Affective Issues in Semantic Educational Recommender Systems

Olga C. Santos and Jesus G. Boticario

aDeNu Research Group. Artificial Intelligence Dept. Computer Science School. UNED
C/Juan del Rosal, 16. Madrid 28040. Spain
ocsantos@dia.uned.es, jgb@dia.uned.es
http://adenu.ia.uned.es

Abstract. Addressing affective issues in the recommendation process has shown their ability to increase the performance of recommender systems in non-educational scenarios. In turn, affective states have been considered for many years in developing intelligent tutoring systems. Currently, there are some works that combine both research lines. In this paper we discuss the benefits of considering affective issues in educational recommender systems and describe the extension of the Semantic Educational Recommender Systems (SERS) approach, which is characterized by its interoperability with e-learning services, to deal with learners' affective traits in educational scenarios.

Keywords: Educational Recommender Systems, Affective computing, Emotions, Technology enhanced learning, E-learning services.

1 Introduction

Affective issues have been considered to personalize the system response taking into account the corresponding affective states modelled. Two competing 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 [7]. Regarding the latter, the dimensional model was introduced by Mehrabian [14] as the pleasure-arousal-dominance space, which describes each emotive state as a point in a three-dimensional space. The pleasure dimension has been referred to as valence by many authors and the dominance dimension is often not considered. In any case, valence accounts for the pleasantness of the emotion, arousal for the strength of the emotion and dominance describes whether the user is in control of her emotions or not.

From the educational point of view, there is agreement in the literature that affect influences learning (e.g. refer to the references compiled in [17, 2, 25]). Many research works on user's affective state in education have been carried out in the field of intelligent tutoring systems [5, 23, 19]. Moreover, from the recommender systems field, several experiments have shown some improvements when considering affective issues in the recommendation process [11, 1, 25, 18, 26].

In this paper we discuss, from the modelling viewpoint, how to deal with affective issues in the recommendation process in educational scenarios from a generic and interoperable perspective by extending the approach of Semantic Educational Recommender Systems (SERS) to deal with the emotional state of the learner.

The paper is structured as follows. First, we present related research, commenting on how affective issues are managed, introducing how emotions are considered in recommender systems and finally, reporting examples of recommender systems that deal with affective issue in educational scenarios. Then, we introduce the SERS approach and its modelling issues, highlighting its interoperability features with existing e-learning services. After that, we describe how the SERS modelling approach can be extended to deal with affective issues. Finally, we comment on the ongoing works.

2 Related research

Affective modelling [4] is a sub-area of affective computing [16] that involves i) detection of users' emotion and ii) adaptation of the system response to the users' emotional state. Aesthetic emotional responses (i.e. those produced by investigating the intrinsic emotions contained in the observed elements) can be either collected 1) *directly through questionnaires* such as the Self Assessment Manikin - SAM [3] which follows the dimensional model of emotions, or 2) *inferred* through data gathered from the analysis of i) *physiological sensors to detect internal changes* [15], ii) eye positions and eye movement measures with an *eye tracker* [6]; and iii) *observation* of user physical actions in an unobtrusively manner, such as from a) *keyboard and mouse* interactions [8]; b) *facial and vocal* spontaneous expressions [28] or c) *gestures* [12]. Combinations of multiple sources of data and contextual information have improved the performance of affect recognition [28].

The idea behind considering affective issues in educational recommender systems is that emotional feedback can be used to improve learning experiences [25]. Two strategies can be carried out related to emotions feedback [2]: 1) emotional induction, when promoting positive emotions while engaged in a learning activity, and 2) emotional suppression, when the focus on an existing emotion disrupts the learning process. Anyway, it is difficult to determine how best to respond to an individual's affective state [19], so there are open issues to be investigated, such as "at which emotion state will the learners need help from tutors and systems" [25]. 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 [17].

Moreover, students' personality characteristics can also impact on how students respond to attempts to provide affective scaffolding [19] and accounts for the individual differences of emotions in motivation and decision making [27]. Personality is commonly measured with the Five Factor Model - FFM [9].

In this context, to date there have been a few recommender systems in educational scenarios that have considered affective issues. For instance to better recommend courses according to the inferred emotional information about the user [10] or to customize delivered learning materials depending on the learner emotional state and other issues from the learning context [25]. These systems are typical applications of recommender systems in the educational domain, which mainly focus on recommending courses or learning objects [13, 22].

Last but not least, note that as for interoperability issues are concerned, although most recommenders are stand-alone applications, efforts are recently being made to integrate affective recommendation support with existing e-learning services, like the SAERS approach (introduced in the next section) or the Learning Resources Affective Recommender (LRAR) widget[1]. This widget aims to provide the list of most suitable resources given the affective state of the learner, provided that the learner fills in i) her current affective state (flow, frustrated, etc.) and ii) her learning objectives.

In summary, works in several related fields suggest that educational recommender systems can benefit from managing learners' affective states in the recommendation process. A key research question is how educational recommender systems can model the affective issues involved during the learning process to be able to properly detect them and provide appropriate recommendations to learners. For this, the involvement of educators has been suggested. Moreover, to take advantage of existing technological infrastructures in current educational scenarios, interoperability with external components should be achieved.

3 Semantic Affective Educational Recommender Systems

In this section we present the modelling issues involved in developing Semantic Affective Educational Recommender Systems (SAERS), which consider affective issues in the so called SERS (i.e. Semantic Educational Recommender Systems) approach [20]. As in the SERS approach, this extension takes advantage of existing standards and specifications to facilitate interoperability with external components.

3.1 The SERS approach

The SERS approach [20] enriches the recommendation opportunities of educational recommender systems, going beyond aforementioned typical course or contents recommendations. It has been proposed to extend existing e-learning services with adaptive navigation support, where 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 terms of learning efficiency (use less amount of learning resources to achieve the learning goals), learning effectiveness (more learning activities done and more learners achieving the learning goals), satisfaction (better perception of the course experience), course engagement (more continuous and frequent accesses to the

[1] http://www.role-widgetstore.eu/specification/learning-resources-affective-recommender

course) and knowledge acquisition (better scoring in the course evaluation). Here recommendations are offered as a list of links of suggested actions, which provide access to explanations and feedback on demand [20].

This adaptive navigation support can be offered in terms of a service oriented architecture that provides interoperability with the different components involved: 1) **e-learning service** -initially applied to learning management systems, but extensible to personal learning environments- where the learner carries out the educational tasks, 2) **user model**, which characterizes the learner needs, interests, preferences, etc., 3) **device model**, which stores the capabilities of the device used by the learner to access the course space, 4) **SERS admin**, which supports the recommendations design, and 5) **SERS server**, which is the reasoning component. The goal of the SERS admin is to support the recommendations design process in two complementary ways: i) involving educators in the recommendations elicitation process with the user-centred design methodology called TORMES (Tutor Oriented Recommendations Modelling for Educational Systems) [21] and ii) applying recommendation algorithms. In turn, SERS server consists in 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, etc.) in her current context (including course activity, course history, device used, etc.). The information that is modelled and managed among the different components can be described in terms of available standards and specifications (e.g. IMS, W3C, ISO), as discussed elsewhere [20].

With respect to modelling these recommendations, they are described in terms of a recommendations model which semantically characterizes the recommendations in order to bridge the gap between their description by the educator and the recommender logic when delivering recommendations in the running course. The recommendation model consists of the following 5 elements:

- **type:** specifies *what* to recommend, that is, the action to be done on the object of the e-learning service. For instance, post a forum message.
- **content**: defines *how* to convey the recommendation, in terms of the textual information presented to inform the learner about the recommendation.
- **runtime information**: describes *when* to produce the recommendation, which depends on defining the learner features, device capabilities and course context that trigger the recommendation.
- **justification**: informs *why* a recommendation has been produced, providing the educational rationale behind the action suggested.
- **recommendation features**: additional semantic information that compiles features *which* characterize the recommendations themselves, such as i) their classification into a certain category from a predefined vocabulary, ii) their relevance (i.e. a rating value for priorization purposes), iii) their appropriateness for a certain part of the course, and iv) 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).

Details about the SERS approach and the recommendations model can be read elsewhere [20]. Next, we comment how the SERS approach can be extended to model affective issues in an interoperable way.

3.2 From SERS to SAERS

In this section, we present how to consider affective issues in the SERS approach, assuming also a multimodal enriched environment where sensors (obtain data from the users in the environment) and actuators (produce data to the users in the environment) interact with the learners. Correspondingly, it is named SAERS (Semantic Affective Educational Recommender System). This extension involves modelling and interoperability issues: 1) user centred design of the recommendations, 2) enrichment of the recommendation model and 3) definition of new services in the architecture.

3.2.1 User centred design of the recommendations

From Section 2, dealing with affective information in educational recommender systems is an open issue. Some authors (see [17]) have proposed applying observational techniques on tutoring actions to facilitate the externalization of the tutors' decision-making processes during the tutoring support in order to find out how and when to respond to the learners' affective states.

Following that approach, TORMES methodology can be used to involve educators in identifying when, what and how the emotional feedback needs to be provided to each particular learner in each educational scenario. In particular, TORMES adapts the ISO standard 9241-210 to guide educators in eliciting and describing recommendations with educational value for their scenarios [21]. The application of TORMES involves several educators in the process, so it is costly in terms of resources. However, in our view, this is the most informative way to get the knowledge needed to be able to properly take into account affective issues in educational recommendations. This approach pays off since the recommendations can be provided and adapted to different courses and situations, and eventually are managed by the recommender, which takes into account the learner evolving process. When a large sample of educational affective recommendations generated with TORMES is available, the research question should move from identifying recommendation opportunities that deal with affective issues to finding appropriate algorithms that design affective recommendations with or without the involvement of educators.

TORMES methodology can be carried out at any time in the course life cycle. However, if the course has not been run yet, the input data would come from similar past courses and the associated educational experience in them. Four activities are defined: 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. In each of these activities, relevant information to consider the affective issues in the recommendations process during the course execution can be gathered, as follows:

- **Context of use.** The goal of this activity is to identify the context of use where the recommendations are to be delivered. Information can be gathered from two sources. On the one hand, individual interviews to educators that can serve to elicit best practices from their educational experiences. Here, the interviewer should ask the educator if she takes into account the emotional state of their learners, and if so, what features she takes into account to detect the learners' affective state (educator detection approach) and how she reacts to it by describing the emotional feedback provided (educator adaptation approach). On the other hand, data mining analysis can be done on data gathered from learners interactions in the course to complement the initial description of the context of use obtained from the interviews, mainly adding precision (e.g. from the interview, the educator can mention the she thinks that learners with very infrequent contributions in the course space are low motivated, and the data mining techniques can be used to cluster learners in several groups regarding their engagement in the course and their motivation level in order to identify the particularities of low engaged learners with low motivation). To extract relevant information regarding affective issues, the data mined should include, if available, i) the answers given by the learners to specific questionnaires such as the SAM to compute the emotions along predefined dimensions and the FFM to obtain the learners' personality traits, ii) the data gathered by physiological sensors and eye-trackers, and iii) from non-obtrusive observations such as keyboard and mouse interactions, facial and vocal spontaneous expressions and gestures.

- **Requirements specification.** Following the scenario based approach [29] that proposes the definition of a problem and its counterpart solution scenario, the information obtained from the activity 'Context of use' is used to build representative scenarios of the tutoring task in order to identify recommendation opportunities in them, where the problem scenario identifies the situations where learners lack of support and the solution scenario avoids or minimizes those problematic situations by offering appropriate recommendations. The goal is to extract knowledge from the educators on what the requirements are for the recommendations within the given context of use and identify an initial set of recommendations. The information mined in the previous activity can be used here to propose specific values for the applicability conditions of the recommendations proposed. For instance, following the above example, if most low engaged and low motivated learners are characterized as solitary in the extraversion trait of the FFM and they have entered in the course no more than 12 times, these quantitative information can be used by the educator to fill in the corresponding applicability conditions (e.g., the recommendation is to be delivered to learners with the following values in their user model: *extraversion* = *solitary* and *number_of_sessions_in_course* < *12*). As a result, an initial version of each of the recommendations proposed is described in terms of the recommendations model. The affective issues are to be included in this description. Hence, the recommendation model needs to be enriched with this information (see Section 3.2.2).
- **Create design solutions.** The goal of this activity is to validate the recommendations proposed in the previous activity by a group of experienced educators. Specifically focus groups are used to involve several educators in validating the initial set of recommendations elicited from the scenarios in the previous activity in order to revise the recommendations obtained in the solution scenario and come to an agreement. Educators involved in the validation should

have experience with affective computing to be able to validate the recommendations from that perspective.
- **Evaluation of designs against requirements.** In this activity, affective designed recommendations can be delivered in the e-learning system and allow educators and learners to evaluate them in their context by rating their relevance and classifying them in terms of their conceptual model. Preferably, the running prototype can be a functional system, but if that is not possible, a Wizard of Oz can be used to simulate the response of the system.

In this way, TORMES helps educators to understand the recommendation needs in their scenarios and supports them in eliciting sound recommendations that address cognitive, meta-cognitive, social and affective issues required when learners interact with their courses online. Moreover, TORMES also supports the changing of educational needs since the process is iterative and new recommendations can be added at any time during the course execution. Eventually, a set of semantically described oriented recommendations are ready to be automatically delivered to learners following a rule-based approach.

3.2.2 Enrichment of the recommendation model

As anticipated during the description of the activity ‘Requirements specification’ in the previous section, the SERS recommendations model needs to be extended to be able to describe the affective recommendations elicited with TORMES. In particular, up to now, we have detected the need to extend three elements of the recommendations model to include the modelling of affective issues.

The **content** element defines how to convey the recommendation to the learner. In the SERS approach, the recommendations are offered as a list of links of suggested actions. Therefore, the information to provide is the text to be shown to the learner in the recommendation areas of the course space. However, in a multimodal enriched environment, recommendations can be delivered to the learners in different ways. Therefore, this element needs to be extended with an attribute that describes the ***modality*** in which the recommendation has to be delivered to the learner, for instance, text or voice. Moreover, the actuators can produce the recommendations to the learner in different ways, and these ways can depend on the emotions handled [30]. For instance, a recommendation to be delivered by voice can be done with a calm tone or with an angry tone. Thus, another attribute needs to describe the ***emotional delivery state***.

The **runtime information** element that describes the applicability conditions that trigger the recommendations has to consider also the ***user personality*** (e.g. to describe the extraversion trait of the FFM) and ***emotional states*** as attributes that describe the user features to be taken into account.

The **justification** element provides the educational rationale behind the action suggested, so the affective issues considered should explicitly be mentioned in the justification text. A new attribute with this information can be added (e.g. ***affective support***).

3.2.3 New services in the architecture

To cope with the aforementioned modelling issues, from the architectural point of view, new services need to be added to the original service oriented architecture. The purpose here is to support new functionalities to cover the detection of emotions and the provision of emotional feedback in a multimodal environment. These services are: 1) *emotional data processing*, which collects the input from the different sources of emotional data available, 2) *multimodal emotions detection*, which combines the different sources of emotional data gathered to recognize the emotional state of the learner, and 3) *emotions delivery*, which delivers the recommendation to the learner in the corresponding affective modality. These services can be provided by the corresponding components, as shown in Figure 1. The sense of the arrows indicates the initiator of the information flow (request or sending).

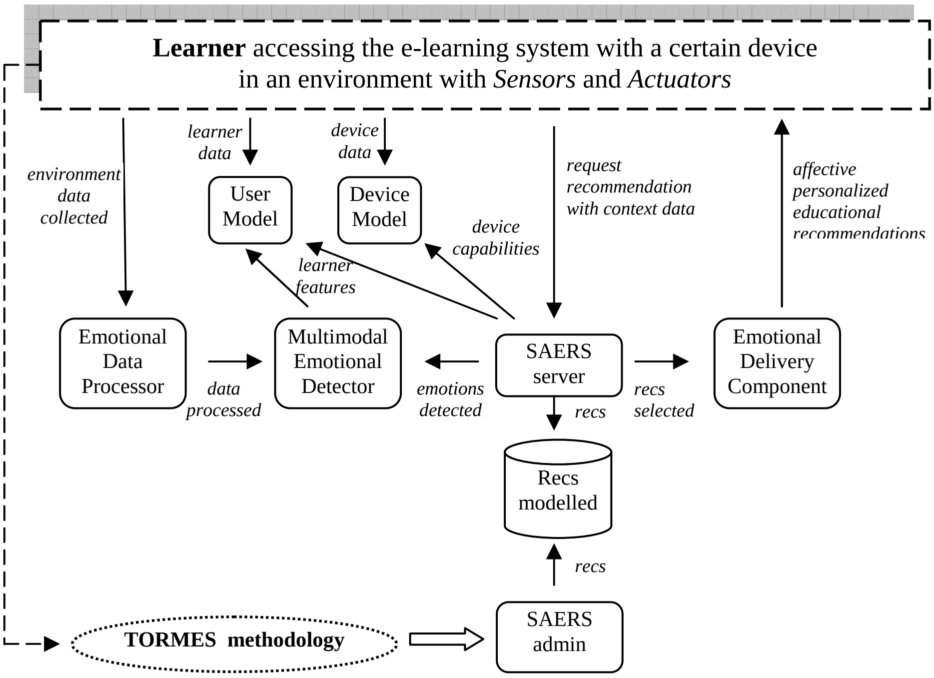

Figure 1. Components and data flow in the SAERS approach

The figure shows that the learner can be placed in a rich environment where sensors (defined in a general term) get data from her and actuators provide data to her at the same time that she is taking a course in an e-learning system through a certain device (e.g. PC, laptop, mobile, etc.) which might be combined with assistive technology (e.g. Braille line, speech recognition software, screen magnifier, among others) if the user requires some accessibility support.

At 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 and the device used to access. As in the SERS approach, the

SAERS server request data about the user and the capabilities of the device to the corresponding User Model and Device Model. Now, the SAERS needs additional information about the emotional state of the user, which can be requested to the Multimodal Emotional Detector. This component computes the affective state of the learner from the data received by the Emotional Data Processor as well as the information about the learner's personality stored in the User Model. The data gathered from the environment's sensors by the Emotional Data Processor consists in physiological data, eye positions and movements and physical interactions of the user (movements of the mouse, uses of the keyboard, voice or gestures). As a result, the Multimodal Emotional Detector can recognize the emotional state of the current learner and pass it to the reasoning component (SAERS server) so it can select the appropriate recommendations taking into account the current affective state of the learner.

Therefore, with that information, the SAERS server looks for exiting recommendations whose applicability conditions matches the user features and emotions, the device capabilities and the educational context. These recommendations have been designed and properly modelled through the SAERS admin with TORMES methodology. The resulting selected recommendations that are instantiated for the given request are passed to the Emotional Delivery Component, which adds the corresponding affective state to the response sent back to the environment, so the actuator selected can deliver the personalized educational oriented recommendations to the learner with the appropriate affective state.

As described in [20], the information exchanged by the different components involved in the SERS approach follows existing standards and specifications from IMS, ISO and W3C. To deal with the emotional information, the Emotion Markup Language (EmotionML) [24] proposed by the W3C to allow a technological component to represent and process data, and to enable interoperability between different technological components processing the data can be used. W3C EmotionML is conceived for 1) manual annotation of data such as videos, of speech recordings, of faces, of texts, etc., 2) automatic recognition of emotion-related states from user behaviour including information from physiological sensors, speech recordings, facial expressions, etc., as well as from multi-modal combinations of sensors, and 3) generation of emotion-related system behaviour providing responses, which may involve reasoning about the emotional implications of events, emotional prosody in synthetic speech, facial expressions and gestures of embodied agents or robots, the choice of music and colours of lighting in a room, etc.

4 Ongoing works

In order to evaluate our approach we are running several experiments in the context of the MAMIPEC project (Multimodal approaches for Affective Modelling in Inclusive Personalized Educational scenarios in intelligent Contexts - TIN2011-29221-C03-01). Our goal is twofold. On one hand, detect emotions from users' interactions in the e-learning environment through multiple sources (i.e. questionnaires and sensors). On the other hand, use that information to elicit appropriate recommendations with

TORMES methodology that take into account the emotional needs of the learners, and deliver affective educational oriented recommendations personalized to the learner through the e-learning environment by the extended SERS approach, that is, the SAERS.

Up to now, we have carried out a pilot with two users to test the appropriateness of the activities designed to induce emotions while the learner is taking the course activities. Participants were asked to perform mathematical exercises with several levels of difficulty and varied time restrictions. At the beginning they filled in the FFM questionnaire, and after each exercise they were asked to fill in the SAM scale to measure the caused emotions with the dimensional approach. With that experiment, we aim to check if the induced emotions can be measured with the technological infrastructure that we have prepared, which combines diverse sources for gathering emotional data from users. The pilot was successful in the sense that we were able to integrate and record data from different sources simultaneously, namely, 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. We are currently processing the data obtained trying to automate its processing for forthcoming sessions.

The next steps consist in revising the educational scenario proposed for this pilot and applying the TORMES methodology to elicit and design affective educational oriented recommendations taking into account the extensions to the SAERS approach to deal with the modelling issues, such as the new attributes proposed for some of the elements of the recommendations model (i.e. modality, emotional delivery, user personality, emotional state, affective support). The development of the components to provide the services required (i.e. emotional data processing, multimodal emotions detection and emotions delivery) is also part of future works. The W3C EmotionML language is to be considered to facilitate the exchange of the affective information among the components of the service oriented architecture.

Acknowledgments

Authors would like to thank the participants of the pilot study for their participation in it as well as the colleagues from the MAMIPEC project who were involved in the preparation and running of the pilot. Authors would also like to thank the European Commission and the Spanish Government for funding the projects of aDeNu research group that have supported this research work. In particular, MAMIPEC (TIN2011-29221-C03-01), A2UN@ (TIN2008-06862-C04-01/TSI) and EU4ALL (FP6-2005-IST-5). Moreover, Olga C. Santos would like to thank TELSpain for being awarded a mobility grant to attend the workshop RecSysTEL at EC-TEL 2012, where this work is presented.

References

1. Arapakis, I., Moshfeghi, Y., Joho, H., Ren, R., Hannah, D., Jose, J., Gardens, L. Integrating facial expressions into user profiling for the improvement of a multimodal recommender system. In: Proceedings of the IEEE International Conference on Multimedia and Expo, p. 1440–1443, 2009.
2. Blanchard, E.G., Volfson, B., Hong, Y.J. Lajoie, S.P. Affective Artificial Intelligence in Education: From Detection to Adaptation. In Proceedings of the 2009 conference on Artificial Intelligence in Education: Building Learning Systems that Care: From Knowledge Representation to Affective Modelling (AIED 2009), 81-88, 2009.
3. Bradley, M.M., Lang, P.J. Measuring Emotion: The Self-Assessment Manikin and the Semantic Differential. Journal of Behavior Therapy und Experimental Psychiatry, 25 (I), 49-59, 1994.
4. Carberry, S., de Rosis, F. Introduction to special issue on affective modeling and adaptation. User Model. User-Adapt. Interact. 18(1), p. 1–9, 2008.
5. Craig, S. D., Graesser, A. C., Sullins, J., Gholson, B. Affect and learning: An exploratory look into the role of affect in learning with AutoTutor. Journal of Educational Media, 29 (3), 241-250, 2004.
6. de Lemos, J., Sadeghnia,G.R., Ólafsdóttir, I., Jensen, O. Measuring emotions using eye tracking. Proceedings of Measuring Behavior, p. 226, 2008.
7. Ekman, P.: Basic emotions. In: Dalgleish, T., Power, T. (eds.) Handbook of Cognition and Emotion.Wiley, New York, 1999.
8. Filho, J., Freire, O. On the Equalization of Keystroke Time Histograms. Pattern Recognition Letters. Elsevier, Vol. 27, Issue 12, pp. 1440-1446, 2006.
9. Goldberg, L.R. The structure of phenotypic personality traits. American Psychologist 48 (1), p. 26–34, 1993.
10. Gonzalez, G., de la Rosa, J.L., Montaner, M.., Delfin, S. Embedding Emotional Context in Recommender Systems. In Proceedings of the 2007 IEEE 23rd International Conference on Data Engineering Workshop (ICDEW '07). p. 845-852, 2007.
11. Kuo, F.F., Chiang, M..F., Shan, M.k:, Lee, S.Y. Emotion-based music recommendation by association discovery from film music. In Proceedings of the 13th annual ACM international conference on Multimedia (MULTIMEDIA '05), 507-510, 2005.
12. Mahmoud, M., Baltrušaitis, T., Robinson, P., Riek, L. 3D corpus of spontaneous complex mental states. In Proceedings of the International Conference on Affective Computing and Intelligent Interaction (ACII 2011). Lecture Notes in Computer Science, 2011.
13. Manouselis, N., Drachsler, H., Vuorikari, R., Hummel, H., Koper, R. Recommender Systems in Technology Enhanced Learning, in Kantor P., Ricci F., Rokach L., Shapira, B. (Eds.), Recommender Systems Handbook: A Complete Guide for Research Scientists & Practitioners, 2010.
14. Mehrabian, A. Pleasure-arousal-dominance: a general framework for describing and measuring individual differences in temperament. Curr. Psychol. 14(4), p. 261–292, 1996.
15. Oehme, A., Herbon, A., Kupschick, S., Zentsch, E. Physiological correlates of emotions. Workshop on Artificial Societies for Ambient Intelligence. Artificial Intelligence and Simulation of Behaviour, in association with the AISB '07, 2-4 April, 2007.
16. Picard, R.W. Affective Computing. MIT Press, Cambridge, 2000.
17. Porayska-Pomsta, K., Mavrikis, M., Pain, H. Diagnosing and acting on student affect: the tutor's perspective. User Model. User-Adapt. Interact. 18(1-2): 125-173, 2008.
18. Qing-qiang, L., Zhu, J., Kong, T. RSED: a Novel Recommendation Based on Emotion Recognition Methods. International Conference on Information Engineering and Computer Science (ICIECS 2009), 1–4, 2009.

19. Robison, J.L., McQuiggan, S.W., Lester, J.C. Developing Empirically Based Student Personality Profiles for Affective Feedback Models. Intelligent Tutoring Systems 2010, 285-295, 2010.
20. Santos O.C., Boticario J.G. Requirements for Semantic Educational Recommender Systems in Formal E-Learning Scenarios. Algorithms. 4(2), 131-154, 2011.
21. Santos, O.C., Boticario, J.G. TORMES methodology to elicit educational oriented recommendations. Lect. Notes Artif. Intell. 6738, 541–543, 2011.
22. Santos, O.C., Boticario, J.G. (Eds.) Educational Recommender Systems and Techniques: Practices and Challenges. IGI Publisher, 2012.
23. Sarrafzadeh, A., Alexander, S., Dadgostar, F., Fan, C., Bigdeli, A. How do you know that I don't understand? A look at the future of intelligent tutoring systems. Computers in Human Behavior, Volume 24, Issue 4, July 2008, 1342-1363, 2008.
24. Schröeder, M., Baggia, P., Burkhardt, F., Pelachaud, C., Peter, C., Zovato, E. Emotion Markup Language (EmotionML) 1.0. W3C Candidate Recommendation 10, 2012 May 2012
25. Shen, L., Wang, M., Shen, R. Affective e-Learning: Using "Emotional" Data to Improve Learning in Pervasive Learning Environment. Educational Technology & Society (ETS) 12(2), 176-189, 2009.
26. Tkalcic, M., Burnik, U., Kosir, A. Using affective parameters in a content-based recommender system for images. User Model. User-Adapt. Interact. 20(4), 279-311, 2010.
27. Yik, M., Russell, J.A., Ahn, C.k., Fernandez Dols, J.M., Suzuki, N. Relating the five-factor model of personality to a circumplex model of affect: a five-language study. In: McCrae, R.R., Allik, J. (eds.) The Five-Factor Model of Personality Across Cultures, Kluwer Academic Publishers, New York, 79–104, 2002.
28. Zeng, Z., Pantic, M., Roisman, G.I., Huang, T.S. A survey of affect recognition methods: audio, visual and spontaneous expressions. IEEE Trans. Pattern Anal. Mach. Intell. 31(1), 39–58, 2009.
29. Rosson, M. B. and Carroll, J. M. Usability engineering: scenario-based development of human computer interaction. Morgan Kaufmann, 2001.
30. Baldassarri, S., Cerezo, E., Seron, F.J. Maxine: A platform for embodied animated agents, Computers and Graphics, 32 (4), 430-437, 2008.