Exploring Arduino for Building Educational Context-Aware Recommender Systems that Deliver Affective Recommendations in Social Ubiquitous Networking Environments

Olga C. Santos(✉) and Jesus G. Boticario

aDeNu Research Group, Artificial Intelligence Department,
Computer Science School, UNED, C/Juan del Rosal 16, 28040 Madrid, Spain
{ocsantos,jgb}@dia.uned.es

Abstract. One of the most challenging context features to detect when making recommendations in educational scenarios is the learner's affective state. Usually, this feature is explicitly gathered from the learner herself through questionnaires or self-reports. In this paper, we analyze if affective recommendations can be produced with a low cost approach using the open source electronics prototyping platform Arduino together with corresponding sensors and actuators. TORMES methodology (which combines user centered design methods and data mining techniques) can support the recommendations elicitation process by identifying new recommendation opportunities in these emerging social ubiquitous networking scenarios.

Keywords: Contextual recommender systems · Educational recommender systems · Ubiquitous computing · Affective computing · Arduino · Sensors · Actuators · ISO 9241-210

1 Introduction

Recommender systems in educational scenarios can be used to support learning [1]. Their capability of observing learners' behavior and making personalized suggestions accordingly reaches its full potential when context is taken into account [2]. Furthermore, recommender systems are nowadays integrated in applications available in the cloud, mainly following a centralized approach and produced at the recommendation server [1]. Therefore, they can integrate information sources coming from different components.

Context-aware ubiquitous learning is a computer supported learning paradigm for identifying learners' surrounding context and social situation to provide integrated, interoperable, pervasive and seamless learning experiences [3]. Several studies have reported on the benefits of context-aware ubiquitous learning, for instance in the promotion of learning motivation [4] and the improvement of learning effectiveness [5]. In this way, the learning system is able to sense the real-world situation of the learners, interact with them and provide them with adaptive support accordingly [6].

Y. Chen et al. (Eds.): WAIM 2014, LNCS 8597, pp. 272–286, 2014.
DOI: 10.1007/978-3-319-11538-2_25

As discussed in [2], contextual information can be captured by sensors. However, from the review done to 11 context-aware educational recommender systems and reported in Sect. 2, it results that the automated gathering of contextual information when dealing with learners' affective states is still a challenge. This challenge is to be tackled due to the interplay between the cognitive aspects of learning, the external behavior showed by the learner and affect [7]. In fact, there are benefits in creating sensor based personalized affective feedback for each individual student in a classroom environment, and this can be done with minimally invasive sensors [8].

In this situation, there is a need to understand the human and social factors of making recommendations in Social Ubiquitous Networking Environments (SUNE). By SUNE we refer to those environments that support social interactions and are interconnected through different networks (e.g., Internet and wireless local networks) and provide advanced computing features, where computing is made to appear everywhere and anywhere using any device, in any location, and in any format, involving sensors, microprocessors, as well as new input/output user interfaces. There is a widely used open source physical computing platform called Arduino[1], which is characterized by its flexible and simple to use hardware as well as a relatively easy to use C like programming language. This prototyping platform seems appropriate for building complex electronics at low cost, such as those that can support SUNE.

Thus, in this paper, we explore the potential of Arduino for delivering contextualized recommendations in e-learning SUNE. First, we analyze the contextual features considered in technology enhanced learning scenarios and how educational recommender systems deal with them. Next, we review the usage of Arduino to deal with contextual features, with emphasis on those that are the most challenging (i.e., affective states). After that, we propose TORMES methodology to identify context-aware affective recommendation opportunities in SUNE. Following, we discuss some open issues identified, and end with some conclusions and the outline of future work.

2 Context in Educational Recommender Systems

As learning environments are increasing their diversity and richness, the incorporation of contextual information about the learner in the recommendation process is attracting major attention [9]. After discussing several approaches to categorize the context, Verber et al. have proposed a context framework that considers 8 categories (i.e., computing, location, time, physical conditions, activity, resource, user, and social relations) for classifying context-aware recommender systems in technology enhanced learning scenarios [2]. In order to understand how recommender systems deal with context in educational scenarios, we have analyzed those found in our review of the literature. Table 1 compiles the 11 educational recommender systems analyzed. For each of them, the analysis has identified the application scope, the context considered, the recommendation approach followed and the evaluation carried out (if any). First, they are chronologically ordered, and then by system name (when available).

[1] http://arduino.cc/

Table 1. Main features of reviewed context-aware educational recommender systems

System	Scope	Context	Recommendation approach	Evaluation
CALS Yau and Joy, 2007 [10]	activities	Retrieve contextual information from the scheduled events database (time available for learning and type of location) and two sensors (GPS for location detection and a microphone for noise detection). Other types of sensors to detect other environmental attributes are mentioned (light levels and temperature).	Identifies the learning context which the learner is currently situated in, and then recommends appropriate learning activities for them based on the learning context using if-then rules.	n/a
SPA Gonzalez et al., 2007 [11]	course	Emotional features from tests and interactions (which theoretically can include physiological signals obtained through wearable computing).	Generate emotional arguments with predictive models to suggest enrolling a course (by activating or inhibiting excitatory attributes to be shown in the message).	Proposed predictive models were evaluated with data extracted from users registered in a website.
Affective e-learning model Shen et al., 2009 [12]	learning materials	Information collected from physiological sensors (skin conductance, blood volume pressure and electroencephalograph activity, heart rate) tagged with self-reports from the learner.	Emotion-aware recommendation rules implemented on a intelligent content recommender.	Physiological data from 1 subject (several weeks, close-to-real world setting). Recommendations evaluated by analyzing the times the user changed content recommended.

(Continued)

Table 1. *(Continued)*

System	Scope	Context	Recommendation approach	Evaluation
PL-CR2 Luo et al., 2010 [13]	course	The context sensor module collect dynamic activities data from learners, such as connecting mode, bandwidth and resource access response time (download time).	A resource is recommended using a hybrid recommendation algorithm that consider if the resource's type matches learner's connecting mode and the resource access response time satisfies learner's lowest requirement.	Simulations to evaluate recommendation algorithm performance.
Semantic Learning Space + ELAA Yu et al., 2010 [14]	learning content	Aggregates context information gathered from physical sensors (camera, microphone, RFID, GPS, pressure sensors) and virtual sensors (calendar service, organization workflow, etc.) aimed to identify the learning schedule and task.	Recommended content defined by the personal context such as prior knowledge, goals, user's situation context (i.e., subject studied for a long time, recommend another subject) and the presentation by the infrastructure context (device, network) are managed in terms of ontologies.	14 participants used the system and answered a questionnaire to measure the user acceptance based on the content provisioned, response time, and user interface.
n/a Wang and Wu, 2011 [15]	resources	RFID is used to sense the location of the learning objects in the actual environment.	Once the system detects learning targets in the actual environment, the learning recommendation module automatically generates a recommendation list that matches the learner requirements.	30 participants in a control vs. experimental group analysis to verify with a t-test the effect on learning effectiveness (i.e., if provided learning support helped learner to complete task quicker and more accurate)

(Continued)

Table 1. *(Continued)*

System	Scope	Context	Recommendation approach	Evaluation
SCROLL Li et al., 2012 [16]	learning content	Collects learner's context information from: (i) activity (motion and actual action, such as listening to music, surfing Internet), (ii) device status (battery, Internet connection, ring tone), (iii) environmental data (location, time, temperature, weather).	When physical learning objects are detected nearby, recommend location-dependent quizzes or information shared by other learners on that object. Additionally, if the learner is in her preferred learning context, the system will show messages to encourage her to study.	11 students used the system to support their learning. Engagement, system usability, user satisfaction and stimulation to learn were measured.
A3 Boff and Reategui, 2013 [17]	peers, contents, exercise	Questionnaires and GUI controls to let the learner indicate her affective states.	Recommendation provided in natural language through a virtual character. The type of language and the emotional appearance of the virtual character depend on the learner's affective state. Peer recommendation takes into account the mood state of the peer to be recommended.	Performance of recommended items' descriptions in terms of processing time and accuracy
Auto-Tutor D'mello and Graesser, 2013 [18]	response given by a pedagogical agent	Detects the emotions (boredom, flow/engagement, confusion, frustration) of a learner by monitoring conversational cues, gross body language, and facial features.	Synthesizes affective responses through animated facial expressions and modulated speech to address the presence of negative emotions. Production rules informed by theories on emotion and learning as well as recommendations made by pedagogical experts.	Performance of classification techniques when detecting learners' affective states using experimental simulations.

(Continued)

Table 1. *(Continued)*

System	Scope	Context	Recommendation approach	Evaluation
BISPA Kaklauskas et al., 2013 [19]	learning materials	Learners control from a GUI the gathering of the physiological measures (skin temperature, skin humidity, skin conductance, touch intensity, heart rate, blood pressure) computed with external equipment every 45 minutes.	Recommendations to improve learning productivity are selected from a database of 5000 recommendations.	Data from 1 student was used to compare her learning productivity and interest in learning with her physiological parameters.
LRAR Leony et al., 2013 [20]	peers, activities and resources	Learners select affective state from a static list. Future work is to develop plug-ins to include sensors to gather the affective state (galvanic skin response, face gesture recognition).	The recommendation engine is developed on top of Apache Mahout machine learning engine and the algorithm to calculate the recommendations is left for the implementation of each case.	n/a (plans focus on evaluating performance in terms of the response time of a recommendation request to the server).

The application **scopes** identified (i.e., what is recommended) are ***peers*** [17, 20], ***courses*** [11, 13], ***learning items*** (referred as activities, materials, contents, resources and exercises) [10, 12, 14–17, 19, 20] and ***responses*** provided by pedagogical agents to respond to learners' affective and cognitive states [18].

Regarding the **context**, reported systems involve several dimensions of the aforementioned contextual framework [2], as follows: (1) ***computing*** (dealing with networks, hardware and software characteristics) [13, 14, 16], (2) ***location*** (information to place the learner, either at a high grain such as classroom, home or outdoor, or at a lower grain by specifying geometric coordinates) [10, 14–16], (3) ***time*** (during which contextual information is known or relevant, either at a higher grain such as week, month, etc., or at a lower grain by given the time span) [10, 14, 16], (4) ***physical conditions*** (environmental conditions where the system or user is situated, commonly including measures for heat, light and sound) [10, 16], (5) ***activity*** (i.e., the task, objectives or actions of the learner) [10, 14, 16], (6) ***resource*** (used for learning) [14, 15], (7) the ***affective information*** within the user dimension [11, 12, 17–20], and (8) ***social relations*** (describing associations, connections or affiliations between two or more persons) [none].

Recommendation **approaches** followed are ***rules*** [10, 12, 16, 18, 19], predictive ***models*** [11], recommendation ***algorithms*** [13, 15, 17, 20] and ***ontologies*** [14].

As for the **evaluation**, users were involved in the evaluation of less than half of the systems analyzed [12, 14–16, 19]. Only in one of them (i.e., [15]) the effect of recommendations provided on learning effectiveness was statistically evaluated.

From this analysis of context-aware recommender systems in technology enhanced learning scenarios follows that most recommendations focus on learning items, affective information is the most common contextual feature considered while no system dealing with social relations contextual features has been found, recommendation approaches are mainly rules or recommendation algorithms, and the evaluation of the learning effectiveness with statistical significance is hardly carried out.

Having this in mind, in the next section we analyze if affective recommendations can be produced in educational context-aware recommender systems with a low cost approach using the open source electronics prototyping platform Arduino together with corresponding sensors and actuators.

3 Arduino Support for Contextualized Recommendations

Arduino is a tool for making computers sense and control the physical world, taking inputs from a variety of sensors, and can affect its surroundings by controlling lights, motors, and other physical outputs (i.e., actuators) [21]. Arduino projects can be standalone, or they can communicate either with software running on a computer via a serial communication or with an external component using various wireless mechanisms (Wi-Fi, Bluetooth, GSM, GPRS, Xbee, etc.).

We have researched in the literature the usage of Arduino to produce context-aware recommender systems that deal with related affective information. This implies two perspectives: (i) gathering context information, and (ii) delivering context-based feedback.

Regarding context information gathering, we found 10 works that report the usage of Arduino to gather physiological measures. Although in most cases the data collected was not used to detect the affective state of the user, the same data can be used (as reported in the corresponding works in Table 1) with these other purpose. Thus, in Table 2 we compile the works found in the literature that use Arduino for gathering physiological data and identify the system goal, the type of Arduino board, and the sensors used. In addition, it is specified if sensors have been developed by the authors or an available component was used, stating in the former case the manufacturer and/or model. All works have been published in 2013, which suggests that this is an emerging research line with a trend in the appearance of more research and thus, an opportunity to be caught up by educational context-aware recommender systems. Works reviewed have been ordered alphabetically with the first authors' last name.

Works compiled in Table 2 take measures through physiological sensors that can be used to detect affective states [33]. Additionally, some of them also consider physical measures, such as movement with the accelerometer [23, 27, 32]. All the systems analyzed (except [26]) include the validation of the system developed, showing that the deployment carried out properly detects the physiological signals aimed to be recorded with the Arduino infrastructure.

Regarding the delivery of context-based feedback, [33] suggests audiovisual adaptation to reflect or evoke certain affective state in the user by making use of either music or light. We have found 2 works in this respect. In [22], Arduino was used to indicate with color lights (specifically, red-green-blue light emitting diodes - RGB LEDs) the popularity of the recommended item (in this case, a bottle of wine). In [23], the system provides an actuator, specifically a LED to give visual feedback to the user through changes in the light conditions.

Although works reported are not specific for the educational domain, the usage of Arduino in educational context-aware recommendations seems of interest to manage contextual information about the learner. This information can be of value to deliver affective recommendations in SUNE that take into account learners' affective state.

4 Affective Contextual Recommendations in SUNE

From previous sections, it seems that integrating Arduino low cost infrastructure for sensing the learning context is of potential interest in SUNE. In particular, it seems feasible to build the physiological infrastructure for affective contextual information gathering using Arduino boards and available physiological sensors, such as the e-Health platform used in [29]. However, new recommendation opportunities in SUNE that go beyond those already identified in technology enhanced learning settings have to be identified. These are to take into account the possibilities of existing sensors and actuators that can be used to deliver affective educational recommendations.

The works reported in Sect. 2 already provide some ideas for educational context-aware affective recommendations. In particular, in [12] the following emotion-aware recommendation rules are used: (1) if learner is engaged, deliver contents according to subject's learning progress and objective; (2) if learner is confused, deliver examples or case studies in line with current knowledge; (3) if learner is bored, deliver video/music

Table 2. Arduino works that deal with physiological signals. Physiological sensors acronyms: **ECG:** Electrocardiography; **EDA:** Electrodermal Activity, **EEG:** Electroencephalography, **EMG:** Electromiography; **GSR:** Galvanic skin response; **HR:** Heart Rate.

System	Goal	Board	Sensors
BITalino Guerreiro, 2013 [23]	Multimodal biosignal acquisition for rapid prototyping of end-user applications in physiological computing.	Arduino Uno	ECG (developed), EMG (developed), EDA (developed), accelerometer (Analog Devices), phototransistor (TEMT6000).
Kishore et al., 2013 [24]	Recognize human activities, such as if the user is sitting or standing.	Arduino	Pulse Sensor[a] to evaluate HR variability.
Koga et al., 2013 [25]	Capture the transition of mental conditions.	Arduino Mega ADK	EMG (Oisaka Electronic), EEG (Mindflex headset by Mattei), HR (Polar).
Lotlikar et al., 2013 [26]	Help people measure vital signs at home and keep their record.	Arduino Duemilanove	Pulse, skin temperature, blood pressure (manufacturer not specified).
Lung et al., 2013 [27]	Person monitoring to extract behavioral patterns for assistance.	Arduino ChipKit Max32	HR (chest belt BM-CS5R) and accelerometer (EZ Chronos watch).
Mansor et al., 2013 [28]	Remote health monitoring system.	Arduino Uno	Body temperature (LM35); HR also considered but not reported.
Orha and Oniga, 2013 [29]	Assessment of health status for disease prevention. Emotion determined from GSR data.	Arduino Uno	Body temperature, blood pressure, respiratory rate, ECG and GSR (all from the e-Health platform[b])
Sinha et al., 2013 [30]	Polygraph tests for lie detection.	Arduino Uno	GSR and HR (developed)
Rahim, 2013 [31]	Check the stress level on the user.	Arduino Uno	Temperature sensor (LM 35), GSR (developed) and pulse sensor (same as in [24]).
Roy et al., 2013 [32]	Wearable electronic rescue system that detects abnormal condition of heart as well as sudden accidental fall.	Arduino Mega	ECG (developed) and accelerometer (ADXL 345).

[a] http://pulsesensor.myshopify.com/

[b] http://www.cooking-hacks.com/documentation/tutorials/ehealth-biometric-sensor-platform-arduino-raspberry-pi-medical

according to subject's preference to ease the tension; and (4) if learner is hopeful, deliver music according to subject's preference to enhance meditation. In [19], the following examples have been identified: (1) learning the most difficult subjects is recommended in the morning, leaving the easier ones for the evening, (2) limit contacts with people who cause negative stress, (3) for students who get up in the morning in bad mood get recommendations on ways to improve their learning efficiency, which are different than those given when she is studying in the evening and in good mood. In [20] some use cases are suggested: (1) recommend peer in good mood with adequate level of knowledge and who felt the same sensations when carrying out the activity in which the current learner is blocked, (2) if the learner is confused, recommend to read related exploratory material, (3) recommend a resource accessed by similar learners (in terms of having the same affective state when accessing other resources). Finally, when pedagogical agents are used to deliver recommendations, the user's affective state can be considered when choosing the type of language for the character to talk at a given moment [17]. In addition, in the pedagogical agent presented in [18], rules are also dynamically adapted to each individual learner, such as if the current emotion is classified as boredom and the previous emotion is frustration then the learner can be told "Maybe this topic is getting old. I'll help you finish so we can try something new".

However, the above sample rules compiled from the literature do not consider the particularities of SUNE, which aim to support social interactions and are interconnected through different networks where computing is made to appear everywhere and anywhere using any device, from any location and with any format. In addition, we already commented in Sect. 2 that no recommender system dealing with social relations contextual features was found in the review of the state of the art.

In order to identify recommendation opportunities in e-learning SUNE that properly take advantage of available contextual information, TORMES methodology can be used. TORMES [34] follows the standard ISO 9241-210 and is based on: (1) user centered design methods to gather educators' tacit experiences in supporting learners emotionally in e-learning scenarios, and (2) data mining techniques to detect learners' emotional states during interactions with the system. Regarding data mining for emotions' detection, it follows a multimodal detection approach as described elsewhere [35, 36].

To apply TORMES, we will contact some educators with experience in social ubiquitous learning. In this way, we expect to elicit relevant SUNE scenarios where educational context-aware recommendation opportunities are identified and managed in terms of emotion-aware recommendation rules. The required infrastructure to deploy these scenarios can take advantage of current progress in the field (e.g., cloud support for the recommendation logic that automatically collects contextual information from sensors). To cope with interoperability, a semantic modeling of the recommendations elicited is to be done [37], which considers available emotional focused specifications, such as W3C Emotion ML [38].

Contextual features such as sound, light, environment temperature and so on that can also be managed with Arduino through corresponding sensors and actuators will be specially taken into account as they can potentially enrich the way recommendations are delivered. To facilitate the elicitation process regarding the recommendation possibilities offered to support ubiquitous learning, we are considering the use of the board

Arduino Esplora,[2] which already provides a number of built-in, ready-to-use set of on board sensors and actuators for interaction. In particular, it has onboard sound and light outputs, and several input sensors, including a temperature sensor, an accelerometer, a microphone, and a light sensor. For testing other sensors and actuators, the Groove system[3] (which plugs into an Arduino) might also be an interesting option.

5 Discussion

Human factors such as users' affective states matter during the recommendation process in SUNE, for instance when rating a resource to feed content-based or collaborative filtering recommendation approaches. Therefore, there is a need to automatically gather this information with a low cost infrastructure so educational context-aware recommender systems can take that information into account during the recommendation process. However, although this is a relevant feature for building educational context-aware recommender systems, the state of the art compiled in Table 1 shows that existing recommenders do not have that capability. It is also relevant to note that during 2013 several works have been published showing how Arduino open source electronics prototyping platform was successfully used to measure physiological signals (although with different goals than those pursued by educational context-aware recommender systems, mainly dealing with medical and health related projects[4]). Therefore, this recent trend can also be followed for affective states detection with Arduino based approaches.

However, several open issues exist. For instance, although sensors have been shown to accurately measure physiological aspects, the translation from physiological aspects to affective states is all but straightforward. Thus, it has to be further researched how accurate are these sensors in capturing affective states and how accurate do they need to be to fit the recommendation delivery process. Moreover, even if these sensors are very accurate, it has to be investigated how much can these measurements contribute to the recommendation process and check if recommendations delivered get perceptibly better by including affect in the prediction process. Finally, even if the predictions get better by including affective states, it is also needed to evaluate if this has an impact on actual learning and these potentially better recommendations indeed translate into observably improved learning outcomes. In fact, evaluating adaptive systems (such as recommenders) is very challenging, even more if they are deployed in educational scenarios. This situation is also reflected in our analysis of the state of the arte of educational context-aware recommender systems, as only 1 system from the 11 analyzed has attempted to verify an effect on the learning effectiveness. This requires developing an appropriate user-centric evaluation framework for educational recommender systems in SUNE, which should be informed by available approaches to evaluate generic recommender systems [39, 40] as they can help to determine the

[2] http://arduino.cc/en/Guide/ArduinoEsplora

[3] http://www.seeedstudio.com/wiki/GROVE_System

[4] http://medicarduino.net/

behavioral and attitudinal improvements, as well as the potential mediating variables that could explain these effects.

Another issue that requires further analysis deals with the implementation, that is, how the different technological parts involved might work in conjunction to cope with the scenarios obtained with TORMES. In particular, TORMES application will serve to show the kind of learning scenarios (formal, non-formal, informal) that are best supported, the sensors that are to be used to capture the affective state, how the recommendations are to be provided through appropriate actuators and how they should look like, as well as the most appropriate context for Arduino based affect detection. Privacy issues are also to be considered.

For a real world deployment, wearable electronics (which are included as part of the users' cloths or complements such as watches, bracelets or glasses) are to be used. In this sense, there is already a wearable version of Arduino microcontroller called Lylipad.[5] LilyPad is a set of sewable electronic pieces designed to build soft interactive textiles and it can also sense information about the environment and act on it.

6 Conclusions and Future Work

In this paper we have explored the potential of Arduino for producing contextualized recommendations in e-learning SUNE and discussed if an Arduino prototyping approach can help to identify the human factors involved in the recommendation process, both in the input (i.e., detecting contextual information that reflects learners' affective states) and the output (i.e., delivering the affective recommendation) within the context in which the learner is placed.

Addressing affective issues is of relevance for e-learning SUNE as emotional intelligence is "a type of social intelligence that involves the ability to monitor one's own and others' emotions, to discriminate among them, and to use the information to guide one's thinking and actions" [41]. Additionally, social-affective information seems to be of value for promoting the communication and collaboration among learners [17].

Acknowledgements. Authors would like to thank Spanish Ministry of Economy and Competence for funding MAMIPEC project (TIN2011-29221-C03-01).

References

1. Drachsler, H., Verbert, K., Santos, O.C., Manouselis, N.: Panorama of Recommender Systems to Support Learning, 2nd edition (under review)
2. Verbert, K., Manouselis, N., Xavier, O., Wolpers, M., Drachsler, H., Bosnic, I., Duval, E.: Context-aware recommender systems for learning: a survey and future challenges. IEEE Trans. Learn. Technol. **5**(4), 318–335 (2012)

[5] http://lilypadarduino.org

3. Yang, S.J.H., Okamoto, T., Tseng, S.-S.: Context-aware an d ubiquitous learning (guest editorial). Educ. Technol. Soc. **11**(2), 1–2 (2008)
4. Chu, H.C., Hwang, G.J., Huang, S.X., Wu, T.T.: A knowledge engineering approach to developing e-libraries for mobile learning. Electron. Libr. **26**(3), 303–317 (2008)
5. El-Bishouty, M.M., Ogata, H., Yano, Y.: PERKAM: personalized knowledge awareness map for computer supported ubiquitous learning. Educ. Technol. Soc. **10**(3), 122–134 (2007)
6. Hwang, G.J.: Paradigm shifts in e-learning: from web-based learning to context-aware ubiquitous learning. In: Huang, R., Spector, J.M. (eds.) Reshaping Learning. New Frontiers of Educational Research, pp. 253–271. Springer, Heidelberg (2013)
7. Blanchard, E.G., Volfson, B., Hong, Y.J., Lajoie, S.P.: Affective artificial intelligence in education: from detection to adaptation. AIED **2009**, 81–88 (2009)
8. Cooper, D.G., Arroyo, I., Woolf, B.P., Muldner, K., Burleson, W., Christopherson, R.: Sensors model student self concept in the classroom. In: Houben, G.-J., McCalla, G., Pianesi, F., Zancanaro, M. (eds.) UMAP 2009. LNCS, vol. 5535, pp. 30–41. Springer, Heidelberg (2009)
9. Manouselis, N., Drachsler, H., Verbert, K., Duval, E.: Recommender Systems for Learning. Springer Briefs in Electrical and Computer Engineering. Springer, New York (2013)
10. Yau, J., Joy, M.: A Context-aware and adaptive learning schedule framework for supporting learners' daily routines. In: Second International Conference on Systems, (INCOS, 2007), pp. 31–36 (2007)
11. Gonzalez, G., De la Rosa, J.L., Montaner, M., Delfin, S.: Embedding emotional context in recommender systems. In: IEEE 23rd International Conference on Data Engineering Workshop, pp. 845–852 (2007)
12. Shen, L., Wang, M., Shen, R.: Affective e-learning: using emotional data to improve learning in pervasive learning environment. Educ. Technol. Soc. **12**(2), 176–189 (2009)
13. Luo, J., Dong, F., Cao, J., Song, A.: A context-aware personalized resource recommendation for pervasive learning. Cluster Comput. **13**(2), 213–239 (2010)
14. Yu, Z., Zhou, X., Shu, L.: Towards a semantic infrastructure for context-aware e-learning. Multimedia Tools Appl. **47**(1), 71–86 (2010)
15. Wang, S.L., Wu, C.Y.: Application of context-aware and personalized recommendation to implement an adaptive ubiquitous learning system. Expert Syst. Appl. **38**(9), 10831–10838 (2011)
16. Li, M., Ogata, H., Hou, B., Uosaki, N., Mouri, K.: Context-aware and personalization method in ubiquitous learning log system. Educ. Technol. Soc. **16**(3), 362–373 (2013)
17. Boff, E., Reategui, E.: Mining social-affective data to recommend student tutors. In: Pavón, J., Duque-Méndez, N.D., Fuentes-Fernández, R. (eds.) IBERAMIA 2012. LNCS, vol. 7637, pp. 672–681. Springer, Heidelberg (2012)
18. D'mello, S., Graesser, A.: AutoTutor and affective autotutor: learning by talking with cognitively and emotionally intelligent computers that talk back. ACM Trans. Interact. Intell. Syst. **2**(4), 23:2–23:39 (2013). (Article 23)
19. Kaklauskas, A., Zavadskas, E.K., Seniut, M., Stankevic, V., Raistenskis, J., Simkevičius, C., Stankevic, T., Matuliauskaite, A., Bartkiene, L., Zemeckyte, L., Paliskiene, R., Cerkauskiene, R., Gribniak, V.: Recommender system to analyze student's academic performance. Expert Syst. Appl. **40**(15), 6150–6165 (2013)
20. Leony, D., Gélvez, H.A.P., Merino, P.J.M., Pardo, A., Kloos, C.D.: A generic architecture for emotion-based recommender systems in cloud learning environments. J. Univers. Comput. Sci. **19**(14), 2075–2092 (2013)
21. Banzi, M.: Getting Started with Arduino. O'Reilly Media, Sebastopol (2009)

22. Garcia-Perate, G., Dalton, N., Conroy-Dalton, R., Wilson, D.: Ambient recommendations in the pop-up shop. In: Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '13), pp. 773–776 (2013)
23. Guerreiro, J.A.: Biosignal embedded system for physiological computing. Instituto Superior de Engenharia de Lisboa. Master Thesis (2013)
24. Kishore, P., Saraf, S.S., Onkari, S.M.: Human activities – their classification, recognition and ensemble of classifiers. Int. J. Comput. Appl. **76**(14), 6–11 (2013)
25. Koga, K., Nakayamal, I., Kobayashi, J.: Portable biological signal measurement system for biofeedback and experiment for functional assessment. In: 13th International Conference on Control, Automation and Systems (ICCAS 2013), pp. 412–416 (2013)
26. Lotlikar, S., Dolas, K., Rane, A., Paradkar, D.: Smart phone based e-health. In: International Conference on Computer Science and Engineering (CSE), pp. 12–15 (2013)
27. Lung, C., Oniga, S., Buchman, A., Tisan, S.: Wireless data acquisition system for IoT applications. Carpathian J. Electron. Comput. Eng. **6**(1), 64–67 (2013)
28. Mansor, H., Helmy, M., Shukor, A., Meskam, S.S., Rusli, N.Q.A.M., Zamery, N.S.: Body temperature measurement for remote health monitoring system. In: Proceedings of the IEEE International Conference on Smart Instrumentation, Measurement and Applications (ICSIMA), pp. 1–5 (2013)
29. Orha, I., Oniga, S.: Automated system for evaluating health status. In: IEEE 19th International Symposium for Design and Technology in Electronic Packaging (SIITME), pp. 219–222 (2013)
30. Sinha, A., Pavithra, M., Sutharshan, K.R., Subashini, M.: A MATLAB based on-line polygraph test using galvanic skin resistance and heart. Aust. J. Basic Appl. Sci. **7**(11), 153–157 (2013)
31. Rahim, S.N.Z.B.: Stress detector. University of Technology of Malaysia, Master Thesis (2013)
32. Roy, J.K., Deb, B., Chakraborty, D., Mahanta, S., Banik, N.: The wearable eletronic rescue system for home alone elderly- labview & arduino evaluation. IOSR J. Electron. Commun. Eng. **8**(6), 50–55 (2013)
33. Novak, D., Mihelj, M., Munih, M.: A survey of methods for data fusion and system adaptation using autonomic nervous system responses in physiological computing. Interact. Comput. **24**, 154–172 (2012)
34. Santos, O.C., Saneiro, M., Salmeron-Majadas, S., Boticario, J.G.: A methodological approach to eliciting affective educational recommendations. In: Proceedings of the 14th IEEE International Conference on Advanced Learning Technologies (ICALT '14), pp. 529–533 (2014). doi:10.1109/ICALT.2014.234
35. Saneiro, M., Santos, O.C., Salmeron-Majadas, S., Boticario, J.G.: Towards emotion detection from facial expressions and body movements to enrich multimodal approaches. Recent Adv. Inf. Technol. **2014**, 14 (2014). (Article ID 484873)
36. Salmeron-Majadas, S., Santos, O.C., Boticario, J.G.: Affective state detection in educational systems through mining multimodal data sources. In: D'Mello, S.K., Calvo, R.A., Olney, A. (eds.) 6th International Conference on Educational Data Mining. pp. 348–349. International Educational Data Mining Society, Memphis (2013)
37. Santos, O.C., Boticario, J.G., Manjarres, A.: An approach for an affective educational recommendation model. In: Manouselis, N., Drachsler, H., Verbert, K., Santos, O.C. (eds.) Recommender Systems for Technology Enhanced Learning: Research Trends & Applications, pp. 123–143. Springer, New York (2014)
38. Schröder, M. (ed.): Emotion Markup Language (EmotionML) 1.0, W3C Candidate Recommendation, Cambridge, Mass, USA (2012)

39. Pu, P., Chen, L., Hu, R.: Evaluating recommender systems from the user's perspective: survey of the state of the art. User Model. User-Adap. Inter. **22**, 317–355 (2012)
40. Knijnenburg, B.P., Willemsen, M.C., Gantner, Z., Soncu, H., Newell, C.: Explaining the user experience of recommender systems. User Model User-Adapt. Inter. **22**, 441–504 (2012)
41. Mayer, J.D., Salovey, P.: The intelligence of emotional intelligence. Intelligence **17**, 433–442 (1993)