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FACULTAD DE INGENIERÍA DE PRODUCCIÓN Y SERVICIOS

ESCUELA PROFESIONAL DE INGENIERÍA DE SISTEMAS

Policies Selection for Pedagogical Agent based on the Roulette Wheel Algorithm

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Asesor:
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Mag. Carlos Eduardo Atencio Torres
Asesor

Resumen

Los agentes pedagógicos como entidades computacionales se implementan para interactuar con los usuarios y brindar oportunidades de aprendizaje, usualmente necesitan entrenamiento para seguir un conjunto de órdenes para un intercambio efectivo personalizado de conocimientos y tareas. En este estudio se propone evaluar la efectividad de un modelo basado en políticas y su nivel de satisfacción en su interacción de uso con y sin agente pedagógico. Utilizando el algoritmo bioinspirado de selección por ruleta. El enfoque es cuantitativo, con un estudio exploratorio y descriptivo. Los resultados revelaron que nuestro agente seleccionado con la estrategia de políticas logró una gran aceptación en sus usuarios que lo calificaron como inteligente, amigable y confiable. Como hallazgo se revela que el agente puede influir en las actitudes, percepciones y comportamiento de uso dado por el tiempo de permanencia que lo lleva a un aprendizaje autorregulado.

Palabras clave— Agente pedagógico, ruleta, aprendizaje

Abstract

Pedagogical agents are computational entities that interact with users and facilitate learning opportunities. They usually need to be programmed to follow a set of commands for an effective personalized exchange of knowledge and tasks. In this study, we evaluate the effectiveness of a policy-based model and its level of satisfaction about the interaction without and with the pedagogical agent using the bio-inspired roulette selection algorithm. The approach is quantitative, with an exploratory and descriptive study. The results revealed that our agent achieved great acceptance among the users who rated it as intelligent, friendly, and reliable. It is evidenced that the agent can influence the attitude, perception, and behavior of the user to reach better self-regulated learning.

Keywords— Pedagogical agent, roulette, learning

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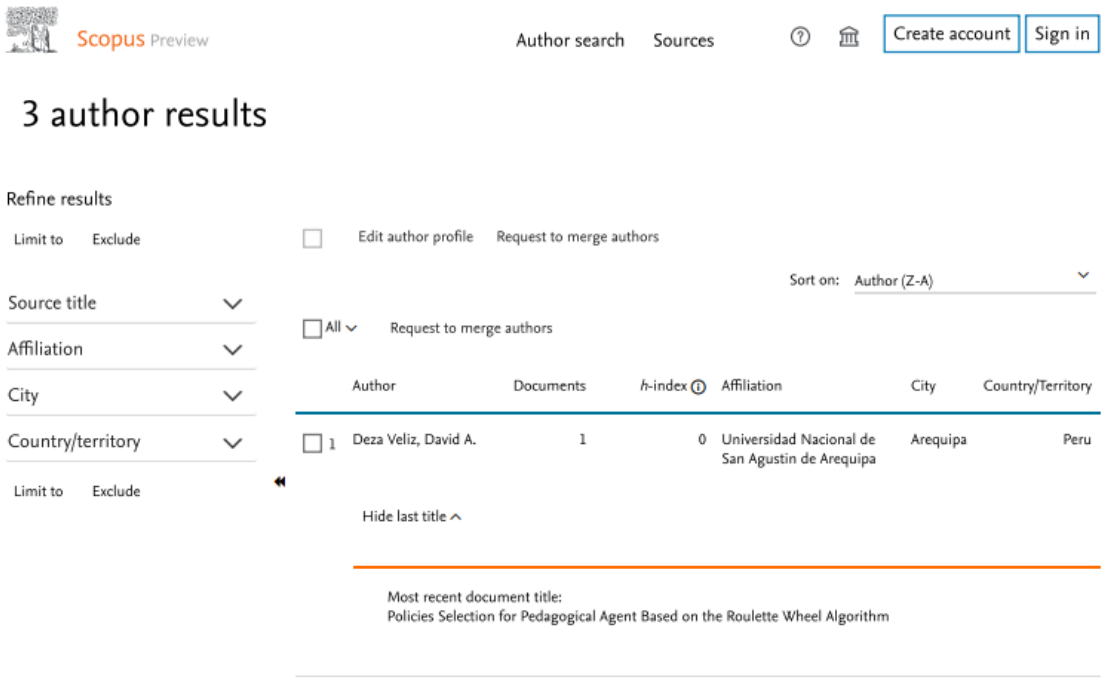

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Policies Selection for Pedagogical Agent Based on the Roulette Wheel Algorithm(Conference Paper)

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Abstract

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Policies Selection for Pedagogical Agent Based on the Roulette Wheel Algorithm

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Keywords—pedagogical agents, roulette, learning

I. Introduction

Pedagogical agents are virtual beings who work online, providing help and guidance, in learning [9], [16]. They are receiving more attention in e-learning systems because they can be designed in various learning environments [10], providing a new model for human-computer interaction through its image, appearance, message, voice, and interactivity [2]. Currently, there are various types of pedagogical agents: animated characters, to improve the learning of students; and agents who act as tutors [9], [12]. Their purpose is to improve learning, guide the student or assume the role of a teacher among others [10]. In educational contexts, an animated pedagogical agent is a type of virtual agent that is embedded in a computer-based learning environment to deliver instruction through verbal and non-verbal forms of communication [8].

Our institution approved in 2018 the ELORS project (E-learning object recommendation System) which consists of a system that contains a dataset of learning object about mathematics for high school students and it suggests suitable objects to the students according to their preferences. The system runs on an online platform that is available to students from different institutions in the city of Arequipa-Peru.

In this platform, we installed an agent that we baptize as Elors and it has the shape of a robot that interacts with the student offering help, messages of encouragement, greetings, etc. to make the experience more entertaining and personalized. With it, we intend to allow the student to manage his learning and influence his attitudes, perceptions, and behavior according to the study needs.

In the educational field, there are approaches based on pedagogical agents related to improving emotional states [8], as well as guiding students in problem-solving, focused on content, advice, and recommendation [1], also to analyze a written text and identify the feelings associated with it, providing suggestions and comments to users [7]. Another study focused on the user model to develop a mathematical agent that helps students understand problems and solve them progressively [16] and from the sociocognitive perspective of learning, affective experiences were developed through three anthropomorphic agents who assume the role of expert, motivator, and mentor with instructive and motivational messages, highlighting the latter in the choice of students [6].

Given the different uses of pedagogical agents, we find a theme related to the area of mathematics, specifically about the interface design and the role that these pedagogical agents assume, noting that it is important to evaluate their usability and consistency support in their activities [1, 20]. For this reason, it becomes interesting to investigate how much this pedagogical agent can influence the attitudes, perceptions, and behavior of the students in their interactions on the platform.

In this research, we explore the development of policies and strategies, in the impact of the use of our platform. We measured the usability and satisfaction of the students when interacting on the platform with and without the advice of the pedagogical agent and we found positive results with the presence of the agent that corroborate previous works, as for example:

- Friendly interfaces improve motivation and concentration in a short period of time, as was evidenced in [16].
- The agent provided opportunities for social interaction, similar to the study case in [18].
- The satisfaction survey showed that the student titled the platform as intelligent and friendly, similar to the study in [6].

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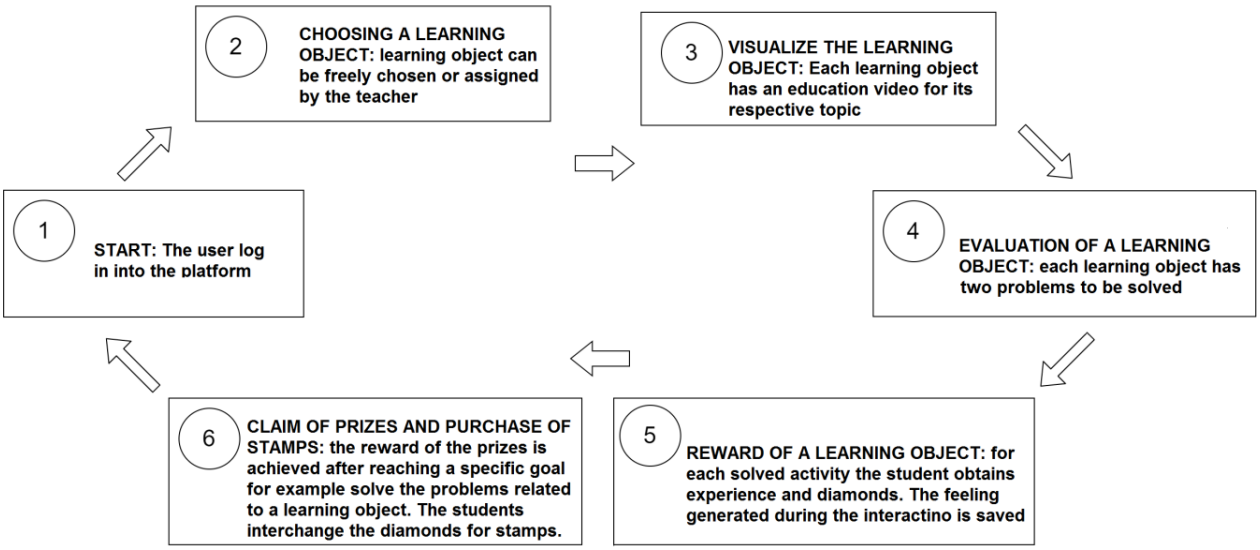

Fig 1. Operation of the ELORS Gamified Platform.

- The agent can enhance learning processes as was studied in [2].

II. ELORS SYSTEM

A. Online Platform

To make the LOs available for the students, an online platform has been created which presents a pedagogical circuit with 6 steps explained in Fig. 1.

When starting, the student enters the platform with his username and password. He will find up to 150 learning objects (LO) available that may be freely chosen or assigned by the teacher. Each of them contains two mathematical problems associated with alternatives. Once the student solves any of the problems he receives diamonds or experience as rewards in the platform. Likewise, the feeling produced during the interaction can be evaluated to analyze the degree of emotion in the interactions. Finally, the student can exchange their accumulated points for objects from the virtual store.

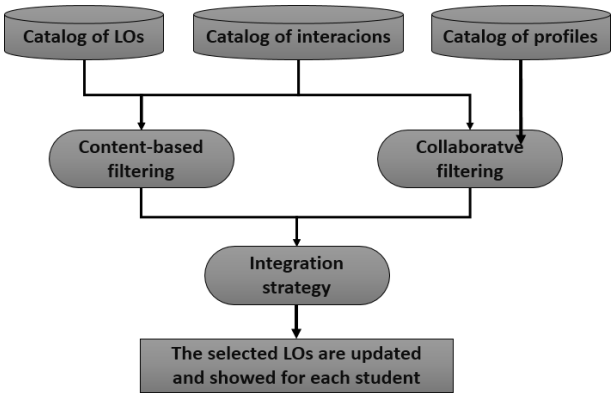

Fig. 2: Learning objects recommendation process in the ELORS platform

B. Recommendation System

To develop the recommendation system we considered three modules to personalize the selection of LOs for each student. Fig. 2 shows the recommendation process.

1) Content-based filtering

This is a module that, based on the textual characteristics of the LO, applies a word-embeddings algorithm that transforms the description of a LO into vectors, to generate a list of new learning objects to recommend.

2) Collaborative filtering

The student profile data is processed together with the demographic, multiple intelligences test, and type of player results to obtain a similarity between the students that keep a similar preference and recommend them the same type of LO.

3) Hybrid strategy

It classifies the results of the modules based on content and collaborative filters considering the interest of the student concerning to their interaction on the platform.

III. POLICY SYSTEM

A. Pedagogical Agent

Pedagogical agents are an interesting option to accompany learning since they interact through natural language and give voice or text messages [4]. Therefore, we have to specify that our pedagogical agent will recite educational information in the form of a monologue for the students.

An artificial intelligent agent is a policy-driven piece that follows rules and uses technologies to guide the reasoning and/or behavior of the avatar or virtual character [11]. Guided by policies, such agents following some conditions to execute

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specific actions [20]. In education, policy-driven agents have long been a fundamental part of intelligent tutors and adaptive learning [15], which are programmed with social training simulations involving scenarios and role-playing in an interactive manner [13].

The pedagogical policies interpreted as an action or advice lead to: (1) to decide what to advise; (2) to decide when to advise; (3) to determine a common action language to adequately express advice among heterogeneous agents; and (4)to communicate advice effectively, ensuring its accurate and quiet reception [5]. Therefore, pedagogical policies are divided into two categories: Theory-based approaches and data-based approaches. In the first case, it looks for implementing cognitive theories that have difficulties to execute the rules for each decision, for example, values, aptitude, among others [17]. In the second, it is based on reinforcement learning, which derives directly from the student-system interaction records, with pedagogical policies defined according to the generated conditions [20].

B. Roulette Algorithm

1) Origins

In the area of Bio-inspired Computing and especially in the subject of Genetic Algorithms (GA), the roulette selection algorithm is used to choose the best of a population of solutions [3]. A GA combines a series of probabilities with selection, mutation, and crossover [19].

The subject of GA is a fairly well-known subject in computing that is based on Charles Darwin's theory of evolution where the fittest survives. Likewise, to implement this model in a computational model, the following is considered:

- There is a problem that we want to solve and possible solutions. Each solution is associated with a fitness value that indicates how close we are to the optimal solution to our problem.
- The solutions are considered as individuals and grouped in a population. Then these will produce other populations and in this way, it is expected that in a future generation the best solution for the proposed problem will be found.
- There are evolutionary operations that are crossing and mutation, which occur with a certain probability in individuals of one generation.
- By applying these operations to a population they generate other individuals and increase the current population.
- Then, a selection algorithm is applied to choose the best solutions that will make up the next generation. Two examples of algorithms for selection:
- By tournament: Pairs of individuals in the population are compared and the best ones are chosen.
- By roulette: Each individual has a probability according to their fitness value to be selected to the next population. The roulette wheel is turned, or rather, one of the individuals is chosen randomly.
- The process is repeated, each repetition is called an epoch and after a certain time, it is guaranteed that there is a better solution than the initial solution.

2) Roulette selection algorithm

- We associate a weight to an individual that, as we saw in previous paragraphs, an individual can be a solution or some representative of some piece of a model that we want to represent computationally.
- The weight is established in some way, the suggestion is its standardized fitness value.
- We calculate the accumulated weight for each individual.
- We spin the wheel and choose an individual. This interpretation in computation means generating a random number between 0 and the maximum value of the accumulated weight and then selecting one.

C. Proposal

1) Design of a policy

Every policy has a precondition, a postcondition, and an associated priority value [12].

A precondition consists of a set of events that must occur to activate a certain policy. For example, if the policy is *words of encouragement*, then the precondition can be (one or more):

- When the user is on the home page.
- When the user obtains an achievement.
- None (in this case, at any event, the policy can be executed).

A postcondition refers to the set of final events. In our case, the post-condition will be the message that will appear on the screen by the pedagogical agent ELORS.

The policies (π) we were worked on are the following:

π_1 Words of encouragement

π_2 Congratulations on the achievements

π_3 Recommendations for each multiple intelligence:

- Linguistic
- Mathematical
- Musical
- Naturalistic
- Spatial
- Interpersonal
- Intrapersonal

π_4 LO recommendations

For each policy there are different behaviors where some of them will show a simple message on the screen through the pedagogical agent and others will need data from the database

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to show a certain message. These behaviors can be shown in the next figures (Fig. 5-8).

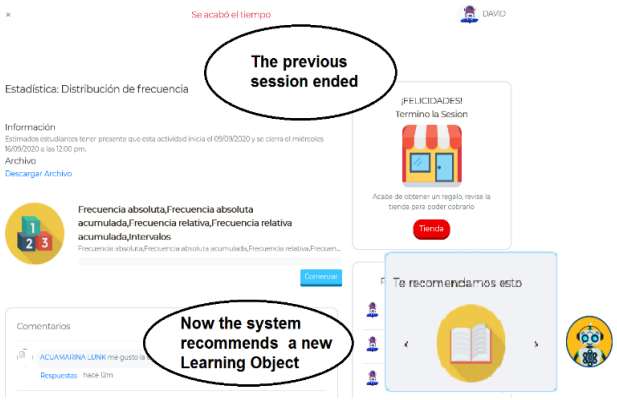

Fig. 5. Postcondition of the policy recommendations for each multiple intelligence, fulfilling the precondition of being in the first interaction.

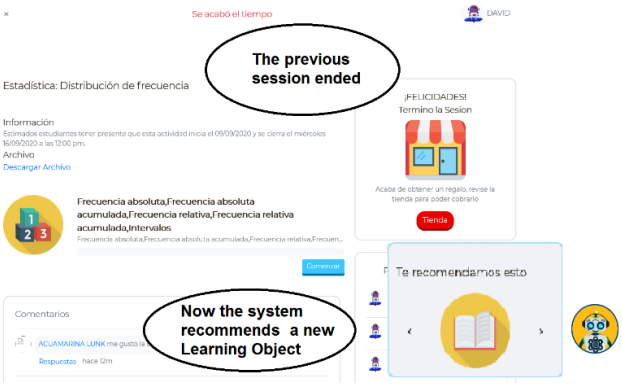

Fig. 6. Postcondition of the policy recommendations for learning objects. The precondition is that the user just ended visiting a Learning Object or it just entered into the platform.

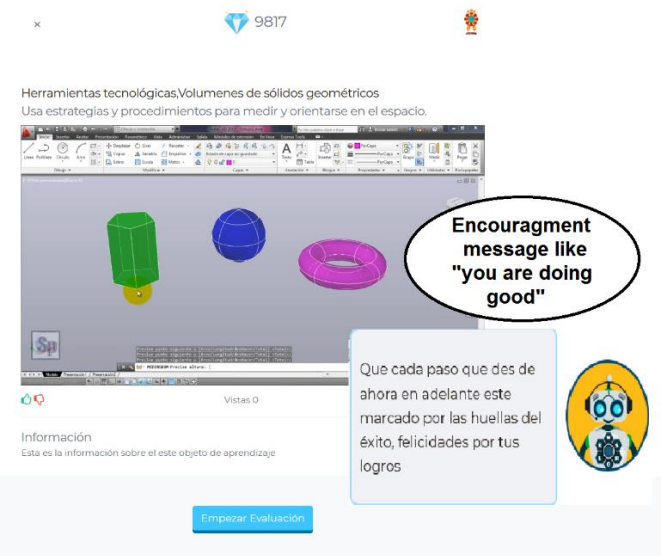

Fig. 7. Postcondition of the policy words of encouragement, fulfilling the precondition of being in the visualization of the learning object.

Fig. 8. Postcondition of the policy congratulations for the achievements obtained, fulfilling the precondition of being in the evaluation of the learning object

Appliying the roulette

As described above in Section III.B.2, to apply the roulette selection algorithm we need to calculate the cumulative weights of a population and for our case, the population is constituted by the policies and their corresponding priorities. For example, if we have the next priority distribution:

π_1 => 5 (high priority)

π_2 => 2

π_3 => 4

π_4 => 1 (low priority)

We calculate the accumulated weight obtaining:

π_1 => 5

π_2 => 7

π_3 => 11

π_4 => 12

Therefore, when a student launches any event for example just a click, a random number is chosen in range 1-12 and the selected policy is activated.

Random number: 6 => $\pi 2$ is selected

Random number: 2 => π_1 is selected

Random number: 12 => π_4 is selected

As we can see, those policies that have a higher priority will be more likely to be selected than others. But also, although a policy has a low priority, it still has a certain probability of being selected.

2) Strengths

This form of policy selection allows the system to be dynamic, that is, it does not always behave in the same way and offers new information to users.

The policy system will also allow the configuration of the system with a certain tolerance. That is, the most likely policies will come out more quickly to the user but not always, so users

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will not feel that the system is intentionally programmed for a single task.

IV. Experiments

A. Population

The study population was made up of 49 second-year high school students, who interacted on the gamified ELORS platform, making it a census study. It was executed through a questionnaire in google forms to identify the level of student satisfaction regarding the interaction with the pedagogical agent. Because of their age (all are less than 18 years old and considered minors), they have the permissions of the educational institution and the parents, keeping the information confidential. For interaction with and without the agent, only 20 students who interacted in all the activities scheduled on the gamified platform were considered.

B. Procedures

They occurred in stages:

a) First Stage: The platform was designed with gamification mechanics to capture the interests of students and learn by playing.

b) Second Stage: The recommendation system and the pedagogical agent were implemented within the platform.

c) Third Stage: The pilot tests were taken with and without the intervention of the pedagogical agent. And the records were only captured based on the longest interaction time, of the students who have participated in the problem-solving activities.

d) Fourth Stage: After the study participants completed the activities on the platform, a satisfaction questionnaire was conducted from their experience with the agent.

C. Instruments

Two instruments were considered: The first, to measure the effectiveness of the policies implemented through councils, there are records of time in the interactions assumed by the students on the platform with and without the intervention of the agent.

Second: The survey technique was used, with a questionnaire with 5 dimensions and 12 items, to be able to verify the level of satisfaction about the use and level of interaction with the pedagogical agent.

TABLE I. Dimensions of Satisfaction Regarding the Use of the ELORS Platform

Dimension	**Items**
Confidence To check if the platform provided a sense of trust for its use.	The ELORS pedagogical agent was entertaining and friendly. The ELORS pedagogical agent is an effective teaching agent.
Attention The platform has an eye-catching design or if it made a positive impression on the students.	The ELORS pedagogical agent helped you to stay focused. The movement of the pedagogical agent ELORS made an impact on you. The company of ELORS during your learning is pleasant.
Helpful To verify if the ELORS agent assisted to the student.	ELORS was helpful and helped you manage your learning. You felt comfortable and safe during the learning activities and the set of aids encouraged you to continue interacting on the platform. ELORS messages were meaningful and relevant to strengthen your learning. The learning activities allowed you to strengthen your learning supported by recommendations.
Intelligence Inspired by the Turing Test, we want to verify if the student considers our agent as intelligent.	You think ELORS is smart.
Friendliness Check if the platform is student-friendly.	You like the colors of ELORS. You enjoyed using the platform.

For each dimension, we stipulate 4 degrees of measurement: almost always, always, sometimes, and never. This instrument was adapted from [6], then it was standardized in 3 levels: high, medium, and low satisfaction. The reliability of 0.894 was obtained in Cronbach's alpha.

TABLE II. Reliability Statistics

Cronbach's alpha	Cronbach's alpha based on standardized elements	Number of elements
,894	,904	12

D. Analysis of data

Statistical processing in SPSS 23 was used for the questionnaire, with tables of frequencies and percentages to find the level of student satisfaction.

V. Results

To analyze the implementation of the policies, the interaction time based on the permanent participation of 20 students who have been active on the platform with and without the pedagogical agent was considered (see Fig. 9).

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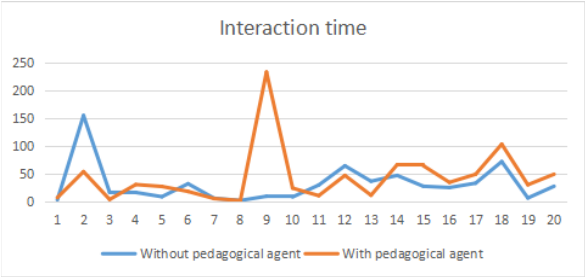

Fig. 9: Interaction time of 20 students with and without a pedagogical agent.

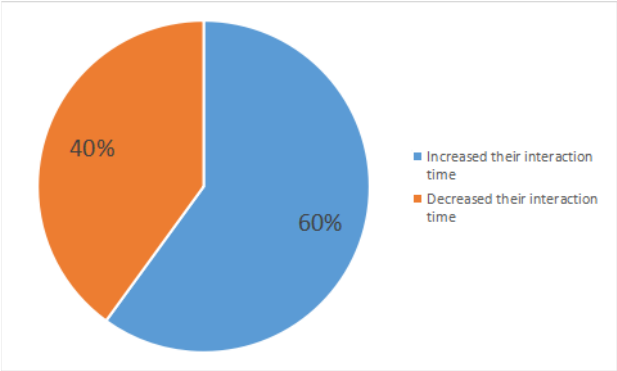

Fig. 10: Percentage of students who increase and decrease their interaction time.

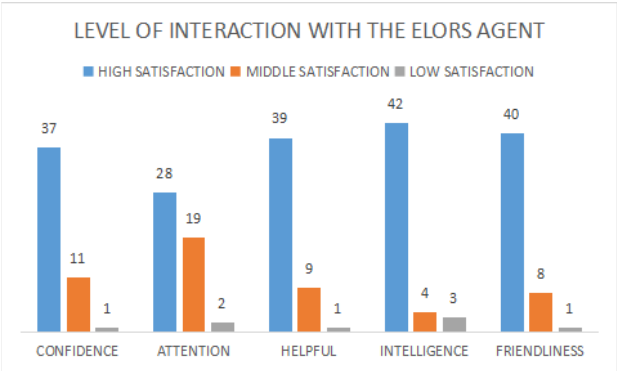

Fig. 11: Results of user satisfaction level.

Demonstrating that the interaction with the pedagogical agent is more fluid and lasting. Where 60% of students increased their interaction time in the use of the platform (see Fig. 10).

The results show, from the students' perception their level of satisfaction is high and they consider the ELORS pedagogical agent intelligent, followed by frequencies of acceptance, friendliness, help, and trust.

VI. Discussion and Conclusions

We begin by examining the strategy of our pedagogical agent that, through messages, have increased the permanence of the user, and it was evidenced in Figure 10 where we note an increase of the average time up to 60% which lead us to conclude that the pedagogical agent motivated the students to increase their permanency in the platform.

Similarly, the induced group significantly outperformed the random group with the pedagogical policies implemented, and in a qualitative study on the reaction of the students, it revealed that despite the little time in which the students interacted with the agent, the levels of motivation and concentration were higher in the test group. This shows that the agent then acts as an activity partner and therefore provides opportunities for social interaction.

About the satisfaction survey, the results showed that the students consider the pedagogical agent as intelligent and friendly. Keeping a close relationship where a study showed the most outstanding qualities that students wanted were the teaching (knowledgeable) and motivating (friendly and kind) roles.

Another finding shows the high level of satisfaction about the intervention of the pedagogical agent. The students considered dynamic and flexible the form of communication that helped them to conduct their learning process and maintaining their perception that the agent is intelligent, friendly, offer help, and gives confidence. Therefore, agents using appropriate instructional strategies can enhance learning processes.

Some limitations were found in the study and are referred to as the low level of digital literacy of teachers, despite the need to work with the use of different technological resources that are available in the cloud. Many teachers of educational institutions were invited but due to this confinement, few teachers supported us, and the fear of what was different persisted. The implementation of the pedagogical agent also took place belatedly in mid-December, when the students were finishing their school stage, working with data from 20 of the 49 students, who have freely continued working on the platform out of motivation and self-interest, achieving self-regulate your agent-mediated learning.

The possibility of establishing policies in Elors system allows to guide students in a learning path but without being monotonous and allowing dynamism to attract more and more users and potential users.

As a future line of research from this study, it may be considered adding new forms of interaction with users, such as placing a conversational agent that interacts with students. Also, the data that is generated could generate interesting statistics to establish better teaching policies for the pedagogical agent.

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