An Approach for an Affective Educational Recommendation Model

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Abstract There is agreement in the literature that affect influences learning. In turn, addressing affective issues in the recommendation process has shown their ability to increase the performance of recommender systems in non-educational scenarios. In our work, we combine both research lines and describe the SAERS approach to model affective educational recommendations. This affective recommendation model has been initially validated with the application of the TORMES methodology to specific educational settings. We report 29 recommendations elicited in 12 scenarios by applying this methodology. Moreover, a UML formalized version of the recommendations model which can describe the recommendations elicited is presented in the paper.

Keywords Affective computing • Educational recommender systems • Recommendation model • Semantic affective educational recommender systems

Introduction

Affective issues have been modeled to personalize systems that account for the affective states of users. Two competing modeling approaches exist to study the affect: (1) the categorical representation of discrete states in terms of a universal emotions model assuming that affective experiences can be consistently described by unique terms between and within individuals, and (2) the dimensional representation of affective experiences which assumes that the affect can be broken down into a set of dimensions. As to the former, several authors have proposed their own set of universal emotions, being probably Ekman's work the most popular [15]. Regarding the latter, the dimensional model was introduced by Mehrabian [26] as

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the pleasure-arousal-dominance space, which describes each emotional state as a point in a three-dimensional space.

From the educational point of view, there is agreement in the literature that affect influences learning (see section “Related Research”). Moreover, from the recommender system field, several experiments have shown some improvements when considering affective issues in the recommendation process [2, 22, 32, 44, 49].

In a previous work [38] we introduced the discussions, from the modeling viewpoint, of how to deal with affective issues in the recommendation process in educational scenarios. The approach follows a generic and interoperable perspective by extending Semantic Educational Recommender Systems (SERS) so that they are able to deal with the emotional state of the learner. In this paper we deepen the modeling of affective recommendations and present the resulting formalized version of the recommendations model in UML, which has been improved to account for an experience focused on modeling affective recommendations elicited with TORMES methodology.

The paper is structured as follows. First, we present related research, commenting on how affective issues are managed in learning environments, introducing how emotions are considered in recommender systems, and finally reporting examples of recommender systems that deal with affective issues in educational scenarios. Then, we introduce the SEARS approach and its modeling issues, highlighting its interoperability features with existing e-learning services. Thereafter, we present the application of the TORMES methodology to elicit affective educational-oriented recommendations in several educational settings and present the feedback received by 12 educators who were asked to validate 29 recommendations elicited in 12 scenarios. Following, we present the UML description of the SAERS. Finally, we discuss the findings, present some conclusions and outline future work. This research is framed in the context of the MAMIPEC project [40].

Related Research

In the last decade, the feedback between e-learning and pedagogical research on the interplay between affect and learning has been of benefit to both [30]. The effectiveness of intelligent tutoring systems, which have traditionally focused on the diagnosis and amendment of cognitive errors of students while learning, can be improved by considering the affective dimension [12, 33, 42]. Tutoring systems have been enriched with e-learning materials that are pleasant, enjoyable, motivating, etc., in brief, designed to favor a positive affective attitude towards learning [5]. In this context, affective modeling [10], a sub-area of affective computing [29], involves detection of users’ emotion and adaptation of the system response to the users’ emotional state. Affect detection is usually the result of human observation [47] or analysis of hardware sensor data [3, 51]. Multidisciplinary research is thus an outstanding characteristic of this emerging and promising field, as illustrated elsewhere [7, 51].

Thus, affective e-learning systems face two complex tasks: detecting affective states in learners, and reacting appropriately to these states when intervention is suited to support the affective dimension of learning [43]. Ideally the reaction should be adapted both to the individual student and to the learning context, and should be consistent with a long-term instruction strategy [7] that considers students' evolving characteristics. Thereby, the literature about affective e-learning addresses mainly three topics.

The first one is detecting relevant emotions in educational settings. In affective e-learning, the student interactions with the e-learning platform have to be dynamically collected focusing on data relevant to the learning progress and on behaviors that can be seen as affect expressions (e.g. inappropriate task strategies, procedural errors, misconceptions, problem-solving behavior, questionnaire responses, time spent on hints, number of hints selected, etc.). Additionally, physiological parameters that can be disturbed by affective states can be monitored through technology common to other affective modeling areas (e.g. heart rate sensors embedded within office chairs [1]). In particular, physiological sensors can detect internal changes [28], eye positions and eye movement can be measured with an eye tracker [13], user physical actions can be observed in an unobtrusively manner, such as from keyboard and mouse interactions [16], facial and vocal spontaneous expressions [54] or gestures [24]. Combinations of multiple sources of data and contextual information have improved the performance of affect recognition [54]. In this context, machine-learning techniques can be used to discover correlations between affect (e.g. revealed in a post-survey) and observable behavior [20], such as correlations between either emotion indicators or learning attitudes [47] or between student behavior and emotional state [3, 51].

The second topic deals with integrating affective issues in learner models, which is an area that has received a great interest in recent years as a wide range of affective variables have been assessed within interactive learning environments, such as emotional valence (positive or negative emotions), Ekman's basic emotions (e.g. anger, happiness, and fear), cognitively complex states (e.g. joy and shame) or recently to more cognitive-affective states that are more specific to the educational domain (e.g. boredom, frustration, and uncertainty) [14].

Moreover, personality characteristics—commonly measured with the Five Factor Model FFM [18]—account for the individual differences of emotions in motivation and decision making [53]. For instance, students' personality characteristics impact on how students respond to attempts to provide affective scaffolding [33]. Moreover, the learner modeling has to be sensitive to the complex relationship among affect, meta-cognition and learning [45].

The third and last topic focuses on defining pedagogical interventions in response to student emotional states. Affective learning is still an open discipline, relying on general theories, such as constructivist theories, that provide no clear guidelines about instructional practice. It is difficult to determine how best to respond to an individual's affective state [33], so there are open issues to be investigated, such as at which emotion state will the learners need help from tutors and systems [44]. To answer this question, observational techniques on tutoring actions can be carried out to facilitate the externalization of the tutors' decision-making processes during the tutoring support [30]. Given the lack of solid and widely accepted theories, pedagogical interventions are normally based on heuristics that are defined ad-hoc for each particular tutor. These interventions do not only depend on the current emotional state of the student but are also customized for each student and each context via a learner model [30, 33]. Besides including general heuristics, affective e-learning systems often make use of machine learning optimization algorithms to search for strategies to give affective support adapted to individual students [4]. In this context, different pedagogical intervention approaches can be found in the literature: (1) Basing intervention on emotionally animated agents that play the role of affective mirrors or empathetic learning companions [5, 6, 9, 48, 52], or give realism to the interaction with a virtual tutor as in [27]; (2) Teaching meta-affective or meta-cognitive skills about emotion management strategies or affect awareness [7, 44]; and (3) Handling emotions by means of two strategies [7]: (a) emotional induction, when promoting positive emotions while engaged in a learning activity, and (b) emotional suppression, when the focus on an existing emotion disrupts the learning process.

In this context, to date there have been a few recommender systems in educational scenarios that have considered affective issues. They have been used to (1) recommend courses according to the inferred emotional information about the user [19], (2) customize delivered learning materials depending on the learner emotional state and learning context [43] and (3) provide the list of most suitable resources given the learner affective state, provided that the learner fills in (a) her current affective state (flow, frustrated, etc.) and (b) her learning objectives [23]. These systems are typical applications of recommender systems in the educational domain, which mainly focus on recommending courses or content [25, 37, 50]. Furthermore, as for interoperability issues are concerned, although most recommenders are stand-alone applications, the third system (i.e. [23]) shows recent efforts being made to integrate affective recommendation support with existing e-learning services. This is in line with the SAERS approach presented in the next section.

In summary, works in several related fields suggest that educational recommender systems (as part of e-learning systems) can benefit from managing learners' affective state in the recommendation process. From the aforementioned key research questions, in this paper we address how educational recommender systems can model the affective issues involved during the learning process, considering that this modeling has to be managed and integrated with the rest of existing e-learning services. Moreover, given the open issues in affective learning theories, the heuristic knowledge that is applied in everyday instruction practice in learning institutions might be of great importance. As for the current literature on this topic, large parts of this knowledge have not yet been collected. For this, we propose the involvement of educators in order to carry out an exhaustive and methodical compilation of heuristics concerning affective learning, as already suggested in the literature (e.g., see [30]), by applying a user-centered methodological approach combined with data mining techniques [39]. To this end, we are using the TORMES methodology [36], as described below.

Semantic Affective Educational Recommender Systems

To address the aforementioned key research issues, we have investigated the development of Semantic Affective Educational Recommender Systems (SAERS), which take advantage of existing standards and specifications to facilitate interoperability with external components. In particular, in this section we present the modeling issues involved in their development. To support the required semantic characterization and guarantee interoperability, existing standards and specifications should be used. Thus, the information exchanged by the different components involved in the SAERS approach can take advantage of existing standards and specifications from IMS, ISO and W3C, integrating meaningful stand-alone XML fragments from those specifications. In [35] it was discussed which standards and specifications are applicable to describe the different attributes defined in the SERS recommendation model. In addition to those already reported, to deal with the emotional information, the Emotion Markup Language (EmotionML) [43] proposed by the W3C can be used to allow a technological component to represent and process emotional data, and to enable interoperability between different technological components processing these data.

Thus, the SAERS approach [38] is an extension of SERS [35] to deal with affective issues in a multimodal enriched environment where sensors and actuators are key to collect and produce learners' interaction data. This extension involves issues that deal with: (1) user centered design of recommendations, (2) enrichment of the recommendation model and (3) definition of new services in the architecture to support new functionalities to cover the detection of emotions and the provision of emotional feedback in a multimodal environment. As in SERS, SAERS enriches the recommendation opportunities of educational recommender systems, going beyond the aforementioned typical course or content recommendations. In fact, in this approach, both passive (e.g. reading) and active (e.g. contributing) actions on any e-learning system object (e.g. content, forum message, calendar event, blog post, etc.) can be recommended to improve the learning performance, in as much as they are related to educational issues involved [39].

To support the required interoperability SAERS design follows the principles of a service-oriented architecture [11]. The different components involved in the architecture, shown in Fig. 1 using the UML syntax for component diagrams, encapsulate categories of functionalities to be offered as reusable services. The diagram shows the behavior of the main components defined in terms of both provided (symbol ○) and required (symbol C) service interfaces exposed via ports (symbol □). Some of the components exhibit an internal structure where subcontracting of services is represented by means of delegation connectors. These components are: (1) **Learning Environment Interface**, concerning the interface through which the learner carries out the educational tasks with a certain interaction agent (i.e. a device) in an environment where there are information flows from sensors and actuators; (2) **Learner Profile**, responsible for modeling learner needs, interests, preferences, progress, competences, affective states, etc.; (3) **Interaction Agent Model**, responsible for modeling the capabilities and configuration information of the interaction agent used by the learner to access the course space; (4) **SAERS admin**, which supports the recommendations design; (5) **SAERS server**, which is the reasoning component and implements a recommendation knowledge-based system, and (6) **Learning context**, which gathers the interaction data from different sources, such as interaction agent, learning environment and emotional information gathered from sensors. In particular, the latter consists of the **Emotional Data Processor** with the

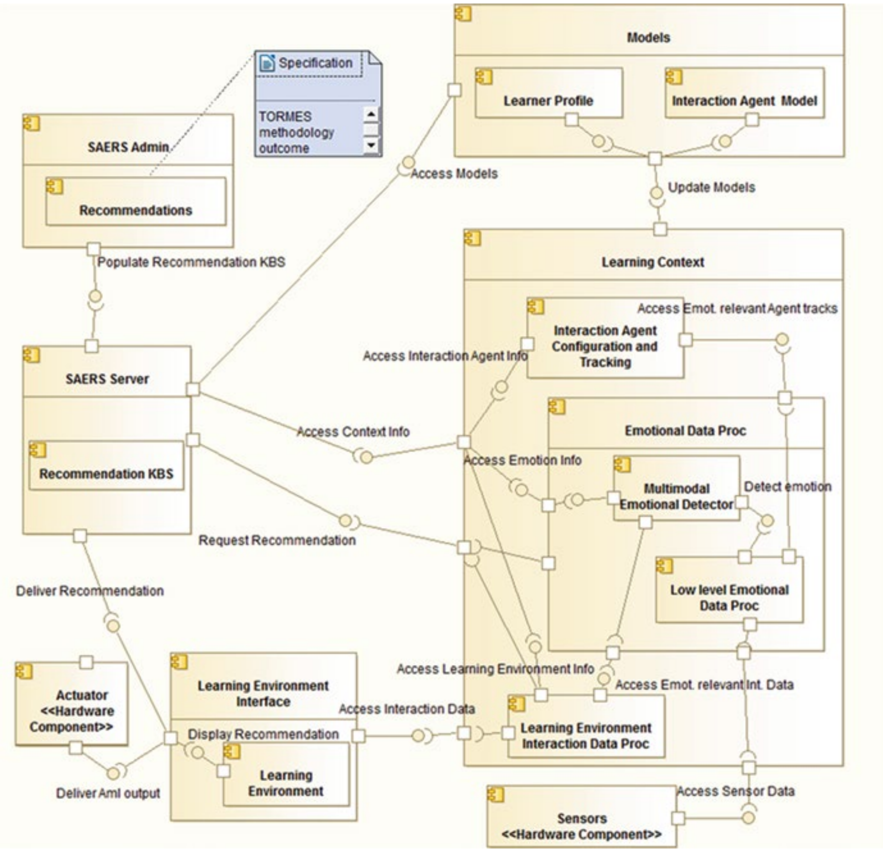

Fig. 1 Main components in the SAERS approach

following subcomponents: (a) **Low Level Emotional Data Processor**, which collects the input from emotional data available such as physiological data, eye positions and movements and physical interactions of the user (movements of the mouse, uses of the keyboard, voice or gestures) and (b) **Multimodal Emotional Detector**, which combines different sources of emotional data gathered to recognize the emotional state of the learner.

In the SAERS approach the learner of a course in an e-learning system is placed in a rich environment where sensors (defined in a general term) get data from her interactions and actuators provide personalized responses through a given interaction agent (e.g. PC, laptop, mobile, etc.), which might be combined with assistive technology (e.g. Braille line, speech recognition software, screen magnifier, among others) when the user requires some accessibility support.

To broadly understand the system dynamics let us assume that at a certain point during the learning process, a recommendation request is received by the *SAERS server* for a specific learner with details about her context in the learning environment, the interaction agent and affective state. To attend the request, the SAERS server requests additional data about the user and the capabilities of the interaction agent to the corresponding models (i.e. *Learner Profile* and *Interaction Agent*), as well as from the context of the user. This information is managed by the *Learning Context*, which processes the information about (a) the configuration and tracking of the interaction agent (b) the emotional state of the user, which is computed from the data received by the *Emotional Data Processor* and (c) interaction data in the learning environment. With this information, the reasoning component (SAERS server) selects the appropriate recommendations taking into account the current affective state of the learner. SAERS server consists of a knowledge-based recommender that store rules, which are managed according to their applicability conditions in order to recommend appropriate actions to be carried out for the current learner (with her individual features, preferences, affective state, etc.) in her current context (including course activity, course history, interaction agent used, etc.). Therefore, with that information, SAERS server looks for recommendations whose applicability conditions matches user features and emotions, interaction agent capabilities and educational context, and take into account predefined runtime restrictions (i.e. constrains). These recommendations are those that have been designed and properly modeled through the *SAERS admin* with the user-centered design methodology called TORMES (Tutor Oriented Recommendations Modeling for Educational Systems) [36]. The resulting selected recommendations that are instantiated for the given request are delivered to the learner by the corresponding actuator in the appropriate affective mode.

In order to facilitate the information exchange among the aforementioned components, a recommendation model is required to semantically characterize the recommendations and bridge the gap between their description by the educator and the recommender logic when delivering affective recommendations in the running course [38]. This recommendation model can be defined along the dimensions of "6 Ws and an H"—What, Where, How, Who, When, Why and Which—(inspired by Sundaresan's reporting of dimensions [46]):

- *What* is to be recommended, that is, the action to be done on the object of the e-learning service (for instance, to post a message in the forum).
- *How* and *Where* to inform the learner about the recommendation, which in a multimodal enriched environment, should describe the modality in which the recommendation has to be delivered to the learner (e.g. text or voice) as well as how the emotions are handled by the actuators when presenting the recommendations to the learner. For instance, a recommendation to be delivered by voice can be provided with a relaxed tone or with an angry tone. This emotional information can be described using the W3C EmotionML specification. In particular, the attribute 'expressed-through' for the modality and the element 'category' for the emotional output.
- *When* and to *Who* produce the recommendation, which depends on defining the learner features, interaction agent capabilities and course context that trigger the recommendation. It describes both the restrictions that may limit recommendation delivery as well as the applicability conditions that trigger the recommendations.

- *Why* a recommendation has been produced, providing the cognitive and affective rationale behind the action suggested.
- *Which* features characterize the recommendations themselves, such as (a) their classification into a certain category from a predefined vocabulary (e.g. active participation; technical support; communication; relevant information; accessibility; motivation, evaluation activities; course materials; progress in knowledge; profile), (b) their relevance (i.e. a rating value for prioritization purposes), (c) their appropriateness for a certain part of the course (e.g. getting used to the platform or if doing course activities), and (d) their origin, that is, the source that originated the recommendation (e.g. proposed in the course design, defined by the tutor during the course run, popular among similar users, based on user preferences).

As commented above, the goal behind this model is to facilitate the recommendation description among the actors involved, both educators and software components. As it is described in the next section, this recommendation model has been validated with some educators, who have applied the TORMES methodology to elicit affective recommendations for their scenarios. In section "Affective Recommendation Model for a Knowledge Based System Approach," we present the resulting UML structure for the affective recommendation model.

Application of the TORMES Methodology

TORMES methodology focuses on involving educators in identifying *when*, *who*, *what*, *how*, *where* and *why* emotional feedback needs to be provided to each particular learner in a given educational scenario, as well as on *which* features characterize the recommendations [38]. In particular, TORMES adapts the ISO standard 9241-210 to guide educators in eliciting and describing recommendations with educational value for their scenarios [36]. Four activities are defined in an iterative way: (1) understanding and specifying the context of use, (2) specifying the user requirements, (3) producing design solutions to meet user requirements, and (4) evaluating designs against requirements.

To validate the appropriateness of the affective recommendation model proposed in [38] three educators from the Psychology School and three educators from the Computer Science School of the Spanish National University for Distance Education (UNED) were asked to elicit affective oriented recommendations following TORMES methodology. The educators were chosen for several reasons. First, they have been teaching distance-learning courses for more than 10 years each. Second, these distance-learning instructors have also enough experience as classroom instructors. This matters for dealing with emotional aspects since, to date, affection has been neglected in distance learning and mainly addressed in face-to-face courses. However, there are distinctive and unique affective experience issues intricately linked to the computer interaction experience (supported by e-learning platforms).

In addition to that, these participants have been also involved in educational programs focused on dealing with educational innovation and functional diversity, where the pedagogical approaches integrate affective aspects.

Given the lack of straightforward information on student affective states in this context, information was obtained from various sources, such as forum and email messages, as well as occasional telephone calls that express emotions more or less directly. Frequency of learners' communications and interactions in virtual courses may also indicate hidden emotional states. There is no doubt that it is difficult to assess with certainty the emotions involved, their intensity, their permanency, etc. only from these information sources. Nevertheless, educators reported in the interviews that however the circumstances they are able to detect learners' emotional issues that let them react with the appropriate affective support to enhance learning.

TORMES methodology was applied to these six educators by two researchers. Educators completed the following activities of the TORMES methodology: 'Context of use,' 'Requirements specification' and 'Create design solutions.' As a result, an initial set of recommendations was elicited, identifying *when* a recommendation opportunity arises for a particular learner (*who*) in a representative educational scenario, *what* the appropriate recommendation has to be about, *why* it has been selected, *how* and *where* it has to be communicated to the learner, and *which* are the recommendation features.

As for the first activity of TORMES, in order to enrich the context of use educators took into account—apart from their own experience—data from a pilot experiment carried out in July 2012 [40] and the large scale experiment at the 2012 Madrid Science Week that took place in November 2012 [41]. Both experiments informed about the affective detection possibilities available. In these experiments participants were induced emotions while taking some mathematical activities with several levels of difficulty and varied time restrictions. Emotions were detected from their interactions in the e-learning environment through multiple sources, namely questionnaires to gather information about the user personality and sensors to get information about learners' interactions (i.e. eye movements from an eye tracker, face expressions from Kinect, video from a web cam, heart and breath parameters from physiological sensors, and mouse and keyboard movements). After each exercise they were asked to fill in the Self Assessment Manikin (SAM) scale [8] to measure their emotions in a dimensional space.

All that information was considered during the second activity of the elicitation methodology, where relevant educational scenarios were built according to the proposed scenario based approach [34] for the 'Requirements specification.' In this activity, the information obtained from the context of use (i.e. *when*, *who*, *what*, *how*, *where* and *why*) is used to build representative scenarios of the tutoring task in order to identify recommendation opportunities in them. Here there are two types of complementary scenarios: a problem scenario that identifies the situations where learners were lack of support, and a solution scenario built from the problem scenario that avoids or minimizes those problematic situations by offering appropriate recommendations.

After that, in the third activity, the recommendations proposed were validated in a focus group where educators and researchers were involved. In that process, the recommendations were redefined and described in more detail following the recommendation model, adding the recommendation features to be considered (*which*). Moreover, the resulting recommendations were also presented for evaluation to other educators. Details are provided next.

Some Scenarios and Recommendations Elicited

In this section we report some of the scenarios and recommendations elicited by the three Computer Science educators after applying TORMES as described above, as well as some qualitative outcomes from the evaluation carried out with additional educators who were not involved in the elicitation process. In this initial analysis, 12 affective scenarios were selected for evaluation and are compiled in Table 1. Note that different emotions are considered as responses to the same situations (e.g. Sc3a and Sc3b), proposing different recommendations either in tone or content when different emotions are involved, as shown in Table 2.

To illustrate the result of the elicitation process in terms of a particular recommendation, Tables 2 and 3 provide respectively description and modeling involved for one of the above recommendations. Thus, Table 2 illustrates the first of the above elicited recommendation (Rec-1). The output obtained from the educators' description pointed out the aforementioned key questions, i.e. *when*, *who*, *what*, *how* and *why* the recommendation is to be delivered.

Table 3 shows the above recommendation described in terms of the recommendation model after the focus group validation of the third activity. The attributes of the recommendations (i.e. those to answer the question '*which*') were also added. In order to describe the recommendations, the affective recommendation model proposed in [38] was used as a starting point. However, the practical experience suggested some minor changes in that structure (mainly naming issues), which turned into the up-to-date affective recommendation model presented in the next section in UML.

As introduced above, in the third activity, the scenarios and recommendations in Table 1 were evaluated by 12 educators (six men and six women; age range 30–55) of representative profiles, who have not taken part in the elicitation process. They were questioned to find out their feelings about the scenarios and recommendations elicited by the other three educators. They all had higher education qualifications and experience on both teaching through e-learning platforms and face to face teaching. Ten of them have also been distance learning students. The research field (Recommender systems in e-learning platforms) was well known by seven participants, while two of them had only a vague idea of it, and the remaining three never had heard of it. Their opinions about the relevance of providing affective support to students were diverse. In particular, four considered this issue of critical importance, while other four appreciated its importance but do not regarded it as crucial, and for

Table 1 Affective scenarios and recommendations elicited

ID	Situation addressed	Emotions involved	Recommended content	Tone
Sce 1	Getting used to the platform	Anxiety/frustration/ helplessness	**Rec-1**: Advise a presentation in the forum "Getting started." **Rec-2**: Point to the user manual. **Rec-3**: Technical assistance if required.	Kind, reassuring, understanding, patient, friendly, encouraging
Sce 2	Difficulties defining work plan	Anxiety/confusion/ frustration/ helplessness	**Rec-4**: Advise taking it easy and reassure about own capacities to manage learning. **Rec-5**: Advise about planning in distance learning. **Rec-6**: Advise planning in the base of the course working plan.	Kind, calm, suggestive, friendly
Sce 3a	Where to start?	Distraction/indolence/ apathy	**Rec-7**: Point to working plan. **Rec-8**: Point to next learning objective uncovered. **Rec-9**: Point to appropriate learning objects.	Kind but firm & slightly critical
Sce 3b		Anxiety/confusion/ frustration/ helplessness		Kind, reassuring, suggestive, friendly
Sce 4a	Exam imminence. Going from one learning object to another without focus or focus on inappropriate objects with regards to exam, knowledge & competencies	Anxiety/depression	**Rec-10a**: Point to appropriate learning objects focusing on gaps in knowledge & competencies, & exam objectives **Rec-11a**: Advise study plan review **Rec-12**: Highlight key learning objectives achieved	Empathetic, confident, convincing, encouraging
Sce 4b		Distraction/ detachment	**Rec-10b**: Point to appropriate learning objects focusing on gaps in knowledge & competencies, & exam objectives **Rec-11b**: Advise study plan review **Rec-13**: Highlight importance & imminence of exam	Kind, firm & slightly critical
Sce 5	The learner is critical either of organization, study materials or exam approach	Aggression/sarcasm/ disrespectfulness	**Rec-14**: Thank the criticism, give explanation **Rec-15**: Acknowledge the criticism foundation **Rec-16**: Respect the emotional expression **Rec-17**: Welcome future criticisms **Rec-18**: Ask for a serene tone in future criticisms	Kind but firm, confident, conciliating

(continued)

Table 1 (continued)

ID	Situation addressed	Emotions involved	Recommended content	Tone
Sce 6a	The learner is having problems dealing with certain instructional material. She has successfully completed a significant part of the course	Anxiety	**Rec-19a**: Point to lack of knowledge & misunderstandings underlying the blockage **Rec-20**: Point to appropriate learning objects of less difficulty/review notes/glossary **Rec-21**: Post question for teachers/class mates **Rec-22**: Advise changing activity **Rec-23**: Point to relaxing/amusing learning objects (ed. games)	Empathetic, understanding, cheering, affectionate
Sce 6b		Boredom	**Rec-19b**: Point to lack of knowledge & misunderstandings underlying the blockage **Rec-24**: Point to a more suggestive and entertaining appropriate learning objects addressing the same objectives (i.e. interactive, amusing, interesting, stimulating, inspiring)	Empathetic, confident, convincing, encouraging
Sce 6c		Despair	**Rec-19c**: Point to lack of knowledge & misunderstandings underlying the blockage **Rec-25**: Point to enjoyable appropriate learning objects of less difficulty addressing the same objectives **Rec-26**: Advise share worries with class mates in same situation	Firm, animating
Sce 6d		Impatience	**Rec-19d**: Point to lack of knowledge & misunderstandings underlying the blockage **Rec-27**: Point to more motivating, interesting and entertaining appropriate learning objects of less difficulty addressing the same objectives	Reassuring, critical
Sce 6e		Relaxation/ confidence	**Rec-19e**: Point to lack of knowledge & misunderstandings underlying the blockage **Rec-28**: Advise persevere in challenging learning objectives **Rec-29**: Point to enjoyable, motivating, interesting appropriate learning objects of less difficulty addressing the same objectives	Determined, slightly critical, motivating

Table 2 Description of one of the recommendations elicited

ID	Rec-1
TITLE	Advise a presentation in the forum "Getting started."
DESCRIPTION	Foster the learner to send a message to the forum "Getting started" when is new to the platform, has a nervous personality and is anxious.
WHEN and WHO	The learner is getting used to the e-learning platform. She has had just a few sessions in it and has not contributed to any of the platform services. Seems to be a nervous person and appears anxious.
WHAT	Post a message in the forum "Getting started" to present yourself (a link to the forum e-learning service is provided).
HOW and WHERE	In a calm voice from an avatar integrated in the e-learning platform.
WHY	The learner is getting used to the platform, and appears to have much trouble with it. She has not yet used the available services. She seems to be a nervous person and is experiencing quite a lot anxiety. For all these reasons, she should calm down and carry an easy non-educational task (e.g. speak about herself) to practice with a simple task and get confidence with the platform usage before going to the course tasks.

Table 3 Rec-1 described in terms of the recommendation model (see section 6)

Recommendation attributes (which)	ID	Rec-1
	Description	Foster the learner to send a message to the forum "Getting started" when is new to the platform, has a nervous personality and is anxious.
	Category	Technical support
	Stage	Getting used to the platform
	Origin	Tutor
	Relevance	4.2
Recommendation rules (when and how)	Runtime constrains	Context Learning Environment inv self.e-learning services els → exists(els ǀ (els.type = forum) &(els.name = Getting started)) Context Interaction Agent Model inv self.standards supported std → exists(std ǀ std.name = HTML 3.0)
	Applicability conditions	Context Deliver Recommendation(l: learner) post l.learner_behaviour_record.platform_sessions < 5 l.learner_behaviour_record.service_contributions = null l.learner_profile.personality = nervous l.learner_current_affective_state = anxious
Recommended action (what)	Content	Present yourself in the forum "Getting started"
	E-learning service	Context Deliver Recommendation post result = r ǀ r.e-learning service.type = forum result = r ǀ r.e-learning service.name = Getting started
	Action	Context Deliver Recommendation post result = r ǀ r.e-learning service.action = Post a message

(continued)

Table 3 (continued)

Justification (why)	Message	You are new to the platform and you have not yet used the available services. Since according to your personality profile you trend to be a nervous person and appears to be experiencing some anxiety, you should calm down and carry out an easy non-educational task (e.g. speak about herself) to practice with a simple task and get confidence with the platform usage before going to the course tasks.
	Cognitive	Competence Progress = null Course Progress = null
	Affective	Personality = nervous Affective state = anxious
Format (how and where)	Emotional delivery (tone)	State = calm Actuator = platform avatar
	Output	Modality = voice

Constraints are described using the OCL constraint specification language

the remaining four it was considered dispensable. Moreover, five of participants stated that they were interested in the aims of the research, and two of them were particularly interested in developing strategies to integrate in their teaching practice.

This preliminary study has not shown any gender bias in the questionnaire answers, or any other correlation with the participants' profile.

Preliminary qualitative results showed that each of the 12 scenarios was identified by at least 4 of the educators as recurrent scenarios they often have to deal with in their common virtual teaching practice. Scenarios Sce-2 and Sce-3/b were scored with the highest occurrence rates, while scenarios Sce-4/, Sce-4/b and Sce-6/e were scored with the lowest occurrence rates. Nevertheless, an affective pedagogical intervention was judged as very important also in the later cases. The educators mainly pointed scenarios Sce-1, Sce-2, Sce-5, Sce-6/a and Sce-6/c as those that more clearly demanded pedagogical intervention.

Regarding the recommendations, most of them were considered quite valuable by the educators. The best rated were the recommendations Rec-2, Rec-19/a, Rec-19/b and Rec-14. These recommendations do not fully coincide with the most common interventions of the educators (Rec-2, Rec-19/b, and Rec-20 were identified as most practiced). In particular, educators appreciated very much Rec-14 but this recommendation only ranked third as practiced recommendation for the given scenario. With regard to Rec-8, Rec-7/a and Rec-9/a, some educators stated that they were beyond their capabilities given the lack of the knowledge of the students they required. The lower scores were for Rec-22, Rec-23 and Rec-27.

It is significant that the scenarios that were more familiar to the participants were related to difficulties of the students in learning management. This underlines important weaknesses of virtual courses currently delivered through the e-learning platform that recommender system research is addressing.

It is also remarkable that despite only four of the educators surveyed stated originally that they considered of crucial importance affective teaching, all of them made a fairly positive assessment of the proposed pedagogical interventions. Our analysis also suggests that distance learning educators might not intervene in certain valuable affective ways due to the lack of both resources to detect information about the student and knowledge on the appropriate intervention strategies considering the affective dimension. Furthermore, the educators interviewed considered it important to intervene mainly when the students experience negative emotions, while pedagogical studies show that attitudes involving either indifference or over-optimism can be just as detrimental for academic progress [17]. From the above it would appear that there is little awareness and little training regarding affective educational dimension but a latent sensibility to the issue. Integrating affective recommender systems in e-learning platforms could contribute to raising awareness and training for an affective teaching. Thus, an affective recommender system such as the SEARS proposed here could provide undoubtedly added value to e-learning platforms.

Affective Recommendation Model for a Knowledge Based System Approach

The initial recommendation model that deals with affective information was proposed in [38]. When trying to describe the TORMES elicited recommendations in terms of the recommendations features, some changes in the model structure were identified. The resulting recommendation model has been formalized in UML specification. This model is the formalization of the SAERS specification (based on reusable service oriented components) which considers the elicited knowledge from the affective recommendations. The aim for this formalization is to clarify the architectural issues involved towards the system development, thus specifying the system components, its functionalities and their interoperability. In fact, modeling decisions lie on the advantages of the system architecture, which in the SAERS approach involves standards-based interactions among the different components in an interoperable way.

In Figs. 2, 3 and 4 we present some extracts of this specification showing the more significant classes and associations. The '*when*' and '*who*' questions are addressed with the Learning Facts class—see Fig. 4. In turn, the '*which*' question is

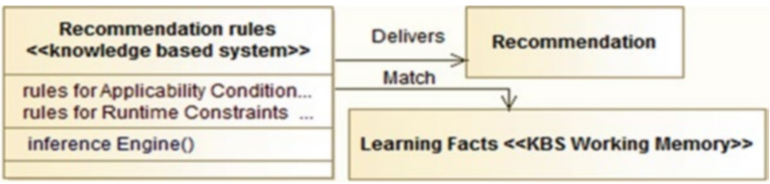

Fig. 2 Main model classes

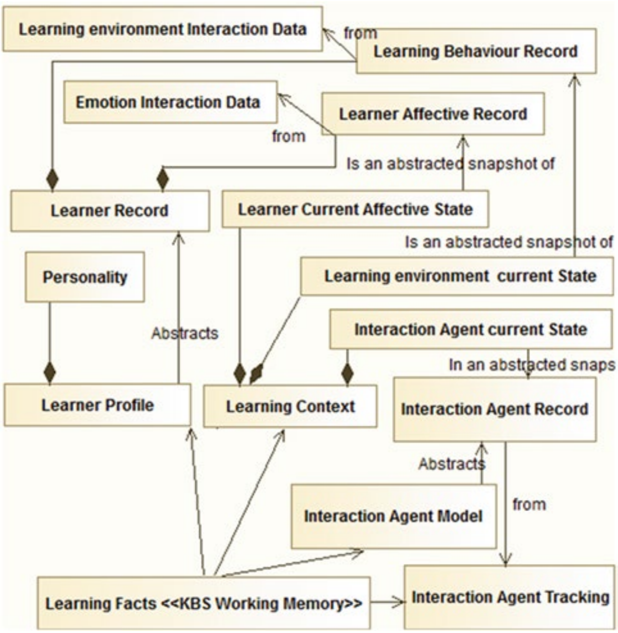

Fig. 3 Learning facts class diagram

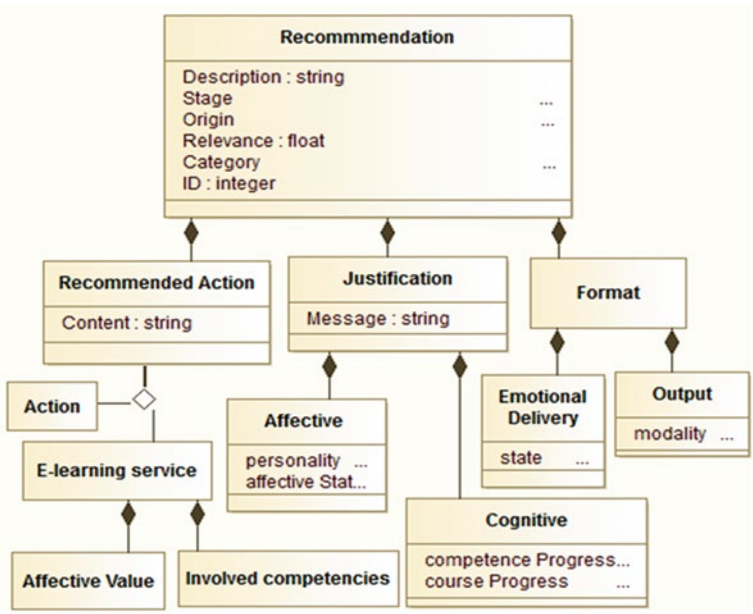

Fig. 4 Recommendation structure

addressed with the *Recommendation* class, the '*how*' and '*where*' questions with the *Format* class, the '*why*' question with the *Justification* class, and the '*what*' question with the *Recommended Action* class—see Fig. 3.

In Fig. 2, the class *Recommendation rules* is stereotyped as << *knowledge based system*>> (KBS) since it is implemented following the knowledge based system paradigm. The class *Learning Facts* is stereotyped as <<*KBS Working Memory*>>, meaning that the facts about the learner and the current learning context constitute the working memory of the *Recommendation Knowledge Based System*. Figure 3 highlights that the facts about the learner consist of a static part (*Interaction Agent Model* and *Learner Profile*) that can be actualized through the learning process, and a dynamic part (*Learning Context and Interaction Agent Tracking*) extracted from the online interaction records.

Black diamond links represent the aggregation relationships. Notice in Fig. 4 that *Recommended Action*, *Action* and *E-learning service* are liked by a ternary relationship, meaning that a customized exclusive action on a specific e-learning service and playing a particular role in a given recommendation is offered. The other two classes (*Justification*, *Format*) reflect the rest of elements identified.

If compared to the previous version [38], the recommended features are the attributes of the *Recommendation* class and subclasses, the type is described with the *Recommended Action* class and subclasses, the content is described by the *Format* class and subclasses and the applicability conditions and runtime restrictions are described in the *Recommendation rules* class and subclasses. The justification did not change the name but added a couple of subclasses, i.e. *Affective* and *Cognitive*.

This formalized version of the recommendations model in UML, which considers the elicited knowledge from the affective recommendations obtained with the modeling experience carried out with TORMES methodology, is meant to facilitate SAERS development in terms of the interoperable standards-based components presented in section "Semantic Affective Educational Recommender Systems."

Discussion, Conclusions and Future Work

This paper has provided some details of the issues to be considered when eliciting affective recommendations in educational recommender systems. In particular, the process proposed follows the SAERS approach, which is focused on bringing educators to the recommendations elicitation process and which is characterized by considering interoperability issues between recommendations and the rest of e-learning services. In particular, the paper provides an overview of the issues involved in such process and illustrates the main modeling aspects that are to be considered to design affective educational recommendations. These recommendations are elicited following the TORMES methodology, which deal with learners' affective traits in educational scenarios.

The paper has also provided some details of the elicitation process followed by six experienced educators, who were asked to fulfill the modeling issues involved, including the "6 Ws and an H" questions. TORMES has supported them throughout the whole process. Thus, following the scenario based approach recommendations were placed in relevant course situations aimed to emotionally support learners in their interaction within the learning environment. Afterwards, a focus group was used to refine the recommendations and describe them in a more structured way. For this, the recommendation model in [38] was used. Recommendations were properly designed provided that some adjustments were done to the model. The UML description of the model, which considers the elicited knowledge from the affective recommendations obtained with the modeling carried out with TORMES methodology, has been reported in section "Affective Recommendation Model for a Knowledge Based System Approach" to guide the SAERS development in terms of the interoperable standard-based components presented in section "Semantic Affective Educational Recommender Systems." Moreover, scenarios and recommendations elicited were evaluated by 12 additional educators. In general terms, they found them as valuable affective pedagogical interventions. However, in some cases, educators pointed out that applying them into real practice was beyond their capabilities given the difficulties involved in detecting them in real learning scenarios. This shows that distance learning educators might not intervene in certain valuable affective ways due to the lack of resources related to dealing with the student affective state and applying appropriate intervention strategies. As a result, it is expected that an affective recommender system, such as the SEARS proposed here, provides added value to e-learning platforms.

In the context of the MAMIPEC project we aim to progress on this research, mainly by carrying out a compilation of heuristics concerning affective learning by applying the TORMES methodology for eliciting educational recommendations, which later can be delivered in the learning scenarios with the SAERS. Given the lack of sound theories on affective learning, the heuristic knowledge that is applied in everyday instruction practice in learning institutions is of great importance. Judging from the current literature on this topic, large parts of this knowledge have not yet been collected. Several research questions can be posed in this respect, such as (a) "Does affect improve recommendation accuracy compared to a non-affective recommender systems?," (b) "Do affective recommendations improve student satisfaction?," or (c) "Do affective recommendations increase student performance?."

Regarding interoperability, we have considered the W3C EmotionML specification. However, there are other specifications that might be of interest, such as the Attention Profiling Mark-up Language (APML)[1] and the Contextualized Attention Metadata (CAM).[2]

A large scale experiment is to be carried out to evaluate the effects of the affective recommendations elicited when they are delivered in the e-learning system, as described in the fourth activity of the TORMES methodology (Evaluation of designs against requirements). The infrastructure provided in the experiment carried out in

[1] APML: http://apml.areyoupayingattention.com/

[2] CAM: https://sites.google.com/site/camschema/home

the 2012 Madrid Science Week to investigate the detection of changes in the emotional state of learners is being extended to deliver the recommendation support following the SAERS approach. In order to design the evaluation plan, user centered-evaluation frameworks [21, 31] are to be considered to explain the user experience.

In summary, open issues in the field deal with the detection of learners affective states while interacting with the e-learning platform, the elicitation of proper strategies to support learners in these situations and their automatic delivery through SAERS.

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