Designing and Evaluating
Emotional Game-based Learning Environments

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Abstract

Research in game-based learning environments aims to recognise and show emotion. This chapter describes the main approaches and challenges involved in achieving these goals. In addition, we propose an emotional student model that can reason about students' emotions using observable behaviour and responses to questions. Our model uses Control-Value Theory (Pekrun et al. 2007) as a basis for representing behaviour and was designed and evaluated using Probabilistic Relational Models (PRMs), Dynamic Bayesian Networks (DBNs) and Multinomial Logistic Regression. Olympia, a game-based learning architecture, was enhanced to incorporate affect and was used to develop *PlayPhysics*, an emotional game-based learning environment for teaching Physics. PlayPhysics' design and emotional student model was evaluated with seventy nine students of Engineering at Tecnológico de Monterrey, Mexico City campus (ITESM-CCM). Results are presented and discussed. Future work will focus on conducting tests with a larger population of students, implementing additional game challenges and incorporating physiological signals to increase the accuracy of classification.

1 Introduction

Computer tutoring has developed over time in order to adapt to students' expectations (Oblinger 2004) and has proven more effective than traditional classroom instruction (Regian et al. 1996). Intelligent Tutoring Systems (ITSs) offer advantages, such as following students' performance over time, generalising pedagogical actions to different problems and domains and understanding and responding suitably to students' needs (Clancey and Buchanan 1982).

On the other hand, serious games have emerged as a field that combines serious aspects, e.g. teaching, learning, communicating or informing, with playful characteristics of entertainment activities (Alvarez 2007). Serious games employ attractive features that can achieve and hold students' attention and are also used for the delivery of learning content. As a result, the term edutainment was created to define a specific application of serious games. Edutainment is an approach that combine education and entertainment (Qianping et al. 2007).

Edutainment enhances the significance of games by incorporating pedagogical techniques to deliver educational content, present education in a less stressful way than traditional methods and enable students to enjoy the learning process and increase their interest in content. In addition, edutainment environments take advantage of students' technological skills to incorporate attractive features that support the learning process. Similarly, the characteristics of edutainment environments can be aligned to students' varied learning styles to achieve learning objectives (Cela 2008).

Cognitive and affective mechanisms have proven deeply interrelated (Norman et al. 2003). Emotion influences learning, performance, motivation, interactions and personal growth (Pekrun et al. 2007). The research field of Affective Computing (Picard 1995) merged with ITSs and edutainment. As a result, researchers have focused on the creation of a new generation of ITSs and educational games, which are capable of recognising and showing emotion (Picard et al. 2004; Sykes 2006). The ultimate goal is to encourage students' learning and understanding whilst achieving and maintaining students' motivation and interest. Our research is mainly focused on this endeavour.

The challenges involved when reasoning about students' emotions are to know how and when emotion arises, to understand which factors determine an emotion or an affective state and determine what emotions are relevant to the learning experience. In addition, it is important to know that personal preferences and differences influence the presence and communication of an emotional state (Conati and Maclaren 2009). Therefore, it is important to deal with the inherent uncertainty of the emotional domain. Also, in education, the effects of positive and negative emotions are not totally understood. It is also not always clear what should be the appropriate response to a student's emotion (Alexander and Sarrafzadeh 2008; Lepper et al. 1993; Schutz and Pekrun 2007). Additionally, the creation and acceptance of educational games involves creative design and academic concerns, such as the difference between game content and curriculum content and resis-

tance to the idea that games can be an effective method of teaching (McFarlane et al. 2001).

In this chapter, we focus mainly on how to develop an emotional student model that can reason about students' emotions using observable behaviour, i.e. interaction data, and questions answered during game dialogue. Our emotional student model is focused on reasoning about achievement emotions, which are experienced in academic settings and arise in response to activities and their outcomes when the quality of achievement is judged according to established standards (Pekrun et al. 2007). Therefore, our emotional student model uses Control-Value theory from Pekrun et al. (2007) as a basis for representing emotion. The theory is an integrative framework that assumes that control and value appraisals are the most significant factors when determining an emotion. Control-Value Theory has not previously been employed to create a computational and emotional student model. Our approach employs Probabilistic Relational Models (PRMs) to facilitate the derivation of Dynamic Bayesian Networks (DBNs), which enable us to handle uncertainty effectively. In addition, we discuss what features an emotional game-based learning environment of this nature must have in order to achieve this goal.

This work is summarised in six sections. In section 1, we provide a succinct overview of the challenges involved and we discuss the state of the art of educational game-design, evaluation of affective applications and emotional game-based learning environments and the different research approaches employed by the new generation of ITSs to recognise and respond to emotion. Section 2 focuses on our proposed research approach, emotional student model and the description of an affective enhancement of the Olympia architecture (Muñoz et al. 2009). In section 3, we discuss the application of our research proposal to a specific case study - the design and implementation of PlayPhysics, an emotional game-based learning environment for teaching Physics at undergraduate level. PlayPhysics was developed using Java, the Unity Game Engine, 3D Studio Max and Hugin Lite. Section 4 discusses the results of the evaluation of our proposed emotional student model. Tests were conducted on 79 students enrolled in an engineering undergraduate course at Tecnólogico de Monterrey, Mexico City campus (ITESM-CCM). In section 5, we discuss our findings in the context of related work. Finally, we conclude by outlining the advantages of our research approach and discussing future enhancements.

2 Background and related work

Our research focuses on recognising and responding to emotions effectively in a game-based learning environment, which will ensure students' learning and understanding and hold students' interest and motivation. To achieve this endeavour, it is necessary to be aware of existing approaches and the challenges involved.

2.1 Challenges of emotional game-based learning environments

Advances in psychology, cognitive science, multimodal applications, neuroscience, cinematography and artificial intelligence (AI) have promised dramatic changes in computer tutoring. Research efforts have focused mainly on two main challenges: achieving the most accurate perception of students' needs and responding in the most suitable manner to these needs in order to nurture and grasp student's knowledge, understanding, motivation, attention and interest (Du Boulay and Luckin 2001). When ITSs were incorporated into game-based learning environments to offer adaptable instruction and ensure the achievement of specific learning goals (Blanchard and Frasson 2006; Conati and Maclaren 2009), the learning environments inherited these challenges.

Student modelling is an area focused on achieving an abstract knowledge representation of the student (Woolf 2009). Research focused first on the representation of students' cognitive state. Clancey and Buchanan (1982) noted that students' errors were related to students' misconceptions about domain knowledge and endeavoured to represent teaching and problem solving knowledge in the GUIDON ITS. Research has also attempted to characterize students' learning styles (Jungclaus et al. 2003) and more recently, students' personality traits, attitudes (Arroyo and Woolf 2005), motivation (Del Soldato and Du Boulay 1995; Rebolledo-Mendez et al. 2006), self-efficacy (McQuiggan et al. 2008) and affect and emotion (Conati and Maclaren 2009; D'Mello et al. 2008; Sarrafzadeh et al. 2008). AI techniques, such as semantic nets, rules, constraints, plan recognition and machine learning, are applied to make computers capable of reasoning about knowledge (Woolf 2009).

The interest in researching the influence of emotion in education has been relatively recent and still not completely known (Pekrun et al. 2007; Picard et al. 2004). It is noted that diverse factors influence the presence and communication of people's emotion, e.g. personality traits, attitudes, preferences, goals and cultural and social conventions. Hence, an expert human identifies affect or emotion with approximately 70% accuracy (Robson 1993). In an attempt to identify the relevant factors that determine an emotional state and the relevant affective and emotional states, researchers in the computing field have focused on observing, annotating, recording and analysing students and lecturers' interactions (Alexander and Sarrafzadeh 2008; D'Mello et al. 2008) or reviewing research in education and

cognitive psychology (Conati and Maclaren 2009; Del Soldato and Du Boulay 1995). It is important to emphasise that there is not a universal classification of emotion (Ortony et al. 1990). Additionally, the context, where emotion arises, influences the type of emotions that are frequently observed (Pekrun et al. 2007). Therefore, determining the relevant emotions to the specific learning experience also constitutes a challenge.

Two key features that must be accomplished by computer tutoring, in order to effectively adapt to students, are: (1) effectiveness of representing and handling domain knowledge to achieve flexibility in different teaching situations and (2) believability of the communication of pedagogical responses (Lester et al. 1997). Therefore, research has focused on implementing Embodied Pedagogical Agents (EPAs) (Lester et al. 1999) and synthetic characters (Dias et al. 2006). Their common challenges are adapting to changes in the environment, incorporating planning and execution mechanisms and performing collaborative activities (Johnson et al. 2000; Mateas 1997). Since emotion modelling is a relatively new and unknown field, it is not clear how computers should respond effectively to students' emotions (Pekrun et al. 2007). As a result, research has focused on observing teaching-learning interactions to identify suitable responses (Lepper et al. 1993; Porayska-Pomsta et al. 2008).

2.2   Game design principles, frameworks and models

In addition to the challenges that are faced when creating a game-based learning environment capable of recognising and showing emotion, there is the challenge of ensuring that the environment is also capable of delivering effective learning and understanding that it is aligned with the academic curriculum. The Games-to-teach research team, created at the Massachusetts Institute of Technology (MIT) and Microsoft, outlined some design principles that should be considered whilst creating educational games (Squire 2003). From these principles, we selected what we consider the most important:

- Originate the educational game's creation from a standard simulation
- Enhance the basic attributes and abilities of game features and characters through the incorporation of learning objects as intrinsic motivators
- Identify real-world applications of the concept that is going to be taught
- Design goal-based scenarios, decisions, consequences and join goals

Game-based learning environments should have as features challenge and fantasy, must be capable of offering a sense of control and evoke curiosity (Malone 1981). In addition, it is important to spend time on designing the *gameplay*, since this comprises the core of the game. *Gameplay* does not have a single definition. It is a mixture of diverse entities and the resultant interaction between them (Rollings and Adams 2003). A way of creating *gameplay* is setting challenges, which can be of different types. Types of challenge highly related with the educa-

tional domain are: (1) *logic and inference challenges*, which confront player's skills to take the best course of action by grasping and using information; (2) *knowledge-based challenges*, which depend on the player's knowledge, which can or cannot be acquired through the game world; (3) *moral challenges*, which rely on meta-ethics and the player's view, develop from general aspects to more specific ones and may be of universal, cultural, tribal and personal character, and (4) *applied challenges*, which are comprised by a combination of pure challenges, e.g. races, puzzles, exploration, conflict, economies, concepts, applied to a specific situation.

On the other hand, there are design paradigms, which describe how to incorporate games into learning environments. As an example, the Fuzzified Instructional Design Development of Game-like Environments (FIDGE) model is an instructional design development model (IDDM) for designing, developing and implementing game-based learning environments. It is comprised of phases, e.g. preanalysis, analysis, design, development and evaluation. The progression between phases is not linear and is without clear established boundaries (Akilli and Cagiltay 2006). Its key characteristic is an awareness of real-world uncertainty, since it was created using real life scenarios for reference. The strategies proposed by the FIDGE model offer time management efficiency, early decision making about the technology to use, continuous evaluation and flexibility and modularity of the final product.

In addition, it is important to remember that the adoption and acceptance of the final product depends on understanding correctly the learners and lecturers' needs. As an example, the Demographic Game Design 1 (DGD1) is a design model used to take into account the player's styles or preferences during the design process.

2.3   Approaches for recognising emotion

As mentioned earlier, our work is focused mainly on reasoning about student's emotions, i.e. creating an emotional student model. ITSs are beginning to incorporate emotional aspects in their architectures. There are three discernable approaches: (1) identifying the physical effects of emotion, (2) reasoning about emotion from its origin and (3) a hybrid approach, which comprises the first two approaches.

To identify the physical effects of emotion, it has been necessary to enhance computer perception through the incorporation of cameras, microphones and sensors, which are capable of capturing a variety of interaction data, e.g. facial gestures, eye movement, voice prosody and inflection, galvanic skin response, heart rate and body posture (D'Mello et al. 2008; Sarrafzadeh et al. 2008; Pasch et al. 2009). However, to be capable of reasoning about this information it is necessary to employ AI techniques, such as artificial neural networks. In addition, it is necessary to associate distinguishable patterns of interaction with specific emotional states. To attain this goal, expert judges and students' self-reports are employed. A

challenge of this approach is its general unavailability online, since sometimes the hardware employed is expensive and difficult to find. Therefore, students typically have to travel to a lab where they can interact with an application of this nature (Burleson and Picard 2007).

For reasoning about emotion, researchers often use a cognitive theory of emotion as a basis (Jaques and Vicari 2007). The most common theory employed in the literature is the Ortony, Clore and Collins (OCC) model, which reasons about attitudes, standards and goals (Ortony et al. 1990). Jaques and Vicari (2007) adapted the theory to learning context. However, there is no evidence of the effectiveness of the approach. Its main challenge is how to be aware of students' attitudes, goals and standard. The OCC model has been employed more effectively to reason about emotions in text (Li et al. 2007), since Ortony et al. (1990) based the rationale of their theory using the specific case of study of experiences registered in personal diaries.

Existing student models that reason at a cognitive level about observable behaviour, motivation (Arroyo and Woolf 2005; Del Soldato and Du Boulay 1995; Rebolledo-Mendez et al. 2006) and self-efficacy (McQuiggan et al. 2008) models have proved the most effective.

A hybrid approach reasons about the variables that determine an emotional state at a cognitive level and employs analysis and classification of interaction data to ensure that the emotion inferred has occurred (Conati and Maclaren 2009). This approach inherits the challenges of previous approaches.

Recently in the field of cognitive psychology and emotion in education, emotion has proven to be interrelated with motivational and cognitive factors (Pekrun et al. 2007). In the context of achievement, where activities are performed in the light of their possible outcomes, students experience *achievement emotions*, which are mainly determined by control and value appraisals. This is known as the Control-Value Theory of *achievement emotions* (Pekrun et al. 2007). Control is related to students' beliefs about being capable of initiating and performing an activity, whilst value is related to the attainment of success and the prevention of failure. At present there is no computational and emotional student model based on this theory.

2.4   Affective evaluation of game-based learning environments

The evaluation of affective applications focuses on two key goals: (1) knowing whether the emotion demonstrated by the computer application was genuine, i.e. naturally expressed (Höök 2005) or (2) ensuring that the emotion experienced by the student was accurately identified (Conati and Maclaren 2009; Conati 2002). Context and cultural differences have to be considered when attempting to achieve effective emotion modelling employing EPAs or synthetic characters. The aims are to understand how end users react to applications that show emotion or affect and to achieve design that ensures effectiveness and facilitates the application's

acceptance. Methods employed to evaluate these systems are quantitative-scientific and open-ended interpretation (Höök 2005). Quantitative-scientific methods encounter difficulty trying to capture a more detailed view of end-users' interaction experience. Open-ended interpretation offers results that are temporary and culturally dependent. However, it provides results that are user-specific instead of results that can be generalised to a particular population.

Höök (2005) proposes an evaluation method at two different levels of interpretation about cases where the system was unsuccessful at trying to communicate its intention. The first level is related to knowing if the student understands the expressed emotion, and the second level is about determining if the system can understand students' emotions accurately. The most frequent problems experienced in the design and implementation of these kinds of emotional applications are synchronization, contextualisation, users' interaction control, timing and realism. The latter is related to users' beliefs and expectations about the response that avatars that look like humans should be capable of offering.

Wizard of Oz is a method employed to design and evaluate emotional applications and involves making users believe that they are interacting with the computational system when they are actually interacting with a human (Andersson et al. 2002) . Its main advantage is that the possible answers to users' interactions are unlimited.

On the other hand, focusing on the problem of evaluating the accuracy of an emotional system recognising or reasoning about emotions, research has included interfaces to register students' self reports at anytime or to interrogate students about their emotional state over time (Conati 2002). Statistical methods are then employed to search for a significant correlation between the interaction data and the reported emotion. This method may be perceived as intrusive. Another method employed is to use expert judges for observing, annotating and reviewing interaction videos or other type of material. The judges determine the emotions experienced over time by users (D'Mello et al. 2008). As was mentioned earlier, an expert human can recognise emotion with approximately 70% accuracy, which represents a limitation for this approach.

In the next section we focus on describing in detail our proposed emotional student model taking the reviewed state of the art into account, the research methodology involved and the affective enhancements proposed for the Olympia architecture. Olympia (Muñoz et al. 2009) combines ITSs and game-based learning environments. It was applied to the specific case study of teaching Physics at undergraduate level, since a key challenge was to encourage learning to assist students understand the underlying theory.

3 Formalisation of emotional student model

Our aim is to create an emotional student model capable of reasoning about students' emotions using answers to questions posed during game dialogues, observable interaction data and control-value theory. Once the model is defined, it has to be evaluated. Accordingly, we created a research methodology, which uses students' self-reports and Multinomial Logistic Regression. The latter was chosen since control and value appraisals are categorical variables. In addition, Olympia was enhanced by incorporating this emotional student model and a motivational modulator, which comprises affective and motivational strategies.

Achievement emotions are dependent on the teaching domain, since the factors that determine an emotion also depend on it (Pekrun et al. 2007). As an example, a student learning History experiences different types of *achievement emotions* than a student who is learning Physics. In addition, types of *achievement emotions* are defined according to the focus and time frame. For example, when the student is focused on the future outcome of an activity or task, the student may experience *outcome-prospective* emotions, such as anxiety and hope. On the other hand, if the student is focused on the activity at present, the student may experience *activity* emotions, such as enjoyment and frustration. Finally, according to this theory the student may be focused on the latest outcome after performing a task or activity. Hence, the student might experience *outcome-retrospective* emotions, such as shame or pride. It is important to signal that if an appraisal of control or value is lacking, it is assumed that an achievement emotion is not present. Pekrun et al. (2007) created the Achievement Emotions Questionnaire (AEQ) (Pekrun et al. 2005) through Structural Equation Modelling (SEM) to determine through students' self-report whether *achievement emotions*, were present in classroom instruction, independent learning or tests.

Emotional student modelling involves handling the uncertainty of the emotional domain, in order to reason about the possible causes of emotions and infer whether emotions are present or not (Woolf 2009). Dynamic Bayesian Networks (DBNs) are an AI technique used to model dependencies when prior domain knowledge is available (Jensen and Nielsen 2007). Random variables comprise the nodes of each DBN. They are two steps involved in creating a DBN: (1) defining the causal dependencies, i.e. structure and (2) defining the probabilities on the Conditional Probability Tables (CPTs). To facilitate the derivation of DBNs structure, Probabilistic Relational Models (PRMs) are employed (Sucar and Noguez 2008), the key advantage of which is to enable the handling of information and random variables simultaneously. PRMs are an object oriented representation of the domain.

Using these ideas as a basis, first we focused on creating a general PRM of control-value theory, which is shown in Figure 1. This PRM schema was then used to derive three specific PRMs, each one corresponding to one of the types of *achievement emotions* defined by Pekrun et al. (2007). Control-value theory is a framework that uses motivational, cognitive, physiological and affective factors to ensure that students experience an *achievement emotion*. The PRMs corresponding

to the *outcome-prospective*, *activity* and *outcome-retrospective* emotions are shown in Figures 2, 3 and 4 respectively. It is important to note that the random variables used are not always available and come from different sources. The random variables for the *outcome-prospective* emotions (Figure 2) were selected from the AEQ, e.g. attitude beliefs towards Physics and confidence towards the possible level of performance. For this time frame, the variables involved comprise students' beliefs and expectations. Therefore, to enquire about these, we created questions that were incorporated into the game dialogue.
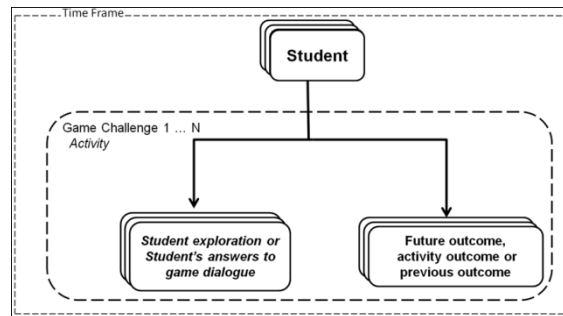
Fig. 1 General PRM of control-value theory
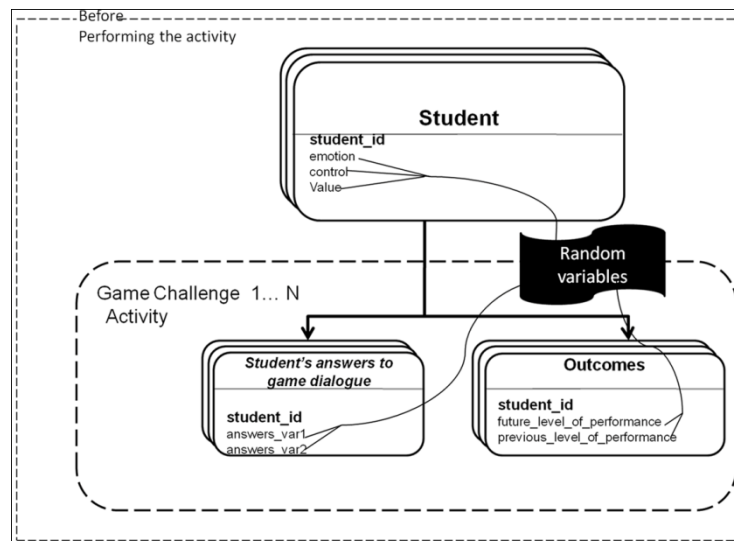
Fig. 2 Outcome-prospective emotions PRM

To select the interaction random variables that we assume related to students' control and value appraisals during or after the student interaction with the game challenge, we considered the observable variables employed by models of motivation (Del Soldato and Du Boulay 1995) and self-efficacy (McQuiggan et al. 2008)

that have proven effective and that are highly related to the factors incorporated into the AEQ and the type of game challenges that we want to implement. For the *activity* emotions (Figure 3), we selected the following random variables:

- Type of outcome, i.e. *outcome_type*, corresponds to the end condition of the challenge. If it is the result of an error, the kind of domain misconception identified is registered. As an example, the student may not understand that acceleration is a vector quantity, and fail as a result.
- Outcome, i.e. *predicted outcome* or *latest_outcome*, is the quantitative percentage of completion of the task. A percentage below 70% indicates a failed mission.
- Number of times that the student asked for help, i.e. *num_times_help_asked*, is related to the number of times the student requested a hint or consulted the learning assistant.
- Number of attempts that the student takes to solve the challenge alone, without the learning companion's help, i.e. *num_attempts_alone.*
- Independence is calculated by comparing the number of times the student asked for help and the number of times the student tries to solve the challenge alone. At the beginning it is zero, which does not provide any information about the student's level of independence. If the student asks for a hint, the level of independence is decremented by one. However, if the student tries to solve the challenge alone a one is added to the student's level of independence. Therefore, a positive index above zero is an indicator of an independent student, while a negative index indicates that the student's independence is lacking.
- Total attempts, i.e. *total_attempts*, is the total number of attempts by the student with or without the learning companion's help.
- Average quality of tutoring feedback, i.e. *average_quality_tutor_feedback*, is related to students' perception about the effectiveness of the hints provided to achieve the learning goals during a session by the learning companion. A session begins when the student starts to interact with the game and finishes when the student ends his or her interaction. The student evaluates the hints provided and classifies them into one of three possible categories of helpfulness: (1) low, (2) medium and (3) high.
- Interval of interaction, i.e. *interaction_interval_seconds*, is the total time that the student has interacted during a session.
- Student's focus level, i.e. *mouse_focused_coarsed_value*, is an average value corresponding to the position of the mouse on the screen while the student is interacting with the game during a session. The position of the mouse was selected, since users usually move the mouse where their sight is located.
- Time to achieve the learning goal, i.e. *time_to_achieve_goal*, is the time that the student has taken to achieve the learning goal for the first time.

For the *outcome-retrospective* emotions (Figure 4), we employed the same random variables selected for the *activity emotions* (Figure 3) and we added the random variable related to the student's decision to publish the achieved result, i.e.

result published, which allows all the students to view each other's progress. At the end of each challenge a list with the ten best scores is displayed to give the students the possibility of competing for the best result.
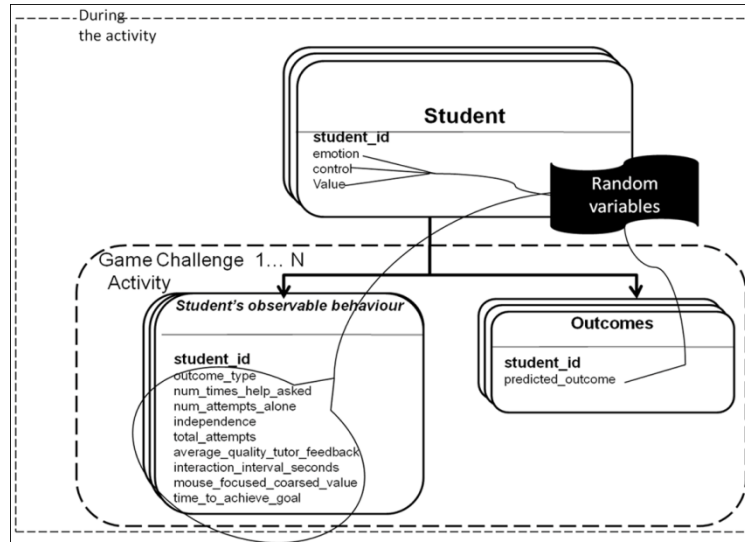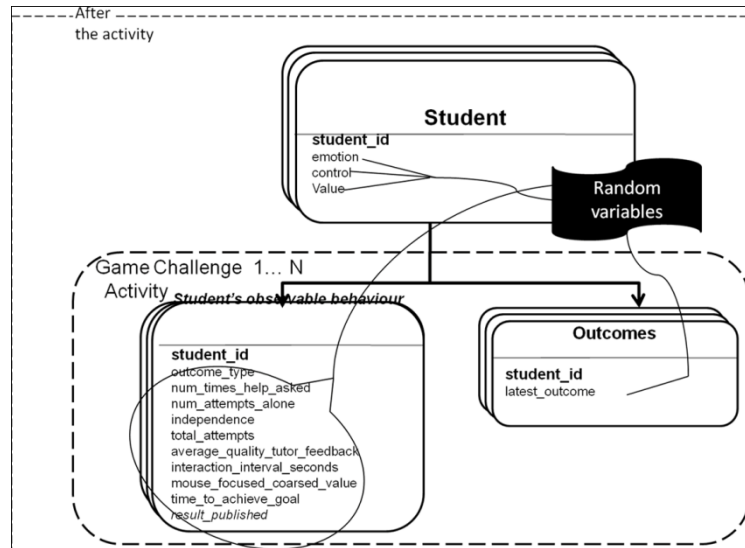

Fig. 3 Activity emotions PRM

Fig. 4 Outcome-retrospective emotions PRM

From PRMs in Figures 2 to 4, three DBNs were derived employing random variables. The *outcome-prospective* emotions DBN derived from the PRM in Fig-

ure 2, is shown in Figure 5. As a first approach, it is assumed that all these variables are related to appraisals of control and value. However, we need to know which variables are actually relevant when identifying category membership. Multinomial Logistic Regression is employed for this purpose, since control and value appraisals are qualitative regressors, i.e. categorical variables. This approach does not hold assumptions of multivariate normality or homogeneity of variance-covariance matrices (Kinnear and Colin 2010). As an example of the possible categories, Table 1 shows the corresponding appraisals of control and value for the *activity emotions* according to control-value theory. Once the interaction data is analysed through Multinomial Logistic Regression and we change the structure of the DBN according to these results, we can employ probabilistic methods based on the data of our population to calculate the probabilities on the CPTs.
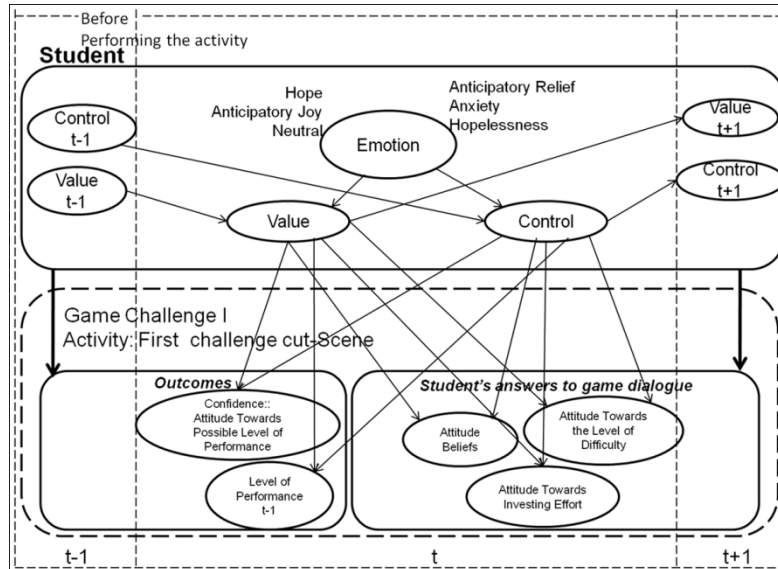

Fig. 5 Outcome-prospective emotions DBN

Focus/time frame	Value appraisal	Control appraisal	Emotion
Activity/present	Positive	High	Enjoyment
	Negative	High	Anger
	Positive/Negative	Low	Frustration
	None	High/Low	Boredom

Table 1. Control and value appraisals for *activity* emotions by Pekrun et al. (2007)

The interface of the game-based learning environment is designed to enable students to report their emotional state at any time. Hence, the emotional student

model is validated by comparing the number of cases that were accurately classified against the number of cases, where the reported emotion was not correctly identified.

3.1   Olympia architecture

The Olympia architecture combines game-based learning environments and ITSs (Muñoz et al. 2009). It has previously been applied to the specific case study of teaching Physics at undergraduate level, since we noted that undergraduate students usually find it difficult to understand the underlying principles. Here, Olympia (Figure 6) has been modified to reason about students' emotions and to show emotion. It comprises an *affective student model* and a *motivational modulator*. The former uses observable behaviour and answers to questions during game dialogues. The latter is comprised of a learning companion, which is focused on mirroring students' behaviour, encouraging the student over animated expressions and offering help. As mentioned earlier, it is still not clear what the emotional response to students' emotions should be.
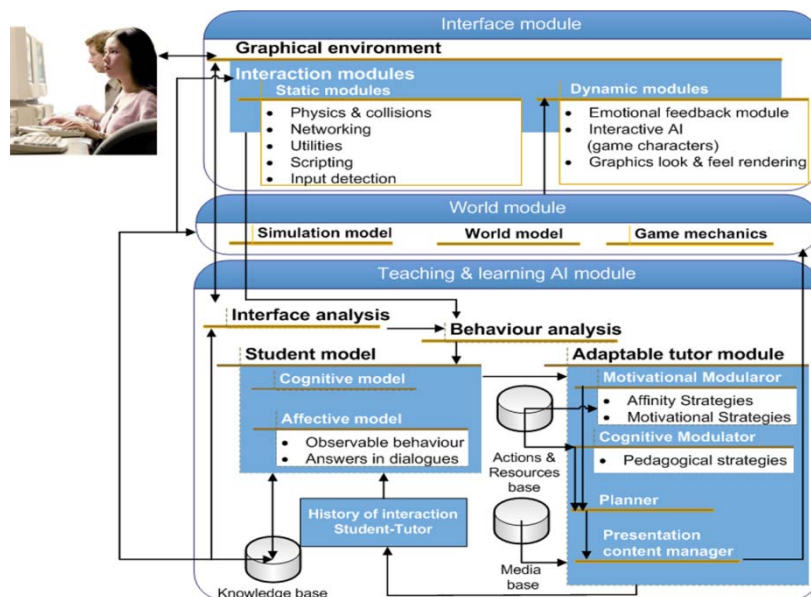

Fig. 6 Olympia architecture comprising emotional aspects

Olympia is a semi-open environment (Bunt and Conati 2003), where the student explores the game guided by the achievement of specific learning goals or outcomes. The interface analysis module filters the events that provide information about students' cognitive and motivational states. The selected events are sent

to the behaviour analysis module to be appraised. The evidence is forwarded to the student model, where cognitive and motivational needs are identified. The results are communicated to the tutor model.

The planner of the tutor module selects a suitable response. Cognitive and motivational modulators choose the media and information to communicate the message. The presentation content manager modifies the game-mechanics, i.e. action-challenge relation, and the world model, which is related to the dynamic modules. The dynamic modules are adapted according to the message that is to be communicated and may comprise music, colours and game characters.

Olympia, extended with the described emotional enhancements and our formalised emotional student model, was applied to the specific case study of creating *PlayPhysics*, an emotional game-based learning environment for teaching Physics at undergraduate level. The next section is focused on *PlayPhysics*' design and implementation.

4 PlayPhysics case study

As mentioned earlier, involving the user in the design, implementation   and evaluation loop is important when attempting to achieve an effective and functional application. Hence, to determine the design and implementation requirements of *PlayPhysics*, we conducted an online survey with 4 lecturers and 53 students at undergraduate level in an introductory Physics course at Tecnológico de Monterrey (ITESM-CCM) and Trinity College Dublin. It was noted that students reported that the most difficult topics of Physics are Newton's laws for particles and rigid bodies, principles of circular and linear kinematics, vectors, collisions and linear momentum.

PlayPhysics is a Role Playing Game (RPG), where the student is an astronaut on a mission to save his or her mentor, who has been trapped on a space station. The mentor, Captain Foster, is injured and was unable to escape when the rest of his crew abandoned the space station, after the station's computer, VNUS, was attacked as the result of a computer virus. The first level of the game is about docking the spaceship, Alpha Centauri, with Athena, the space station, using the student's knowledge of Physics. To ensure alignment with curriculum requirements, an expert in Astrophysics assisted us in modelling the domain knowledge, the marking scheme and the pedagogical feedback of *PlayPhysics*. *PlayPhysics* was implemented using Java, the Unity Game Engine, 3D Studio Max and Hugin Lite.

To ascertain students' expectations and beliefs involved in determining if the student experiences an *outcome-prospective* emotion, we enquire about them during the game dialogue. Figure 7 shows a fragment of the game dialogue enquiring about the student's self-efficacy expectancy. This game dialogue introduces the first level and the mission. To accomplish the first level the student has to perform four challenges: (1) after being launched from Earth, Alpha Centauri acquires a relative velocity with respect to Athena and the lieutenant has to activate its front engines to stop at some distance from the station on its rotational axis, (2) the student has to use upper and lower engine trust to align the Alpha Centauri's longitudinal axis with the station's longitudinal axis, (3) the student has to achieve the same frame of inertia of Athena station by activating Alpha Centauri's lateral engines, i.e. achieving the same rotational velocity, and finally,(4) the student has to enter to the docking bay, where the Alpha Centauri has to acquire a very slow movement around its rotational axis.

Focusing only on the first challenge, the spaceship, Alpha Centauri, is initially travelling at speed v_i at a Distance D from Athena and moving towards it along a linear path, see Figure 8. The restriction variables set randomly by *PlayPhysics*, are the distance D and the maximum limit Time, T, to not exhaust the spaceship fuel. The ranges are: $D \in [15, 70]$ km and $T \in [180, 120]$ s.
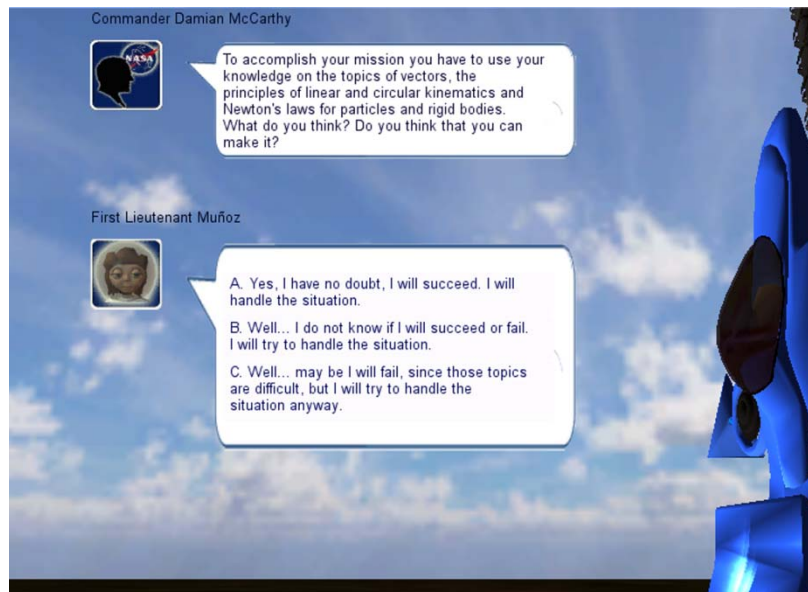
Fig. 7 *PlayPhysics* **game dialogue enquiring about students' self-efficacy**
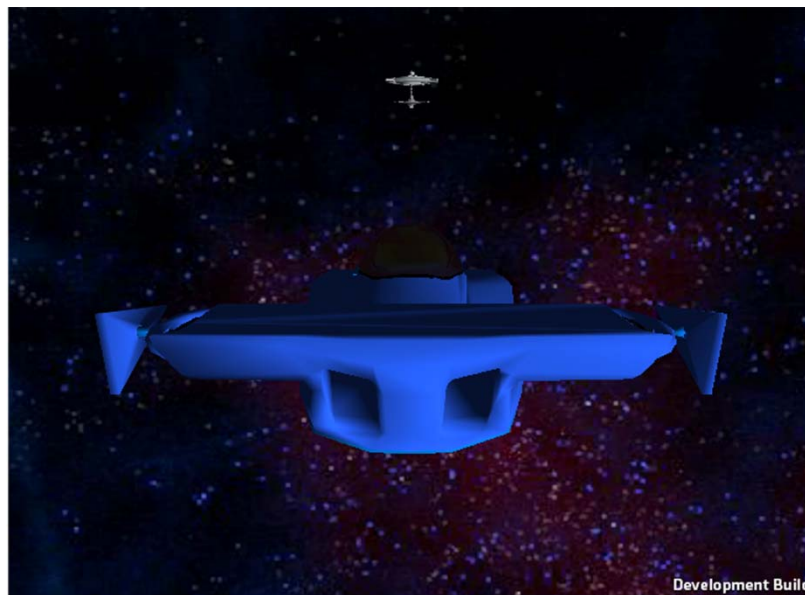

Fig. 8 External view of Alpha Centauri approaching lineally Athena station

To complete this first goal, the user is prompted to select suitable values for: (i) the direction of the acceleration, (ii) its magnitude, and (iii) the spaceship's initial speed, v_i (see Figure 9). These are the exploration variables for this scenario. The

possible choices for the direction of the acceleration are towards or away from Athena's position. The available range values for the spaceship's acceleration and initial speed, which the student has to choose from, are respectively: $a \in [0,100]$ m/s^2 and $v_i = [1000, 2000]$ m/s.

Fig. 9 Internal view of Alpha Centauri approaching Athena

Note that, first of all, the student should choose the acceleration direction away from Athena, in other words, the opposite direction to Alpha Centauri's initial velocity, in order that the spaceship decelerates and stops just below Athena's rotational axis. If the student chooses the acceleration towards Athena, which is in the same direction of the spaceship's velocity, the spaceship will accelerate forever and so will never stop and hence it will be lost in space.

Once the student chooses the correct deceleration direction, he or she has to select the appropriate values for a and v_i, from the given value ranges, which make the Alpha Centauri decelerate and stop just below Athena's rotational axis. The student has to realise that the spaceship's motion has to be rectilinear with constant deceleration. To calculate both, the distance travelled by the spaceship, d, and the required time to stop, t, equations (1) and (2) are applied.

$$\text{From kinematics we know that } d = \frac{v_i^2}{2a} \tag{1}$$

$$\text{and } t = \frac{v_i}{a} \qquad (2)$$

Additionally, there are some constraints that should be taken into account:

- The acceleration magnitude, a, should not be greater than 40m/s². This value is nearly four times the gravity acceleration on Earth's surface, i.e. approximately 4g. Otherwise, the student feels sick, dizzy and blacks out. When this occurs and the student asks for a hint. *PlayPhysics'* learning companion, *M8* robot, tells the student what the error is, enabling the student to select a smaller value than this limit.

- The calculated distance d has to closely match the distance, D, which is randomly assigned within a predefined range by PlayPhysics. From the selected values for a and v_i. *PlayPhysics* calculates d using Equation (1) and compares it with the value of D. PlayPhysics also calculates the relative error of the distance, which is defined by:

$$e_d = \frac{|d - D|}{D} \qquad (3)$$

We assume that the maximum allowed relative error is 0.05, or 5%. If the error is equal to or less than 2%, the student achieves the best performance. When the relative error e_d is less than or equal to 0.05, we assume that the spaceship did stop at the right position just below Athena. Otherwise, the distance travelled by the spaceship was too short ($d<D$) or too far ($d>D$) from Athena's rotational axis. In this case, the *M8* robot explains to the student the error, if the student asks for a hint after committing this mistake. The relative error can be modified, if the lecturer wishes to make it more challenging.

- The required time to stop Athena, t, should not exceed the allowed time T for this mission. From the selected values for a and v_i, *PlayPhysics* calculates t according to Equation (2) and compares it with the value for T, which is generated randomly. If $t>T$, the *M8* robot explains to the student that the fuel was exhausted so has to start the challenge again.

In order to succeed at this first challenge, the three constraints previously discussed must be satisfied. If the student succeeds he or she is congratulated (see Figure 10) and allowed to continue with the next stage and choose to publish their score, making it available for viewing by other students.

The values corresponding to the restricted variables D and T, and the interaction variables, a and v_i, were selected so that the problem solution is non-trivial. The difficulty level of the problem depends on the initial values set for T and D. If T and D are large quantities, there is a wider range of values to choose for both a

and v_i, so that a and t do not exceed their limit values ($a<40$m/s^2 and $t<T$). On the other hand, if T or/and D are small quantities, the range of values that can be chosen for the values a and t is smaller. Therefore, there is a larger probability of exceeding the respective limits of these variables. As an example, if *PlayPhysics* initialises $D = 60$km and $T = 90$s, a successful selection of values may be $a=-25$m/s^2 and $v_i = 1732$ m/s. As a result, $a<40$m/s^2, 1000m/s $< v_i < 2000$m/s and $t = 69.3$s$<T$. Finally, it is important to mention that for a successful set of selected values corresponding to the interaction or exploration variables, a and v_i, *PlayPhysics* assigns a grade depending on the resultant t value. The student is assigned higher grades for lower t values and lower grades if it is close to the T limit. There is still fuel remaining for future motions if low t values are achieved. Therefore, if the t value achieved is closer to T, it is inferred that the available fuel has been exhausted.

During the interaction with the game challenge, the student's emotion can be reported at anytime, using the *EmoReport* wheel. In addition, the emotion relating to the outcome at the end of the challenge is always enquired, whether the challenge finishes due to an error or misunderstanding or due a successful end. *M8* provides an emotional response every time the student reports his or her emotional state. For example, if the student reports that he or she is frustrated, *M8* offers help and reminds the student that they can ask for a hint.
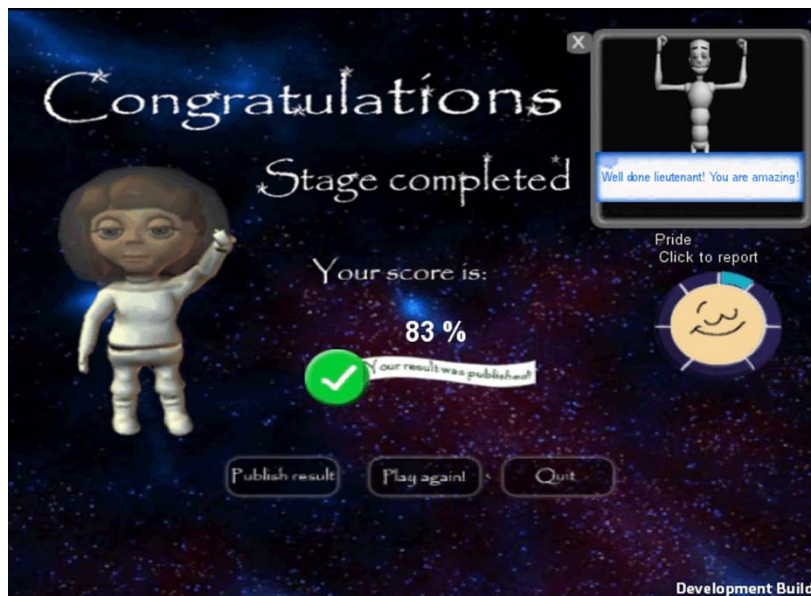

Fig. 10 *M8* **robot congratulating the student for the level of performance achieved**

5 Results and Evaluation

PlayPhysics' first challenge and emotional student model, specifically the *outcome-prospective* emotions DBN, were evaluated through a test with students of Engineering at ITESM-CCM. The evaluation was conducted as follows: first, we asked students to solve an online pre-test, making them aware of their actual knowledge of the topics taught by *PlayPhysics*. Then students started their interaction with *PlayPhysics*' first dialogue and reported their emotional state before performing PlayPhysics' first challenge. While performing the first challenge, students could report their emotion anytime, and the *M8* robot would remind them to do so periodically. Every time that the outcome percentage was displayed to the student, the student reported their emotion towards the outcome achieved.

In previous research (Muñoz et al. 2011), the *outcome-prospective* emotions DBN was designed, calibrated and evaluated to the point of achieving 70% accuracy. We noted that *confidence towards the possible level of performance* and the *attitude beliefs towards Physics* were the relevant random variables for the prediction of category membership of control and value appraisals. Here, we assessed again the accuracy of classification of this DBN with the data obtained from 79 students (54 men and 25 women) aged 18 to 23, when they interacted with PlayPhysics' game dialogue. Results are shown Figure 11. Table 2 shows the contingency table corresponding to these results. Negative and neutral emotions were again classified with more accuracy than positive ones (77.42%). However, positive emotions were reported more frequently.
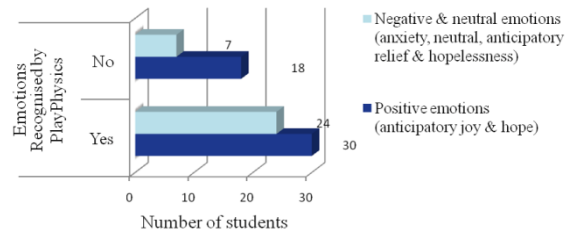

Fig. 11 Reported emotion vs. inferred emotion for the outcome-prospective emotions DBN

Emotion set	Recognised		Total	%Classification
	Yes	No		
Positive emotions (anticipatory joy and hope)	30	18	48	62.5
Negative and neutral emotions (anxiety, anticipatory relief, hopelessness and neutral)	24	7	31	77.42

Table 2. Contingency table corresponding to outcome-prospective emotions DBN

These results validated our previous findings. The final outcome-prospective emotions DBN is shown in Figure 12. To determine the significance of our findings and their generalisation to this specific population of students, we employed a Binomial test or Bernoulli trials, since our population and amount of data collected is small and Chi-square test (χ^2) can be effectively applied on and interpreted using large populations and quantities of data.
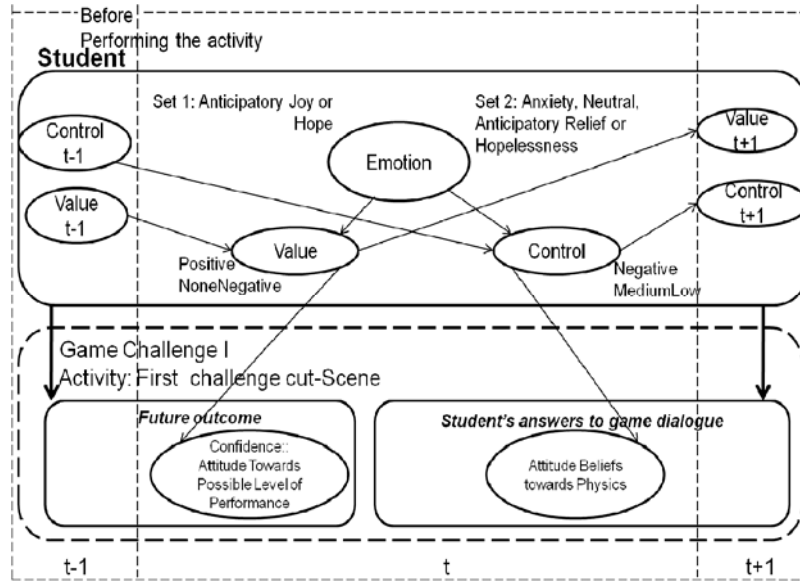

Fig. 12 Final outcome-prospective emotions DBN

The Binomial test is a non parametric test that it is employed in experiments that have the following characteristics: (1) there is a fixed number of indistinguishable experiments or trials, (2) the outcome of each experiment can be divided into two dichotomous categories, e.g. *success* or *failure*, (3) the experiments' outcomes are independent and (4) the probability of a successful outcome is the same in all experiments. The binomial probability model enables us to set a probability to a specific number of observations related to the happening of an event over *n* Bernoulli trials (Kinnear and Colin 2010). To ensure that the statistical test has the sufficient power to reject the null hypothesis we employ the *statistic g*, an index of effect size, which states the difference between two populations. The *statistic g*, Equation 4, is the difference of the proportion of the outcomes in the category (P) and the probability of an outcome supporting the null hypothesis (p).

$$g = \left| P - p \right| \tag{4}$$

The first step for applying Binomial test is to define the null and alternative hypotheses. In our case, we want to validate that the accuracy of classification of our emotional model, e.g. *outcome-prospective emotions* DBN, is at least of 70%, which corresponds to a probability of 0.7. From Table 2, we can signal that 31 cases correspond to negative and neutral emotions reported by students. If our emotional student model has an accuracy of 50%, it is not considered an accurate classifier. Hence, the null and alternative hypotheses are defined as follows:

$$H_0. \; p = 0.5$$
$$H_A. \; p \neq 0.5 \; (\text{At least } 0.7)$$

The observed probability (p), corresponding to the accurate classification of 24 cases of negative or neutral emotions, was calculated as $P = 0.77$[1]. Accordingly, the probability of classifying 7 cases incorrectly is $p = 0.23$. The p-value is 0.003. To know the effect size, we calculated the *statistic g*, $g = 0.27$. Using these results, we can reject the null hypothesis and affirm that our emotional student model identifies the emotions in the negative and neutral set, with an accuracy equal to or above 70%. In addition, the effect size of this test is *large*.

If we conduct the same analysis for the total number of cases correctly classified in the positive and negative-neutral sets, which corresponds to 54 cases out of 79, (see Table 2), we achieved an observed probability of $0.68 \approx 0.7$ and a p-value of .001. The *statistic g* was also calculated for this case, $g = 0.18$. Using as these results, we can signal that there is sufficient evidence to reject the null hypothesis (H_0) and the statistical analysis shows the model permits an accurate inference in c.70 of all cases. Also, the value of the *statistic g* suggests a *medium* effect size.

From the interaction with the first challenge, we obtained a log of interaction with 1640 entries corresponding to 79 students. 1321 entries corresponded to the time during which the student was interacting with *PlayPhysics*' first challenge and 319 entries correspond to the number of times that the student was presented with the final outcome. We analysed this data in two ways: (1) obtaining the descriptive statistics of our data, e.g. frequencies, minimum value, maximum value, mean and standard deviation, and (2) analysing the data using Multinomial Logistic Regression using SPSS to understand which variables are the most relevant for inferring students' control and value appraisals towards the challenge and its outcome. As part of this analysis, we observed that emotions were reported as follows: *neutral* emotion was reported 990 times (74.9% of our population), *enjoyment* was reported 155 times (11.7% of our population), *boredom* was reported 89 times (6.7%) and *anger* and *frustration* were reported 42 (3.2%) and 45 (3.4%) times respectively. We also analysed lecturers and students' comments to improve *PlayPhysics*' first challenge and user interaction.

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[1] SPSS (Statistical Package for the Social Sciences) was employed to conduct Statistical analysis.

6 Comparison with related work

Computational models of self-efficacy, which employ students' observable behaviour, e.g. time in current location and progression, have attained 70% accuracy (McQuiggan et al. 2008). This accuracy increases by 10% when using physiological data, e.g. average heart rate and galvanic skin response. On the other hand, computational models of motivation have also proved effective when using students' observable behaviour, e.g. times that the student asked help and time invested (Del Soldato and Du Boulay 1995; Rebolledo-Mendez et al. 2006). Control-value theory is a framework of assumptions corresponding to other emotional theories. It employs cognitive, motivational, physiological and affective factors to determine the presence of an achievement emotion (Pekrun et al. 2007). It is assumed that these factors are related to control and value appraisals. The AEQ has been employed effectively to assess students' emotions in Physics, Mathematics, German and English domains (Goetz et al. 2007). Results showed that similar emotions are experienced in comparable domains, e.g. Mathematics and Physics. The AEQ was validated conducting tests with 389 students of Psychology.

Some of the motivational and cognitive factors employed in the control-value theory are comprised in the computational models of self-efficacy (McQuiggan et al. 2008) and motivation (Del Soldato and Du Boulay 1995). Therefore, we decided to employ these two models as a basis for our model. Our results show promise, since negative and neutral emotions are classified with accuracy above 70%, which is comparable to the accuracy obtained by McQuiggan et al. (2008). In addition, it is interesting to observe that positive emotions are more frequently reported than negative ones, 48 times out of 79. Statistically, using Binomial test, our model, specifically the *outcome-prospective* emotions DBN, proved that our findings can be generalised to this population of students.

In addition, it was observed that students reported that they experienced neutral emotions more frequently (74.9% of the cases), which is not very different from the results obtained by Alexander and Sarrafzadeh (2008) when they were observing one-to-one human tutoring while teaching Mathematics. They noted that students and lecturers showed a neutral face expression 86% of the time. This may also be due to social and cultural standards and personal preferences, which may bias the study. It was observed that incorporating physiological signals in our model may assist us in reducing this uncertainty. However, if the student does not want to reveal the emotion that he or she is feeling, it is not useful, since physiological data cannot be taken as evidence of emotion and students' self report is still needed. Pekrun et al. (2007) focuses specifically on heart rate. However, Pekrun et al. (2007) only asked students about their physiological sensations, e.g. whether they feel their heart beating very quickly, or whether they feel any stomach pain. Research in physiology and computing has shown more promise when using galvanic skin response signals, and studies demonstrate that these are more sensitive to emotion changes (Rajae-Joordens 2008). This research is based on findings that suggest that skin conductance changes according to the emotions and thoughts that we are experiencing.

7 Conclusion and future work

We described the main challenges faced when designing and implementing an emotional-game based learning environment for teaching Physics, i.e. one that recognises and shows emotion. We focused mainly on two aspects: (1) creating an emotional student model using observable behaviour and questions posed during game dialogue, and (2) designing and implementing *PlayPhysics*, an emotional game-based learning environment for teaching Physics. Our model uses Control-Value Theory as a basis and a research methodology comprising the creation of PRMs to facilitate the derivation of DBNs to handle the uncertainty of the emotional domain. PlayPhysics' challenges, pedagogical feedback and marking scheme were designed with the help of an Astrophysics domain expert. The calibration and structure of the *outcome-prospective* emotions DBN was validated through testing with 79 students of Engineering at ITESM-CCM. Results showed that negative and neutral emotions are classified with above 70% accuracy, which is comparable to the accuracy of a human expert. Neutral emotions are the most frequently reported, though this may be due to social and cultural standards or personal preferences. Future work will focus on analysing the interaction data of PlayPhysics' first challenge to complete and validate the design corresponding to the *outcome-retrospective* and *activity* emotions DBNs. Additionally, students' and lecturers' comments will be taken into account in order to improve *PlayPhysics'* user interaction. Finally, other challenges will be incorporated into *PlayPhysics'* first level and the incorporation of physiological signals to enhance the accuracy of our model will be assessed.

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