Original article

doi: 10.1111/jcal.12075

Journal of Computer Assisted Learning

Open classroom: enhancing student achievement on artificial intelligence through an international online competition

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Abstract

Limitations of formal learning (e.g., one-way communication, rigid methodology, results-oriented approach) can significantly influence the motivation and expectation of students, thus resulting in an academic progress reduction. In order to make learning processes more playful and motivating, this paper presents a new educational experience developed by two groups of Computer Science students at the University of Huelva (Spain). As a result, an authentic real experience was incorporated into the classical teaching of Artificial Intelligence courses where classroom sessions were changed during some days for an international online competition. A comprehensive study considering the competition ranking, the students' opinion and their academic progress was analysed to assess the followed methodology. We found out that the educational experience improved the students' motivation, thereby enhancing their academic performance and personal skills as a result of learning through play. Moreover, additional teaching goals (e.g., learning new programming languages or increasing exam attendance) were obtained because of the positive motivation experienced by the competition. As a conclusion, this paradigm of real-life experience – not otherwise provided by traditional practical lessons – allowed us to ascertain that the process is more important than the outcome, which could be adapted to different teaching scenarios within an institution.

Keywords artificial intelligence, engineering education, online competition, teaching innovation.

Introduction

Traditional classrooms often involve several drawbacks due to limitations of formal learning (Novosadova *et al.*, 2007). Among others, one-way communication fails to encourage the students' proactive participation, additional effort is required by teachers to become aware of student's understanding of problems. Failures are mostly ascribed to learners by a punitive methodology, and rigid timing only adapts to students considering no individual skills or abilities (Dib, 1988). This results in a decrease in students' motivation and interest to study, which is compounded in engineering education (Van Kollenburg & van Schenk Brill, 2009). In effect, practical learning is specially required to be applied by a flexible knowledge rather than a conventional one. In this regard, interactive methods (e.g., problem-solving sessions, computer-based practices,

Accepted: 18 May 2014
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gaming) allow teachers to engage students when they are actively working with educational resources (Adams, Hill, & Slater, 2000). Bearing this in mind, learning through play comes to the teaching scene as one of the most successful learning experiences (Veganzones *et al.*, 2011).

To make learning of Artificial Intelligence (AI) courses more captivating, an educational project based on learning through play has been conducted throughout the classical teaching of a Computer Science degree. In the past, we successfully used intelligent agents and mobile robots as a means of attractively teaching an AI course (Carpio Cañada *et al.*, 2011). In that pilot project, a group of college students changed their classroom lessons for the robotic competition arena for a few days. From the analysis, we found that participating in a robotic competition gave students a broader vision of AI concepts, extra motivation, and the possibility to share knowledge with more experienced students from other universities. Nevertheless, the motivation to study gradually decreased in the following years – turned into lower academic results – as no new teaching experiences were accomplished from 2008/2009.

In order to address this problem, we have incorporated learning through play into traditional classrooms to provide students with an authentic life experience. Considering this aim, we started a new educational activity during two different AI courses. It consisted of participating in a computer-based competition, called *Google AI Challenge*, with two groups of students from the University of Huelva (UHU) during a whole semester. This provided a new scenario with additional settings such as the absence of a physical meeting point and the participation in a worldwide environment. Thereby, this paper describes the followed methodology and reports the students' reactions in their involvement in the international competition. Thus, benefits of learning through play and extra effort required by both teacher and students are provided through this experience. As a result, the *Google AI Challenge* has contributed to significantly improve the achievement and skills of the students, while consolidating theoretical concepts.

The research question this paper aimed to examine was: what are the implications of learning through play for students in Computer Science? It had three main objectives: (1) to explore the importance of playful learning as a motivating factor for the university academic performance; (2) to situate an international online contest within teaching methodology and educational goals; (3) to undertake primary research about the educational experience outcomes using the students' feedback and their academic progress. Thus, the paper is organized according to the following sections: literature review, educational objectives, developed didactic methodology, competition development, educational experience assessment, and conclusions and recommendations.

Literature review

This section provides a theoretical framework on the importance of motivation for the academic achievement and surveys the state of the art of AI competitions in educational contexts.

Motivation and gaming theory

Formal education is characterized by a systematic learning model structured and conducted according to a set of curricular directives, often presenting fairly rigid objectives, contents and methodologies to both teachers and learners (Dib, 1988). Moreover, formal learning represents no natural way of human learning, only comprising between 18.5% and 5.1% for K12 (Kindergarten through Twelve) and graduate students, respectively (Banks *et al.*, 2007). In this setting, formal education will not always stimulate students as they demand higher naturalness, flexibility and interactivity to support their learning experience. In addition, students come to the learning scene with different commitment, ability and learning styles, thus distinctively influencing their degree of motivation (Kirkland & O'Riordan, 2013). As theories state, motivation represents a key factor to learn and attain a successful academic achievement (Amrai, Motlagh, Zalani, & Parhon, 2011; Maclellan, 2005; Williams & Williams, 2011).

Informal education refers to the real-life experience, whereby individual aptitudes, values, skills and knowledge are naturally acquired from the daily practice (Novosadova *et al.*, 2007). Informal education gives students the opportunity to engage in their learning processes by proactively participating through flexible methodologies and different learning styles (Chen &

Bryer, 2012). This broadens personal competencies more so than the ones developed by formal learning (e.g., leadership, discipline, responsibility, teamwork, conflict management, planning, organizing, interpersonal relationships). As a consequence, it is felt by learners as a more favourable, effective and stimulating methodology compared to a largely inefficient and unappealing formal education (Schulz, 2008).

Informal education and play are changing both the way we think about knowledge and learning, as well as the manner in which we structure work and ideas. Learning through play enables learners to construct their own knowledge based on the understanding of their personal experiences, as the educational constructivist theory states (Gagnon & Collay, 2006). Active learning is effective in motivating and improving student achievement by promoting creative thinking and multi-style learning approaches. Kinesthetic is the learning style best adopted by playful methods, but other VARK (visual, aural, read/write and kinesthetic) approaches can also be incorporated (Cannon & Newble, 2000). Learning through play is currently better documented for K12 than for undergraduates (Rice, 2009). The advantages of interactive learning for adults are clear and varied, especially in engineering education where practical knowledge requires direct interaction with phenomena rather than theoretical lessons (Rieber, 2001).

Teaching through play fosters active creativity, development of problem-solving strategies and self-confidence to try new challenges (Lester & Russell, 2008). However, experience is not always enough to achieve learning and some other aspects must be introduced in the educational process (Bolton, 2010). These are observation, analysis, critical reflection, abstraction of concepts and testing of acquired knowledge in new situations. In this context, competition-based learning represents a suitable scenario to provide all components required to achieve constructive learning. Nevertheless, a low percentage of teachers and students take advantage of the high popularity of games for educational purposes.

Active learning through competitions has proven to be a captivating learning factor by enabling students to attain knowledge for themselves through activity and reasoning (Carpio Cañada *et al.*, 2011). This learning approach is characterized by a student-centred perspective where the process is more important than the outcome. Thus, teachers become the means to guide through the learning process, while motivated students learn about a course through problem-solving challenges (Hmelo-Silver, 2004). As benefits, students naturally respond to this type of learning, while games offer a medium to form and reform ideas in a fun and interactive way. As a result, the more motivated and engaged the students are, the more learning occurs (Squire & Jenkins, 2003).

Learning through play in AI

Since *Alan Turing* first established that games could be automatically played by machines using logical algorithms, these have been used as a teaching methodology to train different AI concepts (Turing, 1950). This turned games into potentially successful tools used to teach a wide variety of practical methods because of their ability to stimulate students, providing spontaneity, flexibility and interactivity to support their learning experiences (Moursund, 2007). The more representative examples in education are classic board games as *Backgammon*, used to teach exploring methods by reinforcement learning algorithms (Moursund, 2006); *Checkers*, used to develop search-based problem-solving techniques (Sturtevant, 2008); *Tic-Tac-Toe*, used for min-max and alpha-beta pruning (Michulke & Schiffel, 2011); *N-puzzle*, used for state-based search (Markov, Russell, Neller, & Zlatareva, 2006); or *n-Queens*, used to teach constraint satisfaction problems (Letavec & Ruggiero, 2002), among others.

Teachers have found that the students' motivation plays a key factor in learning and attaining successful academic achievement by the challenges proposed within courses. For example, *The Open Racing Car Simulator* – an open source and highly portable multi-platform framework – has been used as ordinary three-dimensional (3D) car game for the teaching of mechanical principles at the Northern Illinois University (Coller, 2009). Furthermore, several *RoboCode* leagues have been organized in the National University of Maynooth with the aim of teaching programming languages (O'Kelly & Gibson, 2006). In them, students are challenged with the design of intelligent agents – called bots – to compete ones against others trying to mimic human behaviour (Eisenstein, 2003). In other cases, competitions help to discover talented and skilled students from engineering schools. As an example, the *Facebook Hacker Cup* international competition has been proposed since 2011 with this purpose, which consists of solving a number of algorithmic-based problem statements using any programming framework or language (Forišek, 2013). In addition, the Wichita State University has actively used *Lego Mindstorm* for the *First Lego League*. This competition has also proven to be a useful teaching methodology for K12 students whereby individual aptitudes, values, skills and knowledge have been naturally acquired according to informal education (Whitman & Witherspoon, 2003).

With the aim of using AI systems as testing platforms to promote both education and research in this field, several national and international contests have recently appeared. For example, the Stanford University used the *AAAI (Association for the Advancement of AI) General Game Playing* as an excellent development framework for students during a summer competition (Genesereth, Love, & Pell, 2005). Furthermore, the University of Hartford has developed and tested a suite of projects – called *MLExAI* (Machine Learning Experiences in AI) – that can be closely integrated into introductory courses to teach AI through machine learning (Neller, Russell, & Markov, 2008). The University of Essex started the *Ms Pac-Man vs. Ghost League* to compete against bots submitted by other competitors, which was previously tested with success by teachers and learners on AI courses (Szita & Lorincz, 2007). Other recent game competitions regularly held by universities are the *Physical Travelling Salesman Problem*, a single-player game aimed at solving combinatorial optimization problems with AI controllers (Perez, Rohlfshagen, & Lucas, 2012); the *Simulated Car Racing Championship*, an event consisting of three competitions where computational intelligence techniques were applied to car controllers for a racing game (Loiacono *et al.*, 2010); the *Mario AI Championship*, a benchmark used in several competitions related to international conferences on research and/or education (Karakovskiy & Togelius, 2012); and the *StarCraft AI Competition*, an advanced strategy game for which AI-based bots had to beat expert human players in real time (Togelius *et al.*, 2010), among others. These paradigms represent a scenario where observation, abstraction of concepts, critical thinking, analysis and acquired knowledge concur into a successful educational process with the aim of a competition.

In this context, the *Google AI Challenge* appeared as a biannual online contest initially organized in 2009 by the University of Waterloo and sponsored by Google (Savchuk, 2012). A different game is chosen every year and contestants shall submit specialized bots to play against other competing bots (Perick, St-Pierre, Maes, & Ernst, 2012). The topics in these series of competitions have been *Rock-Paper-Scissors* (2009/Fall), *Tron Light-Cycles* (2010/Spring), *Planet Wars* (2010/Fall) and *Ants* (2011/Fall). Although the first edition was based on a widely known game, the following competitions pursued the design of completely original games to try new challenges. This provided a captivating factor to explore new approaches, experiment with different ideas and ultimately find solutions to problems by worldwide students.

In order to focus the framework of this educational project, Table 1 shows an overview of the different competitions involved in the aforementioned educational experiences. The *Google AI Challenge* is distinguished for being an international contest – played online in multiplayer mode – for both university and professional levels. It has been used herein to teach a variety of AI topics (e.g., genetic algorithms, neural networks and fuzzy logic), while illustrating new ways of teaching programming languages through the implementation of intelligent agents.

Educational objectives

One of the pedagogical goals intended with this project has been to improve the motivation and interest of our students to study. In a previous experience, the teachers realized how the fact of changing – for a few days – the traditional classroom for a robotic competition hall influenced learning (Carpio Cañada *et al.*, 2011). In the case of the *Google AI Challenge*, new parameters as the lack of having a real space to play the competition – in contrast with virtual – were added. That is, only a classroom with computers, the Internet and no more special needs were required. From our experience, the lack of a meeting point did not limit the implementation of this teaching project despite being conducted through a virtual environment. Moreover, the *Google AI Challenge* offered no monetary reward to

Table 1. Main Features of Challenges Used as Educational Methodology by Some Authors

Challenge	Competition context	Teaching level	Game mode	Educational goal	Used methodology	Programming language	Project year
FLL[1]	National/physical	K12 students	Team players	Real-world basics related to the sciences	Mechatronic design and robot programming	NXT-G, Robolab	2003
RoboCode League[2]	International/Web server	University	Multiplayer	Language programming	Intelligent agents	Java™, C#, VB, .NET	2003
Pac-Man vs. Ghost League[3]	International/Web server	University	Multiplayer	Artificial intelligence	Reinforcement learning	Java™	2007
MLExAI[4]	Multi-institutional/laboratory	University	Single player	Data mining, neural networks and machine learning	Web recommender and classification, pattern recognition, data mining, games	Java™	2008
TORCS[5]	Laboratory/Client-server	University	Multiplayer	Mechanics	Dynamic systems and control	C++	2009
Mario AI Championship[6]	International/Web server	University	Single player	AI techniques	Reinforcement learning	Java™ , C++ and Python	2009
Simulated Car Racing[7]	International/Client-server	University	Team players	AI techniques	Intelligent agents	C++	2009
StarCraft AI Competition[8]	International/Web server	Professional	Single/multiplayer	Advanced AI techniques	Planning, data mining, machine learning, case-based reasoning	C++	2009
Facebook Hacker Cup[9]	International/Web server	Professional	Two Players	Identify top engineering talents	Algorithmic-based problem statements	Any	2011
Google AI Challenge[10]	International/Web server	University	Multi Player	AI techniques	Intelligent agents	Any	2011
Physical Travelling Salesman[11]	International/Web server	University	Single player	Combinatorial optimization problems	Intelligent agents	Java™	2012

Note. List of the authors' names is given by the superscripts of the challenges: [1](Whitman & Witherspoon, 2003); [2](O'Kelly & Gibson, 2006) & (Eisenstein, 2003); [3](Szita & Lorincz, 2007); [4](Neller *et al.*, 2008); [5](Coller, 2009); [6](Karakovskiy & Togelius, 2012); [7](Loiacono *et al.*, 2010); [8](Togelius *et al.*, 2010); [9](Forišek, 2013); [10](Savchuk, 2012); [11](Perez *et al.*, 2012).

contestants so, unlike other competitions, this was not a factor influencing the students' participation.

Furthermore, we found that an international event was a much more appealing factor for the students' participation. That is, the students felt this experience as an opportunity to measure themselves against students from other universities, many of them prestigious ones. Thus, the students were able to test – without having to physically move to the competition site – the knowledge acquired during their study years within the context of a competition. This way, the students discovered through play that they could solve challenges in the same way than students from influential universities and professionals from all around the world. Consequently, their self-esteem to try new activities was reinforced and caused positive changes in the perception of their abilities (see *Educational Experience Assessment*).

Other educational goals proposed in this project were to promote teamwork and information sharing. In order to achieve these goals, the students were encouraged to work in groups, discuss solutions together and share information about their programs. The teacher allowed this scenario as long as the students implemented their own solutions. This was made possible by primarily using the forum of the competition's website. However, this is not limiting and other electronic resources predominantly used by universities (e.g., blogs, chats, Moodle) can be used by teachers to accomplish similar experiences (Martín-Blas & Serrano-Fernández, 2009). In previous editions of the *Google AI Challenge*, the participants shared information from the very beginning of the competition, thus facilitating the creation of high-quality intelligent agents. However, such spirit was not achieved in the *Google AI Challenge 2011* from the beginning. As an example, the post published by *a1k0n* – winner of the *Tron Light-Cycles* edition – called attention to this circumstance (Sloane, 2011). The message sent to the organizer's forum began with the following paragraph:

> I miss the collaborative nature of the Tron contest where everyone basically revealed their strategy in the forum and generated better ideas. Everyone's been much more tight-lipped since then. So I'm going to reveal mine here and now.

This message claimed the collaborative spirit of the competition and determined the beginning of the collaboration between contestants. Thus, our students found that – regardless of the position obtained in the final classification – information sharing and teamwork were essential to carry out their works.

Developed didactic methodology

The pilot experience started in the academic year of 2011/2012 during which students attended *Artificial Intelligence Laboratory* (AIL) or *Artificial Intelligence and Knowledge Engineering* (AIKE) courses; both in the 3rd and 4th years of their Computer Science degree at the University of Huelva (UHU). The AIL course was optional in contrast with the AIKE course, which was mandatory for the students. This different nature provided an ideal scenario for testing various educational goals addressed with the same experience. Furthermore, the *Ants* game for the *Google AI Challenge* was used as a novel educational methodology, thus providing teachers valuable information to meet new challenges on AI courses.

To conduct this educational project, we extended regular classroom lessons with additional work performed by both teachers and students. It gave our students the possibility to freely discover AI techniques with the aim of competing internationally. Hence, this educational experience was not only felt by the students as a series of practice sessions in lab. Table 2 shows the work carried out by the teacher and students to adapt the *Google AI Challenge* into the programs of AI courses. The two courses have been offered annually maintaining the same structure and length since 2004/2005.

The AIL course comprised a total of 120 h of student work divided into 50 and 70 h of classroom and non-classroom instructions, respectively. The hands-on components usually consisted of recognizing data structures, AI techniques (e.g., evolutionary algorithms, fuzzy logic, neural networks), and learning both programming languages and common tools used on AI. Moreover, the AIKE course comprised a total of 290 h of student work divided into 130 and 160 h of classroom and non-classroom instructions, respectively. The hands-on activities are designed to build intelligent systems for the automatic demonstration of theorems, implement search and planning algorithms, and coordinate intelligent agents in lab practices. In summary, the differences in the courses' structure are

Table 2. Integration of the Educational Experience in the Teaching of Artificial Intelligence Courses

ID	AIL program	AIKE program	Dedication to the competition	Date	Competition status	Teacher work	Student work
1	Overview of AI	Overview of AI	1 session	25 October 2011	Competition starts	Description of challenge goals	Website overview, user account set-up, tools and forum use
2	Genetic algorithms	Statistics, uncertainty and Bayesian networks		–	–	Traditional classroom	Quickstart guide and first basic work entry
3	–	Machine learning		–	–	–	Learn new programming languages (optional)
4	–	Logic and planning		–	–	–	Implement intelligent agents
5	Neural networks	Markov decision processes and reinforcement learning	1 weekend	18 December 2011	First phase	Customize strategies	Testing and debugging own AI algorithms
6	–	Hidden Markov models and filters		–	–	Traditional class work	Share information between students
7	–	Adversarial and advanced planning		–	–	–	Upload bots to online contest
8	Fuzzy logic	Image processing and computer vision	1 session	24 December 2011	Final competition	Bots competition	Get final ranking
9	–	Robotics and robot motion planning	1 session	26 December 2011	Offline competition	Knowledge and skills	Feedback on AI algorithms and intelligent agents
10	–	Natural language processing and information retrieval	1 session	9 January 2012	–	Student achievement	Opinion survey and experience discussion

AI = Artificial Intelligence; AIKE = Artificial Intelligence and Knowledge Engineering; AIL = Artificial Intelligence Laboratory.

that AIL was aimed at introducing AI concepts in a completely practical way by programming AI techniques and algorithms. On the contrary, AIKE – of a more advanced level than the previous one – intended to give students greater theoretical and practical knowledge on AI, thereby including other fields such as robotics and computer vision.

The teaching methodology was as follows. The challenge goals were introduced by the teacher in a first introductory session of 1.5 h (ID1) 2 months before the end of the competition (see Table 2). Then, the students learned to use the competition website, activate their user accounts and sent their first basic entries to the virtual organizer's platform (ID2). During the following preparatory weeks, the teacher explained the game operation and the students were guided on the implementation of their intelligent agents (ID3–ID4).

The *Google AI Challenge* nature allowed our students to start writing simple codes for their bots without high programming skills. Therefore, the students were able to write their algorithms in different languages (e.g., C++, Python, Java^{TM}) using a starter kit available and send them to an application program interface built by the competition organizer. Since most of the students had no previous knowledge of Python programming – one of the educational goals intended herein – they were encouraged to learn some basic language within the context of the competition. Although learning a new language was an additional effort, it allowed the students to acquire new knowledge without affecting their course performance (see *Validation as Educational Experience*).

The first phase of the competition lasted a week (ID5–ID7). For this purpose, a programming marathon was organized by the teacher and students during a weekend. The aim was for students in 3rd and 4th years to meet in a common place to share ideas about their programs (i.e., the classroom). During this phase, the tasks consisted of designing strategies and testing AI algorithms while the teacher followed up their works. During this phase, the students were qualified to make changes in their bots and upload new versions to the virtual platform of the competition. The score was reset to the end of the ranking with each new version. However, this action was not penalized by the organizer as the virtual platform was designed to quickly promote skillful intelligent agents, thus fostering the students' critical reasoning about the construction of their algorithms. During this stage, sharing information between the students to learn the techniques used by their classmates became essential in the progress and quality of the algorithms. From our experience, this short period of time was the most productive of all the time spent on programming. As an example, some students worked up to 30 h from 16:00 h on Friday to 06:00 h on Monday.

Once the final phase of the competition began, it was not possible to upload new versions of bots to the competition's platform (ID8). The waiting time between games was 1–4 h. Hence, participants could only monitor their matches against other players while the problem-solving strategies and educational goals learned were discussed. As a result of the motivation provided by the *Google AI Challenge*, most of the students improved their algorithms and intelligent agents even in the days after the competition. This was possible since the virtual platform of the *Google AI Challenge* was available offline (ID9). Finally, students were asked to ascertain the impact of this educational experience on teaching in engineering (ID10). In summary, the cost of putting into practice this experience required an average time of 24 and 20 h per student in each course, and a total of 22 and 32 h by the teacher, respectively (see Figure 1).

Competition development

The *Google AI Challenge* was held by 7897 contestants from 116 countries. The *Ants* game was used as the basis for the 2011 edition. The strategy of this game consisted of managing an ant colony in order to fight against other colonies for domination. The game took place on a map where participants initially had one or more anthills. The purpose of an anthill was to generate ants, which should be controlled by each bot. Participants had to perform the movements they deemed appropriate through a turn-based system. Actions to get points by bots were to explore the map, attack enemy hills, gather food, avoid collisions and to not block their own anthills. The rules stipulated that each participant had to give a token to the game server, thus indicating the end of movements before the turn expired. If the token was not submitted on time, the player received penalty points and was prevented from making movements in the remaining turns. However, this did not imply the disqualification and a player

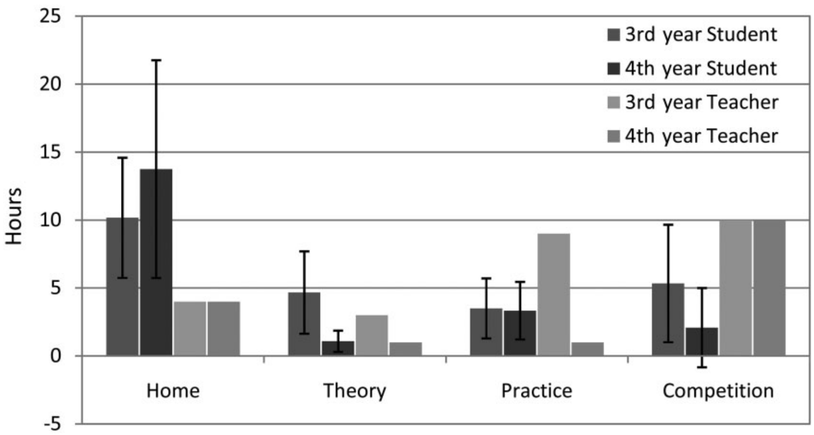

Figure 1 Times Devoted to the Project Development Depending on the Role of the Person

could even win the game if enough points were accumulated (further goals and rules of the *Google AI Challenge* are available at http://aichallenge.org).

Matches were played on the organizer's server during the challenge and contestants were able to play them on the website after each round. Thus, our students were able to upload different versions of their programs to test ideas and improve their intelligent agents. In the final phase, entries were closed, the classification was restored and the latest version of each bot played several matches to determine the final classification (Savchuk, 2012). During the competition, the user ranking was continuously updated through TrueSkill[TM] (Herbrich, Minka, & Graepel, 2007). This tool represents a Bayesian classification algorithm developed by Microsoft Research, which allows you to obtain a ranking based on the skill of each intelligent agent. Henceforward, the skills were tracked by the system after each game to determine the individual abilities of each player over other contestants.

There were no restrictions on the techniques used and any AI algorithm learned in the course could be used to promote the students' creativity. Thereupon, the students in 3rd and 4th years followed two different methodologies for developing their intelligent agents. As a starting point, the students in 3rd year studied some sample bots provided by the organization. After making and testing the initial versions, the students found that the best performance was obtained by combining two basic bots – named *Lefty* and *Hunter* – instead of using an intelligent agent as the single best solution. Thus, the proposed strategy consisted of alternating the two bots in a series of turns, each one with a different behaviour. Figure 2 shows the basic structure of the algorithm used in the competition. The variable *ArraySchedule* sets the number of turns for bots, which allowed controlling the bots' strategies to combat more efficiently. In kind, little variations in the cycles influenced the expansion rate of the ants over the map. This working methodology was used by 90% of our students.

The methodology, although also available for the students in 4th year, was discarded as they preferred to implement their own bots because of their higher knowledge on AI techniques learned. As an example, the techniques taught during the months prior to the competition were the tree search, graph search, breadth-first search, uniform-cost search and A* search, among others. However, the latter was able to find the minimum cost path between two points (Hart, Nilsson, & Raphael, 1968). Consequently, the design of the intelligent agents mostly consisted of searching techniques based on the A* algorithm to compute optimal routes between the ants and targets (Cowley, 2012). In order to illustrate a paradigm of learning through play, Figure 3 shows a match between three

```
function ChooseStrategy()
  initialize ArraySchedule
  for i=0 to size (ArraySchedule)
    if ArraySchedule[i] == 'h' then
      HunterBotMode()
    else if ArraySchedule[i] == 'l' then
      LeftyBotMode()
    end if
  end for
end function
```

Figure 2 Example or Programming Code for Intelligent Agents

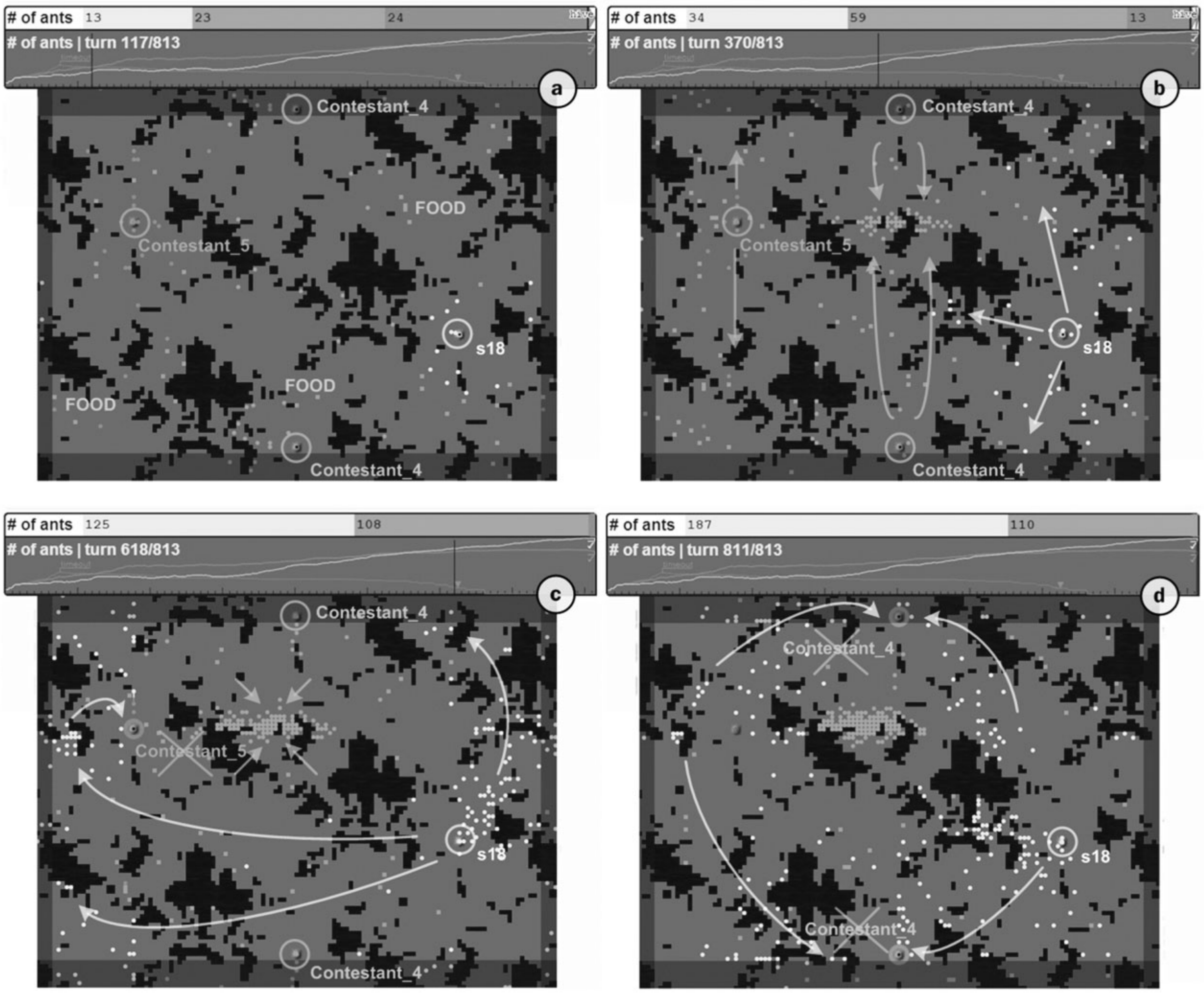

Figure 3 Evolution of Strategies for a Three-Player Match: (a) Location of the Ant's Communities at Turn 117/813, (b) Turn 370/813, (c) Turn 618/813 and (d) Turn 811/813

competitors during 813 turns: the teacher (grey colour) and two contestants (orange and blue). As shown, different behaviours and movements experienced by the bots can be seen. The image sequence displays how the evolution of grey ants (named *s*18) shows higher dispersion than the other communities as a result of an exploration strategy to look for food and enemy anthills. Thus, the students learned that the success of an intelligent agent is determined by a trade-off among several fitnesses; that is, to collect food and attack enemy anthills (brown pixels and circles coloured in Figure 3).

An analysis about the influence of the *Google AI Challenge* on the students' motivation to achieve additional goals – such as learning new programming language – was carried out. Therefore, a *t*-test was applied to over 300 contestants worldwide considering one nominal variable (i.e., programming language) and three measurement variables (program version, skill and bots' position). The null hypothesis was that the mean measurements between two categories of programming language (i.e., C++, Java^{TM} and Python) were the same. Table 3 shows a comparative summary of the official ranking of our students regarding the winners of the competition.

Precisely, we have found out significant differences between the number of versions and the programming language adopted by the contestants. The results of the *t*-test reject the null hypothesis when Python is considered ($p = 0.147$ for C++ vs. Java^{TM}, $p = 0.031$ for C++ vs. Python, $p < 0.001$ for Java^{TM} vs. Python). Besides, the bots with better skills were programmed by

Table 3. Comparison of the Final Ranking of the *Google AI Challenge 2011*

Rank	Username	Role/level	Language	Versions	Games played	Skill
1	*c*1	2nd year student	Java™	3	169	90.68
2	*c*2	Professional	Java™	15	170	89.98
3	*c*3	Professional	C++	5	171	87.37
472	*s*1	4th year student	C++	18	171	65.25
1514	*s*2	4th year student	Python	17	55	51.57
1516	*s*11	3rd year student	Python	13	54	51.54
1812	*s*18	Teacher	Python	41	53	49.06
1873	*s*12	3rd year student	Python	26	51	48.62
2076	*s*13	3rd year student	Python	8	49	47.26
2079	*s*3	4th year student	Python	10	39	47.25
2194	*s*14	3rd year student	Python	3	43	46.53
2254	*s*15	3rd year student	Python	14	39	46.23
2296	*s*4	4th year student	Python	3	38	45.96
2323	*s*16	3rd year student	Python	10	38	45.80
2414	*s*17	3rd year student	Python	4	49	45.31
2647	*s*5	4th year student	Python	1	41	43.79
4139	*s*6	4th year student	Python	29	17	39.99
4450	*s*7	4th year student	Python	1	19	39.56
5157	*s*8	4th year student	Python	21	16	38.29
5265	*s*9	4th year Student	C++	6	17	38.14
6126	*s*10	4th year student	Python	3	13	36.93

contestants who chose C++/Java™ as programming language instead of Python ($p = 0.716$ for C++ vs. Java™, $p < 0.001$ for C++ vs. Python, $p < 0.001$ for Java™ vs. Python). As an example, the winners' bots were programmed in C++/Java™ by contestants – named $c1$, $c2$ and $c3$ – who participated in previous editions of the *Google AI Challenge*, some of them professional programmers (Lichtenberger, 2011; Voronyuk, 2011). On the contrary, the students from the UHU – with positions from 472 to 6126 – mostly used Python as preferred programming language. In fact, the results of the t-test reject the null hypothesis when Python is considered again ($p = 0.513$ for C++ vs. Java™, $p < 0.001$ for C++ vs. Python, $p < 0.001$ for Java™ vs. Python).

As a conclusion, the analysis suggests that C++/Java™, more efficient and robust, is preferred by more experienced users. However, Python, easier and faster to implement, is preferred by many other users, mostly beginners. Although the number of versions required by participants was influenced by the programming language, their final position did not depend on the versions or languages, but the skills achieved by the intelligent agents. As a result, decisions on language had no influence on the students' motivation since the programming language was felt as part of the learning process (see *Educational Experience Assessment*). For these reasons, we considered the *Google AI Challenge* as an appropriate learning experience to try artificial intelligence and additional educational goals. In effect, teachers can encourage their students to learn advanced concepts on Computer Science through play regardless of the programming knowledge.

Educational experience assessment

This section presents the results of a comprehensive study on the applied methodology considering two different areas. Firstly, the students' opinion regarding the educational experience is analysed by means of a questionnaire elaborated by our multidisciplinary research team. Secondly, the students' academic progress is compared over three academic years.

Evaluation of the students' opinion

A statistical study has been carried out on the students of 3rd and 4th years, respectively (see Table 4). All participants were asked – at the end of the experience – to complete a questionnaire based on a five-level Likert scale (1 = strongly disagreed; 5 = strongly agreed). This consisted of covering four analysis areas with the aim of exploring the difference in self-reporting between these student groups regarding the experience.

Table 4. Evaluation Questionnaire of the Students' Self-Reporting about the Educational Experience

Question	Knowledge	Average value	*SD*
1	Previous level on AI	1.89	±0.32
2	Final level on AI	3.42	±0.45
3	The experience enables the consolidation of theoretical concepts on AI	3.73	±0.49
4	The experience allows new theoretical concepts on AI to be acquired	3.89	±0.43
5	The experience allows to discover new own ways to solve problems	3.73	±0.40
6	The experience allows new theoretical concepts on language programming to be acquired	3.47	±0.56
7	My ability to apply knowledge in practical and real problems after the challenge is positive	3.22	±0.43
	Interest/motivation		
8	My general assessment for the course before the experience is positive	3.10	±0.40
9	My general assessment for the course after the experience is positive	4.05	±0.35
10	The general assessment for my degree before the experience is positive	3.36	±0.41
11	The general assessment for my degree after the experience is positive	3.84	±0.44
12	The general assessment for my university before the experience is positive	3.15	±0.34
13	The general assessment for my university after the experience is positive	3.42	±0.34
14	My general assessment for the teacher before the experience is positive	3.73	±0.32
15	My general assessment for the teacher after the experience is positive	3.89	±0.32
16	The mark obtained in the challenge influences learning on AI	2.00	±0.42
17	The mark obtained in the challenge influences interest and motivation	3.00	±0.64
18	Competing in a national context promotes motivation and interest	4.21	±0.42
19	Competing in an international context promotes motivation and interest	4.21	±0.42
20	Programming through the play promotes motivation and interest	4.42	±0.25
	Personal skills		
21	The need to travel abroad to further my education before the challenge is positive	3.63	±0.53
22	The need to travel abroad to further my education after the challenge is positive	3.89	±0.55
23	The value of sharing information before the challenge is positive	3.42	±0.45
24	The value of sharing information after the challenge is positive	4.00	±0.37
25	The challenge has served to better understand personal skills	3.47	±0.60
26	The experience allows knowledge on work organization to be acquired	3.10	±0.46
27	The experience allows knowledge on cooperation and teamwork to be acquired	3.21	±0.54
	Human workload/difficulty		
28	The difficulty and workload of this practice/experience is high	3.68	±0.44
29	This practice/experience is feasible for implementation in the university context	4.15	±0.47
30	The general assessment on development and organization of this practice is positive	3.15	±0.44
31	My working capacity before the challenge is positive	3.42	±0.38
32	My working capacity after the challenge is positive	3.78	±0.42
33	My comprehension before the challenge is positive	3.52	±0.48
34	My comprehension after the challenge is positive	3.78	±0.42
35	My general assessment for this practice/experience is positive	3.78	±0.48

AI = Artificial Intelligence.

That is, knowledge acquisition (Q1–Q7), interest/motivation (Q8–Q20), skills development (Q21–Q27) and human workload/difficulty (Q28–Q34). With this purpose, a total of 19 volunteers participated (7 and 12 students for each course, respectively). In general, the results showed the highest differences mainly in the areas of interest/motivation and human workload/difficulty (see Figure 4).

Regarding the area of knowledge acquired on AI, all the students claimed to have a greater level after the educational experience (Q1 vs. Q2). Subsequently, we found a significant increase with respect to the final

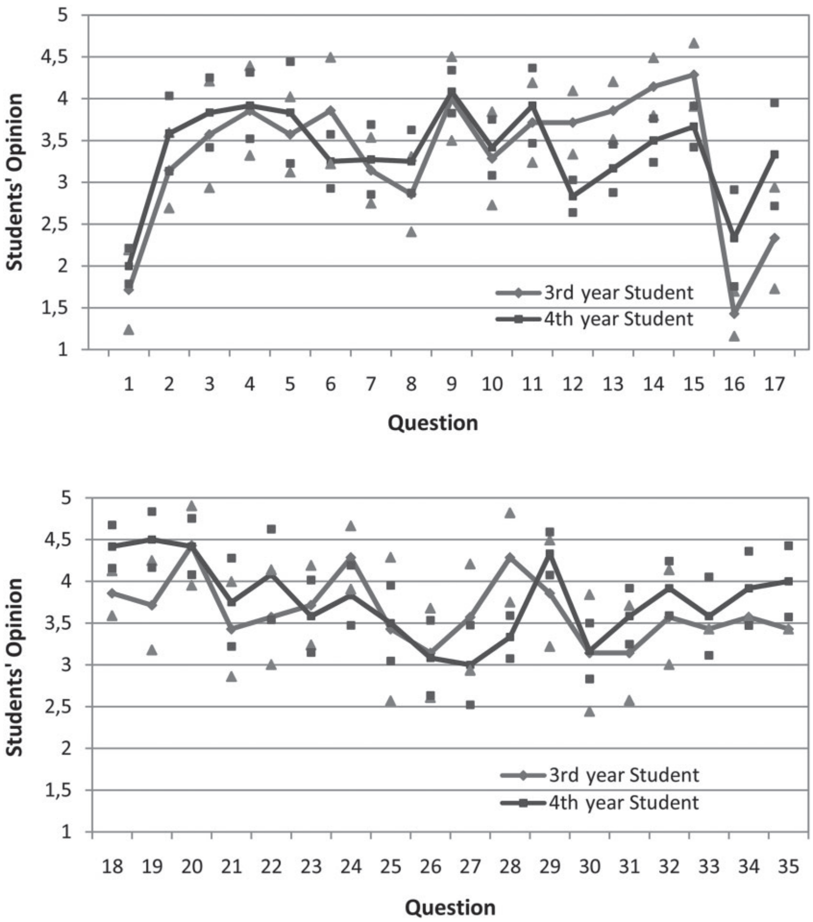

Figure 4 (a) Average Score and (b) Standard Deviation for the Students' Opinion Based on a Five-Level Likert Scale

knowledge on AI acquired by the students as shown in Table 5 (for Wilcoxon signed-rank test, $p < 0.001$). The students strongly agreed that this experience enabled the consolidation and acquisition of new theoretical concepts, allowing them to discover new ways to solve problems (Q3–Q5). Besides, the learning of new theoretical concepts on language programming was well rated by the students (Q6). However, the average score was higher for those students belonging to the 3rd course, which is consistent with the fact that students in the 4th course were more experienced on this matter (see Figure 4).

Regarding the area of interest/motivation, we found a significant increase in the students' opinion about the courses involved in the experience (for Q8 vs. Q9, $p = 0.003$). This suggests that the contest positively influenced the students' feelings about their courses. We discovered that it is also applicable when the students were asked about the general perception of both their degree and university (for Q10 vs. Q11, $p = 0.007$; for Q12 vs. Q13, $p = 0.043$), respectively. Correspondingly, we found that answers from Q12 to Q15 were

Table 5. Wilcoxon Signed-Rank Test for Questions Measuring the Same Construct Before and After the Educational Experience

Before	After	*p* value	Significant
Q1	Q2	$p < 0.001$	✓
Q8	Q9	$p = 0.003$	✓
Q10	Q11	$p = 0.007$	✓
Q12	Q13	$p = 0.043$	✓
Q14	Q15	$p = 0.224$	–
Q21	Q22	$p = 0.043$	✓
Q23	Q24	$p = 0.027$	✓
Q31	Q32	$p = 0.011$	✓
Q33	Q34	$p = 0.043$	✓

more positive for 3rd year students, although very positive in general. Resultantly, 4th year students opined that areas like motivation, interest and AI learning were less influenced as a consequence of the mark obtained in the challenge (Q16, Q7). We suspect that the reason may be that 4th year students had higher expectations as a consequence of joining the international contest than 3rd year students (Q18, Q19). However, both groups of students agreed very similarly that learning through play promoted the motivation and interest in the same level (Q20).

Regarding the area of personal skills development, we noted in all the students a positive change of mind on the need to travel abroad to complete their training after participating in the international competition (for Q21 vs. Q22, $p = 0.043$). Specifically, 4th year students realized the need to go abroad to complete their education to a greater extent than 3rd year students (Q22). As another implication for education, the need for sharing information was highly valued by the students in general as a means to share experiences and provide feedback of their knowledge (for Q23 vs. Q24, $p = 0.027$). Characteristically, 3rd year students found the need to share information after the challenge more valuable than 4th year students (Q23, Q24). These suggest that both beginner and experienced students differently appreciated this form of learning due to their limitations and knowledge of the matter.

Regarding the human workload/difficulty, we found that the students considered the level of difficulty and workload of the practice/experience as medium-high. Respectively, 3rd year students felt that the difficulty and workload was higher compared with 4th year students (Q28). We believe that the reason is because 3rd year students enrolled for the first time in an AI course as opposed to the more experienced 4th graders. This suggests that the assessment that the students made about the implementation of an educational experience was proportional to the degree of the practice's difficulty. Nonetheless, the feasibility to implement this experience in the university context was highly rated in general (Q29). Moreover, we found significant differences about the working capacity developed by the students before and after the challenge (for Q31 vs. Q32, $p = 0.011$), thereby resulting in a comprehensive improvement due to the educational experience (for Q33 vs. Q34, $p = 0.043$). Results are validated in Q35, where the general students' opinion about the educational experience was given as fairly positive and satisfying.

Evaluation of academic results

In order to evaluate the educational impact of this teaching experience, a statistical study considering 83 students along three academic courses has been made (see Figure 5). On the one hand, Figure 6a shows a comparison on the average grade of the students (being A = 8–10, B = 7–7.9, C = 6–6.9, D = 5–5.9, F = 0–4.9 points, respectively). The grades were very similar each course for 3rd year students, being the grade in the last course – where the experience was carried out – slightly higher than the previous ones (7.8, 8.0 and 8.1). By contrast, the average grade for 4th year students in 2011/2012 showed a significant increase regarding the previous courses (5.45, 4.42 and 7.16). On the other hand, Figure 6b shows a comparison on the percentage of students who did not attend

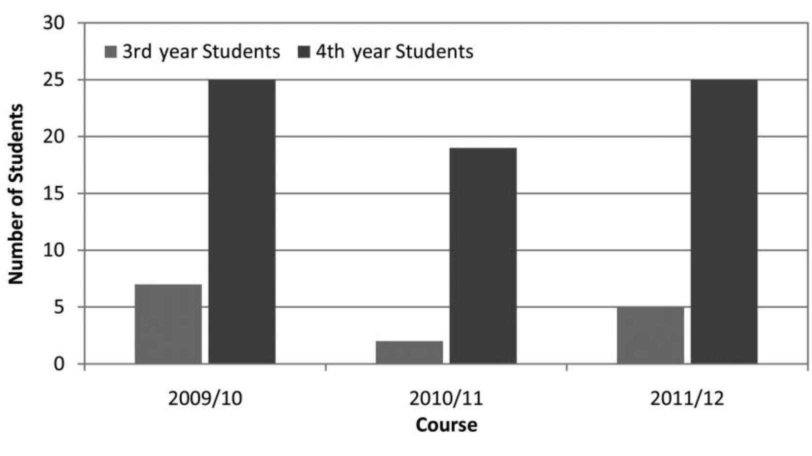

Figure 5 Distribution of the Students Enrolled during the Three Academic Years

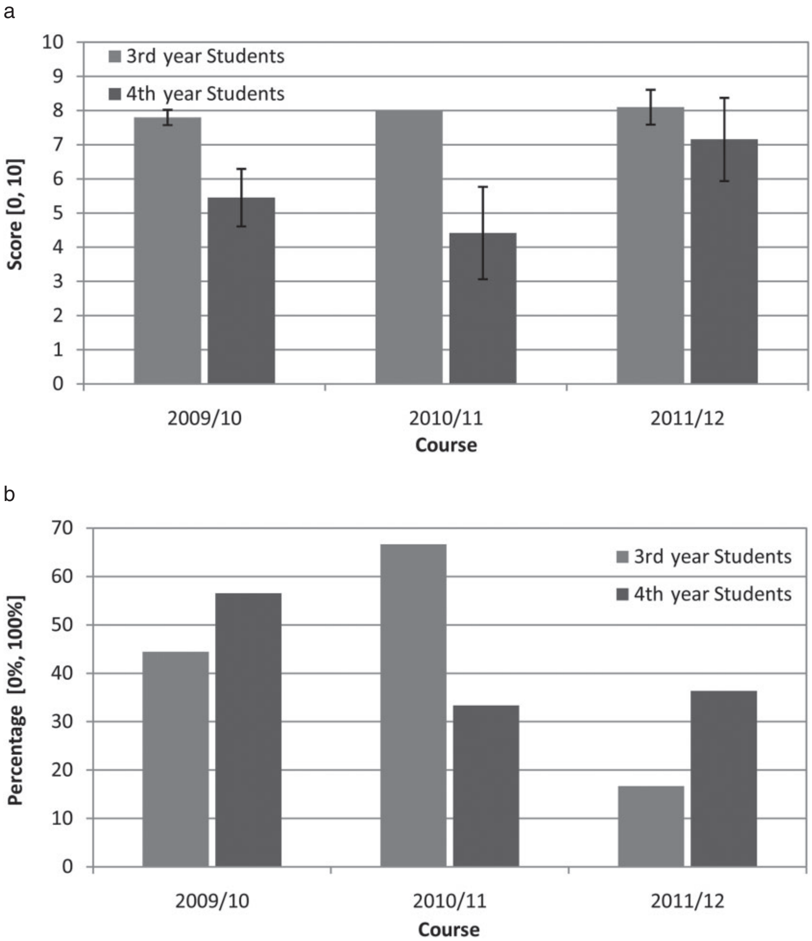

Figure 6 Statistics for 3rd and 4th Year Students: (a) Academic Scores for Students Who Attended the Exams and (b) Non-Attendance for the Overall of Students

examination sessions. In the case of 3rd year students, the number of students not attending exams was drastically reduced in 2011/2012 compared to the previous years (44.44%, 67% and 17% over the total of students, respectively). In the case of 4th year students, the trend during the year 2009/10 remained similar compared to the previous year, and significantly improved compared to the year 2019/2010 (56.52%, 33.33% and 36.4% over the total of students, respectively).

These results may be influenced by a large number of variables, observable or not, although the educational context during the courses' development may provide a better understanding of the students' attitudes. As for the difference in attendance in each course, we point out the optional nature of the 3rd year course as the main possible cause in contrast with the 4th year course, which was mandatory for the students. Moreover, although both courses were affected by different changes of tutor, we believe that this factor could have influenced 3rd year students to a greater extent since introductory courses on complex concepts could be more sensitive to these changes. By contrast, 4th year students were more experienced, had a greater number of teaching hours and thereby could be less responsive to changes of tutor. Regarding the increase in the students' ratings, both courses were structured according to the educational system previous to the European Credit Transfer and Accumulation System. As a principal disadvantage, this educational system – introduced in our country in 1983 – does not take into consideration the development of alternative activities in the traditional classroom or the hours of work–study that students should devote to overcome their studies, which is closer to formal learning. On the contrary, the European Higher Education Area (EHEA) is characterized by a student-centred perspective consistent with constructivist principles, which comes in purposes of our educational experience. Therefore, we believe that the students' grades might have changed more significantly in the 4th year course due to this experience. The reason is because the 3rd year course is eminently practical (i.e., lab-based learning) and the 4th year course is structured in theoretical and practical hours, thus having the most noticeable impact on the practical experience.

Even though the findings cannot be generalized, we believe that a real experience such as the *Google AI Challenge* may positively influence the motivation of beginner students in optional courses – with special focus on practical training in lab – who are more susceptible to changes in teaching (e.g., tutors). Moreover, the learning experience may significantly improve the academic performance of learners in more advanced courses that demand practical study without affecting the levels of theoretical knowledge, which comes in direction of the EHEA. These results suggest that it has been possible to successfully incorporate the *Google AI Challenge* in our teaching system without compromising the educational goals of the courses involved. This may validate the implementation of new educational experiences by both teachers and students, making courses more appealing, as well as improving student achievement.

Conclusions and recommendations

This paper presents a new teaching experience in Computer Science with the aim of improving the academic achievement of students by increasing their motivation and interest. As a result, the authors implemented the idea of a computer-based competition, the *Google AI Challenge*, into students' AI courses.

In order to address the implications of learning through play for engineering education, we examined the importance of an interactive approach towards learning. In order to fulfill this objective, students' opinion considering knowledge, interest/motivation, personal skills and human workload/difficulty was analysed. According to the results, the advantages of participating in a computer-based competition enabled students to consolidate theoretical concepts, improve perception on courses, promote motivation and interest, and broaden personal skills (e.g., cooperation, teamwork, organization, value of information sharing).

The integration of challenge-based interactive learning into AI courses provided our students, unlike other approaches, all the components required to achieve constructive learning (i.e., observation, analysis, criticism, abstraction). Among the positive aspects, learning through play further allows you to apply multi-style approaches (as, e.g., VARK), which helps to stimulate, engage and captivate students, thus responding to the natural human learning process. Without a doubt, when teaching engineering degrees, learning is strongly facilitated by interactive approaches.

In the case of teaching advanced concepts or new programming languages, competition through game generates an added motivation for students. Furthermore, this type of interest is a valuable path towards broadening knowledge.

Playing through international competition gave learners the chance to measure themselves against others, to reinforce their self-esteem and to enrich their knowledge by fostering proactive participation. This provided a real-life experience not always provided by formal education. In addition, playing in an online contest provided teachers additional settings to challenge the students (e.g., absence of a physical meeting point or monetary rewards), thus allowing the learning process to be more important than the outcome. In effect, the implementation of teaching experiences through play (as the *Google AI Challenge*) was possible by using a virtual working environment, even without rewards.

In order to evaluate the academic achievement, a statistical study over three academic years was carried out. The results showed that students increased their average grades after the experience. Moreover, the results point out that interactive learning approaches are highly recommended to decrease the number of students not attending exams because of the positive motivation felt with competitions. Despite requiring a minimal extra work by teachers and students, the successful incorporation of computer-based competitions – as the methodology followed herein – is possible without compromising the educational goals. That is, learning through play can satisfy expectations for adults and improve traditional teaching methodologies in higher education.

The educational experience was conducted around engineering education with students from different backgrounds and motivations (i.e., volunteers and nonvolunteer students from two course levels). While the results are applicable to a wide range of disciplines, it is not clear how it relates to the non-technical studies. The research did not try to examine these implications and future efforts could be addressed in this line of study. Nonetheless, the findings presented herein will help to enable a useful comparison between disciplines.

Acknowledgements

The present work was supported by the national project TIN2011–28627-C04-02 and P08-TIC-03903 awarded by the Andalusian Regional Government. We would like to express our very great appreciation to Dr. E. Gualda Caballero, Dr. A.M. Mora García and P. García Sánchez for their valuable and constructive suggestions that helped improve this research work.

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