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Learner-Players Categorization in a Geographical Learning-Game

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Abstract: Different works offer serious games to learn a subject of exact science such as mathematics. However, there are few games dedicated to civic subjects such as geography, which is considered a frustrating but concrete subject requiring a virtual journey in relation to the real world. Many works in the field of serious games have highlighted the learner's profile characterized by their skills, emotional abilities and memorization. Serious games and in particular the learning game could be used to categorize learners, so we need to understand what happened during the game, to identify the learner-player's behaviour and performance. In this article we propose an approach based on an analytical model to categorize learners in order to maximize their potential according to their profiles. This categorization is based on three profiles: level profile, interaction profile and motivation profile. We illustrate our approach with the geographical learning game, which is designed for the students of Algerian middle school of education to learn geography.

Keywords: Serious Games, Categorization, Petri Network, Hasse Diagram, Learner-Player Profile.

1. Introduction

Parent: "Finish your exercises first, you will play afterwards! "Student: "No, I do both."

Video games dominate the daily lives of children and adolescents who enjoy playing them, these video games have even taken a place in the world economy [1], but instead of our children spending their free time with video games for entertainment, they can devote themselves to serious games to promote what they have learned in class while having fun. Serious games and in particular learning games are considered video games designed with an objective other than entertainment, they use new technologies to serve a serious purpose, to convey an attractive message [2].Today learning games make a remarkable entrance into individualized learning that is much effective than learning in a classroom[3]. It was recognized in [4] that serious games have a huge advantage to promote and improve the motivation of learners. Learning games offer learner-players the opportunity to learn and develop knowledge while playing, so recording behaviours allows educators and game designers to maximize the potential of all learner-players according to their profiles[5].This indicates the need and importance of grouping and categorizing learner-player profiles appropriately in order to adapt the learning game and achieve the learning objective.

Our goal in studying and categorizing player behaviours in our own geographical learning game "GEO" is to provide adaptive learning and to help the teacher quickly gather and know information about the learner-player's knowledge and skills. Often, the learner is assessed on the basis of the knowledge acquired. He can be average but curious and interested, so he is a learner to be encouraged and supervised. The objective of our work is not only to evaluate the knowledge of the learner but also to determine the motivation and interaction profiles to better help the learner in his learning.

Drawing characteristics, observing errors and diagnosing a learner's deficiencies in a classroom (traditional courtyard) are simple tasks for an expert teacher who chooses the right time to intervene with feedback relevant to the learner [3]. In individualized learning with the use of games, understanding the heterogeneity of learner profiles is essential to the game design phase [6], adaptability real-time games require accurate modeling of the learner [7].

In the next section, we describe the state of the art of similar work. Section 3 presents Learning game GEO dedicated to the teaching of geography for students in the middle school. Section 4 details the proposed approach to GEO learn game modeling and the categorization of learners. Section 5 describes the experiment performed. Section 6 presents the results obtained with discussion, and Section 7 concludes our work.

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2. Related Works

Learning game is a video-game learning environment in which more and more companies are investing to support children's cognitive and social development [8].

The purpose of learning games is not to replace traditional forms of education, but rather to complement them, and to make them benefit from the interactivity of graphical interfaces, because the animations of the learning game trigger long-term memories among learners.

In [6] the authors propose a set of factors and characteristics (cognitive, motivation, emotional, physical and psychological) to be considered for modeling when designing the game, making the game suitable and not adaptive. In this article the authors suggest using an engine to process and categorize emotional information dynamically, the work is based on the synthesis of the user's emotions. The limitation of this approach lies in the difficulty of sensing a learner's emotional state, especially when it comes to the user's mood, reaction and event sequence, because these factors are not stable and characteristics change from state to state.

Work [9] discusses how to take the characteristics of players into a serious game. The authors propose cognitive skill game (CGS) which is based on an artificial intelligent agent, it can predict the cognitive character of the player. The Vector Quantification Learning Method (LVQ: Learning Vector Quantization) is used to classify the cognitive level of players, used in (CGS). LVQ is a network of neurons, where some entries have very close range vectors; these vectors will be grouped into three categories (1- doing tests and errors, 2- the prudential and 3- the experts). A gap in this work is the complexity in the way gambling behaviours have been conceptualized.

The work [10] shows how to detect the frustration, stress and motivation of learners- players in the learning game CRYSTAL ISLAND for the field of microbiology. Players are invited every 7 minutes to declare their state of mind and choose an emotion from (07 emotions) within a 55-minute play time to solve a mystery. Bayesian networks have been used to develop a model of predicting learner affect. The elaborate model only recognizes positive emotional states. The advantage of using Bayesian networks is the prediction and resolution of problems in an uncertain environment, the limitations in this work have appeared in the predictions of negative emotional states, these predictions are confounded and it is difficult to understand their inferences. Other work [5] where Bayesian networks were used to obtain the highest accuracy in categorizing players in a serious game (BoTySeGa), the authors integrated in this serious game a mechanism for evaluating learner-players in the field of mathematics, more precisely in the knowledge of parallelograms. The authors used Byes net, Naive Bayes and tree j48. The limitation of this categorization method is that it uses a large number of variables and resources.

[11] Deals with the recognition and modeling of player emotions in a serious game using a combination (facial, body and speech). The authors have created a list of facial expression and corporal actions commonly encountered in a typical game. A bimodal database was created using Microsoft Kinect sensors containing vectors that extract facial expressions and body gestures from players. Later they are used to recognizing specific units of action and classify expressions as emotions. The proposed approach can provide a good level of emotion recognition. The disadvantage of this approach is that each person has their own way of expressing emotions, this difference makes the method not generalizable so the neutral case weakens the recognition rate.

[12] Presents the learner's follow-up in a serious game to analyze the learner's knowledge/skills by a method (Evidence Centred Design EDC) in a learning game "herd's crystals" which aims to have 5th grade students work on fluid physics concepts. This approach seems interesting in learning games dedicated to physics and mathematics where the learner's assessment is easy, but not in other types of games.

The work [13] presents an approach to the prediction of personality (introverted/extroverted) in an educational game "MOPEG". The approach is based on collecting the learner-player's track. Personality prediction is done using expert systems with supervised classification algorithms. For the validation of the proposed approach, the results of this approach were compared with the results of the BFI questionnaire (completed by each learner-player) but it is difficult to understand the interpretations of traces collected and classified using expert systems.

The work [14] presents a synthesis made on the basis of documentary analysis. The authors argue that learner modeling can be done on two main axes: - implicit modeling (action modeling, conversation modeling, interaction trace interpretation, error interpretation, follow learner's path in the game), and explicit modeling: (evaluation of questionnaires, interpretation of body gestures and physiological signals). The document lists several educational games suitable for experimentation. This work does not claim to include all methods of modeling learning using educational games.

Several works propose learning games to learn mathematics as indicated [15], that children (students) can consider mathematics as an abstract, boring and unrelated subject to the real world. We note that among the educational games listed, there are few games dedicated to civic subjects such as geography. The work [16] argues that changes in culture and language that involve play can also change the tendencies and motivations related to play. As a result, we are interested in subjects such as civic education, such as geography, which often puts students off by what is considered a frustrating, concrete subject, which requires a virtual journey in relation to the real world.

3. Geographical Learning Game "GEO"

As part of our research work we present the GEO learning game dedicated to geography and for students of the middle school who have an age range (from 10 to 14 years old). GEO was realized in SIMPA laboratory at the University of Science and Technology of Oran USTO-MB, according to the Algerian National Education Pro-gram. The objective of the learning game GEO is to promote and strengthen the learning of geography by proposing scenarios (activities) that help to acquire and memorize knowledge. The content of the program is summarized as a description and map-ping of the earth's surface (land globes, oceans, mountains...).

Figure1. GEO Learning game interface

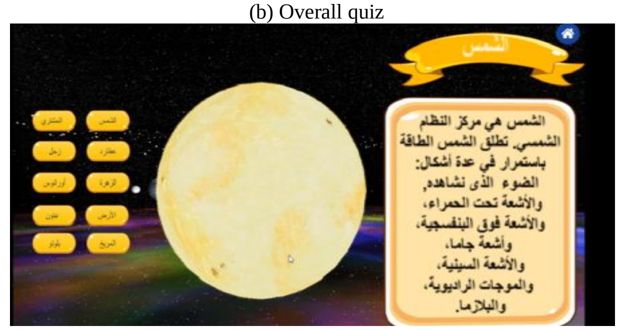
"Fig. 1" presents the interface of the proposed learning game GEO, that combines the educational and the playful aspect. The pedagogy of the game is initially composed of three independent chapters presented in the "Arabic" language.

During the course of a chapter of riddles is offered to the learner-player, he can answer with "true" or "false", as he can ignore the riddle, "see Fig. 2 (a)". Once the chapter is completed, the learner must answer the overall quiz that is noted. The latter is composed of a set of questions with answers to multiple choices, "see Fig. 2 (b)", and finally a "bonus Discovery" is offered to the learner-player, he can explore or ignore it, "see Fig. 2 (c)". The learner-player will be assessed on the correct answers. The "Discovery" bonus is activated at the end of the chapter, provided that the learner-player receives at least one third of the correct answers to the global quiz.

The GEO learning-game is initially structured in three chapters, each chapter is composed of several courses. The first chapter is "the Earth's globe", presented in video and narrative form. The "bonus" is "the discovery of planets". The second chapter is "the seas and oceans", presented in animation and text, i.e. the learner must read the courses in order to answer questions. The bonus is "discovery of fish". The third chapter is "the mountains and the hills", presented in the form of narration, animations and texts. The bonus of this chapter is "the discovery of flowers".

(a) Riddle

(b) Overall quiz



(c) Bonus discovery

Figure 2.The pedagogy of the learning game GEO

Each chapter is defined by an environment and a playful scenario different from the previous one, the courses begin with the search for a reference object of the theme, followed by the progression in the course is through the search for elements that reveal its content. At the end of each chapter, a series of questions offered to the learner-player to enrich his/her own knowledge and obtain a score to evaluate him/her and give him/her access to the bonus Discovery.

For example, the script of the chapter "the Earth globe" offers the learner-player to find the spacecraft, he moves with a character and follows the arrows, once found, he will be able to listen and watch videos. In the chapter "Seas and Oceans", the learner-player finds himself in a landscape that represents a deserted island, he must collect shells, each time he collects one, he will have information that is displayed as animation and text about the contents of the course. In the chapter "mountains and hills", the learner-player is immersed in a forest or finds butterflies that hide information about mountains and hills, he must collect it. In any case the learner-player plays freely without time constraints.

4. Proposed Approach

In order for the course in the learning game GEO to be optimal and adapted to the pedagogical objective and the learner's profile, we have taken into consideration the following criteria:

- GEO modeling by Petri networks to check the consistency of the game and the different routes by detecting blocking situations.
- Generation of the corresponding Hasse diagram to visualize order relation-ships (prerequisites)
- Emphasize the concept of the game by defining weightings associated with the Hasse matrix to bring out player profiles during the course.

A. Modeling of the GEO game by Petri network

In the first place we check the consistency of the GEO game and the different routes by detecting blocking situations. For this we first model the learning game using a network of pets. Petri dishes are mathematically well-founded two-party graphs adapted to model dynamic simultaneous, asynchronous, competitive, and conflict operating systems [17]. The dynamism of the learning game scenarios depends on the player's interaction with the game and the player's actions can change the state of the game. Petri dishes give us a way to test the learning game GEO and raise issues (security and inter blocking), they offer help to model player actions in real time, recheck and validate our learning game GEO.

In our approach we model the sequence of activities of the learning game GEO and the actions (in all possible cases) of an expert (teacher) and the game designer by a network of pets to detect design and implementation errors. The goal is to achieve a development with minimal (if not zero) errors and reliable scenarios.

The Petri dishes network will need to verify the following properties according to the proposed set chart "shown in Fig. 3":

- Any learner-player has the choice to enter one of the three proposed chapters
- Any learner-player, between each course of the chapter, is invited to answer some questions with a "true" or "false", if he wishes otherwise he can ignore them.
- Any learner-player who realizes 30% of the answers just in the overall quiz of each chapter has the right to access the Discover bonus, if he wishes.

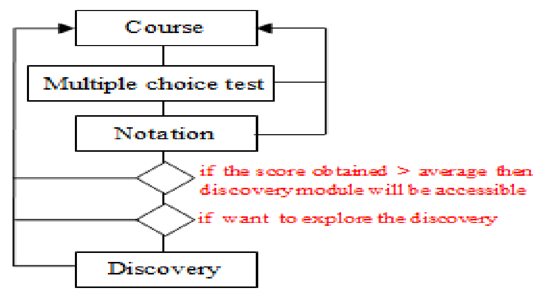


Figure 3. Flowchart of the proposed game

The modeling of the learning game GEO is illustrated in "Fig. 4".

This modeling is useful and simple; it allows us to check the consistency of the different paths of the game by detecting unwanted behaviours.

B. Architecture of the proposed approach

In order to estimate the learner's level in a learning environment typically learning game GEO or the learner-player to learn with pleasure without the game dominating or bored teaching, and in order to build and update his model, it is essential to collect the learner's trace during the game in order to analyze the knowledge level and gener-ate the skill structure, and to do so categorization of learners according to their profiles.

The architecture of the proposed approach is illustrated in "Fig. 5". It consists of four main layers: the scenario of the game, the analysis of the trace (competence structure), the estimate of the level of knowledge (cost function), the model (categorization) of the learner-player.

1) Architecture of the proposed approach

The educational context of the learning game GEO was realized by a teacher of the civic subject according to the Algerian National Education Program. The activities offered in the game are dedicated to students of the middle school. The description of the game scenario is described in the previous section (Section3).

2) Interaction analysis

a) Trace recording

Tracing the learner during navigation in the game environment and analyzing the chronological sequence of actions requires that these interactions be traceable. To do this, we have created a trace file for each learner-player that contains (username, age, sex, score, time spent in the game, number of correct answers, number of solved riddles, access to the discovery section and the path taken).

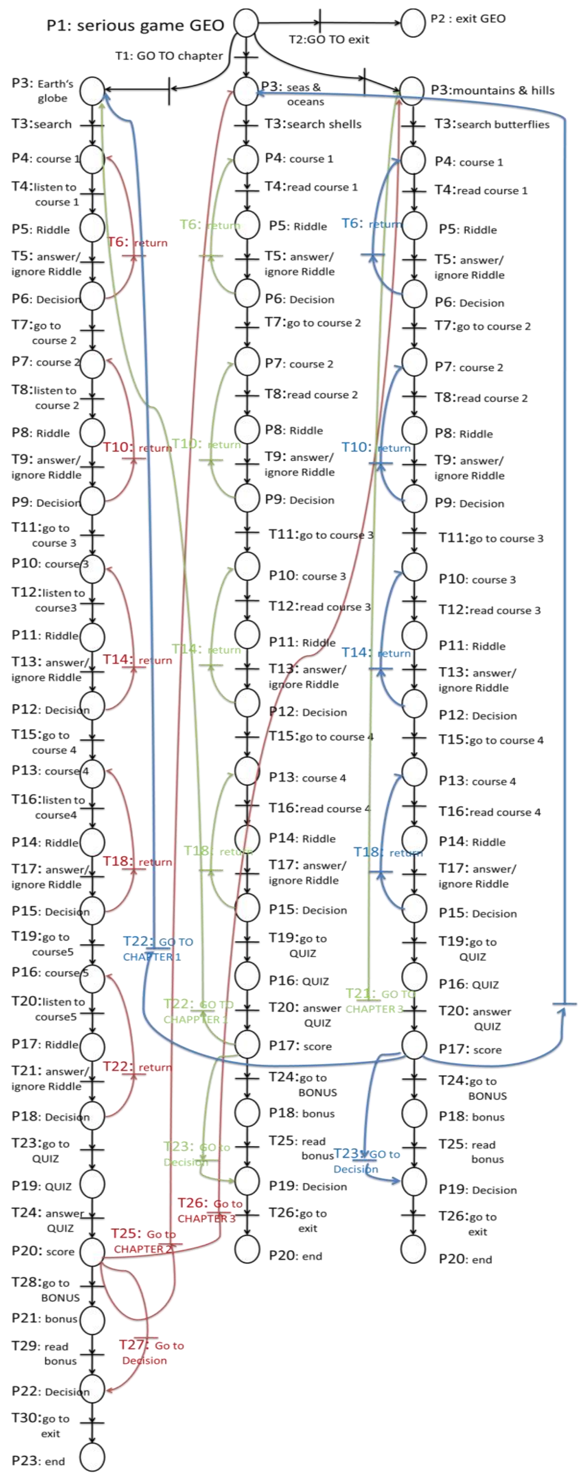


Figure 4. Game modeling with the Petri dish network

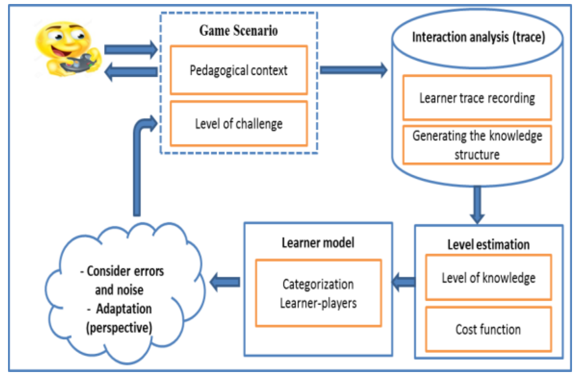


Figure 5.Architecture of the proposed approach

b) *Knowledge structure*

Based on the Competence-Based Knowledge Space Theory (CBKST) [18] to generate structural competence, we need the domain model targeted by learning game that is defined in our case by a teacher (expert) of geography in the middle school. The domain model consists of a finite set of knowledge and the relationships (prerequisite, and composition) of that knowledge.

- The "prerequisite" link between knowledge "a" and "b" indicates that knowledge "a" is indispensable to acquire knowledge "b". It can be represented by (A ⩽ B).
- The "composition" link indicates that knowledge "a" is composed of several sub-knowledge of lower level.

Let us remember that our game is initially composed of three independent chapter scenarios; the first chapter "The Earth's Planet" consists of five (05) structured courses.

"Fig. 6", presents the example of the field model targeted by the teacher of the third "Day and Night" course of the "Earth globe" chapter, and the knowledge structure to be generated from the domain model.

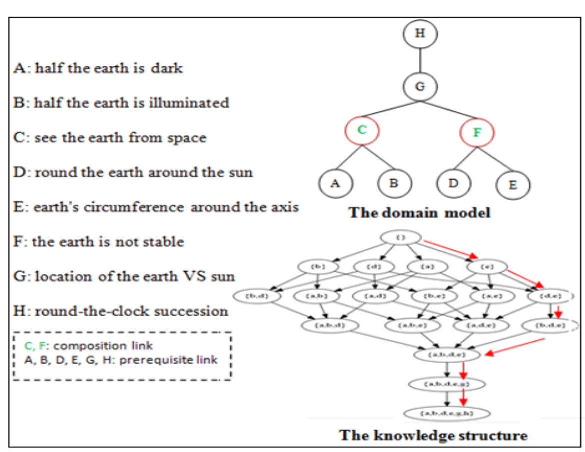


Figure 6.The domain model (bottom-up) and knowledge structure (top-down) of the 3rd course in Chapter 1

The expression of the paragraph of this part is different from one path (in the knowledge structure) has another, for example, the path marked in red specifies that the learner must compose ({}, E, D, B, A, G) respectively in order to reach the final state (H), taking into account the composition links (C, F) as coordination links in the structure of knowledge. (H) is considered a third course title.

Based on the learning objectives of the teacher (expert), we are modeling the over-all scope of the scenario in the first chapter of the GEO game, this domain model consists of 05 parts (courses) (A, B, C, D, E) that make up the final state (F) considered the title of Chapter 1 "Earth globe". We then generate the corresponding knowledge structure (Hasse diagram) to visualize the order relationship (prerequisite) illustrated in “Fig.7”.

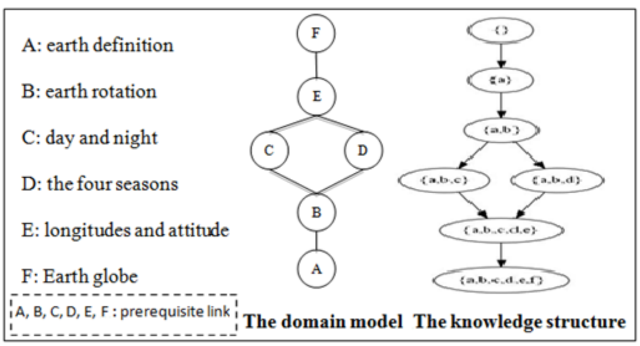
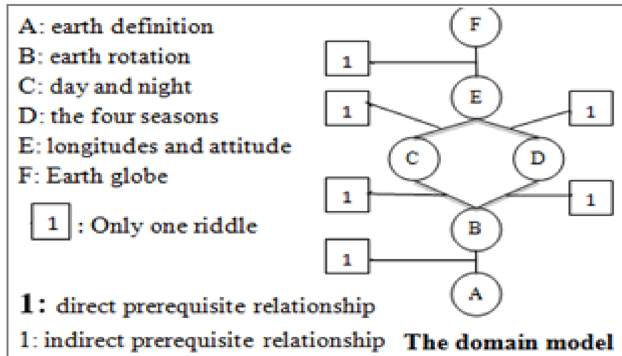


Figure 7. The domain model (bottom-up) and knowledge structure (top-down) in Chapter 1

To highlight player profiles during the course, we represent this knowledge structure by a matrix (Hasse matrix). The choice of matrix representation of the knowledge structure is ideal because we know how to manipulate the matrices. We suggest using a weighted Hasse matrix, i.e. working with a weighted tree (the arcs bear a weighting).

We suggest using a weighted Hasse matrix, i.e. working with a weighted tree (the arcs bear a weighting). Weighting is the number of riddles that can be involved. For example, from part "A" (earth definition) to part "B" (earth rotation) of “Fig. 7”, the arc will have a value of 3 which means that to arrive "B" 3 riddle are available. This weighting tells us the learner-player's journey.

To better illustrate this step, we associate at each step (prerequisites) a single riddle, thus the generated matrix corresponding to the domain model of Part 03 is presented in “Fig. 8”.



≤	A	B	C	D	E	F
A	0	**1**	1	1	1	1
B	0	0	**1**	**1**	1	1
C	0	0	0	0	**1**	1
D	0	0	0	0	**1**	1
E	0	0	0	0	0	**1**
F	0	0	0	0	0	**1**

Table 1- The matrix corresponding to the domain model

Figure 8.The global domain model (bottom-up) and Chapter 1 Hasse Matrix

3)Estimation of level

a) Level of knowledge

On the basis of the matrix representation, we can calculate all paths (including the shortest path), or each path will be represented by a vector, we can infer the possible number of paths (traveled) offered by this modeling. Weightings will be included in the vectors, if necessary, for the calculation of the proposed CF cost function where the learner’s trace will be the vector of the path travelled.

b) Proposed analytic model

In order to estimate the level of the learner-player and deduce his profile during the course of the GEO game, we propose the following analytical model CF (Cost function):

It should be recalled that the transition from Part A to Part B offers a riddle to the learner-player, he has the choice of answering a riddle by "true" or "false" or not answering, in this step, the learner-player’s answer is not rated, his choice of answering or not is weighted, it is called control. Once a chapter’s course has been completed, the learner-player must answer the overall quiz that is noted, it is called the question. The latter is composed of a set of questions with answers to multiple choices. If the learner answers by 30% of answers just then the discovery section (bonus) is activated. The player learner is free to read or not read the bonus.

$$CF = \alpha\ \text{Control} + \beta\ \text{Question} + \delta\ \text{Bonus} \quad (1)$$
$$\text{With } (\alpha + \beta + \delta = 1)$$
$$\text{Control} = \sum \text{Weighting} / \text{Weighting Number} \quad (2)$$

"Weighting" is the answer or not to the riddle, it is considered an appreciation of the student's participation in each course in a classroom.
"Weighting" shall take the following values: 0 if the learner does not respond, 0.5 for a false answer, 1 for a true answer.
"Control" takes the values in the interval [0,1] with a coefficient α = 0.25. It is similar to a continuous assessment of the requirements, we emphasize that the game should not dominate

$$\text{Question} = \sum \text{answers-just} / \text{question number} \quad (3)$$

"Question" is the test score in a classroom. It takes the values in the interval [0,1] with coefficient β = 0.6. This is the learning objective of learning game.
"Bonus" is considered a mark of non-compulsory personal work in a classroom. It is set to 0 or 1 with coefficient δ = 0.15. It is optional, but it must be earned.
<u>*Example of level estimate*</u>
For the control, the learner is presented with two riddles, suppose that he answers the first riddle correctly, he obtains 1, and he gives a false answer to the second riddle, then he obtains 0.5.
So he obtains in Control 0.75 = (1 + 0.5) / 2
For questions, suppose the learner answers 2 correct answers for 5 questions, then: Question = 2/5 = 0.4
At this level the learner has answered more than 30% required for the activation of the bonus. He is entitled to the bonus. He has the free choice to read the bonus so he gets 1, or not to read it, he gets 0.
By applying the formula

$$CF = \alpha\ \text{Control} + \beta\ \text{Question} + \delta\ \text{Bonus}$$
$$\text{with } \alpha = 0.25,\ \beta = 0.6 \text{ and } \delta = 0.15$$

The learner gets CF = 0.58 if he activates the bonus otherwise he gets 0.42. We can deduce that the learner is just average (average level)

4) Learner's model

The learner's model is based on the learner-player's track where the weighting values will be filled during the learner-player's journey in the Hasse matrix. Consider the global field model of the "globe" chapter.
A square (i, j) is initialized by the pair (X, Y) with:
X=0 (no pre-requisite relationship between i and j), otherwise X = 1 (i is the pre-requisite of j)
Y=-1 (no riddles proposed) if no Y = [0 or 0.5 or 1].
Initially Y is -1 when generating the Hasse matrix corresponding to the domain model, the Y update can take one of the three values (0 or 0.5 or 1) during the learner's journey in the game, which we have called "weighting".

The weight (riddle answer) is REP, its value is 0 (no answer) or 0.5 (wrong answer) or 1 (right answer).
The weighted Hasse matrix generated is as follows:

TABLE 2. The Hasse matrix corresponding to the domain model during the learner-player journey

≤	A	B		C		D		E		F	
A	0	**1**	**REP**	1	-1	1	-1	1	-1	1	-1
B	0	0		**1**	**REP**	**1**	**REP**	1	-1	1	-1
C	0	0		0		0		**1**	**REP**	1	-1
D	0	0		0		0		**1**		1	-1
E	0	0		0		0		0		**1**	**REP**
F	0	0		0		0		0		**1**	

However, we can propose N riddles. In this case, the box (i, j) will be represented by the vector of elements (X, Y1, Y2, ...,Yn)

In order to infer behaviours and obtain a precise categorization of learner-players, we extracted all possible cases that a learner-player can present as well as the results obtained by the calculation of the cost function CF, based on the trace of the learner-player.
Depending on the cases derived from the calculation of the proposed CF cost function, we propose to categorize learners by combining the following three sub-categories:

- *Sub -categorization by riddles only*

This sub-categorization is based on the number of responses to riddles or the learner-player has the choice of answering "true" or "false" or not answering. In this step the choice of answering or not is controlled, He informs us about the "interactivity" pro-file of the learner-player with the learning game environment. We propose to segment the number of responses by intervals, "see Fig. 9", and give each interval a pre-categorization as follows:
[0.20%]: zero to 20% response to existing riddles (whether the answer is varied or false) leads the learner to be much more interested in the game, we declare him to be a pure-player learner.
]20%, 60%]: Learner-players who have a response rate between 20% and 60% of answers to the existing riddles, we declare them not very interested in the pedagogical aspect.
]60%,100%]: Learner-players with a response rate higher than 60%, we estimate that they are learner-players interested in the pedagogical aspect.

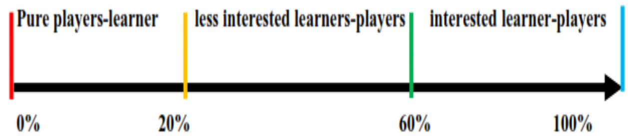


Figure 9.Pre-categorization of Learner-Players by riddles only

- *Sub categorization by correct/false response rate in the overall quiz*

This sub-categorization is based on the number of correct/false responses. The learner must answer the overall quiz that is noted. This step informs us about the "level" of the learner-player. The global quiz consists of a set of multiple choice answer questions. We suggest segmenting the number of responses (correct/false) by intervals, “see Fig. 10”, and giving each interval a pre-categorization:

[0%, 20%] We estimate that learner-players, who are satisfied with 20% or less correct answers to the overall quiz, have a low level of

] 20%, 40%] the response rate in this range indicates that the learner-player did in-sufficient work.

For these two intervals we consider that the playful (pedagogical) goal was not achieved. On the other hand, a response rate of more than 40% is satisfactory, we have broken it down into three intervals as follows:

] 40%, 60%] the learner-players deserve a good grade.

] 60%, 80%] the learner-players have invested more and deserve a very good grade.

] 80%, 100] the learner-players excelled and answered the overall quiz correctly, so they deserve an excellent grade.

This pre-categorization is similar to the assessment of learners in a classroom by a teacher.

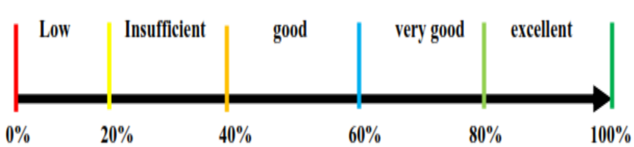


Figure 10.Pre-categorization of learners-players by number of correct/false responses to the overall quiz

- *Sub categorization by access or non-access to bonuses*

This sub-categorization is based on access and whether or not the bonuses offered are read. Note that the learner has the choice of reading the "discovery" bonus, knowing that access to the bonus is conditional on the acquisition of at least 40% of the answers just to the overall quiz. The heterogeneity of learner-player profiles is assumed in our work, where each learner-player has game related characteristics. These characteristics can be grouped by categorization. Since our learning game is based on discovery (curiosity) and knowledge (lessons), and in order to describe the behaviour of the players we have created a list of behavioural traits to study, this list contains three (03) sub-categories of learners-players, namely: learners-player explorers (curious), learners-players accomplishing (satisfied) and learners-players unmotivated. If the learner gets the bonus to read the discovery: you can say that he is curious, otherwise he is satisfied. He who got less than 40% correct answers then he is classified as unmotivated.

5. Experimentation

We led the experiment of the proposed learning game GEO in a middle school for students in the second year. The experience was as follows: In a classical classroom with 34 pupils, the chapter "the Earth globe" with the same content proposed in learning game GEO is presented by a teacher in the field, students have the right to ask questions, the teacher asks the same questions proposed in the riddles of the game and observes the students who participate, at the end of the session, the teacher has done a test, he asked the same questions proposed in the overall quiz of the game GEO.

Later we tested GEO learning game in a computer room for other students of the same level (from another class who do not know the "globe" course). The number of students in the computer room is 23 students, the course in the game is the same "globe", we explained to the students the principle of play.

The results of the two classrooms (classical and computer) are described in the next section.

6. Results and Discussion

The teacher assessed the students on the final test. The results obtained in the classical class are illustrated in “Fig. 11”.

This assessment shows the level of all students without an appreciation of their orientation to the subject of geography education.

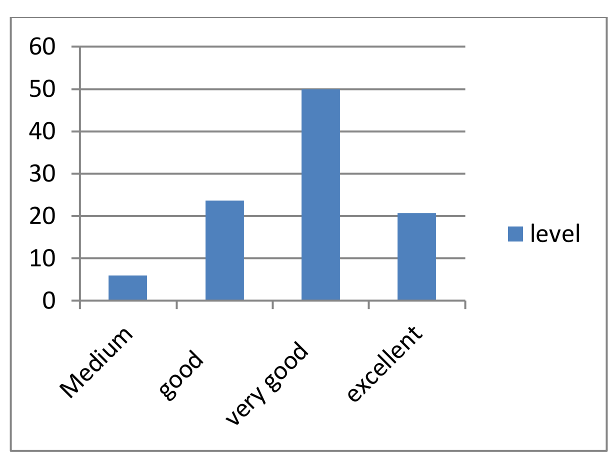
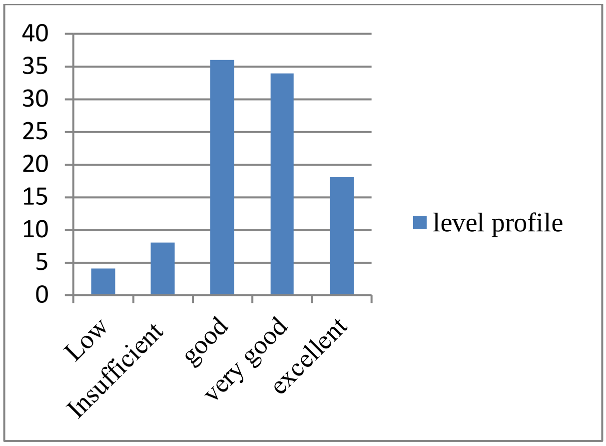
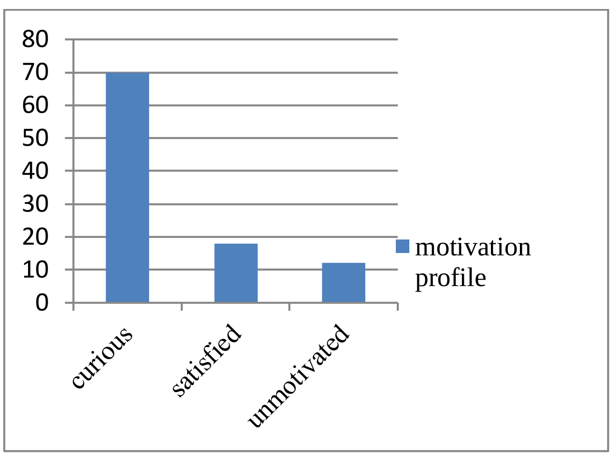


Figure 11.Classroom Student Assessment

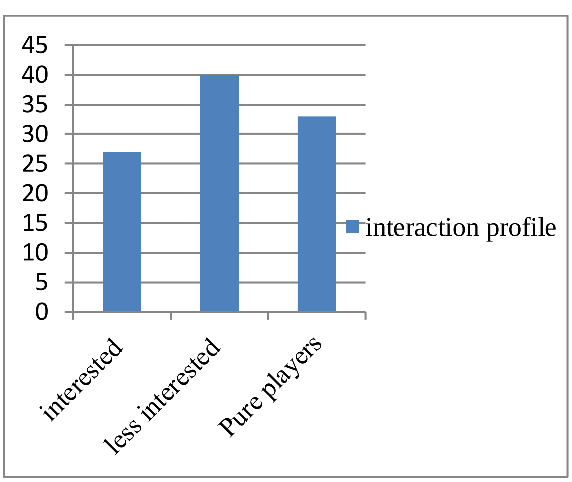
The proposed learning game GEO, allows us to extract different results and present different readings according to the desired objective to reach. These results are dis-cussed below.



(a) Level profile



(b) Motivation profile

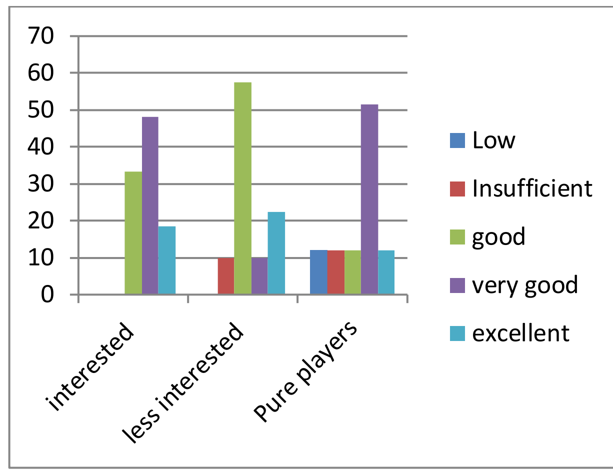


(c) Interaction profile

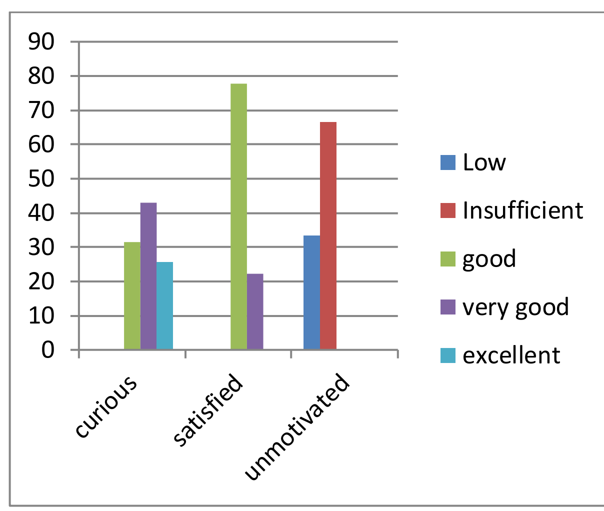
Figure 12.Categorization of learners-players by Level, Motivation and Interaction Profile

"Fig. 12" illustrates the three profiles derived. The level profile tells us how much knowledge the learner-player has acquired. This level is calculated according to the CF formula described above. The motivation profile tells us about the learner's relationship with the subject of teaching, he can be a curious student or simply a satisfied student by content with the minimum knowledge necessary, as he can be an unmotivated student and annoyed by the subject of teaching. The interaction profile tells us about the student's orientation, whether he is a pure-player, or a learner interested or not interested.

From these three profiles, we can combine them to extract typical characteristics to the learner-player.



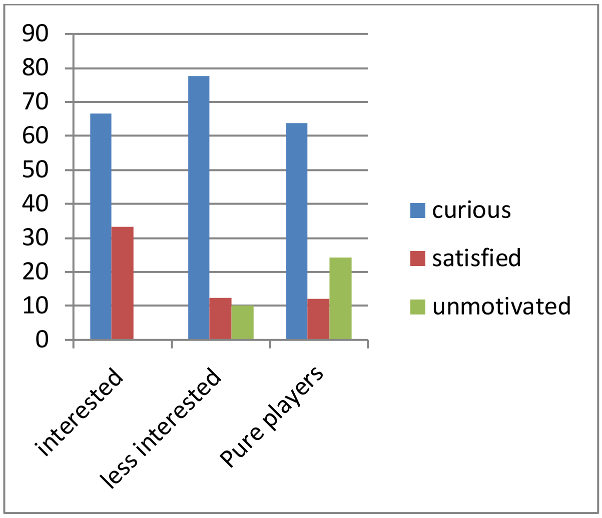
(a) Interaction Profile vs Level



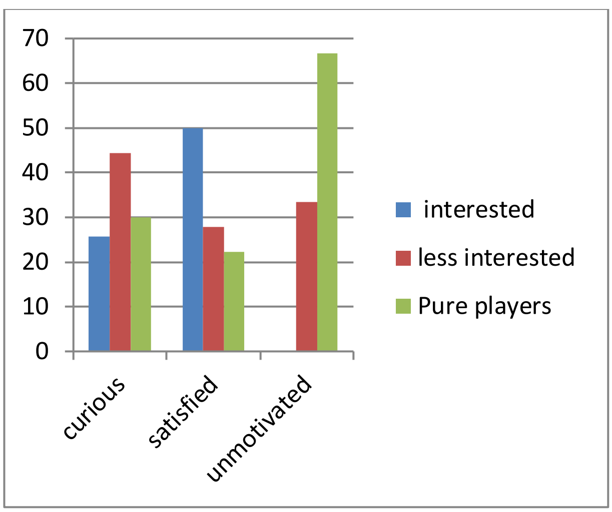
(b) Motivation Profile vs Level

Figure 13.Categorization of learner-players profiles vs Level.

"Fig. 13" illustrates the interaction and motivation vs level profiles. From "Fig. 13(a)", we find that puppet learners (above 50%) can achieve as good results as interested learners. On the other hand, unmotivated learners "Fig. 13(b)" have insufficient or weak results.



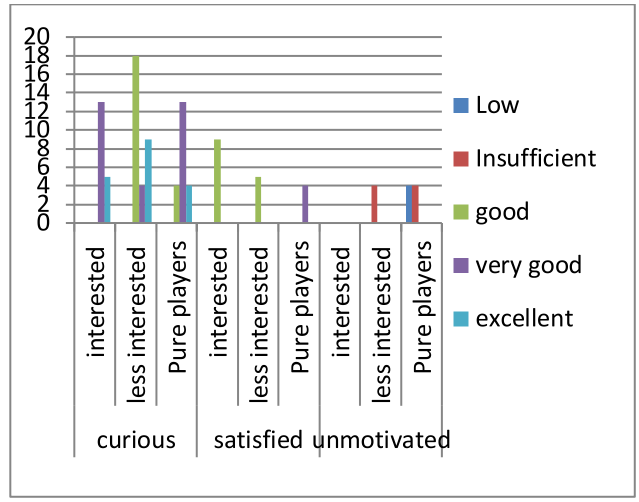
(a) Profile interaction vs motivation



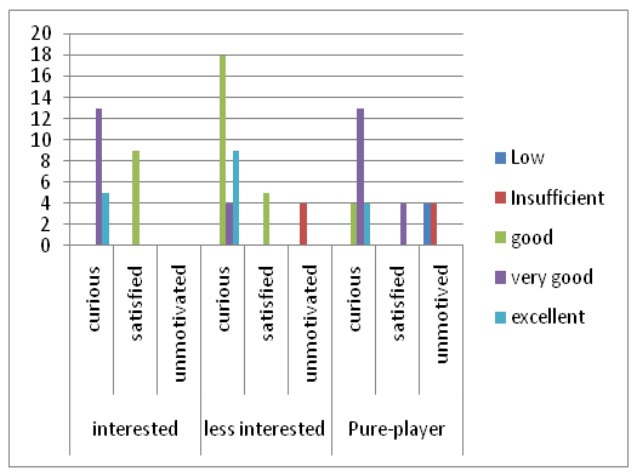
(b) Profile motivation vs Interaction

Figure 14.Categorization of learners-players by combination of interaction and motivation profiles

It is remarkable that the curiosity is strong and dominant regardless of the player's interaction profile with the GEO environment "Fig. 14(a)". On the other hand, in "Fig. 14(b)", we find that the unmotivated learners are mainly pure-players or simply not interested in the GEO learning game environment. Curious learners may not be interested but satisfied learners are generally interested.



(a) Profile motivation/interaction vs level



(b) Profile interaction/motivation vs level

Figure 15.Categorization of learners-players by the combination of interaction and motivation vs level profiles

"Fig. 15" provides another reading of the categorization presented. For example, a curious learner regardless of his or her interaction profile can have good and very good results, while unmotivated learners are limited with insufficient results "Fig. 15(a)". Another reading of "Fig.15(b)" tells us that a pure player-learner can per-form very well if he is curious or simply satisfied.

7. CONCLUSION

The learning games play a very important role in individualized learning, they pro-vide fun and knowledge, and stimulate learners-players by increasing their motivation and knowledge. Several educational games dedicated to scientific subjects such as mathematics and physics are used in literature to model and analyze the state of competence of learners-players, but few educational games dedicated to civic subjects are used to model learners-players. This research work proposes modeling of learners-players in a learning game for learning the geography dedicated to students of the Algerian middle school. It is based on the categorization of the learner-player in order to synthesize and analyze the characteristics of each learner-player.

The results obtained confirm the idea that a learning game can be used to categorize learners-players according to several behaviours. An analysis of the track of learners in the GEO learner-game reveals that this categorization is composed of three sub-categorization categories: sub-category by level profile, sub-category by interaction profile and sub-category by motivation profile. The latter indicates that curiosity in children is strong and dominant regardless of the player's interaction profile with the learning game environment.

This categorization, which is based on the learner's track, allows us to generate its knowledge structure, to feed the analytical model which in turn assesses the degree of mastery of the knowledge acquired during a game sequence. Our aim is to draw the characteristics of the learners and their profiles and to bring them together. The categorization of learners helps us to improve their levels precisely, where each category needs special adaptation, especially for unmotivated learners.

The comparison of the results obtained by the categorization of learners through the GEO learning game and that of the teacher expert in geography who teaches the same students categorized by the GEO game, are very close and well correlated, where categorization via the learning game GEO is very positive notified by the ex-pert teacher in geography who knows his pupils well.

Finally, the adaptation of the course according to the learner-player's derived pro-file is necessary in order to make learning processes and access to knowledge more effective by helping the learner-player advance better in the game.

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