# Editor's Note

The International Journal of Interactive Multimedia and Artificial Intelligence provides an interdisciplinary forum in which scientists and professionals can share their research results and report new advances on Artificial Intelligence and Interactive Multimedia techniques.

This special issue, *Special Issue on Multisensor user tracking and analytics to improve education and other application fields*, concentrates on the practical and experimental use of data mining and analytics techniques, specially focusing on the educational area. The selected papers deal with the most relevant issues in the field, such as the integration of data from different sources, the identification of data suitable for the problem analysis, and the validation of the analytics techniques as support in the decision making process. The application fields of the analytics techniques presented in this paper have a clear focus on the educational area (where Learning Analytics has emerged as a buzzword in the recent years) but not restricted to it. The result is a collection of use cases, experimental validations and analytics systems with a clear contribution to the state of the art.

Gupta et al. [1] explores the use of analytics techniques towards the recognition of human activities (i.e. what a person is doing) using recorded videos as data source. The presented approach automatically detects human gait and uses clustering algorithms and Hu-Moments to construct activity templates that serves for the base of classification. According to the authors, the experimental results show a pretty high accuracy on activity recognition both at indoor and outdoor videos. This is a step forward in automatic activity identification, and provides a quite valuable help on determining if a user should be considered as data source for a certain activity (e.g. track routes for joggers).

Asawa et al. [2] utilizes a Support Vector Machine classifier for the detection of human emotions from different sources. In their study, the authors consider 3 discrete emotions (happy, anger and fear) and use audio/video recordings to determine the current most likely emotion of the recorded person, and the experimental results show a 93% of accuracy on emotion detection. This is a quite interesting result that leverages the potential of raw data for the automatic detection of high-level actions. That is, saying that a person is happy while, for example, doing a learning activity is a great indicator to predict his success in the task, much better than other measures such as the number of times they opened a digital resource.

Yuan et al. [3] analyses how dissemination activities influence the users' attitude in online communities. According to this research, communities have different user profiles where, typically, most of the users are lurkers (just consume information, do not contribute) while a low percentage are contributors. The role adopted by a user is not static, and may change over time if the users are encouraged to participate. This research uses automatic pattern recognition to classify users as lurkers or contributors and presents an experimental setting aimed to analyze how dissemination activities play a role in encouraging users' active participation.

Choudhary et al. [4] applies analytics techniques to provide recommendations to job seekers. Their analysis is feed by curriculum vitae information and by personality surveys. In their approach, they first use a questionnaire to determine the job seeker's MBTI score, which is later translated to the OCEAN model. A combination of the OCEAN classification and the CV information is analyzed in order to calculate the most suitable job for the seeker. The approach, tested with technical-skilled job seekers, showed the potential of the system to guide fresh graduates in the important decision of shaping their professional profile.

Picciano [5] contextualizes analytics methods in the learning area and provides a critical overview of the Learning Analytics field, with a special focus on blended learning situations. The author explains how learning analytics can benefit from the already existing work (e.g. with Herbert Simon's "bounded rationality" theory) with data-driven decision making models and therefore can help in the decision making process for teachers and learners. According to this critical review, analytics is not a panacea but can provide quite valuable tools to improve educational systems. Also, Picciano expresses his concerns related to the data gap that may take place in blended learning situations that may hinder the effective application of Learning Analytics tools.

Corbi et al. [6] carry out a thorough review of recommender systems and techniques, with a special emphasis in the recommendation model LIME. LIME combines categories (Learning, Interaction, Mentoring, Evaluation) and settings (Formal, Informal) to provide a balanced recommendation to the end-user, meaning the learner. In addition, they describe the implementation of LIME, called iLIME, a tutor-lecturer-crafted, rule-based recommender system; after stating the need for quality data capturing methods, the authors analyse how the online learning process can be monitored by using the Experience API. The iLIME recommender system allows teachers and tutors to design and personalize the student recommendations with a simple interface to express the rules that should trigger recommendations. The rule processor is fed by simple student action logs (i.e. user interaction, user profile, and user performance), classified by their role in the learning process. According to Corbi et al., the Experience API provides an elegant vehicle to retrieve, categorise and use the required learner actions from various sources.

Tobarra et al. [7] presents a system that integrates data from different sources in the educational scenario, in order to


DOI: 10.9781/ijimai.2014.270

analyse students' progress. This is a quite important topic, since one of the current problems with Learning Analytics is the difficulty to identify and capture the activity that takes place in all the diverse situations in which learning takes place. More specifically, the authors present a case of study where data from the LMS was combined with data from an automatic assessment system for virtual/remote laboratories, and they analyze two main questions: firstly, if the students are quitting or if they are active, secondly, if the activities were well designed. This contribution is a step forward in the application of analytics algorithms in the educational field.

Cortés et al. [8] foresee the future of higher education as a social learning environment, open and collaborative, where people construct knowledge in interaction with others. Thus, they present a project for the construction of a learning environment based on social networks, ubiquity and mobility, at the time that it suits the needs of a particular social, cultural and ethnographic context in Colombia. The inclusion of digital learning tools as the basis of the university learning environment enables data capturing, thus increasing the potential of analytics techniques.

Dr. Luis de-la-Fuente-Valentín
Prof. Dr. Daniel Burgos
Dr. Riccardo Mazza

## REFERENCES


[1] J. P. Gupta, P. Dixit, N. Singh, V. B. Aemwal. "*Analysis of Gait Pattern to Recognize the Human Activities*", International Journal of Artificial Intelligence and Interactive Multimedia, vol. 2, no. 7, pp. 7-16, 2014. DOI: 10.9781/ijimai.2014.271

[2] K. Asawa, P. Manchanda. "*Recognition of Emotions using Energy Based Bimodal Information Fusion and Correlation*", International Journal of Artificial Intelligence and Interactive Multimedia, vol. 2, no. 7, pp. 17-21, 2014. DOI: 10.9781/ijimai.2014.272

[3] M. Yuan, M. Recker. "*Dissemination Matters: Influences of Dissemination Activities on User Types in an Online Educational Community*", International Journal of Artificial Intelligence and Interactive Multimedia, vol. 2, no. 7, pp. 22-29, 2014. DOI: 10.9781/ijimai.2014.273

[4] R.S. Choudhary, R. Kukreja, N. Jain, S. Jain. "Personality and Education Mining based Job Advisory System", International Journal of Artificial Intelligence and Interactive Multimedia, vol. 2, no. 7, pp.30-34, 2014. DOI: 10.9781/ijimai.2014.274

[5] A.G. Picciano. "*Big Data and Learning Analytics in Blended Learning Environments: Benefits and Concerns*", International Journal of Artificial Intelligence and Interactive Multimedia, vol. 2, no. 7, pp. 35-43, 2014. DOI: 10.9781/ijimai.2014.275

[6] A. Corbi, D. Burgos, "*Review of current student-monitoring techniques used in elearning-focused recommender systems and learning analytics. The Experience API & LIME model case study*", International Journal of Artificial Intelligence and Interactive Multimedia, vol. 2, no. 7, pp. 44-52, 2014. DOI: 10.9781/ijimai.2014.276

[7] L. Tobarra, S. Ros, R. Hernández, A. Robles-Gómez, A. C. Caminero, R. Pastor. "*Integration of multiple data sources for predicting the engagement of students in practical activities*" ", International Journal of Artificial Intelligence and Interactive Multimedia, vol. 2, no. 7, pp. 53-62, 2014. DOI: 10.9781/ijimai.2014.277

[8] J.A.Cortés, J.O.Lozano. "*Social Networks as a Learning Environment for Higher Education*", International Journal of Artificial Intelligence and Interactive Multimedia, vol. 2, no. 7, pp. 63-69, 2014. DOI: 10.9781/ijimai.2014.278


## ACKNOWLEDGMENTS

This Special Issue has been supported by **UNESCO Chair on eLearning – UNIR**.

**Contact details**:

Headquarters / Rectorado
Gran Vía Rey Juan Carlos I, 41
26002 Logroño (La Rioja), España-Spain
Tel: +34 941 210 211

Madrid Premises / Delegación Madrid
Paseo de la Castellana 163, 8ª planta
28046 Madrid, España-Spain
Tel: +34 915 674 391

Web: **http://unesco-elearning.unir.net/**
Email:**unesco.elearning@unir.net**

Twitter**:@UNIRunescochair**

United Nations Educational, Scientific and Cultural Organization

UNESCO Chair on e-Learning Spain