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4 authors:


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A virtual environment for learning computer coding using gamification and emotion recognition

Ramón Zatarain Cabada [a], María Lucía Barrón Estrada[a], José Mario Ríos Félix [a] and Giner Alor Hernández[b]

[a]Tecnológico Nacional de México/I.T. Culiacán, Division of Research and Postgraduate Studies, Culiacán, Mexico; [b]Tecnológico Nacional de México/I.T. Orizaba, Orizaba, Mexico

ABSTRACT

Emotions play an important role in students learning to master complex intellectual activities such as computer programing. Emotions such as confusion, boredom and frustration in the student are important factors in determining whether the student will master the exercise of learning to program in the short and long term. Motivation also plays an important role in learning a programing language. However, it is extremely difficult to motivate students who find themselves in a negative emotional state. We developed an advanced learning environment that detects and responds to student emotions by using machine learning techniques, and incorporates modern motivation strategies by using gamification methods. We conducted two experiments; one to evaluate the acceptance of the learning system and a second one to evaluate the academic performance. The results of the experiments show that intention to use is dependent on perceived enjoyment but not on perceived usefulness and attitude toward the system. Also, better results were obtained in a post-test from students who used the learning system, compared with those who didn't use it.

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Affective computing; computer programming learning; gamification; intelligent learning environment; intelligent tutoring systems

Introduction

Computer programing is one of the most difficult intellectual tasks to learn. This has been reflected in the indexes of dropout or failure in courses of programing languages since the birth of computer science. Different causes like 'learning strategy', 'lack of study', 'subject difficulty', 'lack of effort', and 'appropriate teaching method' have been considered among the most responsible for this problem (Hawi, 2010).

Some works report the key motivating factors and influences affecting learning among students learning computer programing (Coffin & MacIntyre, 1999; Law, Lee, & Yu, 2010). According to Hawi (2010), some of the most important factors are 'individual attitude and expectation', 'reward and recognition', 'challenging goals', and 'social pressure and competition'. On the other hand, the work of Coffin and MacIntyre (1999) found that students who perceive programing computers as an interesting and valuable activity learn better due to factors such as challenge and awareness. There are also research papers on learning to program computers where collaborative work (Serrano-Cámara, Paredes-Velasco, Alcover, & Velazquez-Iturbide, 2014) plays an important role in motivation.

On the other hand, emotions play an important role in learning, and in the case of learning computer programing there is relevant research work that has tackled the problem. Bosch, D'Mello, and Mills (2013) investigated the affective states that students experience when learning to program

CONTACT Ramón Zatarain Cabada rzatarain@itculiacan.edu.mx

computers. They found that flow/engagement, confusion, frustration and boredom represented most of the emotion produced by the students, and boredom was negatively correlated with performance during both parts of the fadeout phase, but was positively correlated with performance during the scaffolding phase. In another similar work, Bosch and D'Mello (2017) studied novice computer programmers. Their results revealed that engagement, confusion, frustration, boredom, and curiosity were the most frequent affective states. On the other hand, anxiety, happiness, anger, surprise, disgust, sadness, and fear were uncommon. Also Bosch, Chen, and D'Mello (2014) investigated learning-centered emotions (e.g. confusion, frustration) in students learning computer programing. They found that Confusion/Uncertainty and Frustration were the most common emotions. Lee, Rodrigo, d Baker, Sugay, and Coronel (2011) discovered that prolonged confusion has a negative influence on student success. However, confusion is positively associated with results in student tests. Confusion can be an emotion that, when learning, is less negative than other emotions such as boredom.

Based on the previous research, which mentions the difficulty of learning to program computers and the importance of emotions in the learning process, we present the integration of learning-based emotion recognition with gamification techniques, implemented in a learning environment that teaches the complex process of algorithms and code construction.

The paper is organized as follows: section "Related work" describes related work of the main topics. Section "Research methodology" presents the research methodology implemented in this study. Section "The design of the learning environment" illustrates the software architecture designed for the system. Section "EasyLogićs functionality" describes the structure and operation of the system. Section "Results and findings" presents the results of two different experiments using the system: the first to measure the acceptance of the technology, and the second to analyze the academic performance obtained through the system. Finally, section "Conclusions and future work" presents the conclusions of the work.

Related work

This section describes research work in areas related to our investigation. The works were classified in gamification and learning environments, and affect recognition.

Gamification and learning environments

There is relevant work related to gamification used in learning environments. Dicheva, Dichev, Agre, and Angelova (2015) presented a study of empirical research on the application of gamification in educational contexts. One of the conclusions of this work was that whenever gamification is well designed and used correctly, it has the potential to improve learning. In another work, De-Marcos, Domínguez, Saenz-de-Navarrete, and Pagés (2014) compared social networking and gamification in an undergraduate course and observed the effect on students' academic achievement, participation, and attitude. Students were using the Blackboard learning management system. The results of their work showed that the use of gamification has a positive impact on student performance in a learning environment. Simões, Redondo, and Vilas (2013) integrated a framework within an existing learning environment (schooools.com), to test the effectiveness of gamification in education. The framework and model proposed in this work are used to design gamified learning contents. In the framework, a teacher can produce learning contents with gamification elements, customized to a learning context and to the profile of the student. Also, some works on gamification in learning environments showed that benefits are not always achieved by using this technology. For example, Domínguez et al. (2013) discovered that students who had used gamification had better grades in hands-on courses, but they also found that these students lowered their grades in written assignments and participated less in classroom activities, although their motivation was higher. Authors concluded that students need immediate feedback to increase their motivation, producing better results. A test through two different courses was presented by Hanus and Fox (2015).

They evaluated student motivation, social comparison, effort, and academic performance among others in a 16-week semester. One course was taught using motivational elements of gamification while the other course was taught in traditional form. Students in the gamified course showed less motivation and satisfaction than those in the non-gamified course. Authors suggested considering certain tactics of gamification (e.g. cooperation and interesting narratives) that may produce more positive results. Monterrat, Lavoué, and George (2013) presented a new architecture with a gamification system designed to be connected and personalized to different learning environments. This work offered a new method to raise motivation in learning situations. Li, Dong, Untch, and Chasteen (2013) showed an application of gamification in computer science teaching an online learning environment. Initial results indicated students had good reactions to the new game mechanics and had better participation in social activities. In other areas of education such as medicine, gamification has proven good results in accordance with the work presented by Nevin et al. (2014). In this work, authors showed a study to evaluate acceptance of a medical knowledge software with gamification elements. The software was assessed with internal medicine residents. Another study (De-Marcos, Garcia-Lopez, and Garcia-Cabot (2016) compared traditional learning approaches (educational game and social networking) against gamification and social gamification in an undergraduate course. Results showed that social gamification produced better results in all types of evaluations.

Affect recognition

In this field, there is much work focused on different fields of knowledge. In their seminal work, Kapoor and Picard (2005), showed a framework for recognizing affective states happening through normal learning conditions. The work focused on spontaneous rather than posed situations, which was the most common to implement. The recognizer obtained a recognition rate of 86%. Zeng, Pantic, Roisman, and Huang (2009) presented a survey with the most recent advances of methods to recognize human affect using spontaneous expressions on the face and voice. At the end of the paper, a discussion of different methods to integrate the output of each recognizer is presented. Another important survey or review is the work of D'mello and Kory (2015). In this paper, authors showed that multimodal recognition was consistently more accurate than unimodal recognition, with an average improvement of 9.83% (median of 6.60%). Soleymani, Pantic, and Pun (2012) described a multimodal affect recognition method using electroencephalogram (EEG), pupillary response, and gaze distance. They identified dimensions arousal (calm, medium aroused, and activated) and valence (unpleasant, neutral, and pleasant). The classification method used a support vector machine and obtained an accuracy of 76.4% for arousal and 68.5% for valence. In education and learning environments, Bahreini, Nadolski, and Westera (2016) presented a framework for real-time emotion recognition in e-learning environments. The software system used web cameras and microphones to identify the student's affective state when he or she was accessing the e-learning environment. The emotions captured are Ekman's basic emotions: sadness, anger, disgust, fear, happiness, surprise, and neutral. The paper only showed results of the recognition of facial expressions. The work of Bosch et al. (2015) identified student's affective states using an interface in the laboratory. The main contribution of this work is that emotions that are identified are learning-oriented and they are recognized from facial expressions and body movements in a real environment such as a school laboratory. Lin, Su, Chao, Hsieh, and Tsai (2016) presented a study applying affective computing to investigate the development of Intelligent Tutoring Systems. A system framework is explained where three modules make up emotion recognition: semantic analysis (sentiment analysis), facial expression, and physiological signals. In D'mello and Graesser (2010), the authors showed the development and evaluation of an affect recognizer that combines emotion detection in dialogues, body language, and facial expressions. The affect recognizer was implemented in a well-known intelligent tutoring system called AutoTutor. Fusion techniques like feature fusion, decision level combination rules, meta-classification, and hybrid-fusion are discussed and compared in Lingenfelser, Wagner, and André (2011). Kim, Lee, and Provost (2013) presented a new model of bimodal emotion recognition where deep learning techniques are used for audio-visual feature selecting.

Research methodology

Our research has an experimental approach, due to the development of an Intelligent Tutoring System (ITS) with which controlled tests were carried out in order to validate the impact of the ITS on students, whose objective was to measure the improvement in academic performance, where the dependent variable was the post-test score. Also, an additional experiment was performed to measure the acceptance of the tool.

For the development of the ITS, the Rational Unified Process (RUP) was implemented, which is a process for software development (Kroll & Kruchten, 2003). This methodology was chosen mainly because it is adaptable to the needs of each development.

The entire investigation process had four important phases:

Design of the Software. In this phase, an architectural design that meets the requirements, pertaining to both function and quality, was specified, including all the components involved and their relationships.

Implementation of the Software. The objective of this phase was to code all the necessary components, according to the proposed design. In this phase, the operative tests of the system were included.

Experiments with Students. In this phase, two different experiments were performed: one to address the acceptance of the technology, and the other to analyze the academic performance obtained through the system.

Analysis of Results. In this phase, different statistical analysis of the data collected in the previous phase was carried out.

The following sections detail the development of all four phases mentioned.

The design of the learning environment

In this section, the design of the software architecture and most significant modules of the developed learning environment (which is named EasyLogic) are presented and explained. EasyLogic implements a Model-View-Controller (MVC) architectural pattern. It divides the application into three interconnected logical components where each of these components are built to handle the different aspects of the application (Curry & Grace, 2008).

Architecture

The architecture design of EasyLogic is presented in Figure 1, in controller section, a controller component was built for each domain object (configuration, home, ITS game, account, and so on). A student controller was build which represents the student model in the ITS. Domain controllers can interact with three modules that provide the main features of the application: Gamification, Assistance, and Emotion Recognition module.

Emotion recognition module

This module processes facial images, to recognize the emotion that students are presenting during the exercises. The output from this module is one of four different emotions: engagement, frustration, excitement, and boredom. These emotions were chosen because they are important emotions that are related to educational contexts (Pekrun & Linnenbrink-Garcia, 2012).

The emotion recognizer uses a Geometric-based method for feature extraction. This method was selected because, unlike other methods, it matches well with the number of facial features used for

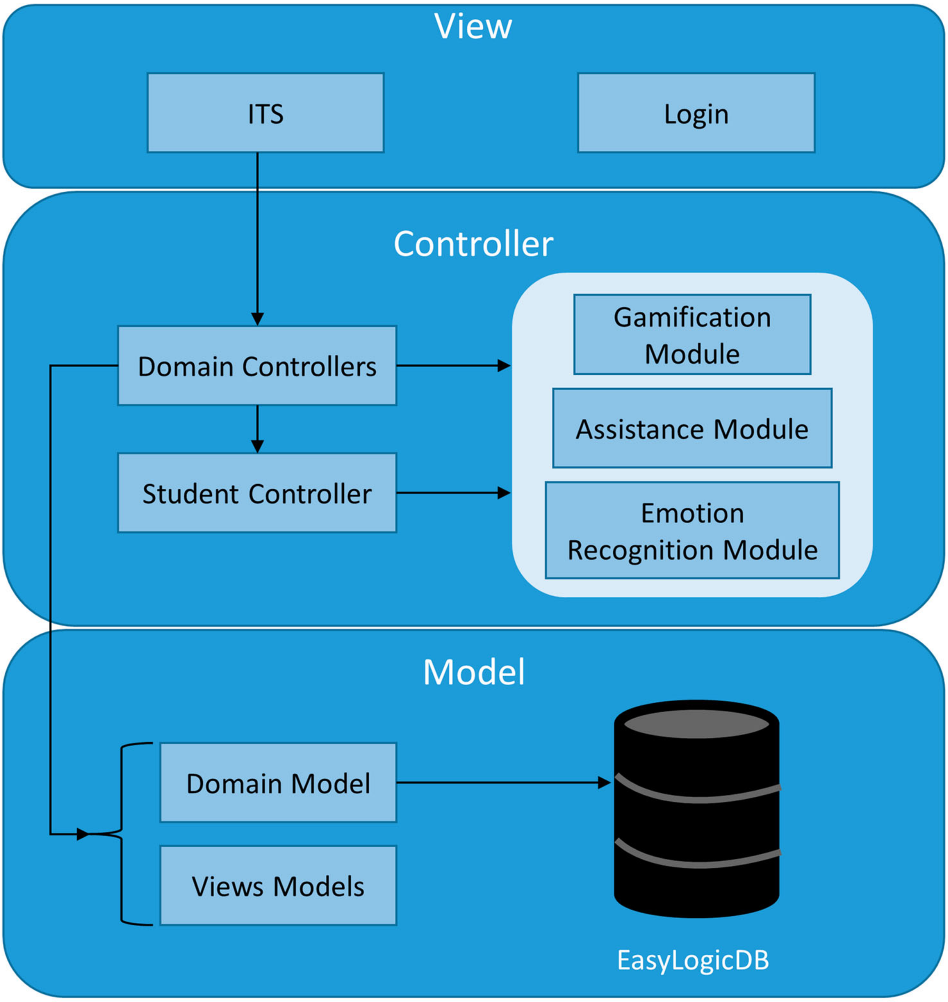

Figure 1. Architecture of EasyLogic.

emotion recognition. The process consists of five steps shown in Figure 2. First (1), 68 reference points are located on the face using a template. These points are associated with places on the face where emotions are expressed. Then (2), a point representing a center of gravity is obtained, this is achieved calculating the average value of both axes (X and Y). Next (3), the distances of every reference point to the center of gravity is calculated. Following, correction angles are then calculated, for both the horizontal axis (4) and for the vertical axis (5), to compensate for the angles, in case the images are

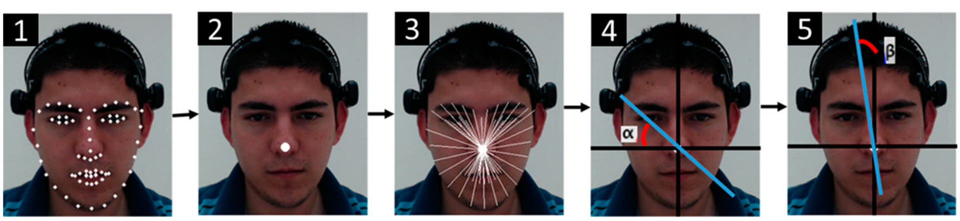

Figure 2. Feature extraction process of the emotion recognition module.

rotated. A support vector machine is used to process the input data (coordinates, distances, and angles) to produce an emotion classification.

The details of the development of this module were presented in Zatarain-Cabada, Barrón-Estrada, González-Hernández, and Rodriguez-Rangel (2017), where a maximum accuracy of 92% was obtained.

Gamification module

This module implements gamification techniques to motivate the students, for which, three elements are used: points, trophies, and ranking score. These elements were selected, since they are the most used in systems with gamification (Seaborn & Fels, 2015). Each solved exercise generates a certain amount of points; this depends on the time and the number of executions required to solve the exercise. There are trophies that are obtained by accumulating a certain amount of points. While solving any of the exercises, the gamification module verifies if the student has reached the necessary score to earn a new trophy. Figure 3(a) shows an example of motivational intervention. Each student can visualize the score that each one of his companions has in real time and the trophies they have managed to obtain. This is intended to encourage them to be competitive and motivate them to use the tool frequently.

Assistance module

The assistance module analyzes the student's behavior while solving exercises, to assess the right moment to perform an intervention in form of aid. Interventions consist of pop-up windows that are automatically displayed when the student is perceived to need them. This is achieved using data collected during the exercises.

Interventions are divided into three types: Initial, Informative and Motivational aid. Initial aids show useful information, when starting to solve an exercise. Informative aids that show useful information for the current exercise, are shown when the user is frustrated or is committed, but takes too long to solve the exercise. Finally, Motivational aids are interventions that try to stimulate students, and are displayed when the system detects that the user is bored. Figure 3(b) shows an example of an informative intervention; both modules (Assistance module and Gamification module) work together to identify the appropriate moment to show an intervention.

Figure 4 shows the process where the described modules work together while the exercises are solved by students. When an exercise is loaded, the system verifies if that exercise is associated with

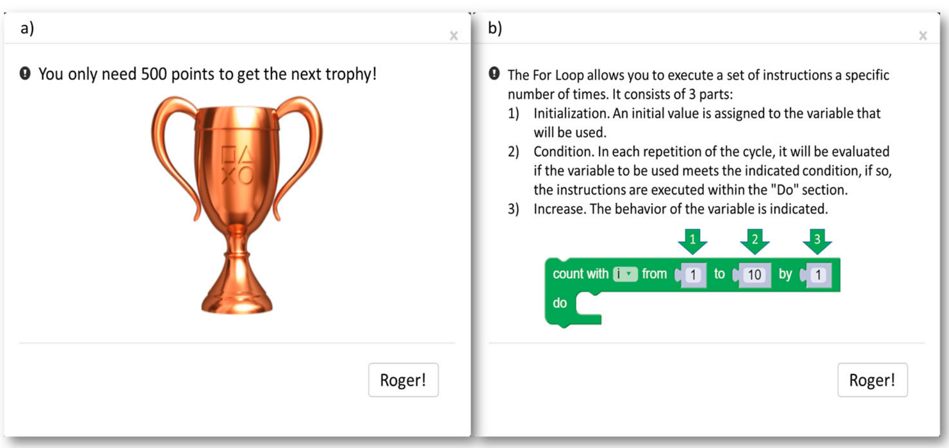

Figure 3. Example of informative and motivational interventions.

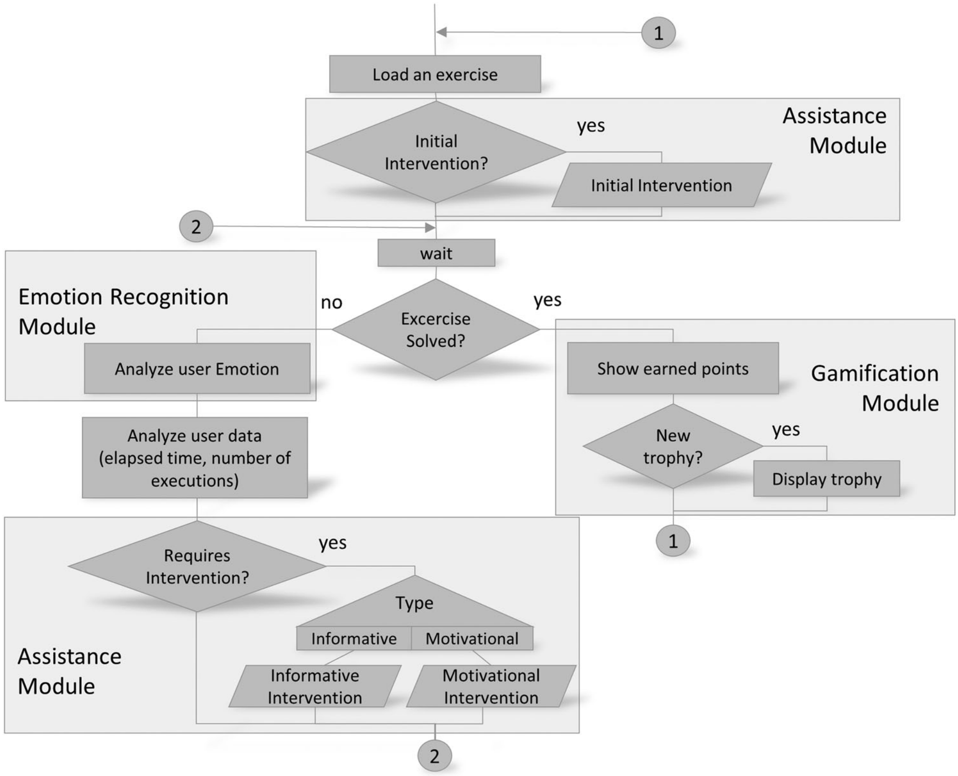

Figure 4. Process followed when a student is solving an exercise.

an initial intervention, in that case, the visual aid is shown. In order to avoid boring the student with already-read messages, the *Assistance Module* saves information of all interventions previously provided to the student, once it has been confirmed that the information has been read.

Once the exercise is loaded, the system leaves the student to work for a specified time. Then, if the student could not resolve the exercise, the system analyzes the student data related to the current exercise and uses the *Emotion Recognition Module* to analyze the student's current emotion. Next, the *Assistance Module* decides if the student requires an intervention and what type of intervention is appropriate. On the other hand, if the student could complete the exercise, *Gamification Module* is employed to motivate the student showing earned points and trophies.

Domain model

The domain in our system is the knowledge of the expert, which includes the information of the course (algorithmic logic), the different exercises, the assistance (aid), and other kind of information. To ensure the system is functioning correctly, all the information about all the courses, assistances, and emotions is stored, as well as the exercises that each of the users has solved, and the points that have been granted for each exercise. Figure 5 provides an overview of the elements used in the domain model.

Easylogićs functionality

The structure of the ITS was designed to provide a progressive way to learn basic programing topics. In this section, details of the structure and main features of the application are described.

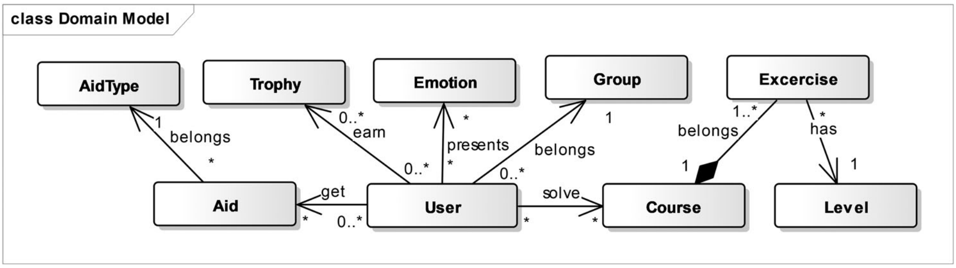

Figure 5. Domain Model used in the system.

Sections in easylogic

EasyLogic includes three sections, with which it is intended to cover the different stages of learning required to understand how to program properly. These sections are:

- Learn:

In this section, the system acts as an ITS, and provides various courses, including a series of exercises, to give lessons of each programing concept, as well as the different control structures used in programing. These exercises are supervised to obtain the affective state that the student is presenting.

- Imagine and Create:

This section allows students to design their own algorithms and then execute them step by step. It can also generate code in a programing language associated with the elaborated algorithm.

- Code:

In this section, students can program directly in JavaScript instead of using the graphic blocks.

Figure 6 shows the interface of the learning section in EasyLogic, which consists of an option bar to redirect to other screens (1), the name of the course being conducted (2), the current exercise level (3), the classification of the graphic blocks (4), an area to create the algorithm by blocks (5), the game to be animated once the algorithm is executed (6), the current number of blocks used (7), and a button to run the algorithm, as well as another to see the code associated to the created algorithm (8).

Results and findings

To test the system, two different workshops with a total of 66 students from Instituto Tecnológico de Culiacán were conducted. Experiments involved students from Computer Systems Engineering and Industrial Engineering. Participants were informed about the data that would be collected through the application, and were asked to sign a consent form. The detail of these experiments is described below.

Evaluation of technology acceptance

The Technology Acceptance Model (TAM) was selected to evaluate the impact of technology on user behavior. TAM (Davis, 1989) is one of the most accepted theories in e-learning acceptance studies

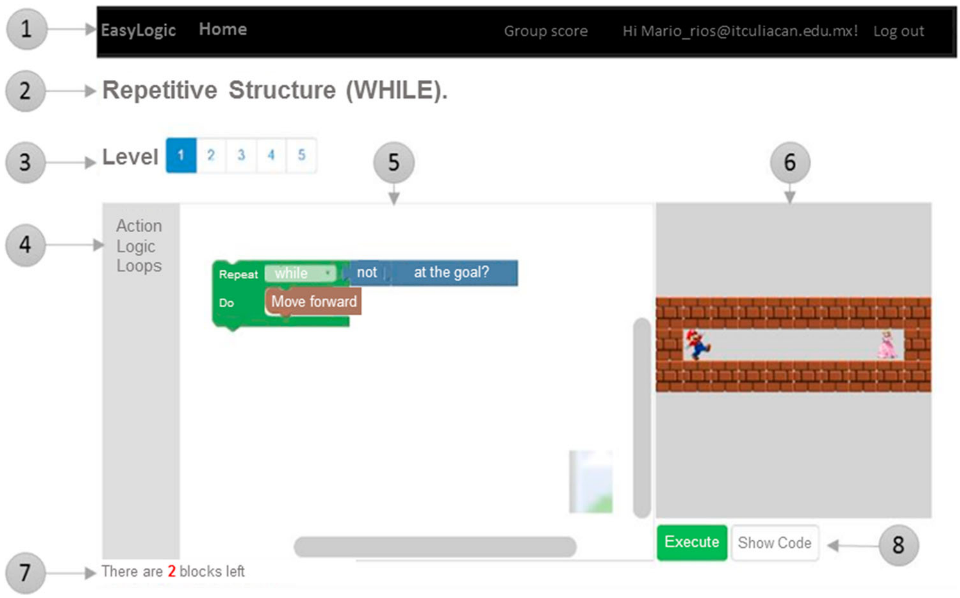

Figure 6. Learn section interface in EasyLogic.

(Teo, 2009), as was proven in (Yousafzai, Foxall, & Pallister, 2007), where 145 papers using TAM were analyzed. An analysis was performed between the relationship of EasyLogic and Perceived Usefulness (PU), Perceived Ease of Use (PEU), Perceived Enjoyment (PE), Attitude Toward Using (ATU), and Intention to Use (ITU). This leads to the following hypotheses:

H1. Perceived ease of use (PEU) will positively affect perceived usefulness (PU).

H2. Perceived ease of use (PEU) will positively affect perceived enjoyment (PE).

H3. Perceived ease of use (PEU) will positively affect attitude through activity (ATU).

H4. Perceived enjoyment (PE) will positively attitude through activity (ATU).

H5. Perceived usefulness (PU) will positively affect attitude through activity (ATU).

H6. Perceived usefulness (PU) will positively affect attitude through activity (ATU).

H7. Perceived enjoyment (PE) will positively affect intention to use (ITU).

H8. Attitude through activity (ATU) will positively affect intention to use (ITU).

A Likert scale ranging from (1) "strongly disagree" to (7) "strongly agree" was used to answer a questionnaire of ten questions.

Participants

For this experiment, a group of 24 students (8 women and 16 men) were used, all of them of Mexican origin. Participants' ages ranged from 18 to 20 years old, with an average age of 19 years old (SD = N).

Procedure

The study was conducted in a single session under teacher supervision. In this session, students were taught to use the system, and two sample exercises were solved so that there were no doubts about how to use the system. This session lasted one hour and was carried out in a computer science laboratory at the Instituto Tecnológico de Culiacán. After this session, students could enter and use the system without supervision for three days. Each student completed an online usability survey after this period.

Data analysis and results

The survey questions and their descriptive statistics are presented in Table 1. All mean values are within a range of 5.71 and 6.29. The standard deviation range was from 0.86 to 1.04.

A reliability analysis was made using Cronbach alpha, to confirm the internal validity and consistency of the items used for each variable. A Cronbach alpha was calculated for the statements belonging to each construct in the research model. Cronbach alpha values below 0.6 are considered poor/unacceptable, from 0.6 to 0.7 are considered uncertain and above 0.7 have good acceptance.

Table 2 shows the result of Cronbach alpha values and the reliability according to the measurement scales. The obtained Cronbach alpha for perceived ease of use and perceived enjoyment are at a good, satisfactory level. For Intention to use, acceptable results were also obtained. In the case of perceived usefulness and attitude toward EasyLogic, a questionable result was obtained.

From the results obtained, students enjoyed using the system and they expressed that it is easy to use, also they denoted interest in continuing to use the system. On the other hand, a questionable result obtained from PU and ATU suggests that according to the students, they do not trust that the system can teach them the skills that allow them to improve their academic performance in basic programing courses, so the system cannot yet replace traditional classes.

To verify all established hypothesis (H1 to H8), a regression analysis was applied to study the relationship between pairs of independent and dependent variables defined in our research model. All tests were performed using a two-sided alpha level of 0.05. The results of the regression analysis are presented in Table 3.

For the H2, H4, and H5, because the *p*-values were less than the assumed significance level of 0.05, the lack of dependence was rejected. Although the $R2$ value is somewhat low, low *p*-values still indicate a relationship between the two dependent and independent variables. On the other hand, H6 and H8 were rejected since the obtained R2 value was very low and the *p*-value value was higher than the assumed significance level. Figure 7 shows the graphic results of the regression analysis.

Table 1. Results of survey with mean scores and standard deviations.

Questionnaire statements	*M*	SD
Perceived usefulness (PU)		
PU1. The use of EasyLogic can help me improve my academic performance in programing courses.	5.88	1.03
PU2. EasyLogic is useful for learning the basics of algorithmic logic.	5.88	0.90
Perceived ease of use (PEU)		
PEU1. The user interface of EasyLogic is easy to use.	6.00	0.88
PEU2. Interacting with EasyLogic is easy because it does not require much mental effort.	5.71	1.04
Attitude toward using (ATU) EasyLogic		
ATU1. Using EasyLogic in the classroom is a good idea.	6.08	0.97
ATU2. Learning algorithmic logic with EasyLogic is more interesting than a traditional class.	6.00	1.02
Perceived enjoyment (PE)		
PE1. I enjoyed learning algorithmic logic with EasyLogic.	6.13	0.90
PE2. It was fun learning algorithmic logic with EasyLogic.	6.29	0.86
Intention to use (IU)		
IU1. I would like EasyLogic to contain more exercises and teach more complex structures.	5.88	0.99
IU2. I would recommend EasyLogic to all my friends.	5.71	1.04

Table 2. Cronbach's alpha obtained values and reliability result.

Variable	Cronbach's alpha	Reliability result
(PU) Perceived usefulness	0.658914729	Questionable
(PEU) Perceived ease of use	0.853807671	Good
(PE) Perceived enjoyment	0.885117493	Good
(ATU) Attitude toward EasyLogic	0.606741573	Questionable
(IU) Intention to use	0.711060948	Acceptable

Table 3. Summary of the hypotheses testing.

Hypothesis	Dependent variable	Independent variable	Coef.	R^2	*p*-Value
H1	Perceived usefulness	Perceived ease of use	0.737	0.543	<0.0001
H2	Perceived enjoyment	Perceived ease of use	0.490	0.240	0.015
H3	Attitude toward EasyLogic	Perceived ease of use	0.767	0.589	<0.0001
H4	Attitude toward EasyLogic	Perceived enjoyment	0.574	0.330	<0.01
H5	Attitude toward EasyLogic	Perceived usefulness	0.566	0.320	<0.01
*H6	Intention to use	Perceived usefulness	0.283	0.080	0.181
H7	Intention to use	Perceived enjoyment	0.687	0.472	<0.001
*H8	Intention to use	Attitude toward EasyLogic	0.403	0.162	0.051

Upon analyzing the results, it was found that the perceived enjoyment has a positive effect on the intention to use EasyLogic, and in turn, perceived ease of use also has a positive impact to PU, PE and ATU. Also, results show that perceived usefulness and attitude toward the tool don't affect the intention to use from students.

To corroborate the results obtained in TAM evaluation, a Structural Equation Modeling (SEM) method (Hooper, Coughlan, & Mullen, 2008) was used. The initial structural model was based on TAM model (Figure 7). However, the model had to be modified because of results from exploratory factor analysis. The SEM analysis, resulted in the model described in Figure 8 with the following characteristics: Chi square (13 df) = 11.97, $p = 0.530$ (>0.05) i.e. non-significant (Chi-square goodness of fit), consequently it is a good model. CFI = 1.000 (>0.09), RMSEA (Root Mean Square Error of Approximation) model fit was equal to 0.000 (<0.05), which is a good fit.

Results show that the regression weight for Usability in the prediction of Intention is not significant ($p = 0.468$). This means that Usability values do not represent an affectation towards the Intention of use of the system. In other words, the results are in accordance with what was obtained in TAM.

Evaluation of academic performance

To evaluate the academic performance of the students who used the tool, an experiment consisting of a pre-test and a post-test was designed. The aim of this experiment was to compare the scores obtained from students who used the tool against the score obtained by students who didn't use the tool.

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Participants

For this experiment, 42 industrial engineering students (non-computer science) participated, and were divided into two groups of 21 students each. Group 1 was made up of the students who

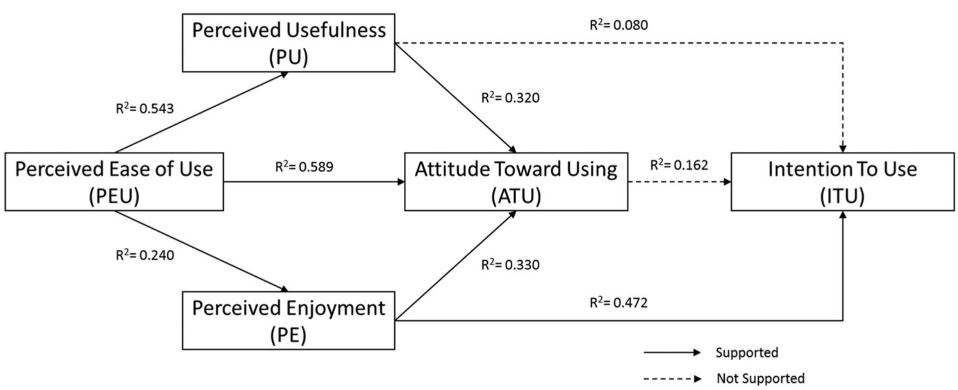

Figure 7. Result of regression analysis.

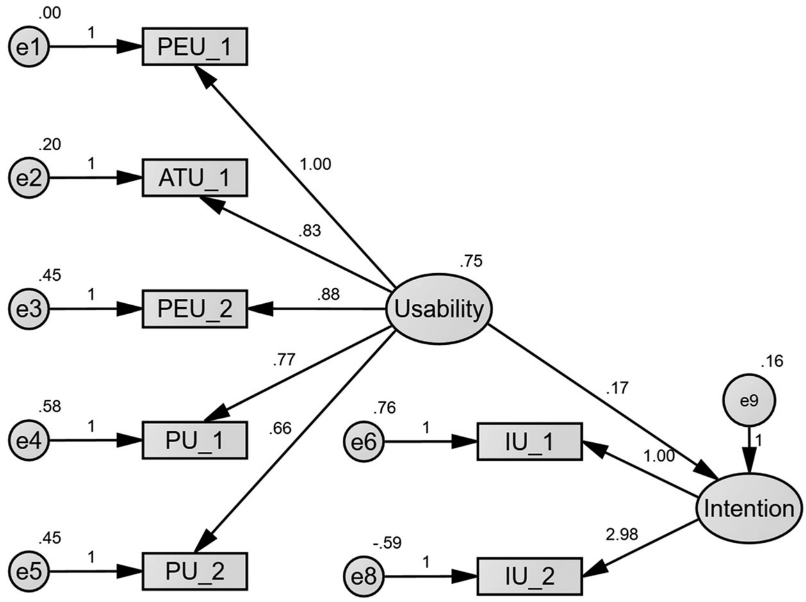

Figure 8. Structural Equation Model for the usability and intention to use of the system.

used the learning environment EasyLogic. On the other hand, Group 2 was integrated by the students who didn't use the tool.

Procedure

Two tests were designed for this experiment: a pre-test and a post-test. Both tests consisted of solving algorithmic logic exercises, during a time of 40 min for each test. After the pre-test, Group 1 was taught to use the tool and were able to continue using it at any time for one week. On the other hand, after solving the pre-test, Group 2 learned algorithm logic only in a traditional way in a classroom. Later, the students of both groups performed the post-test.

Results

Group 1 obtained an average of 82.19 in pre-test and 83.57 in post-test. Group 2 obtained an average of 84.28 and 82.95 in post-test. Based on the previous results, it is observed that in both groups the average of the tests is similar. However, a paired sample t-test was performed to determine whether there is statistical evidence that the intervention (learning environment) between pre-test and post-test of both groups produced a mean difference significantly different from zero. Table 4 and 5 show the results from paired samples t-test.

Analyzing Table 4, Pre-test and Post-test scores were positively correlated for Group 1 ($r = 534$, $p =$ 0.012598). On the other hand, Pre-test and Post-test scores weren't correlated for Group 2 ($r = 314$, p

Table 4. Results of paired samples correlations from Pre-test and Post-test of both groups.

Paired samples correlations							
						95% confidence interval	
	N	Correlation	Sig.	Bias	Std. Error	Lower	Upper
PreTest & PostTest (Group 1)	21	0.534	0.013	−0.006	0.15	0.151	0.78
PreTest & PostTest (Group 2)	21	0.314	0.166	−0.002	0.206	−0.14	0.68

Table 5. Results of paired samples *t* test from pre-test and post-test of both groups.

Paired samples test								
	Paired differences					*t*	df	Sig. (2-tailed)
				95% Confidence Interval of the Difference				
	Mean	Std. deviation	Std. error mean	Lower	Upper			
PreTest – PostTest (Group 1)	−1.38095	11.2093	2.44606	−6.483	3.721	−0.565	20	0.579
PreTest – PostTest (Group 2)	1.38095	12.4679	2.72071	−4.294	7.056	0.508	20	0.617

= 0.166). This can signify that students that used the learning environment were able to increase their knowledge.

Table 5 shows that there wasn't a significant average difference between Pre-test and Post-test scores for Group 1 ($t20 = -.565$, $p = 0.579$), either for Group 2 ($t20 = .508$, $p = 0.617$). On average, Pre-test scores were lower than Post-test scores for Group 1 (95% CI [−6.48, 3.72]), on the other hand, on average, Pre-test scores were higher than Post-test scores for Group 2 (95% CI [−4.29, 7.05]). This confirms that there were better results on the Post-test, with the group that used the learning environment.

Evaluation of emotion recognition and gamification module

During the experiment, the emotional state of the students was constantly monitored by the learning environment; it was decided to use the system with 2 configurations:

Configuration 1: With the full features (emotion recognition, application of gamification with trophies and points). 10 students worked in this way.

Configuration 2: Emotion recognition and gamification modules were deactivated; therefore, motivational interventions were omitted (only initial and informative aids were shown). 11 students used the tool with this configuration.

Data obtained by the tool were compared and better results were observed in students that used configuration 1, with respect to the time it took them to solve the exercises. Time per exercise using configuration 1 averaged 123.3 sec. ($s = 54.9$) against configuration 2, which averaged 168.6 sec. ($s = 85.4$). However, there was no difference in the average of the total number of exercises solved by the students of both configurations.

A positive trend was observed in the increase of the level of learning in the students who used configuration 1 (see Table 6). On the other hand, with configuration 2, a negative trend is shown, but that is not very significant (−1.08). The above indicates that the use of emotion recognition and gamification can help to improve the output learning.

Conclusions and future work

This paper presents a virtual environment for learning basic concepts of coding, taking advantage of current technologies. This system uses an emotion recognition module, which is responsible for monitoring the affective state of the students while using the tool, enabling it to assist students automatically during the exercises. A gamification module was integrated to engage and motivate students to continue using the learning environment.

Table 6. Comparison of test results of students using configuration 1 and using configuration 2.

	Pre-test (Avg)	Pos-test (Avg)	Difference (improvement)
Configuration 1	76	80.42	4.42
Configuration 2	85.16	84.08	−1.08

One of the objectives of this work was to perform a TAM evaluation, to assess the impact of gamification on student's behavior (Hamari, Koivisto, & Sarsa, 2014). Results from this evaluation gave us a clearer view of the students' perception and the attitude toward the environment. Obtained data suggest that perceived ease of use and perceived enjoyment had a positive effect in the acceptance of the system by the students. Similarly, it was found that perceived usefulness has a positive effect on attitude toward Easylogic, but not on the intention to use. Also, a questionable result was obtained from perceived usefulness and attitude toward EasyLogic. Data obtained in TAM evaluation was corroborated using the SEM method. In this sense, data suggests that we must work on making the system more robust and that the subjects taught are consistent with curricula of basic programing courses.

Another goal of this work was the evaluation of the academic performance of the students. To achieve this, a paired samples *t*-test was performed. The *t*-test showed that Pre-test and Post-test scores were positively correlated for the group who used the learning environment. This test also provided evidence that average scores were higher on post-test than in pre-test for this group, unlike the other group who didn't use the learning environment, whose average Pre-test scores were higher than Post-test scores. This corroborates that there were better results on the Post-test from the group that used the learning environment, compared to the group that learned in the traditional way.

This study has some limitations, for example: the sample size was very small, which leads to a lower reliability in the statistical results. Another limitation is that the tests, both the acceptance and the academic performance tests were carried out by students of the same school and of a very reduced age range (18-20 years old). Because the learning environment is intended to be used by students of different ages and diverse levels of education, more experiments should be conducted with a larger number of test subjects and with a wider age range.

For future work, our intention is to increase the number of exercises, in order to be consistent with the content of courses of diverse levels of education. Also, more experiments with larger number of test subjects and with a wider age range are planned. One of the key features of this system is the application of gamification. Many studies reported that gamification has positive effects and benefits the engagement of students with the use of a learning system [41], which is why work will continue to improve the system, so that the learning experience is more enjoyable for students.

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Notes on contributors

Ramón Zatarain Cabada is a Research Professor of the Master and PhD programs of the Instituto Tecnológico de Culiacán. He has a degree in Computer Science graduated from the Instituto Tecnológico de Culiacán, a Master and PhD in Computer Science graduated from Florida Institute of Technology. He is a member of the National System of Researchers in Mexico, level I. His main research lines are Artificial Intelligence applied to Education, Affective Computing and Intelligent Learning Environments.

María Lucía Barrón Estrada is a Research Professor of the Master and PhD programs of the Instituto Tecnológico de Culiacán. She has a degree in Computer Science graduated from the Instituto Tecnológico de Culiacán, Master in Computer Science graduated from Instituto Tecnológico de Toluca and a PhD in Computer Science from the Florida Institute of Technology. She is a member of the National System of Researchers in Mexico, level II. His main research lines are mobile learning and web-based learning. She also works on the implementation of authoring tools for intelligent tutoring systems and in Programming Languages.

José Mario Ríos Félix earned a masteŕs degree in Computer Science from the Instituto Tecnológico de Culiacán (2014-2016). He is currently studying the third year of the Doctorate in Sciences and Engineering at the Instituto Tecnológico de Culiacán. His research areas are Computational Thinking, Artificial Intelligence, Affective Computing applied to Education, and Machine Learning.

Giner Alor-Hernandez is a full-time researcher of the Division of Research and Postgraduate Studies of the Instituto Tecnologico de Orizaba. He received a MSc and a PhD in Computer Science of the Center for Research and Advanced Studies of the National Polytechnic Institute (CINVESTAV), Mexico. His research interests include Web services, e-commerce, Semantic Web, Web 2.0, service-oriented and event-driven architectures and enterprise application integration. He is an IEEE and ACM Member. He is National Researcher recognized by the National Council of Science & Technology of Mexico (CONACYT).

ORCID

Ramón Zatarain Cabada http://orcid.org/0000-0002-4524-3511
José Mario Ríos Félix http://orcid.org/0000-0002-0415-7916

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