Binomial test result (Bernoulli trials)
MLR & cross-tabulation derived (Muñoz et al., 2011) Accuracy ≈ 70% p =0.001, g =0.38 Large size effect	Positive 43 out of 84 cases corresponded to positive value	25 (58.1%)	18 (41.9%)	$p = 0.360$ is not significant Medium size effect $g = 0.26$
	None-negative 41 out of 84 cases corresponded to none-negative value	33 (80.5%)	8 (19.5%)	$p = 1.1222 \times 10^{-4}$ is significant Large size effect $g = 0.6$
NPC structural learning & EM learning derived Accuracy ≈ 70% p =0.001, g =0.38 Large size effect	Positive 43 out of 84 cases corresponded to positive value	25 (58.1%)	18 (41.9%)	$p = 0.360$ is not significant Medium size effect $g = 0.26$
	None-negative 41 out of 84 cases corresponded to none-negative value	33 (80.5%)	8 (19.5%)	$p = 1.1222 \times 10^{-4}$ is significant Large size effect $g = 0.6$

classified by students' confidence and this is owing to more accurately classifying the category none-negative. In Control-Value Theory, value is related to the focus of the student on succeeding or avoiding failure, and hence, it makes sense that the value is related to students' confidence. Also, it is observed that the value agrees with students' valence, which is linked with attractiveness or evasiveness of an event, in this case achieving a successful outcome or failing. A difference of our work compared with the work by Pekrun et al. (2007) is that we are including the neutral or no-emotion category, since in our case, we do not know if the activity is relevant from the student's viewpoint, therefore, we do not know if value or control exists.

Del Soldato and Du Boulay (1995) following the theory of Keller (1983) also noted that effort, confidence and student interest are involved in students' motivation, which, unsurprisingly correlated to student's motivation in our work, since motivation is also influenced by students' emotion. In addition, students' beliefs of confidence are also related to students' self-efficacy. Therefore, McQuiggan et al. (2008) in an effort to identify students' affective aspects focus on classifying students' level of self-efficacy. In addition, our results show that the emotional student model achieved by applying the NPC and EM algorithms is more effective of classifying control, since this model proved to classify correctly 6.3% of the cases related to High control. The model obtained through MLR cannot ensure that 43.8% of the cases classified correctly in this category were not categorized by chance. However, it is noted that 98.1% of the cases classified as medium-low control were correctly classified. As a result, the control perceived is influenced by students' attitude towards Physics, agreeing with what Pekrun et al. (2007) stated about achievement emotions, which depend on the subject domain. Therefore, we can observe that the Control-Value Theory shows promise while employed as a basis for deriving an emotional student model for GBL.

FUTURE RESEARCH DIRECTIONS

This research evaluated the DBN that we derived to classify *prospective-outcome* achievement emotions. As NPC and EM algorithms proved more effective than MLR and cross-tabulation and are less time consuming, we will use them to derive the DBNs corresponding to *activity achievement emotions* and *retrospective-outcome achievement emotions*. We acquired from the interaction of these 84 students at ITESM-CCM approximately 1073 registries, which will be employed to reason about emotion using contextual variables related to the game activity, such as time invested and mouse location. In addition, we will acquire interaction and Galvanic Skin Response (GSR) data corresponding to 10 students to evaluate if data corresponding to the student internal context enhances the prediction accuracy. We selected GSR, since research has shown that it is more effective than Heart Rate (HR) signals (Rajae-Joordens, 2008). However, Pekrun et al. (2005) employ questions about the students' heart rate on the AEQ as evidence to determine if the student is feeling a specific emotional state. In addition, more challenges will be designed for PlayPhysics and research can be focused on identifying how to suitably respond to students' emotion in order to enhance learning and engagement.

CONCLUSION

This chapter reviews the state of the art of Edutainment, ITSs, Student Modeling and Emotion in Computing and Education. Three approaches to recognizing emotion were identified. The Cognitive-based User Modeling (CB-AUM) approach was employed in this work using Control-value Theory of achievement emotions (Pekrun et al., 2007) as a basis. We are the first employing this theory to derive a computational student model of this nature. The model uses answers to questions in game dialogues and contextual variables for

reasoning about emotion acquired through the student interaction with PlayPhysics, an emotional game-based learning environment for teaching Physics that comprises self-reporting capabilities. Results showed promise on classifying negative-neutral emotions, emotion overall is classified with 70% accuracy. Therefore, using Control-Value Theory to derive our emotional model showed potential and can be employed in online GBL environments, since it uses contextual and feasible variables. Two approaches to derive DBNs were compared: (1) using MLR and cross-tabulation and (2) using NPC and EM algorithms. The latter results in being more effective at classifying control and at finding other relevant relationships between variables involved in the classification. In addition, the process is less time consuming. As a result, this approach will be employed to derive the DBNs corresponding to the *activity* and *retrospective-outcome achievement emotions*. PRMs were employed in combination with both approaches to facilitate the derivation of DBNs and the identification of potential observable variables. Data corresponding to the interaction and the student GSR will also be collected in order to determine if evidence related to the internal student context when employed in combination with contextual variables enhances the accuracy of the model.

ACKNOWLEDGMENT

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KEY TERMS AND DEFINITIONS

Achievement Emotions: Are emotions that arise in learning and educational settings where the achievement of activities and their outcomes is pursued.

Control-Value Theory: Is a cognitive theory by Pekrun et al. (2007) in which control and value appraisal are assumed the most relevant to determine emotion.

Dynamic Bayesian Networks: Are a type of machine learning technique used for achieving knowledge representation that are highly effective handling the uncertainty of domains that evolve over time and incorporate previous knowledge of the domain.

Educational Data Mining: Is a discipline focused on developing methods for analyzing data from educational settings in order to achieve an enhanced understanding and awareness of the student and the environment in which he/she learns.

Game-based Learning Environments: Are a type of *Edutainment* environment, i.e. games used with the serious purpose of teaching in parallel to keep students' engagement.

Intelligent Tutoring Systems (ITSs): Are a type of computer tutoring that have the capability of adapting teaching and feedback to students' needs and skills and, in addition, to the capability of reasoning about students' characteristics.

Probabilistic Relational Models: Are an object representation of the domain, i.e. parameters, classes and the relations between them, which facilitate the derivation of Bayesian Belief Networks (BBNs).

Student Modeling: Is the process involved on deriving a knowledge representation of the student comprising needs, skills, knowledge, learning preferences or other characteristics in order to achieve personalization through an enhanced understanding of student behavior.