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An emotional student model for game-play adaptation

Karla Muñoz [a,*], Paul Mc Kevitt [a], Tom Lunney [a], Julieta Noguez [b], Luis Neri [b]

[a] Intelligent Systems Research Centre, School of Computing and Intelligent Systems, Faculty of Computing and Engineering, University of Ulster, Magee, BT48 7JL Derry/Londonderry, Northern Ireland, UK
[b] School of Engineering and Architecture, Tecnológico de Monterrey, Mexico City (ITESM-CCM), Calle del Puente 222, Col. Ejidos de Huipulco, Tlalpan, 14380 D.F., México

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ABSTRACT

Game-based learning offers key advantages for learning through experience in conjunction with offering multi-sensorial and engaging communication. However, ensuring that learning has taken place is the ultimate challenge. Intelligent Tutoring Systems (ITSs) have been incorporated into game-based learning environments to guide learners' exploration. Emotions have proven to be deeply intertwined with cognitive and motivational factors. ITSs attempt to recognise and convey emotion in order to enhance students' learning and engagement. The ITS student model is responsible for attainment of adaptability and understanding of learners' needs. It is not clear which emotions are relevant to the teaching-learning experience, or what antecedents and interpersonal differences are involved in determining an emotion. Therefore, student modelling involves uncertainty. Creating an emotional student model that can reason about students' observable behaviour during online game-play is the main goal of our research. The analysis, design and implementation for this model are our central focus here. The model uses as a basis the Control-Value theory of *achievement emotions* and employs motivational and cognitive variables to determine an emotion. A Probabilistic Relational Model (PRM) approach was applied to facilitate the derivation of three Dynamic Bayesian Networks (DBNs) corresponding to three types of *achievement emotions*. Results from a prototyping exercise conducted along with the outcome-prospective emotions DBN are presented and discussed. In future work a larger population of students will be employed to develop an accurate DBN model to incorporate into PlayPhysics, an emotional game-based learning environment for teaching Physics.

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1. Introduction

Education is focused on fulfilling students' evolving expectations for learning and being engaged [1]. Students' emotions have been proven to influence cognitive processes, motivation and performance [2]. There is still uncertainty regarding emotions that occur and are relevant in a learning-and-teaching context [3]. Social standards and interpersonal differences inhibit the expression and confound the recognition of emotions [4,5]. Game-based learning environments have proven effective at achieving learners' attention [6]. However, it is by incorporating Intelligent Tutoring Systems (ITSs) that they can ensure understanding [4,7], since ITSs guide the learners' exploration, thus guaranteeing the achievement of specific learning goals.

An ITS student model enables understanding and identification of students' needs [8]. However, it is observed that recognising learners' knowledge, understanding, motivation and emotions is a process that involves uncertainty. ITSs are currently incorporating emotional features [9,10]. Approaches to ITSs identifying emotion are: (1) reasoning about emotion from its origin [11], (2) recognising the physical effects of emotion [9,12] and (3) a hybrid approach comprising (1) and (2) [4]. Here, we focus on reasoning about students' emotions from observable behaviour during online game-play and also questions answered by students during game-dialogues.

Our emotional student model uses as its basis Control-Value theory [2], an integrative framework that employs diverse factors, e.g. cognitive, motivational and psycho physiological, to determine the existence of achievement emotions. Achievement Emotions are classified as the emotions that students experience while performing academic activities or attempting to achieve specific learning outcomes, which are evaluated according to defined standards of quality [2]. The background, analysis, design, implementation and preliminary evaluation of our emotional student model are the central focus of our work. Our key goals are the creation of this emotional student model and the design and implementation of PlayPhysics, an emotional game-based learning environment for teaching Physics at undergraduate level. PlayPhysics aims to enable students to explore, to understand concepts, such as Newton's laws for particles and rigid bodies, to

* Corresponding author. Tel.: +44 (0) 28 71675395, + 44 (0) 28 71371247; fax: +44 (0) 28 71675570, + 44 (0) 28 71371247.
E-mail address: munoz_esquivel-k@email.ulster.ac.uk (K. Muñoz).

show emotion and provide suitable guidance. PlayPhysics is being implemented using Java, the Unity game engine, 3D Studio Max and Hugin Lite.

A Probabilistic Relational Model (PRM) approach [13,14] was employed to derive three Dynamic Bayesian Networks (DBNs) [15], which constitute the student model. Each DBN corresponds to one of the three types of emotions defined by Pekrun et al. [2]. The complete model will be evaluated through a prototyping exercise. Results of the evaluation corresponding to the prospective-outcome emotions DBN are discussed herein. Once the emotional model is sufficiently refined it will be incorporated into PlayPhysics. The ultimate goal is to adapt the game-elements of PlayPhysics, e.g. the colours, game-characters and sounds, according to identifiable learners' needs. The outline of this paper is as follows, Section 2 discusses related work, Section 3 discusses the emotional student model, Section 4 discusses requirements analysis, design and implementation of PlayPhysics, Section 5 covers the applied research methodology and results attained from conducting a preliminary evaluation, Section 6 provides a discussion of the findings in relation to other work. Finally Section 7, concludes by discussing the planned refinements of the emotional student model for PlayPhysics and outlines future work.

2. Background and related work

The success of game-oriented learning is attributed to the experience of immediate consequences or rewards, which establish an interactive and emotional link with the student [6,16]. However, not all game-based learning environments are effective at attaining knowledge and understanding or teaching in the target domain and therefore it is essential to follow design principles. For example, Malone and Lepper [17] identify the features 'control', 'challenge', 'fantasy' and 'curiosity' as those factors that are meaningful in ensuring effective learning. In addition, it is important that students receive personalised and adaptive guidance while exploring, since it is probable that otherwise they will not achieve the learning goals. Therefore, ITSs are being included in these environments [4,7]. Affective Gaming is focused on recognising and communicating emotion during game-play [16] and ITSs are also incorporating these capabilities. We review here research methodologies that have been applied to achieve recognition of the student's emotional state, motivational state or personal disposition, and describe recent findings in the Psychology domain that clarify the complex relation cognition and motivation have with emotions in an educational context.

ITSs have used hardware or software approaches for recognising emotion. The emotional state of the learner can be recognised through identifying gestures, body posture, prosodic features and physiological signals [9,12]. However, these techniques imply employing additional hardware equipment, and mapping patterns of emotion, which may be interpreted in different ways and are not considered direct evidence of emotion [18]. For reasoning about students' emotions the Ortony, Clore and Collins (OCC) model [5] is usually employed. A students' focus on events, agents or objects determines their emotional state. However, the OCC model, which focuses only on cognitive variables, needs to be adapted to the learning context and has to overcome the challenge of knowing students' goals, beliefs, standards and attitudes. In addition, there is no evidence of the accuracy of the approach when using observable behaviour [11], the defined types of emotion may or may not be experienced in the specific learning context, since Ortony et al. [5] defined emotions that can be easily identified in text, which can occur in diverse contexts, e.g. a personal diary. A hybrid approach reasons about the possible cognitive effects and validates the existence of emotions by comparing the prediction with the physical patterns [4].

ITSs have also focused on identifying the learners' disposition by recognising their motivation [19,20] or self-efficacy level [21] using observable behaviour. Arroyo and Woolf [19] related motivation to observable behaviour and attitudes using machine learning techniques, e.g. Bayesian Networks, and analysed students' log data in the Geometry domain. Rebolledo-Mendez et al. [20] adapted the motivational model derived from the work by Del Soldato and Du Boulay [22] in an Ecology domain. Del Soldato and Du Boulay [22] linked observable variables to effort, confidence and independence, which are considered effective predictors of students' motivation. McQuiggan et al. [21] focused on identifying students' self-efficacy and recognised that by adding physiological data their model's accuracy increased by 10%.

On the other hand, cognition, motivation and emotion have recently been proven to be deeply intertwined [2,23]. Control-Value theory regards control and value appraisals as most relevant when determining an emotion. These appraisals take place when students perform academic activities that enable them to achieve specific outcomes [2]. Control is related to students' beliefs and skills for performing a specific task or achieving its specific goals. Value is related to the importance of the activity or its outcomes from student's point of view. Motivational, affective, cognitive and physiological variables are antecedents employed to reason about students' emotions. The assessment tool applied by Pekrun et al. [2] is the Achievement Emotions Questionnaire (AEQ) [24], a self-reporting technique defined through Structural Equation Modelling (SEM). This approach has previously proven effective at identifying the achievement emotions of students enrolled in a Physics course at undergraduate level [25].

It is important to emphasise that achievement emotions are domain-dependent. Goetz et al. [25] proved that emotions experienced in similar subject domains, e.g. Mathematics and Physics, have stronger correlations, since the factors considered by the students' appraisals, e.g. self-efficacy expectancies and self-concepts of ability, are domain specific. Therefore, contextualising the emotional experience is fundamental to analysing the possible factors that are taken into account by the student while experiencing an emotional state, since each situation may have a different social structure and function. For example, Pekrun et al. [24] identify three specific achievement situations: *class-related*, *learning-related* and *test-related*, since the boredom that the student may experience in the classroom is different from the boredom that the same student may experience while sitting an exam.

Taking into account the stated facts, it was observed that physiological data can increase slightly the accuracy of the model. In addition, it was noted that there is currently no student model using Control-Value theory as a basis, which employs cognitive and motivational variables to determine the student's emotional state through analysing observable behaviour during game-play. Therefore, the construction of such a computational model is the main objective of our research.

3. Emotional student model

Student modelling enables identifying and understanding student related data, e.g. goals, skills, motivation, emotions and interest [10]. Identifying the factors and features that must be taken into account in implementing a student model is a task that involves uncertainty [8], since there are still questions remaining about how students can attain knowledge and understanding and what factors influence students' motivation and emotions. This section addresses design techniques and describes the methodology followed in deriving our proposed emotional student model.

To handle uncertainty a common Artificial Intelligence (AI) technique, Dynamic Bayesian Networks (DBNs), is employed, since

this approach allows us to use prior domain knowledge and model dependencies in the domain itself. The nodes of the DBN represent random variables or concepts that are well defined with respect to the domain [26]. Probabilistic Relational Models (PRMs) are an object-oriented representation of the domain that facilitates the definition of DBNs [8]. PRMs enable to handle information and random variables. A PRM schema was derived by taking into account the Control-Value theory, the main goals of PlayPhysics, the observable variables comprising the student models defined in [21,22] and the AEQ questionnaire [24]. This PRM schema, shown in Fig. 1, was employed to define three DBNs, e.g. *outcome-prospective*, *activity* and *outcome-retrospective* emotions DBNs. Fig. 2 includes a more detailed description of attributes and random variables for the classes of the PRM shown in Fig. 1. The PRM in Fig. 2 was derived for the time frame prior to performing PlayPhysics' first challenge. It is important to note that before interacting with the first challenge, the only information available

to infer the student's outcome-prospective emotion is previous experience in the Physics domain which includes the specific topics, e.g. previous and future performance, student beliefs, self-efficacy expectancies, self-concepts of ability and attitudes towards Physics. Therefore, the available observable variables are time frame specific.

To determine the outcome-prospective emotions, namely anticipatory joy, hope, hopelessness, anxiety and anticipatory relief, a game dialogue was designed to enquire about variables that are effective predictors of motivation. We refer here to these variables as *motivational variables*, such as confidence. In addition, interaction variables, such as the previous level of performance and level of difficulty, which are strongly correlated with the student's cognitive level, will be referred to here as *cognitive variables*. The time frame and the activity determine the factors and features that can be taken into account to determine the emotion. For example, the student's attitude towards the
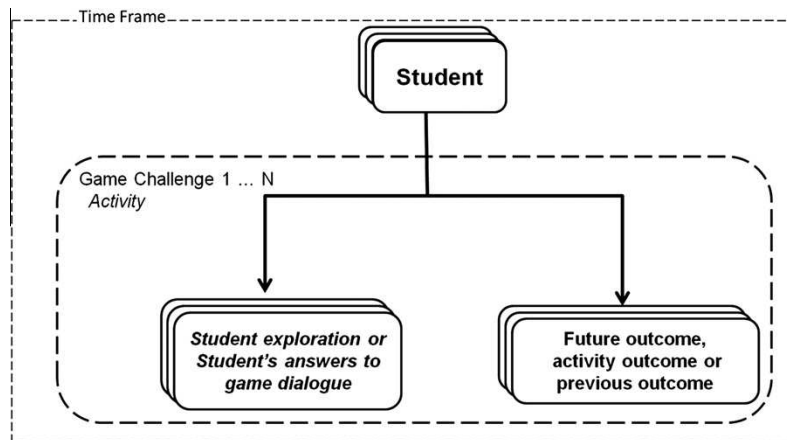

Fig. 1. PRM schema derived using the Control-Value theory as a basis.
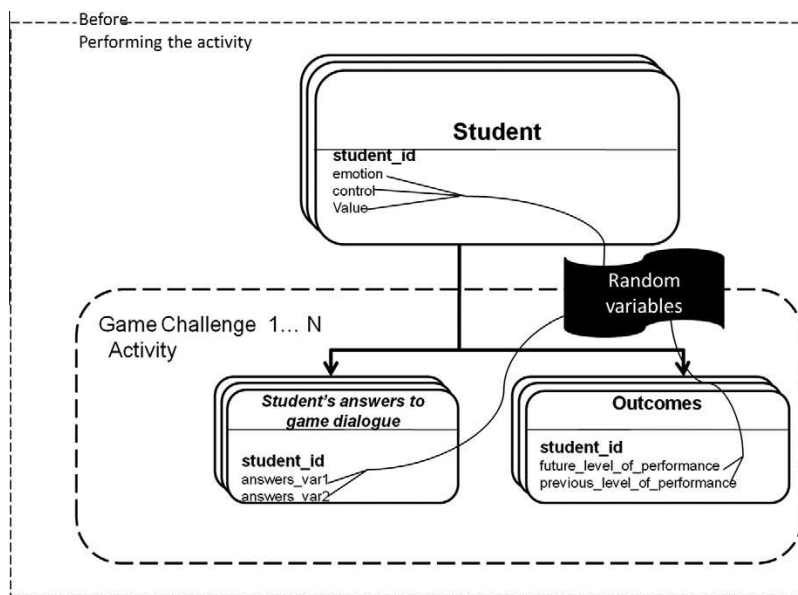

Fig. 2. Detailed PRM classes.

possible level of performance is not required during game dialogue when determining *activity* emotions, such as frustration. Instead the current level of performance is used. A summary of the control value-theory for the outcome-prospective emotions is shown in Table 1.

We analyse items constituting the AEQ questionnaire [24], to determine the variables that will be used to infer the value and control of the student before performing the first game challenge. For instance, one item states, "My confidence motivates me to prepare for class". From this item it was inferred that confidence will be one variable incorporated into the model. However, to ask students about their beliefs and attitudes on the subject we decided to incorporate the questions as part of the in-game dialogue. Therefore, using the AEQ questionnaire and the theory of planned behaviour by Ajzen [27] as a basis, specific questions relating to the identified variables were derived. An example of the implemented game dialogue is illustrated in Fig. 3. It is important to highlight that students solve a pre-test related to the topics taught by Play-Physics before interacting with the game. This test aims to (1) enable the student to gauge his or her actual knowledge in the topics, which probably reduces the uncertainty in the in-game dialogue

items attained due to the role-playing game (RPG), and (2) enable the lecturer to know the student knowledge before interacting with PlayPhysics, which enables us to make a comparison at the end of the interaction with the latest student's level of understanding.

Using these questions and the game-dialogue, we conducted research with 28 students [28]. We set the dependencies between variables and the probabilities in the Conditional Probability Tables (CPTs) based on common-sense relating to the specific teaching and learning experience. The model achieved an accuracy of 60.71%, i.e. the student model identified accurately the emotions of 17 students out of 28. However, some categories of emotions were not reported with the same frequency, e.g. 4 students reported feeling anxiety and 14 students reported feeling hope. In addition, only a few students reported low confidence or negative attitudes towards Physics. We know that a human expert identifies emotion with 75% accuracy [29]. Therefore, it is desired that our model acquires at least 70% accuracy. To achieve this goal, we have to know (1) if all the categories of emotions and categories of random variables are necessary based on the studied population of student subjects and (2) if all the random variables predict category membership with the same accuracy.

As a first hypothesis, we can assume that all the random variables are related to control and value as illustrated in Fig. 4 and that the categories for the emotions and random variables are set as defined by Pekrun et al. [2]. The skeleton in Fig. 4 defines the DBN corresponding to the prospective-outcome emotions and was derived from the model in Fig. 2. Fig. 4 shows more clearly the dependencies between random variables, from parents to children, therefore defining in more detail the Markov blankets for each node in the network. In our model, previous *control* and *value* at time $t - 1$, have an influence over the current value and control at time t. As a result, the current *value* and *control* at time t, will have an influence on the posterior value and control at time $t + 1$,

Table 1
Control and value appraisals for the outcome-prospective emotions (Pekrun et al. [2]).

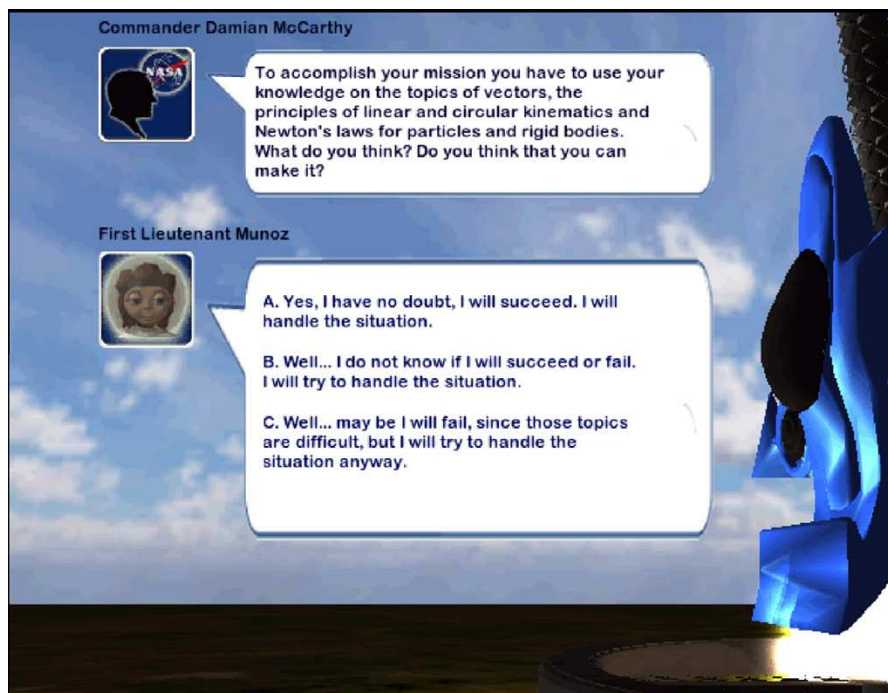| Object focus	Value appraisal	Control appraisal	Resultant emotion
Outcome/ prospective	Positive (the student is focused on succeeding)	High	Anticipatory Joy
		Medium	Hope
		Low	Hopelessness
	Negative (the student is focused on avoiding failure)	High	Anticipatory Relief
		Medium	Anxiety
		Low	Hopelessness

Fig. 3. Sample PlayPhysics game dialogue on student's self-efficacy expectancies.
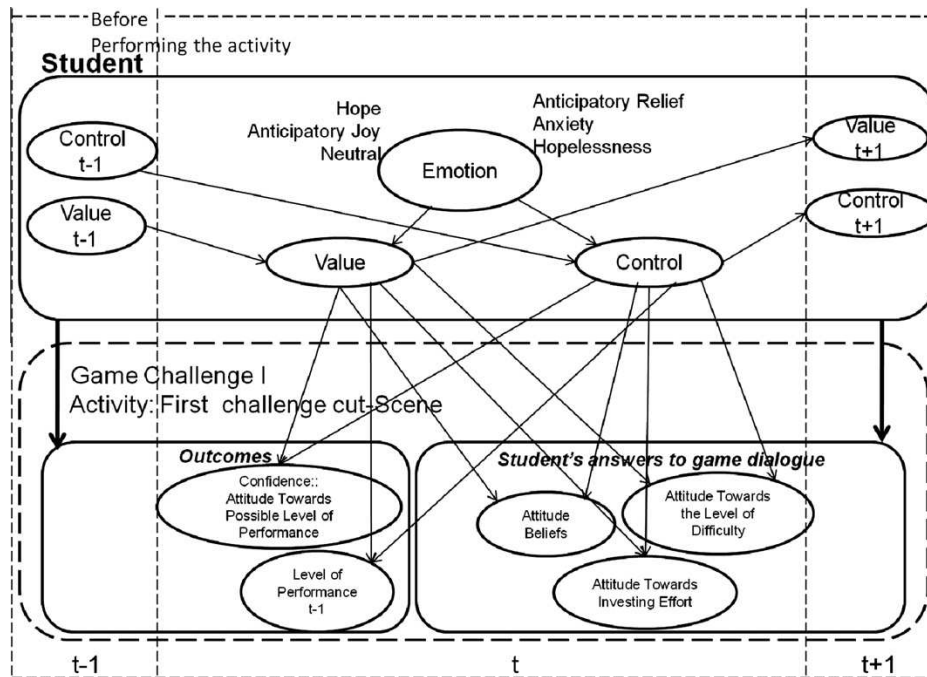
Fig. 4. Outcome-prospective emotions DBN.

i.e. if the student is focused on avoiding failure before starting to interact with the game challenge and the student has low self-efficacy expectancies in the specific topics, it is more probable that the student will find the problem very difficult. Therefore, the student may frequently be more focused on avoiding failure than on mastering skills and succeeding.

Given the categorical nature of our random variables we employ Multinomial Logistic Regression, an approach to predicting category membership that is less sensitive to qualitative regressors than discriminant analysis and does not have to hold assumptions, such as multivariate normality or homogeneity of variance-covariance matrices [30]. This analysis also assists us in determining dependencies between random variables and setting the probabilities in the CPTs based on students' self-reporting. However, to apply Multinomial Logistic Regression, tests should be conducted with a considerable large population of students, e.g. above 50. While interacting with PlayPhysics, students self-report their emotions and these emotions are transformed to their specific categories of control and value. Once the accuracy of the emotional student model has been refined, the model will be integrated into PlayPhysics.

4. PlayPhysics design and implementation

It is noted that students find it difficult to understand and apply the underlying principles of Physics [31]. Therefore, PlayPhysics focuses on teaching these principles. PlayPhysics uses the Olympia architecture, which has proven effective in combining ITSs and game-based learning environments [31]. Olympia will be modified to recognise emotion in order to provide adaptable pedagogical feedback. To identify the most difficult topics in an introductory course of Physics a requirements analysis survey was conducted online with a total of 4 lecturers and 53 students at Trinity College Dublin and Tecnológico de Monterrey, Mexico City campus (ITESM-CCM). The identified topics were vectors, principles of linear and circular kinematics and Newton's laws for particles and rigid bodies.

The story-line of PlayPhysics is a space adventure. The student is a lieutenant who must save Captain Foster, the learner's mentor. The super-computer VNUS attacked the crew. Therefore, Foster is injured in the space station Athena. VNUS was infected with a harmful virus and the student must arrive at the control room to reboot the system and to execute a vaccine that will return Athena to its normal operational state. The learner has to overcome game-challenges based on Physics concepts and principles. The first challenge involves piloting a spaceship to Athena by applying knowledge about the previously identified topics, as depicted in Fig. 5. Two player characters, e.g. male and female, were designed using 3D Studio Max and are also shown in this figure. In addition, PlayPhysics implemented using Java, the unity game engine and Hugin Lite. The latter is a tool employed to implement Bayesian Networks and Influence Diagrams.

PlayPhysics' challenges and domain knowledge are modelled with the assistance of an Astrophysics domain expert at ITESM-CCM. The spaceship's initial position and velocity relative to Athena are randomly initialised to avoid memorisation and triviality. The student can explore the effects of varying the spaceship's mass and rotational inertia, and forces and torques of relevant driving motors. The main goal is to calculate appropriate linear and angular accelerations and decelerations achieved by the spaceship in order to arrive successfully at Athena. Athena has a shape resembling a doughnut and is rotating with an angular velocity around its perpendicular axis, therefore creating an artificial gravity effect, where $g = 9.8$ m/s^2. To dock successfully with Athena, the student has to overcome four challenges:

(1) The spaceship has an initial relative velocity with respect to Athena, since it was launched from the Earth. Therefore, to dock with Athena it has to activate its front engines in order to stop at some distance from Athena, on its rotational axis. This phase corresponds to linear motion with constant deceleration.

Fig. 5. Proposed graphical user interface for PlayPhysics' first challenge and player characters.

(2) The spaceship has to align its longitudinal axis with Athena's rotational axis. To attain this goal, the student has to apply appropriate upper and lower engine thrust.
(3) The spaceship has to match Athena's angular speed, therefore activating its lateral engines.
(4) To approach Athena and enter its docking bay, the spaceship has to acquire a very slow movement around its rotational axis.

The general structure of the cognitive student model comprising the knowledge domain related to this game challenge and its four phases is shown in Fig. 6. This model will be employed to recognise the learner's knowledge and understanding. It is important to emphasise that a key goal is to choose the pedagogical actions that maximise the student's learning.

5. Emotional student model evaluation and preliminary results

An evaluation of the prospective-outcome emotions DBN was conducted with 66 students enrolled in an Engineering course and who took or are taking an Introductory Physics module at ITESM-CCM. The research methodology was as follows. First, the participants were asked to answer an online pre-test about Play-Physics' topics. Once they knew the outcome of this test, they proceeded to answer the questions posed in the game dialogue, which introduces the Physics scenario. At the end of the activity students reported the emotion that they were experiencing before starting to solve the first challenge of PlayPhysics. These emotions were translated into their corresponding value and control appraisals.

While analysing the data, i.e. frequencies, it was noted that the categories 'low' and 'medium' of the random variable 'control' should be joined into a new category, i.e. 'LowMedium'. The same case applies for the categories 'none' and 'negative' of the variable 'value', therefore a new category was created entitled 'NoneNegative'. Accordingly, the emotions were divided into two sets: (1) AnticipatoryJoy_Hope and (2) Anxiety_Neutral_Anticipatory Relief_Hopelessness. When the frequencies of these two sets of emotions were analysed: 38 students reported to feel one of the two categories of emotions in the first set, i.e. 'anticipatory joy' or 'hope', while 28 students reported to feel 'anxiety', 'no emotion', 'anticipatory relief' or 'hopelessness'. However, to apply Multinomial Logistic Regression, there should be a similar number of students in both groups. Therefore, we removed five random students
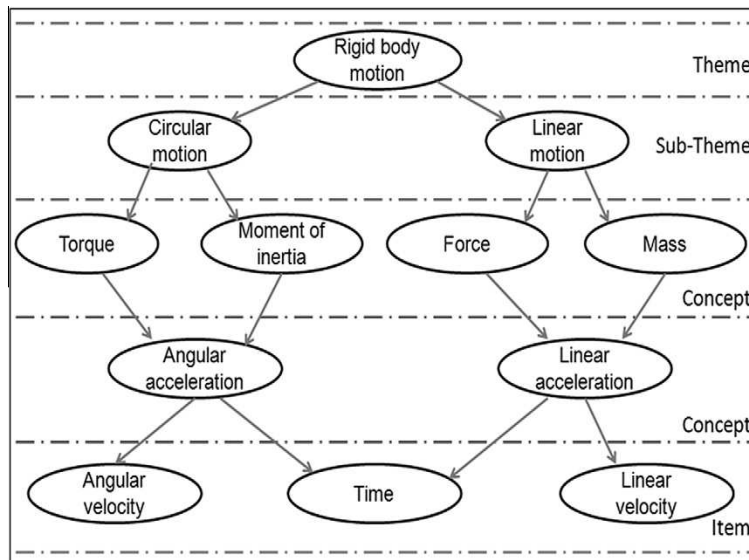

Fig. 6. Cognitive student model corresponding to PlayPhysics' first challenge.

from the first set of emotions. Finally, we conducted Statistical analysis with 37 males and 24 females within an age range from 18 to 23.

As a result of applying Multinomial Logistic Regression employing SPSS and using the Custom/Stepwise method, we found that the only significant predictor selected by SPSS for the dependent variable 'value' was 'confidence: attitude towards the possible level of performance' and for the dependent variable 'control', the only significant predictor selected by SPSS was 'attitude beliefs towards Physics'. These results are shown in Table 2. We also analysed the interaction between the random variables 'control' and 'value' to predict category membership of the two sets of emotions defined. These results are significant with a p-value less than 0.05. Therefore, we defined the latest Outcome-prospective emotions DBN as illustrated in Fig. 7 and we used the data from the Multinomial Logistic Regression and the frequencies to determine the probabilities in the CPTs. For example: if the confidence is 'MediumLow', 21 cases are classified with a 'NoneNegative' value and if confidence is 'High', 11 cases are classified with a 'Positive' value, i.e. $p_{\text{NoneNegative |MediumLow}} = 0.66$ and $p_{\text{Positive |High}} = 0.34$.

Once, the probabilities and the dependencies were set according to the Statistical analysis, the reported emotion by the participants was compared with the inferred emotion by the PlayPhysics, emotional student model. The model attained an overall accuracy of 70.49%. Results are shown in Fig. 8. It is noted that the model is better for classifying negative and neutral emotions than positive emotions, e.g. PlayPhysics emotional student model accurately classified 22 cases out of 33 for the emotion set 'AnticipatoryJoy_Hope', which

corresponds to 66.67% accuracy. In comparison with 21 cases accurately classified out of 28 for the emotion set 'Anxiety_Neutral_AnticipatoryRelief_Hopelessness', which corresponds to 75% accuracy. These two sets of emotions are useful, since if the student feels a positive emotion, such as 'anticipatory joy' or 'hope', it is more probable that the student enjoys the teaching-learning experience, in contrast to a student who feels a negative emotion, such as 'anxiety' or 'hopelessness', where it is likely that the student quits the task or dislikes the activity. In addition, we also do not want our students to feel apathy towards the Subject of physics and the tasks. Furthermore, we do not want a situation where the student achieved the task by chance, and could feel relief in spite of not having any control over the task. As a result, we considered this research approach promising and further experiments and analysis with Multinomial Logistic Regression will be conducted.

6. Relation to other work

From conducting this experiment, it was noted that PlayPhysics' emotional student model is very effective at recognising neutral and negative emotions, such as 'anxiety' or 'hopelessness'. In addition, it was noted that participants reported positive emotions such as 'hope' or 'anticipatory joy' more frequently. If we want to divide 'value' and 'control' into the number of categories determined by Pekrun et al. [2], e.g. control can be 'low', 'medium' and 'high' to make the distinction between several categories of emotion, such as 'hope' and 'anticipatory joy' a larger student population is needed. For instance, when Pekrun et al. [24] proved the effective-

Table 2
Multinomial Logistic Regression estimates of the predictors of control and value.

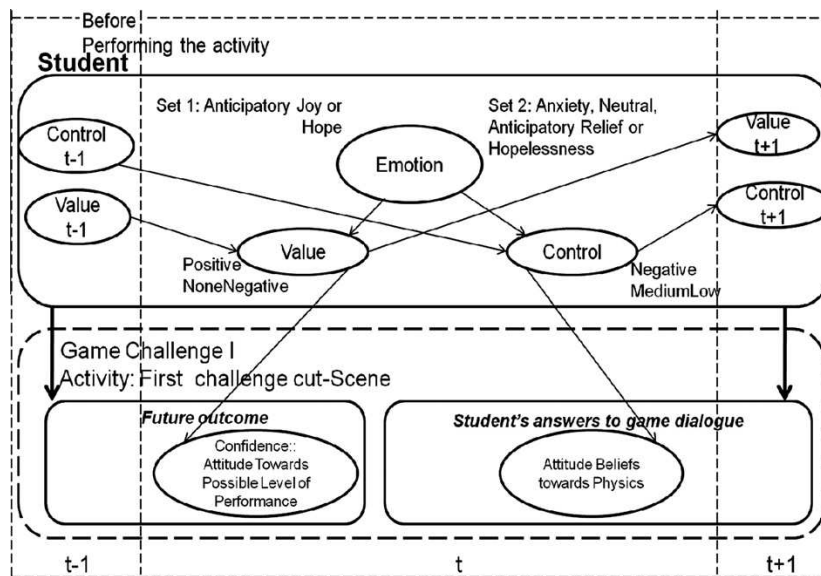| Dependent variable	Predictors	Significance (p-values)	Odds ratios	95% C.I. (confidence intervals)	% Cases correctly classified
Value	Confidence: attitude towards the possible level of performance	.002	6.000	1.957–18.398	70.5
Control	Attitude beliefs towards Physics	.021	7.885	1.364–45.577	88.5

Fig. 7. Outcome-prospective emotions DBN according to Multinomial & Logistic Regression results.
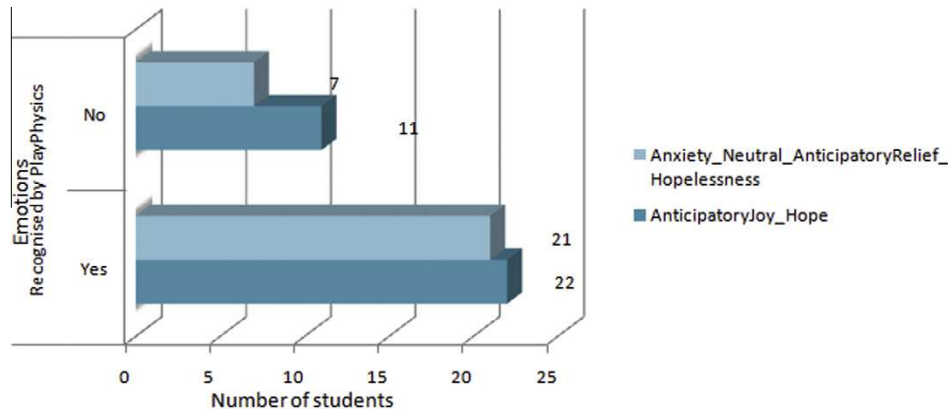
Fig. 8. Prediction of membership by PlayPhysics' emotional student model.

ness of their AEQ questionnaire, they conducted experiments with 389 students of Psychology at undergraduate level. However, for the purposes of our research, this division, i.e. 'Anticipatory-Joy_Hope' and 'Anxiety_Neutral_AnticipatoryRelief_Hopelessness', is sufficient to adapt our emotional game to the learners' identifiable needs. In addition, it is necessary to conduct experiments with the DBNs corresponding to the emotions experienced during and after interacting with PlayPhysics.

McQuiggan et al. [21] and Del Soldato and Du Boulay [22] agreed with the work of Pekrun et al. [2] on employing the variables *confidence* and *effort* in order to measure the student's self-efficacy level and personal disposition. However, the work by Pekrun et al. [2] is the only one that shows how motivation and self-efficacy can be translated into appraisals of *control* and *value* to infer an emotional state. Jaques and Vicari [11] employed the OCC model to recognise students' emotions by adapting the theory to the teaching and learning context. However, they did not report *p*-values and the accuracy of the model overall or per emotion. In addition, it is noted that since there is not a universal classification of emotions, it is easy for students to confuse the emotion that they are feeling with the emotion that was enquired. In order to avoid this problem, a description and example of the emotion that is enquired was incorporated into the game dialogue.

Also, it was noted that the analysis and classification of psycho physiological signals, such galvanic skin response and heart rate, can be employed as random variables in our model to enhance the accuracy of the emotional model, as suggested in the work by McQuiggan et al. [21] and Conati and Maclaren [4]. However, it may be possible that the accuracy of the model improves only slightly when adding these variables. If this is the case we will consider incorporating sensor hardware into an online game-based learning environment as a complementary way of determining students' emotions. This will be performed after endeavouring to achieve a reasonable accuracy without biofeedback signals, i.e. equal to or above 70%.

It is worth mentioning at this point that Pekrun et al. [2] employed the students' self-reporting on the psycho physiological sensations that students have when feeling anxiety, such as feeling that their heart will go out from their chest, which suggests employing heart rate signals. However, from the work by Rajae-Joordens [32], it was noted that galvanic skin response is more sensitive to thoughts and emotional changes than the heart rate. Therefore, an aspect of future work will be acquiring, analysing and classifying galvanic skin response signals that can be employed to enhance the accuracy of our model.

7. Conclusion and future work

This work focuses on creating an emotional student model that can reason about observable behaviour or questions posed during game dialogue while interacting with PlayPhysics. The model is comprised of *cognitive and motivational variables*. In the context of our research *motivational variables* are defined as variables strongly correlated with motivation, such as confidence. Also, the model employs as a basis the Control-Value theory of Achievement Emotions. Since this task involves uncertainty, three DBNs were derived using a PRM approach, which facilitates the selection of domain features and factors.

The evaluation of the outcome-prospective emotions DBN was undertaken with 61 students. Results show an overall accuracy of 70.49%. The model specifically proved effective at identifying neutral and negative emotions, such as 'anxiety'. Multinomial Logistic Regression was employed as an approach to validate the defined categories, dependencies and CPTs. The approach proved successful. However, it is necessary to conduct further experiments with the other DBNs once the implementation of PlayPhysics' first challenge has been completed. While conducting more experiments, each participant will be observed in a Gesell dome by two lecturers while answering the game-dialogue, solving related Physics problems and reporting the experienced emotions. The interaction variables and data will be analysed through Multinomial Logistic Regression to ensure the best prediction of category membership of these DBNs. The refined model will be incorporated into PlayPhysics to automatically adapt pedagogical responses and maximise students' understanding and motivation. PlayPhysics' challenges and domain are being modelled by an astrophysics domain expert at ITESM-CCM. Future work will explore the incorporation of biofeedback signals, e.g. galvanic skin response, which has the potential to enhance the model's accuracy in determining the participant's emotions. Two features will be studied specifically, e.g. skewness and kurtosis. In addition, we will attempt to convey emotional responses through game elements, such as game-characters, colours or sounds, e.g. by adding a game character that provides pedagogical feedback or shows an emotional expression according to the task outcome.

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