Game Elements, Motivation and Programming Learning: A Case Study

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Abstract

The learning of programming is traditionally challenging for students. However, this is also one of the most fundamental skills for any computer scientist, and is becoming an important skill in other areas of knowledge. In this paper we analyze the use of game-elements in a challenging long-term programming task, with students of the 3rd year of a Informatics Engineering degree. We conducted a quantitative study using the AMS scale to assess students' motivation. Results show that with the use of game-elements, students are both intrinsically and extrinsically motivated, and that they consider learning/working fun, which contributes positively to their academic performance.

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1 Introduction

Programming is arguably one of the most relevant skills that computer science students must acquire. With the advent and growing importance of computer science, students in other related fields (e.g. physics, biology, mathematics) are also expected to acquire at least some degree of programming/scripting skills. However, the teaching/learning of programming is admittedly and generally difficult.

In the specific case of learning programming at a higher-education level, some of the most common issues pointed out include the lack of previous knowledge on programming or related tasks, the difficulties in thinking in an abstract manner, the lack of time that must be divided with other demanding subjects, or the changes that occur in the student's life at different levels when they change from secondary to higher education [12]. These difficulties are even more expressive as in computer science courses programming subjects are generally taught starting at the first semester, when students are going through a significant change and still adapting.

Many authors have proposed different strategies, methodologies and theories of learning to try to address this issue and improve the teaching/learning process in the specific domain of Computer Science Education. Ben-Ari proposes Constructivism as a suitable theory

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of learning for this domain, advocating that students do not passively absorb knowledge transmitted by the teacher or the book, but that they rather construct it building recursively on pre-existing knowledge, facts and beliefs [2]. This points towards a specific meaning for the term *teaching*. In this view, teaching becomes a task of helping or assisting someone to learn rather than simply presenting information. This also implies a shared responsibility: if students don't learn it is not (only) their fault.

In this context, Oliver proposes an interesting learning framework in this domain, constituted by three elements [10]. The first element is constituted by the "traditional" learning activities, which in this domain are generally designing/programming/testing tasks. The second element is constituted by the learning resources: materials that provide the content and context of the course, and help students construct their knowledge and meaning. Finally, the third element includes learning supports, which are elements that guide the student into constructing the necessary knowledge. These may range from the presence of the teacher (in a more traditional domain) to scaffolds such as automatic code generation, automatic diagram generation, or other software tools.

Other authors have also proposed specific tools and approaches to facilitate the teaching/learning process, and that can be seen as the learning supports proposed by [10]. Given the often abstract nature of programming tasks (and related/included activities such as designing an algorithm or a plan), visualization tools are often pointed out as an efficient aid in learning programming [7]. These may include program visualization, algorithm visualization or even visual programming tools [3]. Lister et al. propose the use of doodles in a rather informal setting, namely to assess the students' skills in reading and tracing code [8].

This paper describes a case-study in a computer science course in the academic year of 2018/2019. Specifically, we describe the use of gamification in the context of the *Artificial Intelligence* (AI) subject, in the Informatics Engineering degree, in the Higher School of Management and Technology of the Polytechnic Institute of Porto, in northern Portugal. This subject is taught in the second semester of the third year of the degree. Students are thus already expected to have prior experience in programming. However, and as described in Section 3, they must implement a Genetic Algorithm (GA) to solve a specific optimization problem. This is a rather new and abstract form of thinking on problem-solving for these students, and also a new form of programming, so the challenges previously pointed out remain.

Specifically, we describe the problem and the game-elements used with the main goal to motivate students to work in what would otherwise by a rather challenging and possibly dull task. We also describe the perceptions of the students regarding these game-elements and to what extent they contributed to their success and motivation during classes and while working in their assignment.

2 Motivation

Motivation is one of the key indicators for an individual to succeed in the learning process [6], leading the individual to apply her/his effort in order to achieve her/his goals. While motivation may emerge in different ways, it is usual to organize it into intrinsic (IMOT) and extrinsic (EMOT) motivation [14]. The former represents the individual desire to achieve something important. The latter is external, promoted by external factors.

An individual that is intrinsically motivated is one that gets involved in the learning process by the pleasure it gives her/him and because there is a sense of accomplishment. IMOT measures the extent to which an individual participates in a task for internal reasons (e.g. curiosity, willingness to experience and overcome a given challenge) [11]. From the individual's perspective, it is a participation in which the task is an end in itself, intrinsically related to the individual's will. IMOT is composed by the Intrinsic Motivation to Know (IMTK), to Accomplish (IMTA), and to Atimulate (IMTS) [5].

On the other hand, an individual that is extrinsically motivated is one that will try to accomplish the easier tasks, while needing external impulses in order to feel motivated [9]. EMOT relates with the degree of participation of an individual in a task not by her/his own will but for external reasons such as rewards, competition with others, or performance-related reasons. EMOT is composed by four levels of growing degree of self-determination: Extrinsic Motivation External Regulation (EMER), Extrinsic Motivation Introjection (EMIN) and Extrinsic Motivation Identification (EMID) [4].

Usually, the motivation to learn comes from these two dimensions (IMOT and EMOT). However, it can also be affected by a third one: amotivation [13]. This concept (AMOT) was proposed by [5], and is related with a state of dismay, indifference, disinterest, self-discredit, prostration or depression [1]. AMOT represents a lack of interest or willingness in accomplishing a task or, on the other hand, results from a feeling of being unable or uninterested in reaching a goal. According to [5], it may result from frequent failure or negative feedback, leading the individual to assume that goals are not achievable.

3 The Learning Activity

As described in Section 1, in the 2018/2019 edition of Artificial Intelligence subject, the students had to program a Genetic Algorithm to solve a specific optimization problem. Given that this is a third year subject, students are expected to have prior experience in programming. However, the subject of AI is generally novel to them.

In this subject, three of the main paradigms of AI are addressed throughout the semester, namely: the Symbolist, the Evolutionary, and the Connectionist paradigms. Student assessment is done using two instruments: a practical assignment developed throughout the semester, and a written theoretical exam at the end of the semester. While going through these paradigms, students learn about Machine Learning (in its different forms), deduction, induction, and relevant fundamental algorithms such as Genetic Algorithms or Back Propagation.

The practical assignment is always dedicated to one of these three paradigms and aims to make the students devote themselves in depth to the chosen topic, guiding them into consolidating their knowledge through autonomous and practical implementation work, with the guidance of the teacher.

In the edition of 2018/2019, the practical assignment concerned the Evolutionary paradigm of AI. In that sense, they had to code, from scratch, a program to solve a specific optimization problem. In this case, the students had to program a Genetic Algorithm to allow an agent to learn to play the well known Super Mario Bros game. This game, developed and published by the popular video-game company Nintendo, was first published in the 80's and is still very popular nowadays, with new versions being created regularly. Virtually every current student played one or another version of this game and are thus familiar with their gameplay.

As detailed in Sections 3.1 and 3.2, students were provided with several learning supports and resources, to assist them in acquiring and/or constructing the necessary knowledge by the end of the semester.

This section describes the architecture implemented by the teacher to support the students in developing their work, and describes the game elements used to motivate them.

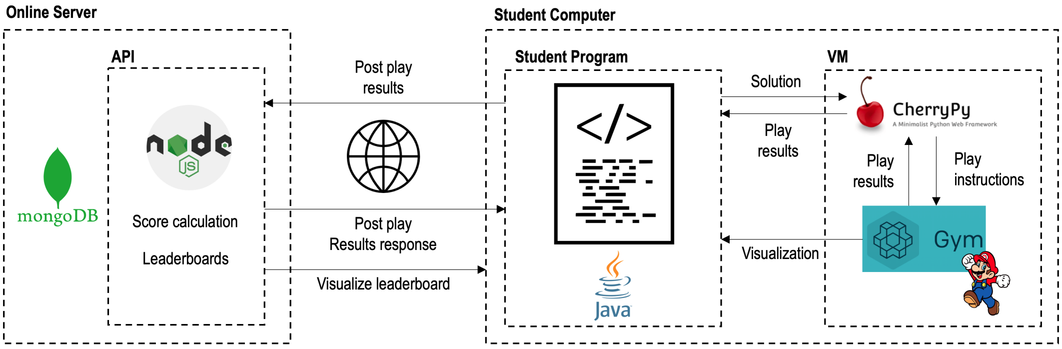

Figure 1 Architecture of the resources prepared for supporting the students to develop, test and validate their work.

3.1 Learning Supports and Resources

The task of programming a GA for a novice student may be challenging: it not only requires programming skills but also significant knowledge regarding evolutionary computation methods. The requirement of using a game emulator and integrating it in their application could further contribute negatively towards the learning goal.

Thus, asides from all the course contents available online, a group of learning supports was also provided to the students, in line with the constructivist view and Oliver's learning framework [2, 10]. These supports include two main elements (Figure 1): 1) an API for interacting with the game emulator and 2) an API for interacting with the Leaderboard.

The first API facilitates the interaction of the students' code with the game emulator. It is implemented in CherryPy and, among other functionalities, allows students to submit the solutions generated by their GA, and returns the result of running their solution. In this context, a solution is a set of game pad instructions starting in a given level. The response of the API includes elements such as the reason for loosing (if applicable), number of coins gathered, final level, number of points, among others. Students may also use this service to visualize their solution being played in the emulator, so as to better understand the practical effects of their decisions in the development of the GA. All these elements were provided in the form of a Virtual Machine (VM) that the students would run in their own computer.

The second API facilitates the interaction with the online Leaderboard. It includes services for students to post the results of their GA, whenever they feel like doing so. It also allows students to get the state of the Leaderboard, whether through the API or through a web page available online.

Both APIs were provided in the same programming language being used by the students to implement the GA (Java). Some examples of using the API were also provided, to facilitate the integration in their own code.

3.2 Game Elements

The importance of motivation in learning in general, and in learning programming in particular, has already been discussed in Section 2. This section details the game elements that were used in the learning activity in order to motivate students.

Given that this was a group work, students were first asked to constitute *teams*, rather than the traditional *work groups*. Each team was constituted by three members and had a name chosen by the members.

Students were then told that the practical assignment would be based on the well-known Super Mario Bros. video game, which was very well received. Students could participate in two different competitions. In the first competition students competed in a very specific level, attempting to reach the highest score in the minimum amount of time. In the second competition students started in the first level of the game and the goal was to get as far as possible, going through the several levels in sequence.

Asides from the use of the game, students were also provided an online Leaderboard that stimulated competition and motivation between teams. Teams would regularly post new top results of their GAs and motivate other teams to work further in order to gain access to the top of the board. Each entry in the Leaderboard included information about the team as well as about the solution (e.g. score, coins, enemies killed, level). The leaderborad included two pages, one for each type of competition.

In order to pass the practical assignment, students needed to participate in at least one competition. In order to score 18 or more values (out of 20) they needed to participate in both. Part of their score was attributed according to their position on the Leaderboard at the end of the competitions.

4 Methodology

A quantitative study was carried out, with data being collected through online questionnaires, using the AMS scale proposed by [14], adapted for students of Artificial Intelligence. Data was processed with SPSS v24, using several techniques such as Multiple Linear Regression (MLR), which allowed to test a model for measuring the motivation of students to study and learn. MLR allows to estimate the value of the dependent variable Intrinsic Motivation to Learn (IMTK) as a function of the independent variables EMER, EMIN, EMID, IMTA, IMTS and AMOT. The goal is to find the best relationship, and a statistically significant one, between the variables, to achieve the model that best explains motivation.

In order to evaluate the model, quality adjustment measures will be used such as Pearson's correlation coefficient, the coefficient of determination r^2, the adjusted r^2, the Variance Inflation Factor (VIF), and the Durbin-Watson Test.

The AMS was applied as an online questionnaire to 26 students of the 3rd year of the Degree on Informatics Engineering who where enrolled in the Artificial Intelligence subject. The questionnaire was applied after the conclusion of the subject.

A research model was tested for the population of the study. Its general expression is:

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_1 X_1 + ... + \beta_k X_k + \varepsilon_i, i = 1, 2, ..., n$$

The proposed research model is given by:

$$IMTK = B_0 + B_1 AMOT + B_2 EMER + B_3 EMIN + B_4 EMID+$$
$$B_5 IMTA + B_6 IMTS + \varepsilon$$

5 Results

The question that was given to the students in the questionnaire was phrased thus:

Why did you dedicate time studying for the Artificial Intelligence subject?

Table 1 Descriptive statistics for Amotivation.

	AMOT1	AMOT2	AMOT3	AMOT 4
Mean	1,19	1,03	1,19	2,39
Total	26 students ($\alpha = 0.847$)			

The answers of the students were given in a 7-point Likert scale, in which an average of 4 for a given sub-scale means that the statement moderately corresponds to the student's opinion. A value between 5 and 6 means that it corresponds significantly and a value of 7 that is corresponds totally.

Thus, for the EMOT and IMOT scales, a score equal or higher than 4 means that students are motivated. On the other hand, a high score in the AMOT scale means that students are less motivated.

5.1 AMOT

Generally, results show that students are motivated to study as the average values of amotivation are very close to the lower end of the scale (the closer to 1 the lower the amotivation) (Table 1).

This scale was composed by the following four questions:

- **AMOT1**: I honestly don't know, I feel like I am wasting my time studying AI.
- **AMOT2**: I don't see any point in attending AI classes and it does not interest me the least.
- **AMOT3**: I don't know. I don't understand what I'm doing in the AI classes.
- **AMOT4**: In the past I had good reasons to attend AI classes, now I wonder whether I should continue.

A global analysis allows to conclude that the large majority of students are motivated to study AI. However, in what concerns question AMOT4, the value is closer to 3, which may point to a certain tendency to amotivation related with the initial expectations towards the subject. This calls for measures and strategies to minimize this tendency in future editions. However, it must also be noted that the questionnaire was administered after the conclusion of the subject, that is, after the students knew the results of the evaluation moments. This result may thus be partly influenced by students who did not achieve the expected marks.

5.2 Extrinsic Motivation

In the EMOT scale, the higher the values, the higher the motivation. Three sub-scales were analyzed: EMER (with an average of 5.3), EMIN (4.69) and EMID (5.98). This points out that students are generally extrinsically motivated to study (Table 2).

The EMER sub-scale was composed by the following questions:

- **EMER1**: Because I need a degree to get a better job in the future and the AI subject is mandatory in the Informatics Engineering degree.
- **EMER2**: In order to obtain a more prestigious job in the future.
- **EMER3**: Because I want to have a "good life" in the future.
- **EMER4**: To have a better salary in the future.

EMER4, which is related with the prospect of a better salary in the future, is the question that scores the lowest, which indicates that money is by itself not a good enough motivator, or that students do not associate AI skills with better salaries.

Table 2 Descriptive statistics for Extrinsic Motivation.

	EMER1	EMER2	EMER3	EMER4	EMIN1	EMIN2	EMIN3	EMIN4	EMID1	EMID2	EMID3	EMID4
Mean	5,38	5,61	5,38	4,84	4,69	4,69	4,70	4,68	6,23	5,46	5,88	6,34
Total	$\alpha = 0.831$				$\alpha = 0.994$				$\alpha = 0.867$			

Concerning the EMIN sub-scale, it was composed by the following questions:

- **EMIN1**: Because when I succeed in any assignment related to AI I feel important.
- **EMIN2**: In order to prove myself that I can pass the AI subject.
- **EMIN3**: To prove myself I am an intelligent person.
- **EMIN4**: Because I want to prove myself that I am an intelligent person.

The analysis of the responses allows to understand that this dimension, although scoring above 4.5, is the one with the lowest score concerning external motivation. This points out that from the external motivators, the ones related with the self are the less important.

Finally, the EMID sub-scale included the following questions:

- **EMID1**: Because I believe that the AI subject will prepare me better for my future career.
- **EMID2**: Because eventually, what I learn in the AI subject will allow me to find a job in a field that I like.
- **EMID3**: Because I believe that AI knowledge will improve my skills as a worker.
- **EMID4**: Because the topics addressed in the AI subject will allow me to make better career choices.

This sub-scale is the one with the highest scores, with values around 6. It is interesting to note that the prospect of a better salary (EMER4) does not motivate the students as much as the prospect of a better job. This may point out that students are oriented towards satisfying jobs, in line with their fields of interest, rather than money. Moreover, they also believe that AI skills will provide them with better options in the future. This is clear in the highest-scoring question EMID4.

5.3 Intrinsic Motivation

Concerning Intrinsic Motivation, the values for the three sub-scales IMTK, IMTA and IMTS are, respectively, 6.16, 5.4 and 5.83. This shows that students generally study AI for the pleasure it gives them and by their own will (Table 3).

Concerning the IMTK scale, it was composed by the following questions:

- **IMTK1**: For the pleasure I feel while overcoming my own limits while learning AI.
- **IMTK2**: For the pleasure I feel while solving academic assignments in the field of AI.
- **IMTK3**: For the pleasure I feel when I overachieve in my personal achievements.
- **IMTK4**: Because the AI subject allows me to experience personal satisfaction on my path towards academic excellency.

The results on the IMTK1 and IMTK2 questions show that students feel significant pleasure and satisfaction while working in this subject, which contributes very positively to their engagement.

Table 3 Descriptive statistics for Intrinsic Motivation.

	IMTK1	IMTK2	IMTK3	IMTK4	IMTA1	IMTA2	IMTA3	IMTA4	IMTS1	IMTS2	IMTS3	IMTS4
Mean	6,46	6,30	5,88	6,01	5,57	5,30	5,61	5,11	6,11	6,01	5,73	5,46
Total	$\alpha = 0.837$				$\alpha = 0.777$				$\alpha = 0.806$			

Concerning IMTA, the following questions were included:

- **IMTA1**: Because I feel pleasure and satisfaction when learning new topics in the field of AI.
- **IMTA2**: For the pleasure I feel when I learn new things.
- **IMTA3**: For the pleasure I feel when deepening my knowledge on topics that I like in AI.
- **IMTA4**: Because the AI subject allows me to learn about topics that I'm interested in.

Although IMTA scored, on average, above 5, it is also the one with the lowest score. IMTA4 was the question with the lower score, which may point out that students may not be so interested in certain topics taught during the subject.

Finally, in what concerns the IMTS, the following questions were considered:

- **IMTS1**: Because I really like to attend AI classes.
- **IMTS2**: Because, for me, AI classes are fun.
- **IMTS3**: For the pleasure I feel when I participate in discussions about AI with interesting teachers.
- **IMTS4**: For the good feelings I experience when I read about AI.

All questions in the IMTS sub-scale were scored with values very close to 6. The two higher-scoring questions were IMTS1 and IMTS2, which show that students like and have fun in classes. This is very likely due to the use of games in classes, which make for a relaxed and fun environment.

5.4 Proposed Model

In order to explain in a more robust way the data, they were analysed through a MLR, selecting statistically significant variables that would provide a thorough model.

We analyzed the assumptions of the model, namely the ones of normal distribution, homogeneity and error independence. The first two assumptions were validated graphically and the third was validated with the Durbin-Watson statistic. The VIF was also used to diagnose the multicolinearity, eliminating variables with strong colinearity. Table 4 details the results of the model tested.

The final model was thus:

$$IMTK = 0.173 + 0.076EMIN + 0.309EMID + 0.460IMTA + 0.498IMTS$$

The final analysis of the obtained model shows a model with $R^2a = 0.810$, with a high explanatory power since the dimensions that compose it explain a large proportion of the IMTK. The dimensions AMOT and EMER did not influence students' IMTK, which shows that their amotivation is reduced. Concerning the fact that EMER is not statistically significant, this show that students are not influenced by external pressures to execute study tasks, not fearing possible punishment and not valuing the rewards obtained with the reealization of the activity.

Table 4 Linear regression model.

Dependent Variable: IMTK				
Dimensions	Initial Model		Final Model	
	B	t	*B*	t
Constant	-.017	-.059	.173	.745
AMOT	.088	1.091	.088	1.091
EMER	-.030	-.504	-.030	-2.296
EMIN	-.069	-1.722	.076**	4.367
EMID	.262***	4.450	.309***	5.766
IMTA	.331***	5.785	.460***	11.918
IMTS	.491***	11.555	.498***	.745
VIF	[1.206 – 2.842]		[1.634 – 2.721]	
R	.903		.902	
R^2	.816		.814	
R^2a	.810		.810	
Durbin-Watson	1.771		1.750	

$^{**}\rho < 0.05$ $^{***}\rho < 0.001$

6 Conclusions

This study focused on the perceptions of 3rd year students of the Informatics Engineering degree, in the AI subject. The study allowed to understand the motivation of 26 students, and more specifically what dimensions of motivation influence their willingness to study. The major limitation of the study is the relatively small size of the population. The main reason for this was that the questionnaire was sent to students *a posteriori*, after they knew the results of their score in the subject. However, most of the students were already not attending school and probably not using their institutional e-mail, which was used to contact them. Still, results are interesting and point out to a positive effect of the use of game elements in student motivation.

Several dimensions and sub-scales of motivation were evaluated. Generally, students show positive values of extrinsic and intrinsic motivation towards study. However, there is also evidence of small groups of students who are less motivated to study.

There is evidence that students are more motivated intrinsically than extrinsically, showing that they are more self-motivated than being pressured by external influences. Levels of motivation increase along the Ryan & Deci's Self-Determination Continuum [4], with IMOT dimensions having a higher relevance than EMOT's.

The building of the model to estimate the structure of IMTK shows that some variables of the initial model were not statistically significant. A new model was tested, removing the dimensions that had not been validated, originating a more robust and significant model, that explains 81% of IMTK.

However, in this model, the AMOT and EMER dimensions were removed, which were no longer significant for IMTK. Concerning EMOT, the EMID dimension ($\beta = 0.309; \rho < 0.001$) was the more important for the construction of students' extrinsic motivation, followed by EMIN ($\beta = 0.076; \rho < 0.05$). Concerning the IMOT dimension, both IMTS ($\beta = 0.498; \rho < 0.001$) and IMTA ($\beta = 0.460; \rho < 0.001$) were relevant for motivation, with a sligh advantage of IMTS.

In conclusion, this study shows that this group of students, who used the previously described game-elements in a complex learning task, saw their motivation positively influenced. Maybe the use of a non-traditional way of studying and working contributes to what may, eventually, make the difference in their academic performance when learning AI. Thus, if the approach considered also facilitates learning, this kind of approaches should be further considered in the future as a facilitator of learning in this and related fields of knowledge.

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