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A design of a multi-agent recommendation system using ontologies and rule-based reasoning: pandemic context

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ABSTRACT

Learners attend their courses in remote or hybrid systems find it difficult to follow one size fits all courses. These difficulties have increased with the pandemic, lockdown, and the stress they cause. Hence, the role of adaptive systems to recommend personalized learning resources according to the learner's profile. The purpose of this paper is to design a system for recommending learning objects according learner's condition, including his mental state, his COVID-19 history, as well as his social situation and ability to connect to the e-learning system on a regular basis. In this article, we present an architecture of a recommendation system for personalized learning objects based on ontologies and on rule-based reasoning, and we will also describe the inference rules required for the adaptation of the educational content to the needs of the learners, taking into account the learner's health and mental state, as well as his social situation. The system designed, and validated using the unified modeling language (UML). It additionally allows teachers to have a holistic view of learners' progress and situations.

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1. INTRODUCTION

At the present time, distance education is commonly used to provide knowledge. It is making a crucial contribution to the education by eliminating the cost of travel, infrastructure, and human resources [1]. In addition to eliminating the risk of contamination in times of the pandemic. Many countries have chosen distance or hybrid learning to limit the spread of the virus, due to the popularity of e-learning, its various advantages, as accessibility, better diffusion of content, personalized teaching, availability and interactivity [2]. Additionally, to the possibility be supported on different forms, like online learning, virtual classrooms, and content delivery via social networks, audio or video, TV, video conferencing, email, and mobile [3].

However, most of the e-learning systems provide the same learning experience for all learners, a one-size fits all approach, without taking into account the differences between the learners. Such as different backgrounds, abilities, personalities, preferences, level of knowledge, which remains an essential and significant element to achieve effective and successful teaching [4]. Without forgetting to mention that in times of pandemic, other characterizations must be taken into consideration, such as isolation and its effects on the mental well-being of the learners, the physical health of the learner, and the risk of being infected him or a member of his family, the possibility of accessing the internet network frequently or not, in particular in countries with a low human development index [5].

Therefore, personalized or adaptive learning environments or recommender systems are the key solutions to deliver a learner-centered learning experience and to provide students with the best learning objects based not only on their preferences, but also on their needs, because there is no fixed learning path suitable for all learners [6]. Hence, to fight the one-size fits all approach, numerous researches took place to offer adaptive learning systems, like [7]. They present an adaptive e-learning system based on a multi-agent approach and reinforcement learning that takes into consideration the learning style, the knowledge level, and the student's possible disabilities. Following the path of [8] that concentrate on learning styles using ontologies and a multi-agent to provide a personalized multi-agent e-learning system. The works of Yarandi *et al.* [9], [10] focuses on adaptive e-learning systems based on ontology knowledge modeling techniques. They produce three separate ontologies; domain model, content model, and learner model, to store information about the learner and calculate his ability using item response theory.

Plenty of other researchers worked on ontology-based adaptive systems and reasoning semantic rules, like the work of [11] which focus on e-learning ecosystem. It implements a framework using four ontologies namely: learner, learning objects, learning activities, and teaching methods, and semantic web rule language (SWRL) to formalize the logic layer for ontologies in their approaches. The four ontologies regroup all the learning aspects. Jetinai [12] presents a resource recommendation approach based on reasoning rules to support semantic search. The proposed approach collects information about users based on the learner's standard and learning style model, and then recommends appropriate learning resource (LR) from learning management systems (LMSs). Nafea *et al.* [13] utilize ontology with an inference engine (rule-based) to represent and build students' learning profiles and match them with their learning style that suits their preferences and personality.

The literature demonstrates a lack in the development of e-learning systems that respond to various situations characteristics of students. Few systems take into account characteristics more than learning style, preferences and knowledge level in the adaptive learning systems. That's why our focus will be on a distinct learner's characteristic that influences his learning experience. The characteristic will be related to mental disorders, physical health, and social context. This paper will focus on offering the learners suitable learning resources and suitable conditions to complete their learning experience in the most favorable conditions in the time of crisis; a pandemic as it is the case with COVID-19 or natural disaster, or even with a family crisis.

In this article, we will present the architecture of a personalization system based on multi-agents and rule-based reasoning. The system will be able to map and recommend learning objects to learners based on their preferences, levels, mental, physical, social situation, confinement, and learning system using if <conditions> then <conclusion> rules. For example, if the learner suffers from a mental disorder, the recommended educational objects will be summaries, generalities with durations of less than 30 minutes, in order to give him the possibility of taking frequent breaks. On the other hand, the system will be able to give reports on the mental and physical state of the learners to the teachers. It will also allow instructors to follow their students and establish connections with them, despite the distance.

The system will be ontology-based in order to provide semantic representations to the learner and content model, which allows the creation of user-profiles and specific content models. Ontologies are the most appropriate means to represent knowledge due to their flexibility and extensibility in the design of concepts and their relationships [14]. And on rule-based reasoning using if-then conditional rules [15], which offers real-time personalization based on the learner's interaction with the system and his model.

The rest of this article is structured as follows. In the following section, the ontological representations of the proposed system will be presented as well as the mapping rules. The third part describes the architecture of the proposed multi-agent system. The fourth section gives a visualization of the adaptation and reporting processes. We conclude in the last section by citing some perspectives and good practices to follow.

2. THE PROPOSED SYSTEM

The proposed recommendation e-learning system aims to recommend a personalized, effective, and engaging learning resource based on students' characteristics and preferences. The principal models adopted in this system are the learner model and the content model. Ontology is proven to be an effective means to semantically present knowledge in a specific domain [16]. It enables people or software to share a common understanding of the information structure; enable people to reuse domain knowledge and to make domain assumptions explicit; assist people to analyze domain knowledge and separate domain knowledge from the operational knowledge [17], [18]. Consequently, we propose an approach where two ontological models are used; learner and content models. Those models gather information about the learners and the learning resources, in order to deliver specific learning resources to specific learners depending on their needs, preferences, contexts, and pandemic effects. The models are described below:

2.1. Learner model

The system aims to recommend learning objects to learners according to their preferences, knowledge levels, mental, physical health, social situation, confinement. The learner model must represent the characteristics and information provided explicitly by the learner himself (questionnaires, multiple-choice questions) or implicitly by automatically retrieving information from the environment, for example, by obtaining the location and type of the device used, or by inference from the analysis of the interaction between the user and the environment [19]. In this system, the ontological learner model developed is based on our previous work [20] with the integration of other learner's characteristics, as shown in Figure 1. The model we used is compliant with the learner information package (IMS LIP) and it includes five dimensions:

- Context: it groups the characteristics likely to affect the learner's situation (the device used, the location, the frequency of access to the system and the type of internet connection).
- COVID-19_history: it determines whether the learner or a family member is or has been infected with the virus, lives in a cluster site (place where the number of cases is higher than expected) or is in complete or partial lockdown).
- Info: this class groups the various attributes of IMS-LIP such as activity, transcription, interest, competence, accessibility, security, and affiliation.
- Mental_disorder: it represents the three mental disorders that learners can suffer from because of the pandemic and isolation, namely anxiety, depression, and post-traumatic stress disorder (PTSD), which are the most common mental disorders in students during a pandemic and their degrees of severity (mild, moderate, severe).
- Preference: such as preferred language and media type (text, audio, video).

2.2. Content model

The content model gives a description of the content and structure of the courses recommended to learners, it portrays the learning objects in a semantic presentation; their features and specifications to make recommendations and reuse easier and affordable [21]. Consequently, the choice of ontologies given its capacity to semantically present the knowledge of a domain [16]. The learning object is the unit of independent and autonomous educational content, predisposed to be reused in multiple educational contexts [22] without neglecting the need to provide a metadata register for each learning object, describing their contexts of potential use [23], [24]. Learning objects have several characteristics, such as indexing, reusability, adaptation, accessibility, granularity, and autonomy [25].

There are many standards on learning object metadata, such as the IEEE learning object metadata (LOM) designed in 2002. It is used internationally to describe and index content in learning content management systems. The IMS learning design (IMS LD) specification developed in 2003. It is defined as a description of a method allowing a learner to achieve certain learning objectives by carrying out certain ordered pedagogical activities, in a learning environment. Sharable content object reference model (SCORM) is a reference for sharing and reusing learning objects. In fact, metadata is not enough. The metadata presents only a few descriptions of the properties of learning objects, but it lacks the capacity for reasoning and reuse. Therefore, the introduction of ontologies to describe learning objects [26], because it presents the same advantages (reasoning, reusability, sharing, and machine-understand ability), and also it ensures a precise and explicit representation of the specifications of the concepts.

The ontological model shown in Figure 2 presents the structure of the content model it includes three levels of hierarchy namely course, chapter, and learning object. They are detailed as follows:

- Course: represent the top hierarchy of the content model, it is composed of chapters, takes part of a domain, and has a goal. And we also included a relation with the learner class as the course is “taken_by” a learner. The course is described by some metadata such as name and keyword attached to this class through associated data properties.
- Chapter: it is composed of learning objects, and it likewise has an objective, a level of difficulty, and is linked to other chapters as a prerequisite for or a prerequisite to. And metadata like (name, keywords).
- Learning_object: is the last in the hierarchy and the smallest part of the learning experience. It is defined by different characteristics as the format (audio, video, image, slides), the type (introduction, example, definition, theory). It consists of a level of difficulty (easy, medium, difficult) as well as a name, keywords, duration (which represents a duration determined by the author of the learning object) and other metadata added as data properties. The learning object may be more suitable for a device (computer, mobile), a mental problem for which it can be designed or may take it into consideration with the "best for" relation. And it is in the form of a type of learning (practice, summary, lecture notes, simulation, guided work).

The ontologies described in this section (learner, content) were implemented with protégé and visualized with ontograf, validated by the integrated reasoner Hermit1.3.8 and designed following the knowledge engineering methodology [27], by defining the classes, relations, properties, then instances.

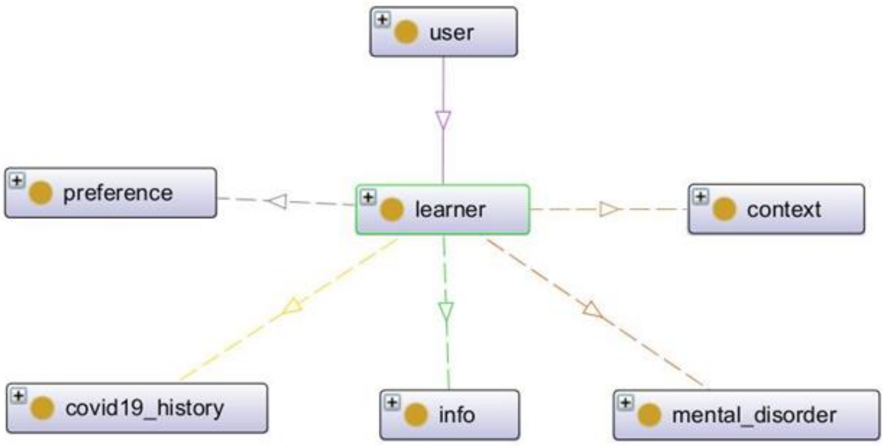

Figure 1. Learner model

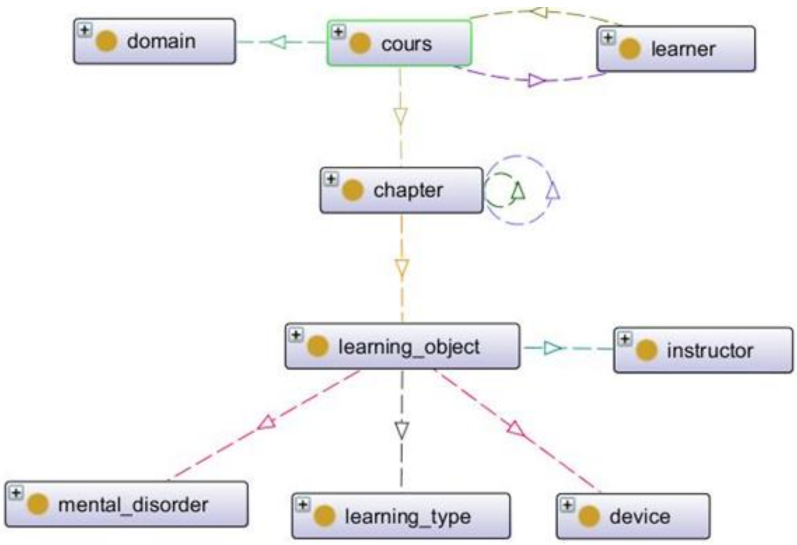

Figure 2. Content model

2.3. Reasoning rules

The aim of this system is not only to create a suitable learning object for students in times of crisis, especially in times of a pandemic, with its difficulties, such as the rise of mental disorders among learners [28] and the rise of social differences that are likely to affect access to education. But the system aims also to connect learners with their instructors despite losing contact due to the hybrid or distance approaches. The first part, which consists of mapping learners with suitable learning objects according to their needs, context, preferences, and health conditions, uses rule-based reasoning, due to their naturalness and their ability to incorporate practical human knowledge in conditional if-then rules [15]. Rules of reasoning are a crucial part of personalized learning to map learners and learning objects. Rules are established for recommending resources. Rules-based inference allows the system to suggest the proper learning object to the suitable learner. The personalization rules maintain five fundamental criteria: i) the learner’s preference, ii) the learner’s covid history, iii) the learner’s mental health, iv) the learner’s social situation (context), and v) the learning object characteristics. Some of the criteria we took into consideration when creating the rules for the proposed approach are listed in Table 1.

Excessively high levels of stress risk affecting learning and the phase of fostering relationships between concepts [29]. This is the reason, after choosing to offer only learning objects of a brief duration (30 minutes for learners with mental disorders). Rosenfeld [30] argues that programmed instruction, and progression in small, manageable steps prevent the interfering effect of anxiety on academic performance.

Table 1. Learner and learning object characteristics

Learner Characteristics	Learning Object Characteristics		
Learner Health (Mental and Physical) and Context	Format	Learning Type	Duration
Anxiety, PTSD	Figure, Video, Charts … (gif, png, mp4, …)	Guided Work, Simulation, Exercise with Solution, Example	Less than 30 min
Depression	Audio, Video, … (midi, mp4, mpeg, …)	Practical, Summary, Lecture Note, Experiment,	Less than 30 min
COVID-19 Positive	Video (Mov, AVI, MP4, …)	Résumé, Exercise Avec Solution	
Low Internet Network (or Instable)	Text, Slide, Webpage (doc, pdf, html, json, ppt, …)	Summary, Lecture Note, Exercise, Example,	

Some personalization rules used to recommend the suitable learning object to learners according to their mental health and physical health (related to COVID-19 contamination) and his network type are presented:

a) Rule 1: if the learner has_mental_disorder is “anxiety” or “PTSD”, then the LO recommended must have duration less than “30 min” and learning_type={guided work, simulation, exercise with solution, example, …} or format={figure, video, …}.
b) Rule 2: if the learner has_mental_disorder is “depression”, then the LO recommended must have duration less than “30min” and learning_type={practice, summary, reading note, experiment, …} and format={audio, video, …}.
c) Rule 3: if the learner has_covid_history is “student_positif”, then the LO recommended must have learning_type={summary, exercise with solution, ...} And format={video, …}.
d) Rule 4: if the learner has_context is “network_non_stable”, then the LO recommended must have learning_type={lecture note, exercise, example, ...} Or format={text, slide, webpage, …}.

Other characteristics from the learner profile and model are equally relevant, like his knowledge level, preferences, and their rules are:

e) Rule 5: if the learner’s knowledge_level is “beginner”, then the LO recommended must have difficulty =” easy” or learning_type = {introduction, definition, example, …},
f) Rule 6: if the learner prefers_media_type is text, then the LO recommended must have format = {text, slide, webpage, …}.

3. SYSTEM ARCHITECTURE

To improve the quality of adaptation, test the effectiveness of our take advantage of the benefits offered by agents such as autonomy, flexibility, communicability and distributed problems solving, we propose an architecture of a multi-agent adaptive learning system based on rule-based reasoning. This section illustrates the structure of the proposed system based on ontologies, and consists of seven components, namely as shown in Figure 3:

– Learner interface: Provide a user-friendly interface for communicating with learners. It conducts the interactions between the learner and the system (registration, login, requests). The interface communicates the user's characteristics to the learner content agent and returns the recommended learning content from the rule-based engine to the learner.
– Learning context agent: His primary responsibility is to keep track of the learner's actions (number of visits, time spent on exercises, amount of time dealt with reading material), progress, the type of his network. The system exploits this information to adapt to the unique needs of the learner. The agent updates the learner model at the end of each session. It also connects with the reporting agent if the learner has an unstable connection, or if their frequency of system use has changed while scanning the log files.
– Learner agent: Is a collection of all data relating to the learner (personal information, course, mental and physical health status, preferences, behaviours). Thus, it calculates the level of knowledge of the learner, the possibility and the severity of mental disorder that the learner may have by following the instructions for the psychological self-assessment tests described in the following section. It also connects with the agent report if the learner suffers from a mental disorder or if they state they are COVID-19 positive.

– Reporting agent: It connects with the learner agent and the learning context agent in order to generate the reports on the learner to the instructors. For example, if a student suffers from a mental disorder affected by COVID-19, he can have more time on the assessments, or if it doesn't have a stable network or only accesses the system weekly, we cannot consider synchronous classes and stick to asynchronous approaches.
– Instructor interface: Provide a user-friendly interface to communicate with the instructor, and allow him the possibility of inserting, updating, and modifying the learning objects, their metadata, the structure of the courses, as well as the management of the students and the recommendation associated with them.
– Content agent: The model stores essential learning objects and describes how the information content is designed. It is responsible for finding the learning objects stored in the repository, which fulfill certain criteria given according to the request of the rule-based agent.
– Rule-based engine: The last and most important component with the primary responsibility of suggesting the appropriate learning object for a particular learner. It obtains data about the learner and the content of the respective agents, and associates them according to the adaptation rules described in section 2. The engine can deliver recommendations for learners to the instructor himself in the case of a hybrid approach.

Rule-based recommender systems are more beneficial than other approaches in the case of adaptive learning [31]. They will help with cold-start problems, as our system will be able to give adaptation depending on the results of the screening tests. Additionally, to the trust between the learner and the system, as it is easy to explain why a specific learning object is recommended for a specific learner, which will enhance trust and credibility. On the other hand, following the rules, the system will present the learner with the resources that he needs depending on his situation (health, social condition). Meanwhile, content-based or collaborative recommendation systems only present him with resources depending on his behavior on the system to match him with similar resources visited by him or by a similar learner.

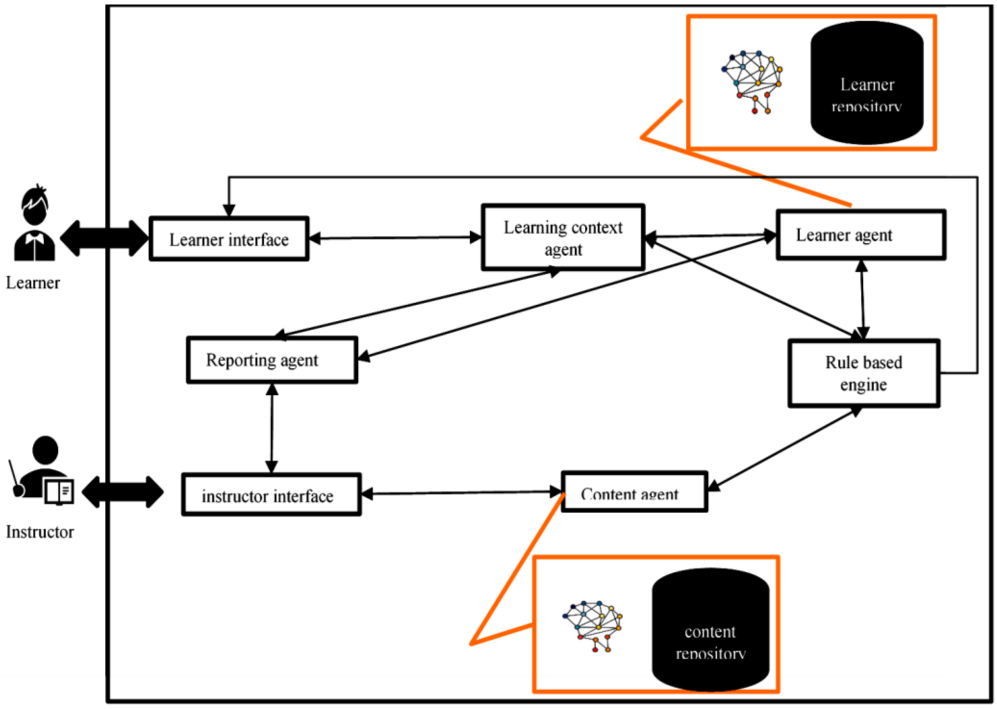

Figure 3. System architecture

4. ADAPTATION AND REPORTING PROCESS

The approach presented in this paper not only recommends suitable learning objects to learners based on their level of knowledge, preferences, mental health, context, and in case of COVID-19 infection, but it forges a connection between instructors and learners. The instructor's role is not limited to creating and indexing learning objects. It goes beyond that to help foster a welcoming environment that will maintain the learning experience favorable for learners, despite their contexts and their circumstances.

Therefore, the proposed system provides instructors with reports on the mental, physical health of learners (related to the time of crisis) and their context, and frequency of accessing the system. This will assist the instructors to take into account their students' profile while offering evaluations, deciding on the amount of work, and scheduling synchronous sessions. Figure 4 describes the process of report's creating.

On the other hand, the personalization process begins with the learner's access to the system. During the first interaction with the learner interface, a new learner must register, fill out a personal information form (contact details, question about their history with COVID-19 as a positive test, contamination, and lockdown.). The next step is to take three self-report screening tests in order to primarily detect the presence of any mental health disorders (anxiety, depression, and PTSD in this work) and to quantify its severity if it occurs [32]. For depression, the learner will answer a short questionnaire that takes 5 to 7 minutes with 16 items, this is the quick inventory of depressive symptomatology (QIDS) a self-report rating scale that reveals the severity of symptoms and symptomatic change. The severity of depression ranges from 0 to 27 as follows (0-5) none, (6-10) mild, (11-15) moderate, (16-20) severe, (21-27) very severe [33]. To detect anxiety disorder, the learner must pass the generalized anxiety disorder scale (GAD-7), a 13-questions survey. GAD-7 has demonstrated good reliability for testing anxiety disorders and for screening symptoms of mild, moderate, and severe anxiety [34]. The last test is to detect any symptoms of PTSD using the PTSD checklist (PCL) which is a self-report scale that consists of 17 items to rate symptoms from 1 to 5 based on their gravity [35] The learner agent will be responsible for calculating the presence and severity of mental illnesses and storing it with learners' personal information.

Once the learner profile is finalized, the learner can start using the system and choose the course he wants to learn. Depending on the course, the content agent offers a test that includes various concepts with different levels of difficulty. After answering the learner agent calculates and determines his level of knowledge (beginner, intermediate, advanced). The rule-based agent then determines the educational objects to recommend according to the learner's profile presented from the learner agent and the choice of the chapter. During the learning experience, the learning context agent tracks and analyzes the learner's interactions with the system and automatically retrieves contextual information such as location and device type. Some interactions are captured in the following sequence diagrams: Figure 5 shows the details of the adaptation process, while Figure 6 shows the learner's first interaction with the system.

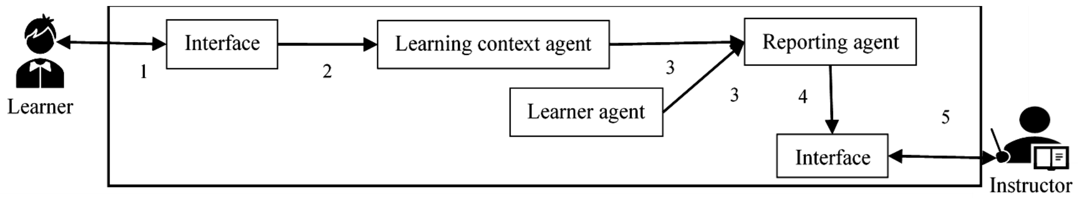

Figure 4. Schematic representation of the report creating process

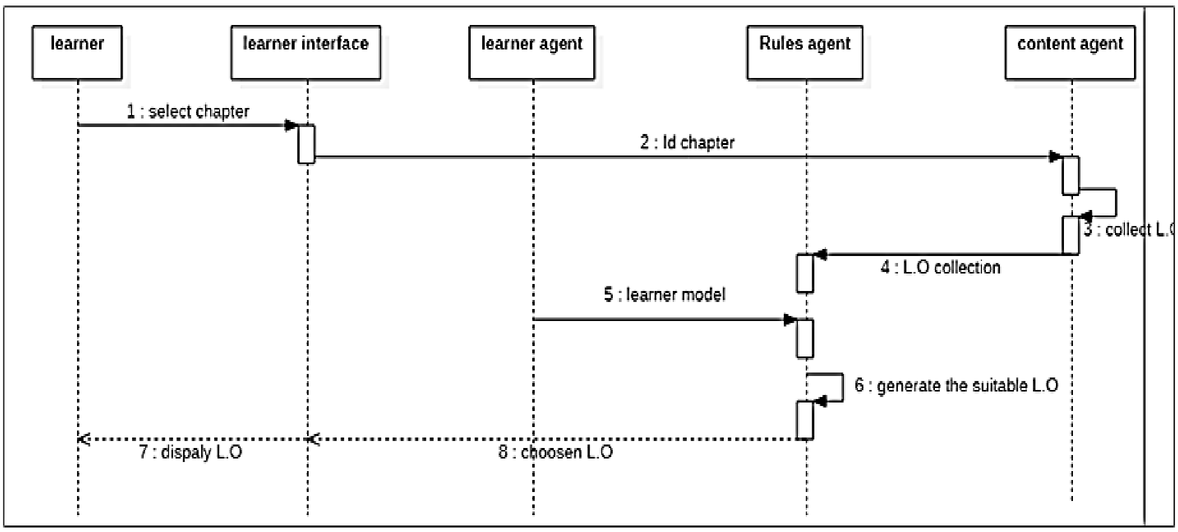

Figure 5. Sequence diagram of the adaptation process

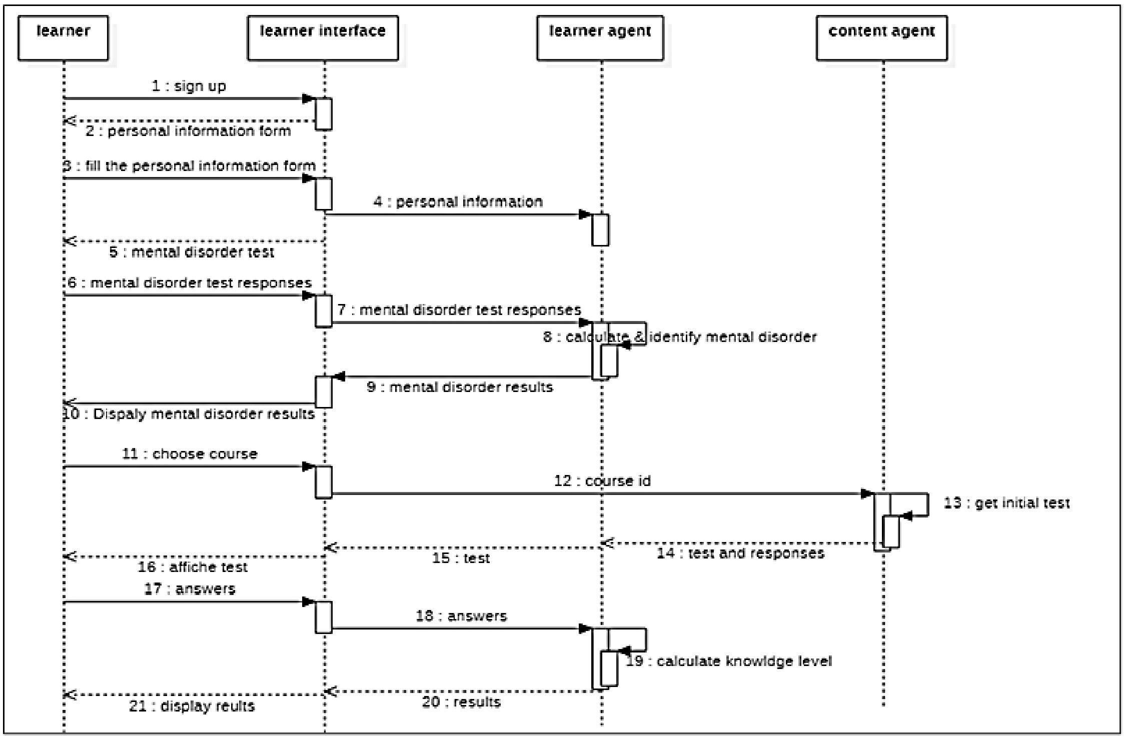

Figure 6. Sequence diagram of the learner's first interaction with the system

5. CONCLUSION AND FUTURE WORKS

In this article, a valid conception due to the UML standards and modules of a system for recommending personalized learning objects based on ontologies and on rule-based reasoning has been proposed. The architecture of the system based on multi-agents. They communicate permanently to ensure the regular operations of the system. We also presented the learner and the content ontologies, the latter of which describes learning objects. The health and context of learners are described on both ontologies, which makes customization more precise and improves flexibility, extensibility, and reusability of learning objects. Moreover, semantic rules facilitate runtime incorporation of discrete adaptivity components to generate flexible personalization during the learning process. The aim of the system is to ensure that the learning experience takes place in the best conditions for every learner, despite his mental well-being or his social situation. The system assures this through two aspects: i) recommending appropriate learning resources to learners depending on information about their respective models, and ii) giving instructors insight into their learners' situation through reports. This system provides for the first time an insight into the mental health of learners, which has not been discussed enough despite its importance, which opens a door for greater gain and benefits from distance education during and after the pandemic.

Some of the important best practice for creating a recommender system based on rule-based reasoning and ontologies are: i) separating the user system from the recommendation system (rule-based engine), ii) precise the needed models to design beforehand with their characteristic, significant metadata, and a complete structure, and iii) ensure a knowledge base for facts and rules from the knowledge acquisition process from experts, books. The system is currently under development. An extensive evaluation is required to validate users' satisfaction: examining whether the recommended resources are satisfactory for learners and whether the report provides additional insight for instructors. The current version of the system provides the learner with specific resources. In future work, we intend to extend the personalization process by providing specific learning paths using the q learning algorithm. As well as improving the reporting tools by providing teachers with learning analytic dashboards.

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