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MOTIVATION ANALYSIS PROCESS AS SERVICE APPLIED ON SERIOUS GAMES

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***Abstract*—Motivation promotes learners to learn new knowledge to advance in learning process, to be retained in an experience and to persevere in its attainment in order to reach desired objectives. Indeed, the concept of motivation is very rich and can be useful in more than one way to analyze the concept of serious games as it is currently developing. This convergence with the edutainment genre will provide us throughout this article, a basis for reflection on the benefits that we can exploit the relationship motivation and serious games. However, we will study and analyze in the first place similar works. Then we will present our analysis study based on a combination of several machine learning algorithms and learning analytic methods. Finally, we conclude with a detailed discussion by analyzing obtained results and making suggestions for further research.**

***Index Terms*—Serious game, learning outcomes, game play, experience, adaptability, game based learning, service oriented architecture, motivation, Data Analysis, Expectation maximization.**

I. Introduction

Serious game is an increasingly studied topic whose popularity continues to grow [1]. however, many research studies are developing to design pedagogical approaches to make training more accessible and more attractive to students [2]. the contribution of serious game in teaching lies precisely in the idea of making learning experience more enjoyable and attractive to learners. it's entertaining and innovative aspect would allow them to become more interested in the mechanisms that govern the search for information. it's as each interactive tools let students practice, analyze their interactions, give feedback on learners actions, and help them to make progress [3]. due to this variety of advantages, a growing number of professionals are looking for learning interactive tools to improve motivation in educational solutions [4].

"people play games because the process of game playing is engaging [...] because they are challenging and relaxing. this formulation seems very close to that magical state of motivation some refer to as 'flow' [...] the reason computer games are so engaging is because the primary objective of the game designer is to keep the user engaged [5]"

nevertheless, it is almost universally accepted that there is a positive correlation between motivation and learning [6]. motivation is considered as the essence of learning. without interest, it is difficult to integrate new notions, to make links with previous knowledge and to persevere in the appropriation of new concepts. however, serious game can contribute by its dynamism and playfulness [7]. when engaged through play, students may forget that they are working to integrate new knowledge. they are motivated by his motivation for making fun and joy by playing and winning.

despite of the effectiveness of serious games in the term of learning [1], [8], students, teachers parents and professionals style suffering from knowledge transfer due to a number of reasons which can be related to motivation, capacity, level of learning which differs from a learner to another and other reasons. in this paper, we study the existing motivational models and their correlation with serious games. then, we propose an approach to measure the learner motivation through the game and help the professionals to attract more learners' attention. afterwards, we present an implementation of the proposal algorithm in a waste sorting serious game, which aims to teach kids how to recycle different waste. finally, we conclude by an evaluation and discussion of how emotional state model proved successful along with an outlook on future research.

II. THEORETICAL BACKGROUND

A. *Related works*

The psychological and cognitive impact of serious games on learners, especially on their motivation, has so far not been the subject of many formal empirical evaluations[8]. More in-depth studies are now needed, especially since they are starting to generate growing interest in many sectors[9].

Serious games are used to ensure a good transfer of

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knowledge in a fun way. However, a number of solutions are conceived to simulate the domain to be taught with which the learner-player can playfully interact. In the design of serious games, the balance between learning transfer and motivation is the major key of success.

There a number forms of introducing motivation in serious games design. In one hand, some projects promote motivation through narration[10]. In the other hand, some projects rely on competition to motivate players[11].Others, like [12]believe that redundant or incorrect actions in the game, giving students the opportunity to perform unnecessary is fundamental to captivate learners' attention and enable them to implement by themselves.

Throughout the learning process, learners will have a lot of ideas had to be dropped and reviewed from the beginning. In total, hundreds of actions have been made. Many times they see that they tend to lose. However, approaching victory more and more with each attempt held them in suspense. And it is thanks to this tension that they can eventually succeed.

In particular there is a need for designers of educational artefacts to understand how users interact with different types of artefacts and how this interaction affects users' educational experience[13]. Generally speaking, user experience is axed on the interaction between product and learner, and he resulting experience in a certain context of use[13]. However, User experience should be considered from physical, sensual, cognitive, emotional, and aesthetic perspectives[13], [14].

Serious games have always been considered to be intrinsically motivated, several mechanics employed in this purpose; the challenge, curiosity, control, interaction and simulation. The motivated learners are more engaged and enhanced skills performance; however learners with a negative emotional state appear a boredom behavior on their interaction with technology and decrease learning benefits[15].

B. Motivational theories

Motivation is considered as a key of success. It makes learner want to accomplish tasks, to learn new knowledge to advance in the process of learning. It is often presented in a central construct of learning theories. It is defined as the tensor of internal and external forces, directed or not directed by a goal, that influence a person cognitively, affectively or behaviorally [16]. It is a process that influences triggering, direction, intensity, persistence and frequency of behavior or attitudes [16].

In cognitive psychology, the motivation for success depends on the individual's desire and expectations, personal sense of self-efficacy, and strengthening or support in the social environment; it is therefore an individual characteristic of the learner. It is defined as a continuum that goes from one extreme, the non-motivation, to another, the intrinsic motivation (which comes from the individual himself), going through the extrinsic motivation (which comes from stimuli external to the individual), as summarized in Figure below:

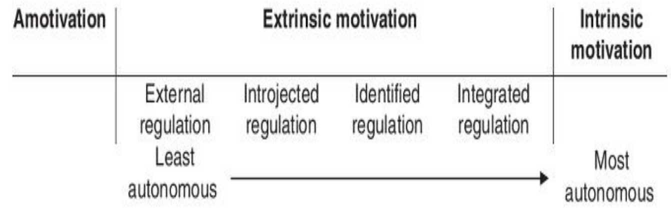

Fig. 1. The self-determination continuum

Motivation is an embedded concept in the learning framework. It is at two levels: that of extrinsic motivation which is caused by an external force of the learner and that of intrinsic motivation which depends on the individual himself. Both are required to engage in a learning process as in any other activity elsewhere.

There are several works focused on the learner motivation in serious game in order to enhance the level of learner motivation related to their interaction with the game.

In 2005, Clark has stressed that the motivation in learning is defined as a pyramid in layers such as environmental factors, psychological factors, motivated behavior, knowledge and learning strategy, and performance. Then, James Keller, educational psychologist, ARCS KELLER model at Florida State University devised a motivational model based on a synthesis of existing research on psychological motivation[17]. His ARCS is an acronym that represents four classes: Attention, Relevance, Challenge, and Success. Finally, Malone [18]goes much further because it provides a conceptual framework for explaining the four conditions that must be met for a video educational game is intrinsically motivating. For him, all the ingredients for good video games are a challenge, curiosity, control and fantasy. Malone model shows the main interest in a coherent and compact disparate elements belonging to various motivational theories. This method was also used by Keller [17] as part of another motivational model applied also to edutainment software. Although this meta-categories Keller (ARCS care for (A), relevance (R), confidence (C), and satisfaction (S)) are different from those that offer Malone, both designs are based on many common references in terms of motivational theories. However, unlike Malone, Keller goal is what he calls the motivational design, that is to say it provides more of a method of design and development.

One of the main benefits of using serious gaming in class is the overall positive impact on student motivation. If we think that the novelty aspect of the introduction of the game in class comes into play, the few studies on the use of games over the long term show that the object "Game serious" [19]. Indeed, an adapted game gives regular returns to the student on his actions, thus maintaining his motivation [20].Gambling, in general, is associated with intrinsic motivation to encourage performance and self-esteem [21].

C. Perception of flow condition

Flow theory[22] is based on a symbiotic experience between challenges and the skills that need to be implemented

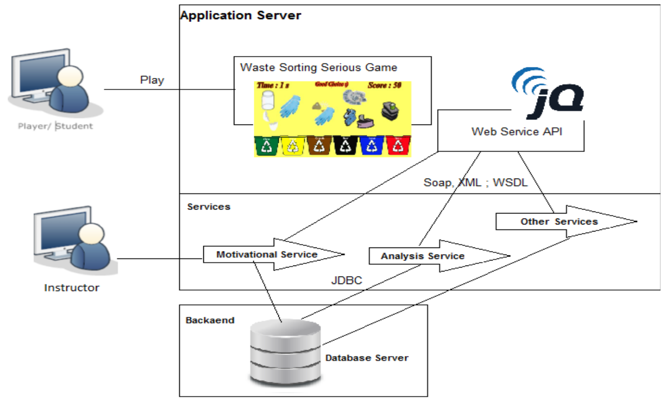

Fig. 3. The proposed Serious game Architecture

to address them. However, flow experience arises when skills are not overtaken or underused, when the challenge is optimal. When the individual plunges into the flow, the involvement in

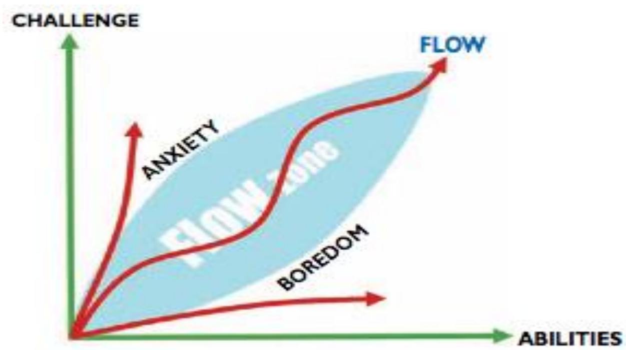

Fig. 2. Flow state[23]

the activity is such that he forgets time, fatigue and everything around him except the activity itself. In this state, the individual operates to the maximum of his abilities and for the flow experience. The activity is performed for itself (as defined in the context of intrinsic motivation), even if the goal is not yet attaint.

Jeanne Nakamura and Csíkszentmihályi[23] identified six aspects surrounding a flow experience:

1. Intense concentration focused on the present moment.
2. Disappearance of the distance between the subject and the object.
3. Loss of self-awareness.
4. Feeling of control and power over the activity or situation.
5. Distorted perception of time.
6. The activity itself is a source of satisfaction.

These aspects can be present independently of each other, but only the combination of several of them can constitute a real flow experience.

The flow has many similarities with the state of hyper-concentration, at least as far as its positive aspects are concerned.

- Flow D1: Sense of control / activity control. We know that the activity is feasible, that the skills are in adequacy, there is neither anxiety nor boredom.
- Flow D2: Altered perception of time. Total concentration on the present, we do not see the time pass.
- Flow D3: Lack of concern about the self. No worries about oneself, feeling out beyond the limits of the ego.Afterwards, feeling to have transcended the ego to the point that we did not believe that possible.
- Flow D4: Feeling of well-being. What produces the "Flow" becomes a reward in itself; Feeling of ecstasy; Impression of being out of everyday reality.

The literature helps us to apply some concept as presented in the next section, in order to evaluate the impact of adaptation of the learning process through serious games.

III. CASE OF STUDY

The main objective of this current paper is to analyze the emotional state of learning across serious games according to Difficulty, learning objectives and learner competence during the game. The description of the proposed serious game and the establishment of the hall system will be described in this section.

Waste sorting serious game [24]is to teach kids how to recycle different waste. The learner should sort different waste into different trash, according to their types e.g. “paper, plastic, metal, glass, and organic, etc”. The sorting is done by catching different objects generated randomly and dropping them in the appropriate container according to their types, this mechanism will be done by using either a mouse or an input device called leap motion[25].

The waste sorting serious game will be equipped by the timer, and the assessment system that evaluates the learners according to their performances; if they make a good choice the reward will be the gain of some points, although however in opposite case the punishment will be the loss of some points. With the assessment system, the timer, and the interactivity based on hand movement the proposed serious game will be more challenging and attractive especially for kids, it will allow them to live a beneficial and unforgettable experience[25].

A. The proposed Architecture

The proposed architecture Fig. 3 is based on service oriented architecture, where the deployed serious games invokes several services e.g. “Motivational service, analysis service, etc.” by the JavaScript API, each service has a specific task in order to improve the learning process by motivating the learning during the game sequence, all the learners behavior during the game sequence are saved into the database. In addition, all the services are developed by using Axis framework that facilitates the establishment of the web service by coding java classes.

This architecture can be reused, in other realization by invoking those services, independently of logic or technology used.

Motivational service has specific inputs (Difficulty Double; Competence Double; X Double; Y Double) and does a specific task, in order, to motivate the learner during the game.

Input: Difficulty; Competence; X; Y

Processing: Y= 1/2X-2 <= Flow <=Y= 1/2X+2

Output: 0; 1; 2

The result is resumed in the emotional state of the learner:

0 : The learner is in the flow state

1 : The learner is in the state of anxiety

2 : The learner is in the state of boredom

Analysis service has as a purpose to classify collected data into a cluster by using Expectation-Maximization [26] algorithm and the data will be analyzed with a decision tree by using C4.5 algorithm. Data will be saved into the database, as shown in the table I, these data will be operated also by the tools of learning analytics and educational data mining, to have a global view on the progression of all the learners.

B. Decision tree

The current paper focused on the implementation of interest service as proof of concept of the global service. It is based on decision tree one of the learning machine algorithms

The proposed decision tree uses the C4.5 algorithm as learning algorithm, it is an algorithm used to generate a decision tree developed by Ross Quinlan often referred to statistical classifier [27]. It will be feed by the motivational output; in the next section, the result of such service will be discussed.

The decision tree is formalism for expressing such mappings and consists of nodes linked to several sub-trees and leafs or decision nodes labeled with a class which means the decision.

The C4.5[27] is the learning algorithm that will generate the three according to the data saved in the database; the proposed algorithm is an extension of ID3 algorithm; it builds decision trees from a set of training data in the same way as ID3 by using the concept of information entropy(1) and The splitting criterion is the normalized information gain (2), the algorithm of C4.5 for building the decision tree is described below :

TABLE I
DATABASE ATTRIBUTES

Knowledge
✓ Id_session
✓ Name
✓ Age
✓ Sexe
✓ Average of response time
✓ Number of wrong answers
✓ Score
✓ Question
✓ Learning objectives
✓ Difficulty
✓ Learner Competence
✓ State
✓ Type

$$\mathrm{H}(S) = -\sum_{x \in X} p(x) \log_2 p(x) \quad (1)$$

Where:

S: The current (data) set for which entropy is being calculated.

X: Set of classes in S.

p (x): The proportion of the number of elements in class x to the number of elements in set S.

$\mathrm{IG}(A, S) = \mathrm{H}(S) - \sum_{t \in T} p(t) \mathrm{H}(t)$ (2)

H(S) Entropy of set S.

T The subsets created from splitting set S by attribute A such that S = U t ∈ T.

P (t) the proportion of the number of elements in to the number of elements in set S.

H (t) Entropy of subset t.

Below the algorithm of C4.5:

Check for base cases

For each attribute a:

Find the normalized information gain ratio from splitting on a.

Let a_best be the attribute with the highest normalized information gain.

Create a decision node that splits on a_best.

Recur on the sub lists obtained by splitting on a_best, and add those nodes as children of node.

The Fig.4 presents an example of the decision tree generated dynamically from database. The attributes “Inputs” that feed the decision tree are: difficulty, competence, state, id_session. By cons the classes “Outputs” are: Flow, Boredom and Anxiety.

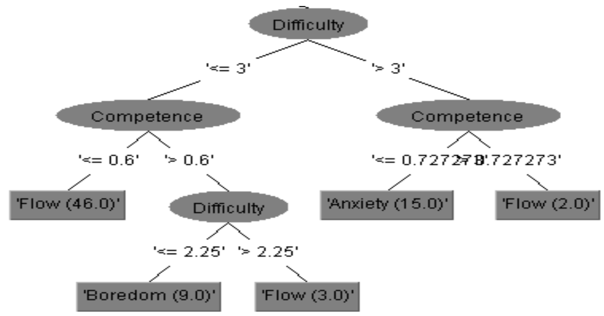

Fig. 4. Decision tree of learner emotional feeling

The resulting decision tree (see figure 4) provides the learner emotional state Flow, Anxiety and Boredom as the potential interest attributes of study.

Following the current analysis, the motivational services provides the employment of decision tree to help the definition of the learner emotional state based on data set of 96 students, but it requires more data set of play to propose good decisions.

The establishment of such service by using several technologies/ frameworks based on web service, during the development process has allowed a big flexibility to improve the approach and use other motivational factors as to progress of development. As known the service will be reused regardless to the technologies or the language used to develop such video games, therefore this solution will be generated to many other realizations by invoking the proposed services.

C. Clustering

The clustering is the task of grouping a set of elements in such a way that elements in the same group called a cluster. A Cluster is a collection of objects which are similar between them and are dissimilar to the objects belonging to other clusters[28]. Clustering is particularly useful in the case where the most common categories within the data set are not known in advance. Clustering can be applied in several communities, for example students in schools could be clustered together to investigate similarities and differences among them, also student actions could be clustered together to investigate patterns of behavior.

Clustering algorithms typically split into two categories (see): we can go “bottom up” in the hierarchical agglomerative clustering (HAC) by grouping small clusters into larger ones, or “top down” in the divisive clustering by splitting big clusters into small ones, as in the divisive clustering provided by several algorithms such as k-means, EM-based clustering and spectral clustering. Although the agglomerative clustering assume that clusters themselves cluster together, the non-hierarchical approaches assume that clusters are separate from each other [29].

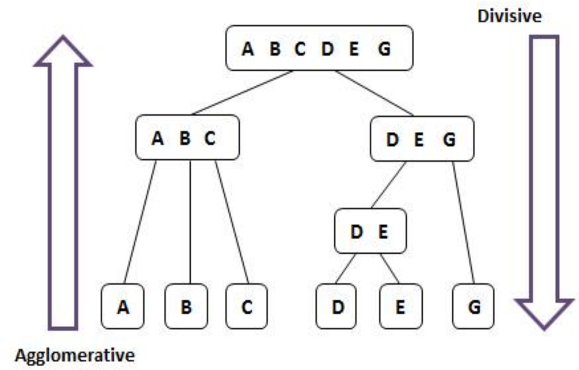

Fig. 5. Clustering categories

Among the clustering algorithms there is Expectation Maximization (EM) algorithm; it’s an iterative method for finding maximum likelihood or maximum a posteriori estimates of parameters in statistical models [30]. The Expectation-Maximization (EM) algorithm defines an extension of clustering to continuous and categorical variables, it assumes an employment of probability model with parameters to describe the probability of an instance to belong to a certain cluster [30]. EM starts by the initialization of the model parameters, then the expectation step computes the probability that an instance x belongs to cluster i, finally the maximization step calculates the clusters means according to the probabilities that all points belong to cluster i. The expectation and maximization steps are repeated until the model parameters converge (see Figure 6).

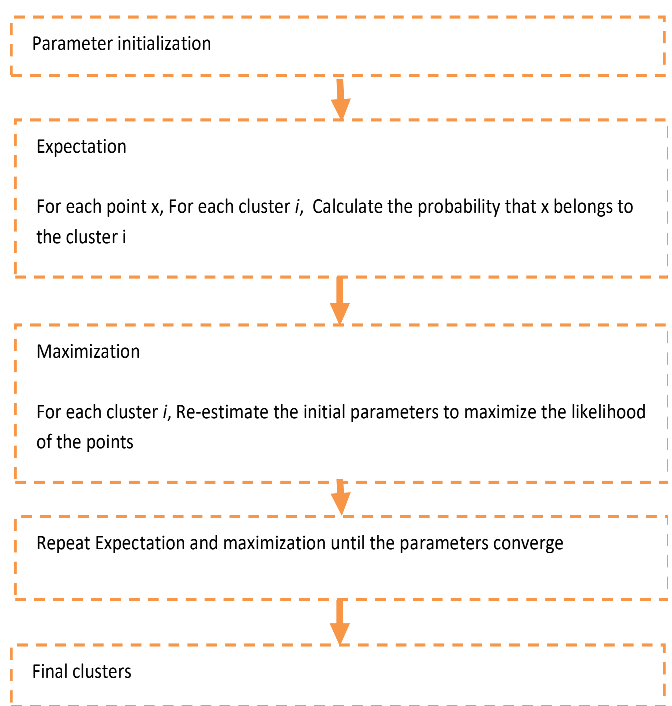

Fig. 6. flowchart of EM algorithm

The EM iteration alternates between performing an expectation (E) step, which creates a function for the expectation of the log-likelihood evaluated using the current estimate for the parameters, and a maximization (M) step, which computes parameters maximizing the expected log likelihood found on the E step. These parameter-estimates are then used to determine the distribution of the latent variables in the next E step. The EM iteration consists of two steps expectation (E) step and maximization (M) steps.

The Expectation (E) Step: Each object assign to clusters with the center that is closest to the object. Assignment of object should be belonging to closest cluster.

The Maximization (M) step: For given cluster assignment, for each cluster algorithm adjusts the center so that, the sum of the distance from object and new center is minimized.

The obtained results will be interpreted and discussed in the next section, in order to evaluate the impact of the adaptation of the learning process through serious games.

IV. Result and Discussion

The aim of this part is to analyze and predict the emotional state of the learner in an experiment in order to ensure optimal emotional state. However, we have seen the flow which is defined as an optimal psychological state that can be felt in various domains, particularly during an experiment and manifested during the perception of a balance between his personal skills and the difficulty of the task.

The game development consisted of two major parts:

Part 1: Difficulty generated arbitrary from database

Part 2: Difficulty is recognized by group of students according to the results of the first experience (competence, difficulty)

The current application has been experimented by data set of 96 young students. There are between 14 and 21 years old. They play the game in classroom supervised by their teachers. We find below the distribution of the data generated by learners which helps us to generate the decision tree.

The data obtained after several uses of the proposed game by several learners, as presented below in the Table II, have been clustered in three categories by using Expectation-Maximization [26] algorithm, an algorithm often used in educational data mining to cluster learner's performances, the criteria used to cluster the learners are "id_session, Competence, right answers, wrong answers, and difficulty", Figure 7.

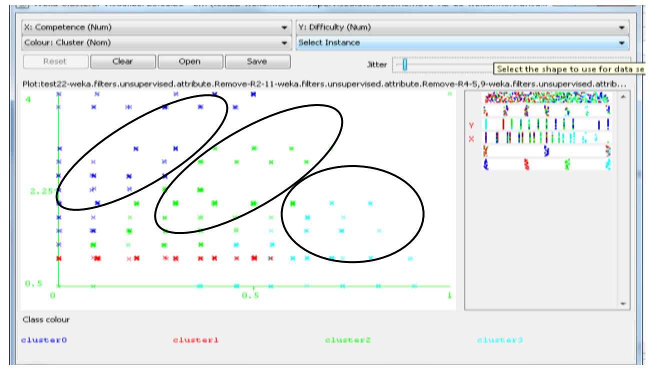

Fig. 7. Learners Emotional state

As presented in Figure 7, there are three categories of learners, clustered according to their emotional state "Flow, Boredom and Anxiety". 54% of them are in the Flow state; 26% are bored, by cons 20% are anxious, according to the given results the majority of the learners are satisfied but the rest have the ability to quit the game according to their feelings as presented in Figure 8.

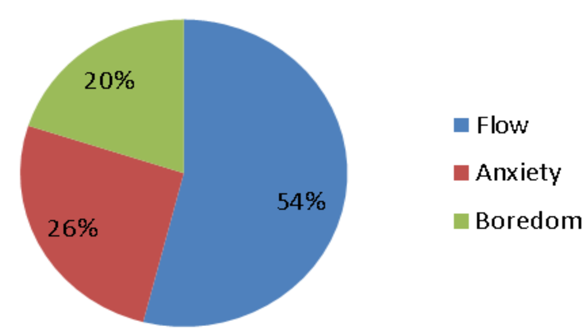

Fig. 8. Pie chart of emotional state before game adaptation

Another way to prove the effectiveness of the proposed serious game, and its impact on the learners, is comparing the adapted and the non-adapted game. This comparison is based on finding the difference of learning degree of each step "Before" the group that uses the non-adapted version of game and "After" the group that uses the adapted version. The Table

TABLE II
Database Attributes

Level	Nbr student	correct answers	Wrong answers	Nbr abandons
Non adapted game	96	376	564	18
Adapted game	96	792	168	3

II details this comparison.

After this study we observed the importance of the adaptation of the game according to the level of competence of each student to keep them in an optimal emotional state during the experiment.

In order to prove the effectiveness of adapting serious games difficulty according to the learner performance, we take a sample of a learner results before and after adapting the game according to skill and difficulty level.

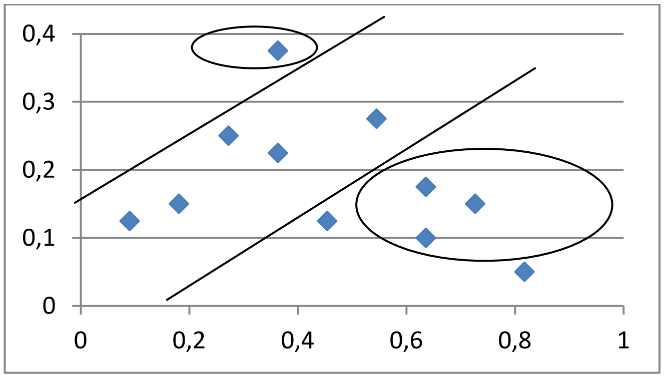

Fig. 9. Distrubtion of learner result before game adaptation

This graph figure 9 shows that the learner may not finish the game because the questions are easy for him. As a result, the learner will have a better chance to leave the game. However, students who feel excited about playing a video game have a higher tendency to experience flow may not have helped them to learn from the game. After the game regulation difficulty, as presented in figure 9, according to the skill of the learner, we obtained the results as shown in the figure below.

As presented in the fig 10 there is harmony between competence and question difficulty. The combination of these element, results a feeling of well-being that the mere fact of being able to feel it justifies a great expense of energy. This feeling creates an order in our state of consciousness and strengthens the structure of self. Self-development occurs only

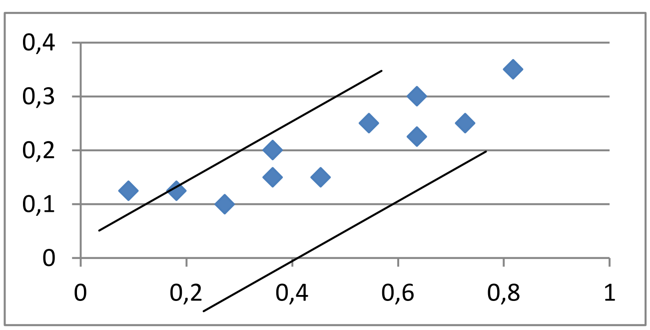

Fig. 10. Distrubtion of a selected learner result after game adaptation

when the interaction is experienced as positive by the person.

The pie chart figure 11 presents the distribution of learner interest according to parameters presented above after adapting the game difficulty according to learner's competence, which they have been designed: F, A, B. We notice that the Anxiety takes 15%, Boredom takes 11%, however the Flow state 74% of the distributions. The obtained

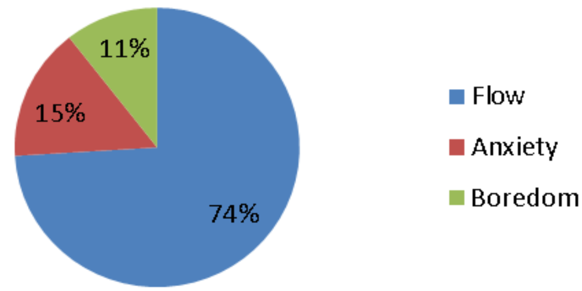

Fig. 11. Pie chart of emotional state after game adaptation

results show that the adapted game is more beneficial for the learners than the non-adapted one.

In order that game bring an effective gain in terms of learning, it is necessary that the learner is able to take a step back and this in order to abstract rules of operation on the simulated world he manipulates. It is at this level that the role of the teacher can be crucial. It can help the learner become aware of what he has done and the elements he has observed, in so doing he can capitalize on what he has learned. For example, if we take the distribution of the students before regrouping them to the sub-team according to their level, we note according to the obtained results that the probability of abandoning the game is too high. On the other hand, if the game is within the learner's reach and is aware of the importance and pedagogical objectives to be attained, and if the teacher urges him to tackle new challenges as his skills evolve, the results will be very satisfactory.

The implementation of such service will allow the improvement of the learning process by attract the learner interest, and motivate him to continue learning withthe game progression. Thanks to the obtained result the proposed solution will be more interesting with a large scale of data saved on knowledge base. Among the perspectives related to this work is the establishment of a system that will adapt serious games according to the prediction given by the proposed system, in order to increase learners' motivation, and keep them playing for more educational benefits.

The attractive field of motivation systems opens the opportunities not only for educational researchers but also for software engineers. The motivational system allows learners to be more immersed across the educational tools especially serious games. As presented below in the decision tree the players or learners are even in the flow emotional state if there is a harmony between competencies and difficulty.

The analysis results based on this study are: performance on a knowledge test; perception of the state of flow during the gambling experience:

The main contribution of this research: A better understanding of Flow in an educational context; Detection of Students at Risk; A new theoretical model linking difficulty and competence; Improvement of the game according to the results of the experiments.

The adaptation based on the learners' emotional state has proved its success, according to the obtained results of both learning analytics or the comparison of the tow version of the proposed game. Results show that students have more facilities to use the game and to progress through out problems after adapting the solution thanks to clustering result.

This study has allowed us also to see that while motivation is at the heart of serious games, it still remains at the moment unknown and its potential is largely underutilized. However, there are several models that could be taken advantage of at many levels. In addition, motivation has been for ten years an extremely prolific research field in which it is possible to draw at the same time approaches, methods and concepts that can guide the design and use of serious games for the future.

V. CONCLUSION

The main objective of the current paper was the establishment of a system oriented services, able to analyze learner's motivation during a game sequence. The integration of both machine learning algorithms and learning analytic methods in different steps of the analysis process has added a new smart layer that can automated the whole process and get relevant results that can be used by experts in order to improve learning process and acquire new skills in an interactive way.

It is obvious that in future works, we will try to answer the raised problems of this work and to take advantage of it to test the other motivational models such as the Malone model and ARCS model by comparing the results with the current work. Also, our work can be expanded into a number of future works exploring other motivational strategies in our game, enhancing the intelligent aspect in the game and enriching the game by other missions for new educational objectives.

REFERENCES

[1] H. Vermeulen and J. Gain, "EXPERIMENAL METHDOLOGY FOR EVALUATING LEARNING IN SERIOUS GAMES."

[2] F. Bellotti, B. Kapralos, K. Lee, P. Moreno-Ger, and R. Berta, "Assessment in and of Serious Games: An Overview," *Adv. Hum.-Comput. Interact.*, vol. 2013, pp. 1–11, 2013.

[3] B. Heeren and J. Jeuring, "Feedback services for stepwise exercises," *Sci. Comput.Program.*, vol. 88, pp. 110–129, Aug. 2014.

[4] J. Parsons and L. Taylor, "Improving student engagement," *Curr. Issues Educ.*, vol. 14, no. 1, 2011.

[5] M. Prensky, "The motivation of gameplay: The real twenty?first century learning revolution," *Horiz.*, vol. 10, no. 1, pp. 5–11, Mar. 2002.

[6] B. Bixler, "Motivation and its relationship to the design of educational games," *NMC Clevel. Ohio Retrieved*, vol. 10, no. 07, 2006.

[7] J. Sánchez and R. Olivares, "Problem solving and collaboration using mobile serious games," *Comput. Educ.*, vol. 57, no. 3, pp. 1943–1952, Nov. 2011.

[8] I. Granic, A. Lobel, and R. C. M. E. Engels, "The benefits of playing video games.," *Am. Psychol.*, vol. 69, no. 1, pp. 66–78, 2014.

[9] A. De Gloria, F. Bellotti, and R. Berta, "Serious Games for education and training," *Int. J. Serious Games*, vol. 1, no. 1, Feb. 2014.

[10] M. A. R. Silva, A. L. Dias, and J. C. Anacleto, "Using Contextualized Narrative Game to Improve Students and Teachers Communication.," in *CSEDU (2)*, 2010, pp. 232–237.

[11] K. Hartness, "Robocode: Using Games to Teach Artificial Intelligence," *J ComputSciColl*, vol. 19, no. 4, pp. 287–291, Apr. 2004.

[12] D. Thomas and J. S. Brown, *A new culture of learning: cultivating the imagination for a world of constant change*. 2011.

[13] K. Kiili, S. de Freitas, S. Arnab, and T. Lainema, "The Design Principles for Flow Experience in Educational Games," *Procedia Comput.Sci.*, vol. 15, pp. 78–91, 2012.

[14] J. Forlizzi and K. Battarbee, "Understanding experience in interactive systems," 2004, p. 261.

[15] L. Derbali and C. Frasson, "Assessment of Learners' Motivation during Interactions with Serious Games: A Study of Some Motivational Strategies in Food-Force," *Adv. Hum.-Comput. Interact.*, vol. 2012, pp. 1–15, 2012.

[16] T. P. Karsenti and G. Thibert, "The Interaction between Teaching Practices and the Change in Motivation of Elementary-School Children.," 1998.

[17] J. Keller and K. Suzuki, "Learner motivation and E-learning design: A multinationally validated process," *J. Educ. Media*, vol. 29, no. 3, pp. 229–239, Oct. 2004.

[18] "CEIT506-EN: Malone, T. &Lepper (1987). Making Learning Fun: A Taxonomy of Intrinsic Motivations for Learning.In Snow, R. & Farr, M. J. (Ed), Aptitude, Learning, and Instruction Volume 3: Conative and Affective Process Analyses. Hillsdale, NJ." [Online]. Available: http://ocw.metu.edu.tr/mod/resource/view.php?id=1311. [Accessed: 24-Sep-2016].

[19] T. W. Malone, "Toward a Theory of Intrinsically Motivating Instruction*," *Cogn. Sci.*, vol. 5, no. 4, pp. 333–369, Oct. 1981.

[20] N. Whitton, "Game Engagement Theory and Adult Learning," *Simul. Gaming*, vol. 42, no. 5, pp. 596–609, Oct. 2011.

[21] R. M. Ryan and E. L. Deci, "Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions," *Contemp. Educ. Psychol.*, vol. 25, no. 1, pp. 54–67, Jan. 2000.

[22] M. Csikszentmihalyi and J. LeFevre, "Optimal experience in work and leisure.," *J. Pers. Soc. Psychol.*, vol. 56, no. 5, pp. 815–822, 1989.

[23] J. Nakamura and M. Csikszentmihalyi, "The Concept of Flow," in *Flow and the Foundations of Positive Psychology*, Dordrecht: Springer Netherlands, 2014, pp. 239–263.

[24] E. Lotfi, B. Amine, and B. Mohammed, "Players Performances Analysis based on Educational Data Mining Case of Study: Interactive Waste Sorting Serious Game," *Int. J. Comput. Appl.*, vol. 108, no. 11, pp. 13–18, Dec. 2014.

[25] L. Elaachak, A. Belahbibe, and M. Bouhorma, "Towards a System of Guidance, Assistance and Learning Analytics Based on Multi Agent System Applied on Serious Games," *Int. J. Electr.Comput. Eng. IJECE*, vol. 5, no. 2, pp. 344–354, 2015.

[26] A. P. Dempster, N. M. Laird, and D. B. Rubin, "Maximum Likelihood from Incomplete Data via the EM Algorithm," *J. R. Stat. Soc. Ser. B Methodol.*, vol. 39, no. 1, pp. 1–38, 1977.

[27] S. L. Salzberg, "C4. 5: Programs for machine learning by j. rossquinlan. morgankaufmann publishers, inc., 1993," *Mach. Learn.*, vol. 16, no. 3, pp. 235–240, 1994.

[28] P. J. Rousseeuw and L. Kaufman, *Finding Groups in Data*.Wiley Online Library, 1990.

[29] R. S. J. de Baker and P. S. Inventado, "Chapter X: Educational Data Mining and Learning Analytics."

[30] G. Nathiya, S. C. Punitha, and M. Punithavalli, "An analytical study on behavior of clusters using k means, em and k* means algorithm," *ArXivPrepr. ArXiv10041743*, 2010.

[31] G. Sehgal and K. Garg, "IMPROVED EXPECTATION MAXIMIZATION CLUSTERING ALGORITHM."