IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 31 May 2023, accepted 11 July 2023, date of publication 20 July 2023, date of current version 27 July 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3297509

RESEARCH ARTICLE

Requirements Elicitation Based on Psycho-Pedagogical Theatre for Context-Sensitive Affective Educational Recommender Systems

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The work of Simon Pickin was supported in part by the Spanish National MCI-AEI-GC Project AwESOMe under Grant PDI2021-122215NB-C31.

ABSTRACT Educational Recommender Systems (ERSs), intelligent tutoring systems that adapt their pedagogical recommendations to each student, are becoming increasingly common. Context-Sensitive Affective Educational Recommender Systems (CSAERSs) personalize the recommendations according to a learning context with multiple dimensions, including the affective dimension and the personality traits of the user. To date, in the field of educational technology, there is little or no research that focuses on offering context-sensitive, personalized, psycho-pedagogical affective support to distance-learning students in real time. Nor do there seem to be any proposals for approaches to the knowledge engineering (term which encompasses knowledge acquisition and knowledge representation) of these systems, in which the relation between the user and his or her context is crucial. There is little work on a systematic approach to the requirements-elicitation phase and to the use of ontologies in the development and validation of ERSs, in general, and CSAERSs, in particular. In this article, we report on a student-centred requirements-elicitation methodology that uses psycho-pedagogical theatre in combination with student surveys. We then illustrate its application in the design and validation of an ontology, together with a semantic-similarity function, that could serve as the nucleus of a CSAERS.

INDEX TERMS Artificial intelligence, adaptive systems, educational technology, intelligent tutoring systems, knowledge acquisition, knowledge engineering, knowledge representation.

I. INTRODUCTION

With the proliferation of big data and network-connected multimedia devices, the popularity of Recommender Systems (RSs) has seen rapid growth over the past decade. Platforms such as Amazon or Netflix use these tools for the recommendation of appropriate content to the users based on their preferences, profile, or past behavior.

More recently, many of the proposals found in the literature concerning RSs have begun to include the concept of context, where this refers to any information useful in characterizing a situation that may affect the way users interact with a system. Villegas et al. [1] present a survey of context-aware RSs and the mechanisms they use to exploit the context information that determines user preferences and situations, with the goal of recommending items that are relevant to changing user needs. The context information used can be very varied, from the current date or the specific location of a user to any type of information inferred through multimedia devices such as sensors or cameras.

In recent years there has been an increase in the number of proposals for RSs in the educational field, where the recommendations are of pedagogical nature and the users are students, in our case distance-learning students.

The associate editor coordinating the review of this manuscript and approving it for publication was R. K. Tripathy.

The distance-learning student is characterized by a learning context with multiple dimensions: space and time, personal problems, interpersonal relationships, technological restrictions associated with studies, etc. The affective dimension and the personality traits of the student are also very relevant and are used by Context-Sensitive Affective Educational Recommender Systems (CSAERSs) to personalize the recommendations. Santos [2] and Mejbri et al. [3] conduct literature reviews in the field of affective e-learning, considering how emotions are detected during the learning process using different supervised classification methods and drawing on a wide variety of emotional information sources.

In the last decade, the use of ontologies for knowledge representation in knowledge-based ERS has also become a significant research area. Ontologies are used to model learners and learning resources, among other things. They promote reusability, and support information retrieval and inference mechanisms, thereby improving the quality of the recommendations. Tarus et al. [4], and George and Lal [5] carry out exhaustive reviews of ontology-based ERSs categorizing the different recommendation techniques in which ontologies are used to achieve personalization. However, according to [6] the use of ontologies in ERS is not addressed in a systematic way and, in fact, the application of any methodology in the development and validation of ontology-based ERSs is lacking.

A search of the literature shows that to date there is little or no research that focuses exclusively on the offer of context-sensitive, personalized, psycho-pedagogical affective support to distance-learning students in real time. Nor do there seem to be any proposals for specific approaches to the engineering of these systems, in the requirements of which the relationship of the user with his or her context plays such a singular role. In this area, the TORMES (Tutor Oriented Recommendations Modelling for Educational Systems) requirements-engineering methodology [7] stands out, its objective being to solve some of the deficiencies in the development of CSAERSs by guiding the elicitation of recommendations, mainly from teachers. We consider it important in the development of ontology-based CSAERSs to complement the TORMES approach to requirements engineering by giving prominence to students via a requirements-elicitation method that combines different approaches and techniques of a high participatory nature, such as user surveys and psycho-pedagogical theatre workshops.

In Section II of this paper, we summarize the current state of research in CSAERSs and theatre-based requirements-elicitation techniques. In Section III, we present our proposal in this area and in Section IV we illustrate its application in the design of an ontology, and associated semantic similarity function in the ontological space, that could serve as a nucleus of different CSAERSs. In Sections V and VI, we present, respectively, an analysis of our results and the conclusions and prospects for future continuation of our research.

II. RELATED WORK

A. CSAERS REQUIREMENTS ELICITATION TECHNIQUES

Requirement elicitation is considered one of the most critical activities in the development of a software system. Many projects fail due to poor requirements specifications and selecting appropriate requirements-engineering techniques is a challenge for most developers [8].

A large variety of techniques have been used to date. Although stakeholder-driven techniques such as interviews, questionnaires, discussion groups, brainstorming, the Delphi method, prototyping techniques, etc., still prevail, there is growing interest in data-driven requirements-elicitation techniques, which benefit from the vast amounts of data currently available from heterogeneous digital sources [9]. In these techniques, Machine Learning is combined with RSs to create open, scalable, and inclusive requirements elicitation processes suitable for the development of large and complex applications where knowledge is distributed among a wide variety of stakeholders. Gamification is also emerging as an innovative way of engaging stakeholders in effective requirements elicitation [10].

Despite the wide range of options available, software engineers tend to choose one elicitation technique over others. Elijah et al. [8] conclude that the combination of multiple requirements engineering techniques is a significant factor for the success of a project in which requirements and knowledge are highly volatile.

Regarding the field of ERSs we highlight the aforementioned TORMES methodology [7], that includes the elicitation, by means of interviews and questionnaires, of educationally sound recommendations that are subsequently validated by users (i.e., educators and students). TORMES emphasizes understanding and specifying the use-contexts of CSAERS: identifying different user profiles, what they will use the system for and under what conditions, and identifying user goals, taking into account the variety of viewpoints and individualities. However, learner users have less prominence than educators in the requirements elicitation. Likewise, [11] proposes a three-step methodology for the development of a school lesson-planning system in the Malaysian educational environment involving multiple elicitation techniques, including interviews, semi-structured interviews, and questionnaires, which are mainly focused on educators.

Unlike most of the proposed approaches, here we suggest the use of a requirements-elicitation methodology that combines student-oriented techniques of high participatory character and focuses on elicitation of student contexts.

B. THEATRE IN ENGINEERING

Theatre is a valuable means of communication that can reach a large audience. In recent years, the possibility of using it in the design and development of new technologies that are more respectful of humans and our common future has begun to be explored.

Theatre has been used to address the problem of designing new technologies for the elderly. This sector of the population usually has difficulty in using new technologies and in understanding their interfaces. Rice et al. [12] examine the use of forum theatre as a requirements-elicitation method that more faithfully represents the knowledge required by the elderly to use new technology. Newell et al. [13] highlight how live theatre establishes a link between audience and actors and stimulates developers' interest and understanding of technological issues relevant to the elderly.

Improvisational, spontaneous, or immersive theatre [14], [15] is a form of improvised performance in which members of the audience are invited to share feelings and tell stories of their lives that are recreated live. Improvisational theatre groups have a director ("facilitator" and "coach"), actors and actresses, and a musician capable of improvising songs related to the stories told. In addition to forum theatre, improvisational theatre has been applied in information systems as a rapid prototyping technique during the requirements-engineering phase. Mahaux and Hoffmann [16] highlight how, through this modality, collaborative creativity can contribute decisively to the requirements-engineering of innovative software. Through theatre, communication between the stakeholders of a software development is improved, increasing understanding, creativity, and empathy. Skirpan et al. [17] present an immersive theatre experience where user performances and fictional design aspects are combined to ensure public engagement on ethics of new technologies. This experience attracts the attention of participants with very different profiles (some of them without technical knowledge) with whom to discuss ethical responsibility in the treatment of information and in the design of responsible technology.

Some improvisational theatre techniques have been applied during the requirements-engineering phase to favor a design based on the concerns, aspirations and lived experience of users, and to identify usage scenarios for the use of systems. This approach facilitates the representation of typical scenarios, which are key elements in the design of innovative systems [16]. Traditional interviews, on the other hand, tend to reproduce conventional perceptions and attitudes, or life stories with detailed chronology which lack interest for the application requirements. Vines [18] presents an approach called Experience Design Theatre, based on improvisational theatre, that involves many different parties during the early design phases. This research arose from the need to involve multiple groups of people in the design of a digital care service. Through theatre, the participants of the experiment contributed to the design of the NetCarer system by transferring their concerns and aspirations to the domain experts.

III. REQUIREMENTS ELICITATION FOR CSAERS

Our research aims to conceive, experiment, and evaluate in a preliminary way a methodology for requirements-elicitation in CSAERSs through the use of psycho-pedagogical theatre, a particular modality of improvisational theatre, in combination with user surveys. This methodology serves to identify study contexts in which the affective dimension has great relevance, as well as the most significant attributes of the student's profile.

A. PSYCHO-PEDAGOGICAL THEATRE WORKSHOP

Improvisational theatre has been used as a research tool in education and psychology as it elicits not only a cognitive, but also an emotional response in the participating members of the public. In this context improvisational theatre is called psycho-pedagogical theatre and its theoretical basis is consistent with Gardner's model of multiple intelligences [19]. Although improvisational theatre has already found use in requirements engineering, as pointed out in the previous section, as far as we know the potential of the psycho-pedagogical approach for the identification of user contexts with an affective dimension has not yet been explored. Our research hypothesis is that psycho-pedagogical theatre could provide qualitative information on the emotional factors involved in distance-learning processes, as well as on the variety of situational contexts in which they show up, thus adding to the set of tools traditionally used in requirements engineering in the field of affective computing.

Manjarrés et al. [20] describe how researchers from the UNED (the Spanish National University of Distance Education) carried out a theatre workshop in the UNED associated center of Madrid-Escuelas Pías, with the collaboration of CEMAV (Audiovisual Media Center of the UNED) and the theatre company Impronta [21]. The purpose of the "Dreamcatcher" workshop was to obtain information from the UNED students themselves about the type of characteristic scenarios with affective relevance in which they undertake their learning and the way in which they manage them. A dreamcatcher is a shamanic amulet that filters dreams by catching nightmares and is burned the next morning in daylight so that they do not come true. Barbarelli, director of Impronta, suggested this name to convey that at the heart of the motivations of UNED students, who are mainly mature students, lies a dream, a vital yearning, a life project hitherto unrealized. In their affective universe, dreams have a central role and, ultimately, the workshop aimed to capture those dreams. Thirty students participated in the workshop.

One of the main benefits of psycho-pedagogical theatre is that it reifies information that the participants initially transmit by non-verbal means of communication but that, after the staging, becomes conscious knowledge that they can verbalize. The stories narrated during the workshop described representative experiences of the affective universe of distance-learning students, showing the most common situations or contexts that arise during a study day. This technique establishes a bond between the participants. As a result of the stories told by their peers, the students were encouraged to share their own anecdotes that revealed various significant contexts that transcend simple study contexts, such as the uncertainty or stress associated with unemployment.

The Dreamcatcher workshop was recorded for further analysis, requiring the prior informed consent of the participating actors and students; the students were anonymous respondents to a call for participation and only appear in the audio, never in the video. The workshop required a preliminary phase, during which the ''cognitive preparation'' took place. This consisted of a meeting of the researchers with Barbarelli to explain the problems of the UNED and to share relevant documentation from the University on the profile of its students, the dropout rate, the most common study contexts, etc. Once the documentation was reviewed, the members of Impronta held an ''emotional preparation'' meeting in which they shared and discussed their own stories related to learning and rehearsed the interpretation of some of them. The workshop held after these preliminary activities had been carried out involved the following steps:

1. Warm-up: Barbarelli conducts the experience. The goal is to establish an emotionally safe environment for participants to open up and feel comfortable. Impronta members introduce themselves and briefly share their own anecdotes related to distance learning. The actors are open and sincere, which favors personal exchange and encourages the students to share their own personal experiences.
2. Interview: Barbarelli asks the students questions in order to obtain basic descriptive data and expression of feelings to stimulate the actors. The student narrator describes the environment and characters of the scene and selects the actors who will represent it.
3. Staging: The actors represent the stories in different ways under the suggestions of the director. Some of the forms used were ''fluid sculpture'', ''antagonistic pairs'', ''story scene'', ''choir'', ''the walker'' and ''story song'' (see examples in Table 1). Many of these forms of representation have their origins in playback theatre and others were taken from other companies or developed by Impronta [14], [15], [22]. At this point the actors seek to capture the spirit and tone of the story by paying special attention to the elements of non-verbal communication: body language, voice and rhythm qualities, eye contact, stress, etc. The actors used humor and resources endowed with great symbolic power. They seek to become a mirror in which the students can see aspects of themselves, becoming aware of their own emotions and discovering other points of view about the shared situation.
4. Acknowledgement: After each performance, the director thanks the student narrator for his or her participation and asks if the performance captured the essence of his or her story. Thus, a conversation in which the student verbalizes content that initially was not verbal begins. As the narratives progress, the environment becomes more intimate, and more students are encouraged to share more and more personal stories.
5. Conclusion: The actors conclude the workshop with ''flashes'' of the stories and feelings shared during the session. Participants thus grasp the essence of the activity: the conversation that has implicitly taken place between audience members through their stories.

TABLE 1. Playback theatre forms implemented at Dreamcatcher.

a) Maybe you've already arrived

Me: Have you seen how high this is?
MyOtherSelf: If we are getting higher and higher then we are closer.
Me: I think I'm going to turn around... it's giving me vertigo...
MyOtherSelf: The secret is to look forward.
Me: But I can't look forward...
MyOtherSelf: I can almost see the top [...] I told you we were already in the snow.
Me: Do you think I can go up?
MyOtherSelf: Maybe you've already gone up and you haven't noticed...

b) ***Exemplary profile***

Exemplary student: 30 seconds... One minute... perfect! Breakfast along the way: I have saved 2 minutes and 45 seconds. Now I can take advantage and study in the subway. "Next station..." Mine!
New student: Have you been studying at the UNED for a long time?
Exemplary student: Have I been at the UNED for a long time? I am the UNED!
New student: I've just enrolled and I'm studying.
Exemplary student: Don't stop, time is money!
New student: I'm not finding enough time to study.
Exemplary student: How long does it take you to brush your teeth?
New student: I haven't timed it.
Exemplary student: Well, from now on, you must time it. Do you want to be a good student? Discipline!! You must save time in every activity!! Life is a matter of self-discipline!!

c) My daughter won't let me study

Paula: Mum
Mum: Not now Paula, I'm studying, go and play
Paula: What are you studying?
Mum: Well, a very interesting thing. Why don't you go and play for a while? This is the future... do you want me to tell you a story? This is like a story.
Paula: Well, tell me the story then mum, tell me.
Mum: The law began in the year 1354, with the Greeks, before Christ, eh!
Paula: But this story has no pictures, there are no pictures!!

a) 'Antagonistic-pairs' form: two people climb a mountain symbolizing the two parts within each of us; the one who ascends with optimism and the one who doubts and is frightened. b) and c) 'Story-scenes' form [15][22][14] (photos published with permission from the actors).

During the workshop, a total of 11 stories were recorded (some scenes can be watched in [20][1]) where each was divided into two videos: the first containing the interview between the director and the student narrator, who describes an outstanding situation that often occurs when he or she

[1]The whole set of videos can be found (password: impronta) at https://docs.google.com/forms/d/e/1FAIpQLSdnCkdeY6OHHsoORSoIehFnRBvX6H04niQq-u7bZJaCG4ZQ_g/formResponse

is studying, and the second containing the representation of the scene by the Impronta actors. The set of shared stories narrated very diverse and representative situations, many of them closely related to:

1. The importance for students of moments of human contact with other people (for example, the visualization of a teacher in a video or personalized teacher responses received by e-mail).
2. The importance of developing skills for time management and discipline, in particular, making use of "downtime" (for example, during a trip on public transport) to study, or the reconciliation of family, work, and study commitments.
3. External pressures, in particular pressures associated with work and family obligations (for example, the demands of a parent who pays for the studies).
4. The "inner guide" that helps the student achieve their goals.
5. Self-talk and individual definition of success.
6. The celebration of the achievements obtained and the important emotional reinforcement they bring the students.

The recorded scenes were carefully visualized by the researchers, who noted all the relevant elements (scenic, personal, visual, auditory, etc.) from which to derive concepts for the definition of student profiles and study contexts. Ideally, this team includes requirements engineers and has a balanced composition to avoid bias, e.g. gender bias: in our case study, the team consisted of two women and two men. The compiled information guided the definition of the survey and allowed a first set of relevant user-profile attributes and study contexts with affective dimension to be identified. In [23] we provide transcripts of the action and dialogue corresponding to some of the recorded scenes and we show how instances and concepts of the ontology are obtained.

B. ANONYMOUS SURVEY

We designed an anonymous student survey and disseminated the corresponding questionnaire online among UNED students (see privacy policy in [24][2]). No sensitive information that would allow the identification of the respondent was stored and the huge number of students in the UNED makes it well-nigh impossible for the data to be de-anonymized. The questionnaire was divided into thematic blocks of 10 questions:

1. General questions: regarding personal information such as the age and sex of the respondents, if they have children, pets, etc.
2. Studies: regarding the studies being undertaken, the degree of satisfaction with them, whether the respondent has a scholarship or not, etc.

TABLE 2. Principal academic performance factors.

Performance factors	Percentage
Lack of teacher support and follow-up	70%
Lack of adequate study materials	46.6%
Lack of personal contact with colleagues	41.1%
Lack of a suitable virtual learning environment (virtual campuses, forums, etc.)	35.5%
Lack of prerequisite knowledge for some subjects	32.2%
Non-availability of a suitable place for studying	15.5%

TABLE 3. Most influential affective factors.

Affective factors	Percentage
Stress generated by a high academic workload	56.6%
Job-related stress	51.1%
Personal problems	45.5%
Nervousness due to the proximity of exam / submission	37.7%
Lack of progress in studies	31.1%
Poor academic results	23.3%
Scarcity of money to continue with studies	14.4%

3. Spatial and temporal study contexts: concerning the most common places of study, the time of day in which the studying is carried out, etc.
4. Performance factors: the different factors (family work, personal, academic) that may influence distance-learning performance.
5. Motivation, mood, and emotions: to characterize the motivation, moods, and emotions of students before and during the study.
6. Description of study situations: to obtain descriptions of representative study situations as well as some traits of the people involved in them.
7. Emotional intelligence test: a total of 24 questions aimed to measure emotional intelligence in three dimensions: attention, clarity, and repair [25].
8. Personality test: summary of the Big Five test with the aim of identifying the five personality components of the respondent.[3]
9. Employment status: to obtain representative data of the respondent's employment situation, such as the sector in which they work, the type of working day or if they have free time to study in their job.
10. Locality: to obtain the geographical context of the respondent.

We strive to guarantee the validity and reliability of the survey questionnaire, thereby avoiding biases and common errors, by defining questions with a small number of responses to choose from, by ensuring clarity, conciseness and impartiality in the questions, and by avoiding excessive length in the

[2]The questionnaire is available at: https://docs.google.com/forms/d/e/1FAIpQLScyt22YydK8KrFMtOR7ZPPbP0xTgXLohlLFy9CI4LO-apjl4A/viewform

[3]The company IDRlabs holds the rights to the short Big Five personality test used (see https://www.idrlabs.com/short-big-five/test.php)

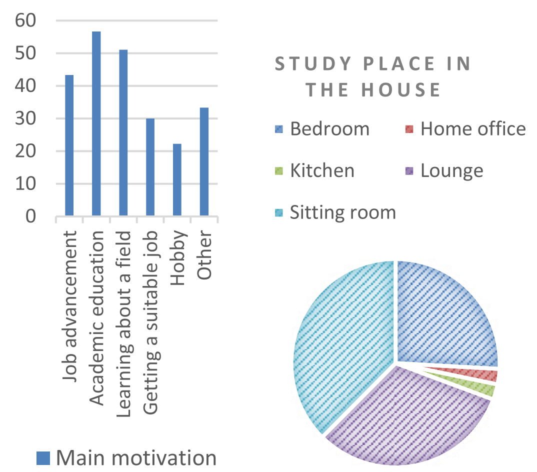

FIGURE 1. Some survey results.

survey to avoid the respondent abandoning it. We benefited from Barbarelli's expertise in this regard. A detailed description of the survey can be found in [23].

A total of 90 students participated in the survey. In Tables 2 and 3 and in Fig. 1 we show some of the results obtained.

Based on the survey results we make the following observations:

1. 8% of respondents study regularly in the library. People in this group are fairly young people (average age of 26 years) who consider that noise and distractions are the factors that most affect their study in the library.
2. Almost 20% of respondents describe study situations where a family member interrupts the study day. These people are older (average age 40) and usually have children. Those who have children (56% of the group) usually describe how caring for them inevitably makes it more difficult to study.
3. 6% of respondents refer to lack of time as a key factor to justify poor academic performance.
4. Academic factors are common (20% of respondents refer to them). Some of the most common situations are complaints about the teaching, the lack of prerequisite knowledge or the accumulation of academic work.
5. Occupational factors are related to unemployment, work stress or the need to stop studying due to a work requirement. 6% of respondents highlight occupational factors as the main factor of performance in their studies.
6. Almost 10% of students consider that they are easily distracted, and that noise affects them decisively during the study day.
7. Obtaining good academic results, understanding a new concept, or visualizing progress in study are extra motivations for distance learners. The vast majority of the students who describe personal achievements of this type (about 8% of the total) claim to be studying as a hobby and to be motivated by an interest in personal growth.

IV. DESIGNING A NUCLEUS FOR CSAERSs

The representation of knowledge is critical in any intelligent system. Its correct definition may be even more important than the implementation of good information-retrieval algorithms. In the development of intelligent systems, knowledge needs to be captured, processed, reused and communicated. Ontologies support all these tasks as they constitute conceptualizations shared by a community in a specific knowledge area.

In this section, we illustrate the usefulness of the proposed requirements-elicitation methodology by designing an ontology and a semantic similarity function in the corresponding ontological space. The ontology and the similarity function will allow us to characterize study contexts and measure the similarity between different contexts.

One contribution of our research consists of the integration of various existing standards and ontologies in e-learning and virtual worlds (concerning modelling contexts, students, affective states, virtual environments…) into a coherent ontology that we then extend using the proposed techniques for requirements elicitation.

Additionally, the proposed semantic similarity function could be used for the identification of semantically similar user profiles and study contexts. Integrated in CSAERS, this function would allow the retrieval of useful information for the personalization of psycho-pedagogical recommendations. Semantic similarity functions make use of hierarchical knowledge of ontologies to calculate the degree of similarity between different instances in an ontological space. The scenes recorded during the workshop manifest rich study contexts that we use as test cases for the validation of our semantic similarity function.

We begin this section by briefly introducing the CSAERS architecture to which our research is oriented: a generic reusable architecture for the integration of case-based reasoning as a mechanism for providing dynamically personalized pedagogical recommendations (see Fig.2). The case-based reasoning module retrieves from the case library those cases that are most similar to a given ontology instance and adapts the associated didactic recommendations to provide personalized support.

A. ONTOLOGY-SUPPORTED CSAERS

The study context of a distance-learning student has multiple dimensions: personal, interpersonal, spatial-temporal, technological…Each context can be refined into many specific subcontexts. Thus, for example, a student can combine his or her study with other circumstances such as travelling by bus, which involves different subcontexts such as waiting for the bus, the bus arriving at the stop and riding on the bus.

CSAERSs personalize the teaching (interface, contents, assistance or recommendations offered …) considering, in addition to the student's profile, dynamic contextual

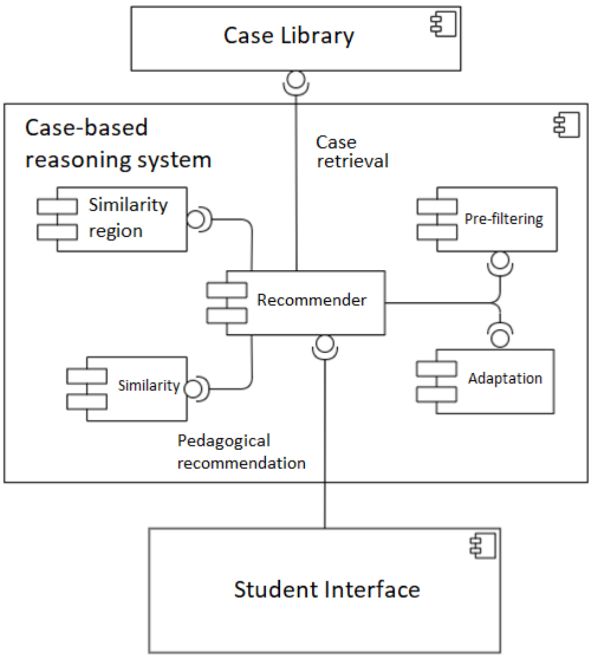

FIGURE 2. **Ontology-supported CSAERS case-based reasoning component.**

information of the learning scenario and giving special relevance to the affective dimension. The context data is captured by various devices (cameras, sensors…) that make it possible, among other things, to establish hypotheses about the mood of the students.

Ontology-supported case-based reasoning techniques are eminently suitable recommendation mechanisms in CSAERSs (see, for examples, [26], [27], and [28]. Pedagogical recommendations can be recovered from case bases of recommendations, and associated user profiles and study contexts. The selection of the most appropriate recommendation for a particular student in a given context can be made on the basis of semantic similarity functions, defined in the domain ontological space, that measure the similarities between users' profiles and between study contexts. Such a recommendation is then adapted to offer the student feedback that is as personalized as possible. Reusing prior pedagogical support experience for new dynamic and personalized recommendations (concerning personalized digital content, etc) is a promising CSAERS approach for which the proposed requirements-elicitation techniques are well adapted. Case-based reasoning is an ideal approach in the situation where building a solution is complex but previous experience in solving similar cases is available.

Fig. 2 shows our proposal for the architecture of a case-based reasoning component for an ontology-supported CSAERS. The Recommender module is in charge of retrieving recommendations from the case library (a case is an instance (student, context) which has an associated recommendation), having access to 4 different modules that are responsible for performing independent tasks:

1. Pre-filtering module, responsible for establishing and determining which concepts (both student profile and context concepts) will be relevant to making comparisons between cases.
2. Similarity-region module, responsible for determining the region or regions of similarity depending on elements of the base case, discarding those cases that do not concern concepts in these areas of the ontology.
3. Similarity module, responsible for performing the similarity measures. Given the base case and a set of cases from the case library (after performing the pre-filtering and establishing the region of similarity), the global similarity measure between the base case and each of the similar cases selected from the case library is calculated, where this measure depends on local similarity measures between individual elements of the cases being compared. The case with the greatest similarity is the case selected as the candidate solution.
4. Adaptation module, in charge of adapting the retrieved recommendation to the target student. In particular, the adaptation module is responsible for determining the student profile and the context information that is needed to personalize the retrieved recommendation.

Below we present the development of a prototype of a CSAERS core from the elicitation techniques presented. This nucleus consists of an ontology together with a semantic similarity function in the ontological space that allows pedagogical recommendations to be retrieved from a library of recommendations in which each recommendation is associated with a student profile and a study context. The set of relationships (student profile, context) –> recommendation form a case library in the context of the case-based reasoning paradigm. Based on this nucleus, a CSAERS can provide pedagogical support to students in accord with their profile and specific context.

B. AN ONTOLOGY FOR CSAERS

For the development of the ontology we have followed both the Neon methodology [29] and the UPONLite methodology [30]. The NeOn methodology has been used for the analysis of different ontologies of interest, with the aim of promoting reuse and guaranteeing interoperability between the different components of a CSAERS architecture, were our contributions to be integrated in such an architecture, as well as guaranteeing their scalability.

NeOn arose from the need to define scenarios for the reuse of already-available knowledge (ontological or not) since some of the well-known methodologies such as Methontology [31], Diligent [32] or OnTo-Knowledge [33] lack processes to help developers in the reuse and adaptation of available resources. NeOn identifies 9 scenarios related to different subproblems, each having different associated processes and activities. The first three scenarios were useful for our purposes:

1. Scenario 1 - From specification to implementation: the requirements specification is defined and then used to check whether there are existing resources that can be reused.
2. Scenario 2 – Reuse and reengineering of non-ontological resources.
3. Scenario 3 – Reuse of ontological resources: the selected existing ontological resources are combined into an ontological network.

The UPONLite methodology was subsequently applied with the aim of completing the ontology. This methodology aims to shift the responsibility for the development of ontologies towards an end-user community through a social and highly participatory approach supported by user-friendly methods and tools. Following this methodology, ontologies can be developed by domain experts (together with users) without the need to receive support from ontological engineers. The latter only take part in the process during the last development step, once the domain knowledge has been obtained, organized and validated, in order to produce a final formalization of the ontology.

UPONLite, enriched with the described requirements-elicitation techniques based on psycho-pedagogical theatre and user surveys, facilitates an agile development that is very appropriate for carrying out our proof of concept.

1) ONTOLOGY REUSE

We highlight four clearly differentiated domains:

1. E-learning: concerning all the information associated with students in an e-learning environment (profiles, academic information, etc.).
2. Contexts: concerning a broad concept of environment or situation in which learning activities can be carried out. Consideration of contexts is important to ensure accurate pedagogical recommendations that are appropriate at a given time.
3. Virtual environments: concerning the representation of stories.
4. Affective states and personality, concerning relevant aspects of the student to be taken into account for a personalized education.

Our ontology has three higher-level concepts: Student, Context, and Story. These superconcepts are broken down into other concepts for which we can reuse some of the existing ontologies:

a: USER PROFILE

The user profile concerns the personal information of the user (in our case the student): name, surname, e-mail, telephone, date of birth, address, etc. It is part of the superclass Student that also represents other useful information such as physical or personality traits and emotional intelligence. Among the available user-profile specifications we chose the ontology vCard [34] that we extended with some additional concepts (such as nationality, hobbies ...).

b: STUDENT MODEL

The ontology presented in [35] is very suitable for the definition of the academic context. Although the complete ontology is not available in the aforementioned publication, the proposed basic ontological structure can be consulted. The academic context is composed of personal information (motivation, dedication to study, satisfaction and previous experience), knowledge, preferences and performance. From [35] we reuse the following information:

1. Motivational state of the student: representation of different motivations for which the student undertakes the studies (learning for its own sake, achieving promotion, finding a job, etc.).
2. Student knowledge: representation of the student's previous education and work experience.
3. Student preferences: includes aspects such as learning style, preferred language, physical limitations, etc. This has been extended with the study schedule, preferred weather, the usual place of study, etc. We have refined physical limitations into a hierarchy where a distinction is made between temporary physical limitations and permanent physical limitations.
4. Student performance: acquired competences, study time in different modules.

c: EMOTIONS AND PERSONALITY

In a CSAERS, the representation of emotions and personality acquire great prominence since the recommendations suggested by the system are influenced by the emotional state and personality of the user. Thus, users who share a similar personality are more likely to share common stories or situations since a person's character affects how they react in a given scenario.

One of the currently most challenging research problems is that there is no consensus on the description of emotions. EmotionML [36] provides a set of descriptive mechanisms that can be employed in different contexts independently or as an annotation plugin. In EmotionML emotions can be represented in terms of four types of description derived from the scientific literature: categories, dimensions, estimated values, and actions. In our case, we focus on the category description since it is enough to cover the interests of our proposal.

EmotionML is suitable because it provides a range of options to select the vocabulary of emotions most appropriate to the interests of the user. Regarding the categories, this markup language proposes up to 5 different vocabularies and gives a wide range of possibilities such as representing emotions through probabilities or indicating the source through which an emotion has been obtained. Based on our objectives, the simple categorization of the student's emotions is more than enough, so we have chosen to reuse the model proposed by [37] where up to 17 common emotions are distinguished. We have considered it pertinent to classify them into positive emotions (affectionate, amused, confident, content, excited, happy, interested, pleased, satisfied, relaxed and loving) and negative emotions (afraid, angry, bored, disappointed, sad and worried). As for the representation of the personality of individuals, the PersonalityML markup language tries to standardize psychological aspects relevant for decision making [38], such as those of the Big Five model.

d: PHYSICAL TRAITS

Physical traits define physical properties of the individual. We have opted to use the ontology Appearances [39] that allows us to record information about hair and eye color, race, skin tone or height. These concepts will need to be complemented with concepts such as weight, complexion or hair type.

e: WEATHER

WeatherOntology [40] can represent very varied information such as the current atmospheric phenomenon, temperature or wind direction.

2) ONTOLOGY DEVELOPMENT

The UPONLite methodology establishes a development in six steps: Domain Terminology, Domain Glossary, Taxonomy, Preaching, Meronyms, Ontology. The first two steps were carried out based on the analysis of the Dreamcatcher workshop videos and the questionnaires.

UPONLite suggests the extraction of the terminology from reference textual documents (such as manuals, textbooks, and whitepapers) or consultation with potential users in different types of deliberative processes. The Dreamcatcher workshop videos and the questionnaires provide in our case the information on the terminology used by the potential users, i.e. the students.

UPONLite puts the focus on the identification of relevant terms. According to this criterion, we selected the terms that appeared most frequently in videos and questionnaires, discarding infrequent or overly specific terms. Also following the UPONLite guidelines, we reflected on the possible existence of terms that different students used with different meanings. We did not find a single case of this, as the concepts used to describe study contexts are not complex and do not give rise to different interpretations. Moreover, the student community has coined terms that are widely used and have an unambiguous meaning.

As previously mentioned, we have identified three superconcepts: Student, Context and Story. Student comprises profile, personality and physical traits, including the concepts of emotions and emotional intelligence which, to date, have not been exploited in the ERSs literature. Context comprises personal, interpersonal, spatial-temporal (see Fig. 3 for an illustration) and academic contexts. Though a student can only have one current context, we also model contexts which a student commonly experiences. The personal context includes mood, which can be calculated as an average of the last N emotional states. Story describes an episode that often takes place in a context. While we have not gone into detail in

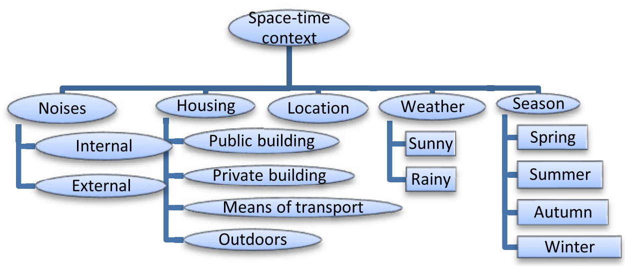

FIGURE 3. Concept hierarchy (ellipses) including some concept instances.

TABLE 4. Examples of axioms of ontology.

Description	Axiom
An interior noise cannot occur in an outdoor living space	not (exists (?X, ?Y) (interior-noise (?X) and (outdoor-living-space (?Y))
A student living in a village cannot travel by subway	not (exists (?X,?Y,?Z) (student (?X) and village(?Y) and subway(?Z) and lives(?X,?Y)) and [travel-by](?X,?Z))
A student with a visual learning style will occasionally employ audiovisual teaching materials	(exists (?X, ?Y, ?Z) (student (?X) and (?Y) and audiovisual-material(?Z) and [employ] (?X, ?Z))

the modelling of this superconcept (which we have not used in our proof-of concept) we can assume that its modelling can be based on ontologies conceived for the representation of animated digital stories, and markup languages of virtual worlds. In future work, we plan to give this superconcept an important role in the calculation of semantic similarity.

In Table 4, we illustrate ontology axioms formalized using a second-order logic notation. While using ontologies for inference purposes in real-time applications is not recommended, heavy ontologies (i.e., enriched with axioms) are used for verification purposes. A detailed description of the ontology can be found in [23] (to date we have only implemented the part required for our proof of concept).

3) SIMILARITY FUNCTION

The concept of ontological semantic similarity makes it possible to estimate the degree of similarity between pairs of concepts belonging to a taxonomy.

There are a large number of proposals in the ERS literature for the use of the hierarchical arrangement of ontologies for comparison. Ibrahim et al. [41] proposes a RS supported by ontological similarity, recommending university courses to potential students based on their interests and the choices of students of similar profile. Tarus et al. [4] proposes a recommendation technique that combines collaborative filters with ontologies to make personalized recommendations of learning material to online students. The similarity is calculated through the adjusted cosine similarity, which is based on the assessment of the learning objects provided by the students. Another paper of interest is [42] where the similarity between different courses is calculated using an approach similar to that presented in the previous work, while the

Pearson correlation coefficient is used for the calculation of the similarity between students.

To define our similarity function, first we have to choose the specific concepts and attributes to be taken into account by the similarity metric between pairs of study-context cases. Once the key attributes have been determined, the ontology is populated. For our proof of concept we have populated only those attributes of the ontology that are required to apply the similarity function.

For these purposes, the results obtained through the Dreamcatcher workshop, as well as those of the survey, have been particularly useful. In this section, we describe the similarity regions that allow the retrieval of cases to be refined by focusing on the relevant taxonomic area. Finally, we present the similarity function that we have defined.

a: RELEVANT CONCEPTS AND ATTRIBUTES

In the previously-presented requirements analysis we identified attributes and concepts which characterize students experiencing similar study stories. Thus, the attributes and concepts selected as relevant to establishing similarity between cases are as follows:

1. Student profile: Emotional intelligence, Personality, Age.
2. Personal context: Emotional state, Mood, Performance factors (family, work, personal, academic), Employment.
3. Academic context: Motivation, Satisfaction, Predisposition to studying, Dedication, Preferred place of study, Accessibility requirements, Previous studies.
4. Interpersonal context: Number and age of children.

Of the above attributes, some are particularly important to the concept of a semantic similarity region that allows retrieval to be refined. Thus, the performance factors or accessibility requirements (either associated with a temporary injury or a permanent disability) of the students are very relevant to the definition of semantic similarity regions. For example, in the case of a student with a permanent disability (e.g. blindness) it is of most interest to make comparisons with other cases that also involve this concept, since it is obvious that students who have this disability will experience very similar or related situations. Similarly, students who have children will share regions of semantic similarity since they also tend to share similar study situations.

From the analysis of the videos we have extracted a total of 7 cases, and from the analysis of the results of the survey a total of 63 cases, after filtering and eliminating those answers that were not considered valid. We consider some blocks of responses to the questionnaire to be invalid if some of the responses of the block lack the required data, for example when the field for the description of the story is incomplete or empty. As we will see, this field is critical to validating the similarity module since the validation proceeds by manually selecting a group of similar cases and then comparing the values of this field in these cases with its value in the cases selected by the similarity module.

TABLE 5. Two instances obtained via the workshop and survey.

Attribute	Workshop	Survey
Age	30	41
Personality attributes	Openness: 75 Conscientiousness: 50 Extraversion: 25 Agreeableness: 70 Neuroticism: 50	Openness: 75 Conscientiousness: 75 Extraversion: 75 Agreeableness: 50 Neuroticism: 50
Emotional Intelligence attributes	Attention: 25 Clarity: 25 Repair: 20	Attention: 35 Clarity: 23 Repair: 31
Emotional state	Sad	Furious
Mood	Low	Normal
Perform. factor	Labor Unemployment	Personal Continuous interruptions
Employed	No	Yes
Study attitude	Anxious	Positive
Motivation	Labor - Getting a job	Academic - specialization
Satisfaction	Satisfied	Satisfied
Studies	Engineering	Engineering
Dedication	High	Low
Place of study	Home	Home
Accessibility	-	-
Number of children	0	0
Age of children	-	-
Marital status	Single	Divorced

By way of illustration, Table 5 shows two examples of instances obtained through the theatre workshop and the survey, respectively.

b: SEMANTIC SIMILARITY REGIONS

In domains where information retrieval is a key factor, similarity regions play a fundamental role since they accelerate the process of case retrieval by avoiding making comparisons between concepts that *a priori* are not related. Assali et al. [43] state that similarity measures are not always applicable to each pair of concepts or instances of an ontology and define the similarity region concept as follows:

"A similarity region is a sub-hierarchy of an ontology where concepts and instances are comparable to each other.".

The definition of regions is made manually; it depends on the application and the judgment of the domain expert who ultimately determines which concepts are aggregated in the same region.

We adopt this approach in our proof of concept as a step carried out prior to the application of semantic measures, allowing us to significantly reduce the number of cases selected from the library. The similarity regions group cases

TABLE 6. Distribution of performance-factor categories.

Factor	Percentage
Familiar	21.4%
Academic	27.1%
Personal	35.7%
Occupational	15.7%

that are conceptually close or which, in the opinion of the experts, are semantically similar.

In our ontology, performance factors (see Table 2) are key attributes for defining similarity regions. We have classified these factors into family, work, personal and academic. When a student is affected by a specific performance factor, those cases in which this factor is present have to be retrieved from the case library, since the requirements analysis shows that the situations and conflicts described by such students are similar. Of the 67 cases available for the proof of concept, the distribution of the performance-factor category most affecting students is shown in Table 6, the most common being ''Personal''.

Accessibility is also a critical concept, since an injury or disability markedly affects the student's environment, their perspectives and, ultimately, their day-to-day life. Although we have not been able to count on the participation of students with disabilities in our survey, the literature on students with disabilities highlights the specificity of the contexts that these students experience.

The survey results reveal other interesting regions of similarity. About 13% of the selected cases describe the library as a regular place of study. 67% of these respondents highlight noise and interruptions as relevant factors affecting their study. Of the students with children (33% of the sample) almost 70% highlight family factors (childcare or family commitments) and personal factors (interruptions during study because ''my child wants to play'') as the most prominent factors that affect their studies.

In summary, we have identified the following 8 regions of similarity: 1) family factors (commitments, child care...), 2) work factors (excessive workload, overtime, work stress, working shifts, being on call...), 3) academic factors (concern about poor performance, excessive workload, lack of support and teacher follow-up..), 4) personal factors (injury, death or illness of a family member, a pregnancy...), 5) library, 6) children, 7) temporary limitation injury (e.g. breakage of an arm), 8) permanent limitation (blindness, paraplegia,...).

c: SIMILARITY FUNCTION

In the articles referenced at the beginning of this section, the calculation of the similarity between student profiles is mainly based on grades without taking into account specific attributes of the student contexts. The hierarchical function that we propose here compares user profiles and their contexts, using different metrics depending on the type of attribute or the concept to be compared. The proposed similarity function is as follows:

TABLE 7. Similarity measure functions.

Concept/Attribute	Function
Age	$\mathrm{Sim_{age}}(i,j) = 1 - \frac{\lvert \mathrm{age}_i - \mathrm{age}_j \rvert}{\mathrm{max_{age}CL} - \mathrm{min_{age}CL}}$
EI	$\mathrm{Sim_{EI}}(i,j) = \sum_{\{\mathrm{EI\_dim}\}} \frac{\mathrm{Sim_{EI\_dim}}(i,j)}{3}$ EI_dim ∈ {attention, clarity, repair} $\mathrm{Sim_{EI\_dim}}(i,j) = 1 - \frac{\lvert \mathrm{EI\_dim}_i - \mathrm{EI\_dim}_j \rvert}{40}$
P	$\mathrm{Sim}_P(i,j) = \sum_{\{\mathrm{P\_dim}\}} \frac{\mathrm{Sim_{P\_dim}}(i,j)}{5}$ P_dim ∈ {openness, conscientiousness, extraversion, agreeableness, neuroticism} $\mathrm{Sim_{P\_dim}}(i,j) = 1 - \lvert \mathrm{P\_dim}_i - \mathrm{P\_dim}_j \rvert$
S	$\mathrm{Sim}_S(i,j) = 1 - \lvert S_i - S_j \rvert / 5$ $S \in \{1, 2, 3, 4, 5\}$ corresponding to: very unsatisfied, unsatisfied, indifferent , satisfied, very satisfied
D	$\mathrm{Sim}_D(i,j) = 1 - \lvert D_i - D_j \rvert / 5$ $D \in \{1, 2, 3, 4, 5\}$ corresponding to: very low, low, medium, high, very high

Given two cases $\mathcal{C}_i$ and $\mathcal{C}_j$ the similarity between the two is calculated as:

$$\mathrm{Sim}\,(i,j) = \frac{\sum_{l=1}^{k} \mathrm{Sim}_{c_l}(i,j)}{k}$$

where k is the number of concepts compared and $Sim_c(i,j)$ represents the similarity between the value of the concept c in cases $\mathcal{C}_i$ and $\mathcal{C}_j$. If the concept c has multiple attributes/dimensions, $Sim_c(i,j)$ is in turn expressed in terms of $Sim_{c\_d}\,(i,j)$, i.e. the similarity between the value of the dimension d of the concept c in cases $\mathcal{C}_i$ and $\mathcal{C}_j$. Our similarity measure is a normalized mean similarity in the range [0,1] with higher values indicating greater similarity.

After applying the similarity region concept to cases in the case library and having obtained a set of cases similar to the base case, the similarity between each case and the base case is quantify using the similarity- function.

Table 7 shows some of the similarity measure functions defined for attributes and concepts that the survey has revealed to be determinant. It should be noted that in some cases the metrics applied are a simplification for our proof-of-concept. We intend to use more refined measures in future; for example, the representation of emotions through a vector approach (analogous to how we handle personality) or a greater categorization of studies to exploit the concept of ontological distance (taxonomizing in humanities, science and technology, etc.).

Note that we have defined emotional intelligence via three dimensions (attention, clarity and repair) [19] in the range [8], [40]. These values were calculated from the emotional intelligence test incorporated in the questionnaire. Similarly, personality is defined in 5 continuous dimensions in the range [0,1]. To compare degrees of satisfaction and dedication to study we have assigned integer values to the different categories considered. We have also considered relevant mood, emotions, attitudes to study, motivation, performance factors, and previous studies.

Mood can take three values: high, medium or low. The similarity between two identical mood values is 1, that between adjacent mood values is 0,5 and that between opposed mood values is 0. As for emotions, we have classified them as positive or negative, an assessment that we call the sign of the emotion. When two emotions coincide in sign but not in value their similarity is 0.5. If the emotions are of opposite sign their distance is maximal and their similarity minimal (value of 0). Attitudes to study are compared in a similar way (positive attitudes: positive, energetic, relaxed; negative attitudes: anxious, apathetic, tired).

The degree of motivation has also been discretized into integer values; additionally, motivations have been typified into academic (getting a degree, learning for learning's sake…), occupational (getting a promotion, getting a job) and personal (personal interest, hobby). When the motivation coincides, the similarity is maximum. If the motivation only matches the type, the similarity is 0.5. If the type is different, the similarity is 0. In the cases of performance factors and studies, if the description of the concepts matches then the similarity is maximum, while if it does not the similarity is minimal.

We assumed that there are no relevant cases outside the regions of similarity.

V. VALIDATION

Validation of recommender-system development typically proceeds by checking end-user satisfaction with the recommendations received. In the work reported on here, however, since our aim is to show the usefulness of a requirements-elicitation methodology for building a generic core for CSAERSs, we have not developed recommender system components that can be validated using the typical approach. Nor is it pertinent to validate our ontological similarity function by comparing its accuracy to other ERS similarity functions found in the literature since, as stated in the previous section, the latter are based on the values of a restricted set of attributes, mainly concerning previous student achievements, and largely ignore the study contexts on which we focus and which are of particular importance for distance-learning students. For these reasons, we validate our ontological similarity function by having education experts manually select the most similar cases to a set of base cases, using a field that is not currently considered by the similarity function: the "story" field, and then comparing the experts' selection with that of the similarity function.

After the respective analyses of the theatre workshop videos and the results of the survey we defined a total of 67 study-context cases. We concluded our proof of concept with a validation of the approach in which we selected 12 cases, leading to 12 experiments. Each of them was compared with the remaining 55 cases in the case library. For each experiment, we applied common-sense criteria to manually select the N most similar cases of the library, based on the "story" associated with each case, this being obtained from the survey and the Dreamcatcher workshop. The value N was set manually for each experiment based on the number of cases defined as being in the same semantic region. Due to the size of our sample and the total number of cases in the library, N was no higher than 6 in any experiment.

TABLE 8. Ontology and similarity-measure validation results.

EXP	Accuracy	Fall-out	A_Accuracy
1	0.66	0.018	0.27
2	0.80	0.02	0.96
3	0.60	0.04	0.54
4	0.66	0.04	0.51
5	0.33	0.038	0
6	0.75	0.019	0.93
7	0.33	0.038	0.27
8	0.20	0.08	0
9	0.66	0.02	0.91
10	0.66	0.019	0.88
11	0.66	0.019	0.27
12	0.80	0.02	0.59
Mean	0.58	0.03	0.51

To evaluate the performance of our selection algorithm we use the metrics of accuracy, failure proposition and average accuracy, widely used as key performance indicators in information-retrieval systems, defined as follows:

Accuracy: the fraction of recovered cases that are relevant to the user

$$\text{Accuracy} = \frac{|\{\text{relevant\_cases}\} \cap \{\text{retrieved\_cases}\}|}{\lceil\{\text{retrieved\_cases}\}\rceil}$$

The relevant cases have been selected according to subjective criteria.

Fall-out: the proportion of non-relevant cases that have been retrieved with respect to all available non-relevant cases.

$$\text{Fall} - \text{out} = \frac{|\{\text{non\_relevant\_cases}\} \cap \{\text{retrieved\_cases}\}|}{\lceil\{\text{non\_relevant\_cases}\}\rceil}$$

$$\text{AverageAccuracy} = \frac{\sum_{k=1}^{N} \text{P}(k) \cdot rel(k)}{\text{Number of relevant cases}}$$

N: number of relevant cases

P(k): accuracy of case k in the list

$rel(k)$: indicator equal to 1 if the element in position k is a relevant case, 0 if it is not.

Our proposed search algorithm is able to locate the most similar N cases after applying our similarity function in combination with the concept of similarity region to orient the search towards the most promising areas of the search

TABLE 9. Comparison between the base case and the most similar case retrieved for experiment 9.

Concept	Attribute	Base	Retrieved	Similarity
Profile	Age	47	45	0.94
	Employed	Yes	Yes	
EI	Attention	15	12	0.9
	Openness	21	23	0.93
	Repair	22	29	0.78
			Average	0.87
Personality	Openness	0.5	0.5	1
	Conscientious.	0.375	0.75	0.625
	Extraversion	0.625	0.125	0.5
	Agreeableness	0.375	0.25	0.875
	Neuroticism	0.625	0.375	0.75
			Average	0.75
Personal-c	Mood	Normal	Normal	1
	Academic	-	-	
	Occupational	-	-	
	Personal	-	-	
	Familiar	Childcare	Childcare	1
	Emotion	Happy	Happy	0.5
Interpers.-c	# Children	3	3	
	Marital status	Single	Married	
Academic-c	Dedication	Low	Medium	0.8
	Motivation	Get. degree	Promotion	0
	Satisfaction	Satisfied	Satisfied	1
	Accessibility	-	-	-
	Place of study	Home	Home	
	Study attitude	Tired	Tired	1
	Studies	Engineer	Engineer	1

TABLE 10. Manually chosen cases in experiment 9.

Order	Description
1	Trying to submit an assignment and not being able to do so because I have to help the children with their studies.
2	When I study at home my little girl does not let me because she requires my attention to play with her.
3	I have planned certain hours of study but I find it impossible to perform them due to a family commitment.
4	Usual interruption of study time to address everyday family life situations.
5	If I study for a long time I neglect my family, so many times I have to study at night until the early hours of the morning, so the next day I am very tired. Despite this, the next day the situation is repeated.
6	When I started the degree, I tried to take as much time as possible to study leaving aside my family responsibilities until I managed to find a balance.

space. The results (see Table 8) are acceptable considering that the case library is quite small. We consider an average accuracy of 0.51 with an average fall-out of 0.03 to be a positive result for a proof of concept, when the percentage of relevant cases is, on average, 5%. The manual selection has been made based on human assessment of the similarity of the descriptions provided by the students (both in the Dreamcatcher workshop and in the survey) concerning situations that frequently arise during their study causing them important emotional responses.

TABLE 11. Similarity measure on retrieved cases in experiment 9.

Order	Description	Similarity
1	Trying to submit an assignment and not being able to do so because I have to help the children with their studies.	0.75
2	When I study at home my little girl does not let me because she requires my attention to play with her.	0.68
3	I have planned certain hours of study but I find it impossible to perform them due to a family commitment.	0.66
4	Usual interruption of study time to address everyday family life situations.	0.60
5	If I study for a long time I neglect my family, so many times I have to study at night until the early hours of the morning, so the next day I am very tired. Despite this, the next day the situation is repeated.	0.59
6	Be studying and find out that a family member is in Emergency Department and have to leave quickly	0.52

We have observed how on many occasions the algorithm not only proposed the same cases as the manual procedure, but also the order in which they were returned (greater to lesser similarity) coincided with the manually-defined order (which is reflected in a high average accuracy in some of the experiments in the table above). Another aspect to highlight is the incorporation of the regions of similarity, which allow filtering to obtain only those cases that are semantically comparable. In our case, this favors the retrieval of cases that describe similar performance factors (see Table 2). Based on this, it is important that a CSAERS is able to classify the user's personal context into some of the four performance factors presented in the student's personal context ontology. The algorithm is able to make a pre-selection of semantically similar cases with a view to subsequently applying the similarity functions.

Finally, as an example we provide our results for the base case of experiment 9: "Continuous interruptions as my daughter wants to play". Table 9 shows the base case and the most similar case retrieved. In Table 10, we present the manually chosen cases that we considered most similar within the case library and in Table 11, the cases retrieved by our algorithm based on our similarity function.

VI. CONCLUSION

In this paper we present a requirements-elicitation methodology for the development of CSAERs, based on psycho-pedagogical theatre and surveys, in which the students play a leading role. The purpose of CSAERSs, which can be integrated into online learning platforms, is to provide students with personalized pedagogical support taking into account a broad learning context that includes the affective dimension. Including the affective dimension is a challenging task since human emotions comprise complex interactions of subjective feelings as well as physiological and behavioral responses that are especially triggered by external stimuli, which are subjectively perceived as "personally significant". Our contention is that enriching the ontologies used in the pedagogical support systems with a wider range of "personally significant" contexts can have a direct impact on optimization of the learning process and increase the pedagogical competence of CSAERs.

Our experiment has shown that psycho-pedagogical theatre has the capability of involving users in the initial phases of information-systems development, revealing relevant requirements that the users may not be able to verbalize without the theatrical representations. A large majority of the students participating in our experiment significantly appreciated the playful and participatory nature of the experience. The Dreamcatcher workshop and the survey have allowed us to obtain very useful information to understand the spectrum of cases and the affective universe of the distance-learning student.

As a proof of concept, we have illustrated the application of the requirements-elicitation methodology to the design of an ontology and associated semantic similarity function in the ontological space, that could serve as the nucleus of a CSAERS. We adopted an ontology-design methodology that combines the Neon and UPONLite methodologies. The integration of various existing standards and ontologies (concerning modelling contexts, e-learning, affective states…) into a coherent ontology that we have extended using the proposed techniques for requirements elicitation is another contribution of our research. From the analysis of the results of the survey and the theatre workshop we have inferred criteria to define the similarity function and, in particular, the similarity regions. We have also obtained data to populate the ontology, obtaining a small case base formed by 67 instances. Of these 67 instances a total of 12 have been used to evaluate the accuracy and performance of the similarity module. Our experiments have shown that the proposed similarity module, based on an approach which, to our knowledge, is original, is able to retrieve quite similar cases.

The definition of semantic similarity functions poses a problem widely reported on in the literature: the need for a significant number of context and profile data items. We trust in the enormous potential of psycho-pedagogical theatre to achieve this purpose. We plan to complete the catalogue of contexts obtained with the identification of new relevant situations by conducting more psycho-pedagogical theatre workshops as well as the definition of a more complete survey to be validated by a greater number of experts and disseminated among a greater number of students. This will enable us to refine the similarity function, in particular, by giving a fundamental role to the superconcept Story. Comparing stories will require the application of natural language processing techniques.

However, the main limitations of this study are those inherent to any qualitative methodology used with the aim of understanding a complex reality such as the role of emotions and feelings in the learning process. Finally, AI in education, as for AI in other areas, does not yet pay sufficient attention to ethics considerations concerning privacy, algorithmic transparency, user control over data collection via informed consent, avoidance of bias and consequent discrimination and, in the case of recommender systems, the possible negative impacts of personalization on student agency, autonomous learning and even personal identity. Careful use of the TORMES methodology, prioritizing pedagogic criteria, will help to avoid negative effects of personalization.

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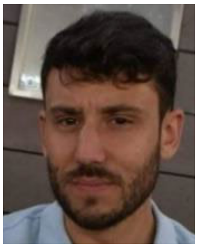

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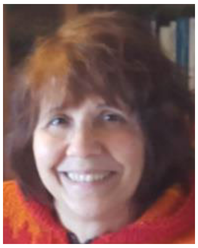

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