



Editorial

Smart Learning

Francisco José García-Peñalvo ^{1,*} , Cristina Casado-Lumbreras ², Ricardo Colomo-Palacios ³ 
and Aman Yadav ⁴

¹ GRIAL Research Group, Computer Science Department, University of Salamanca, 37008 Salamanca, Spain

² Research and Psychology in Education Department, Universidad Complutense de Madrid, Pozuelo de Alarcón, 28223 Madrid, Spain; crcasado@ucm.es

³ Department of Computer Science, Østfold University College, 1783 Halden, Norway; ricardo.colomo-palacios@hiof.no

⁴ Department of Counseling, Educational Psychology and Special Education, Michigan State University, East Lansing, MI 48824, USA; ayadav@msu.edu

* Correspondence: fgarcia@usal.es; Tel.: +34-92-329-4500 (ext. 6095)

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Abstract: Artificial intelligence applied to the educational field has a vast potential, especially after the effects worldwide of the COVID-19 pandemic. Online or blended educational modes are needed to respond to the health situation we are living in. The tutorial effort is higher than in the traditional face-to-face approach. Thus, educational systems are claiming smarter learning technologies that do not pretend to substitute the faculty but make their teaching activities easy. This Special Issue is oriented to present a collection of papers of original advances in educational applications and services propelled by artificial intelligence, big data, machine learning, and deep learning.

Keywords: artificial intelligence; smart systems; machine learning; deep learning; education; learning technologies; extraction information from educational environments; Internet of Things applied to education; educational data mining; cloud computing in education; data mining and big data analysis; intelligent systems for education; machine and deep learning in education; diagnostic and predictive analytics in educational processes; intelligent process applied in specific educational domains; activity recognition in education; data authentication and security in educational environments; privacy-preserving systems for education; computational models in education

1. Introduction

Artificial intelligence has an extensive application area. Nowadays, machine intelligence issues have gone beyond the academic publications to be discussed in closer to general society media such as newspapers, TV shows, etc. [1].

The educational field is not an exception; even artificial intelligence has a very long tradition in supporting the learning processes [2] with intelligent assistants or tutors [3], recommending educational materials [4], predicting students' behaviors [5,6], and managing vast amounts of data [7]. However, big data, machine learning or deep learning techniques provide significant potential for this purpose, leading to new applications, more efficient operations, and more human approaches. These methodologies enable digging massive databases, enhancing the knowledge base and producing new data model-based applications and services for the educational community.

Creating smarter technological learning ecosystems [8,9] has been a shared objective by researchers of computer science and education fields [10]. The concept of smart learning is a learning model based on technology that can detect the students' situation, context, learning needs and style, and the state of their learning process dynamically, and act according to them [11]. Therefore, a smart learning environment is the technology-supported learning environment that makes adaptations and provides

appropriate support in the right places and at the right time based on individual learners' needs, which might be determined via analyzing their learning behaviors, performance, and the online and real-world contexts in which they are situated [12]. In summary, the smart learning approach is a broad term that includes artificial intelligence-based solutions for developing of the teaching-learning processes with particular focus on their personalization. Many different systems might be considered or classified as smart learning environments, with their specificities and goals, but sharing a common ultimate goal: helping students to learn [13].

The development of smart learning services with the technologies mentioned above will allow advancing to more effective teaching-learning services, with powerful possibilities for teachers and new ways to permit a more self and autonomous for students, with special attention to be used in a mixture of formal and informal learning approaches.

The base for a smart learning system is in data and the needed analytics processes [14]. However, despite the potential advantages associated with automatic analysis of educational data, important questions arise, primarily related to the ethical and privacy [15,16] aspects of the teaching-learning process.

The smart learning aborded topic has a continuous interest; however, the worldwide pandemic due to COVID-19 disease has shed light on distance learning technologies and online or blended teaching and learning methodologies [17–19]. Moreover, the human effort, the digital alphabetization, and the existing digital divides of both teachers and students, to change or adapt the face-to-face teaching and learning methods to online-based ones, are significant [20]. The work done to close the 2019–2020 course was an emergency action [21], but the disease has not disappeared; thus, governments, academic institutions, faculty, students, and families have to tackle with a very uncertain situation. Artificial Intelligence may help develop and deploy smarter learning technological-based ecosystems, which do not pretend to substitute the teachers within this process but help and support them with more robust and intelligent services to make easy the follow-up, tutorial, and feedback, etc., activities [22]. The final objective is not only to reduce the teaching effort but to increase the learning possibilities of the student with more significant learning technologies. If these goals are achieved, these smarter learning ecosystems will remain in the Education habits far away from the COVID-19 pandemic, achieving an educational transformation in which the educational methodologies will be more efficient based on the technologies used.

2. A Review of the Contributions in this Special Issue

This Special Issue is oriented to present a collection of 18 papers of original advances in educational applications and services propelled by artificial intelligence, big data, machine learning, and deep learning.

Learning analytics processes [23] support educational stakeholders to make decisions about the academic institutions in a broad sense or the classroom context. Extracting the right data and transforming it into valuable information is key to building smarter processes within the educational realm, such as diagnostic and predictive analysis [24]. Liz-Domínguez et al. [25] do a systematic literature review, following PRISMA guidelines [26], of predictive analysis tools in higher education, highlighting the most relevant instances of predictors and early warning systems used in practice. Sáiz-Manzanares et al. [27] introduce a Moodle plug-in, so-called eOrientation, to detect at-risk students, which is used in junction with a learning analytics module, through which both supervised and unsupervised machine learning techniques can be applied. Moreno-Marcos et al. [28] propose analyzing and measuring two types of persistence based on students' interactions in online courses: (1) local persistence (based on the attempts used to solve an exercise when the student answers it incorrectly), and (2) global persistence (based on overall course activity/completion). Chaparro-Peláez et al. [29] details the architecture design, configuration, and use of the Moodle Workshop Data Extractor application, and proposes an initial validation of the tool based on the current peer assessment practices of a group of learning analytics experts.

Models are essential tools in computing and software engineering [30] that may also be applied in different educational domains. Im et al. [31] make a study to define the affective level of a given set of paragraphs and attempts to analyze the perceived trust of the methodologies in regard to usability. Vázquez-Ingelmo et al. [32] define an information dashboard [33] metamodel that abstracts all these factors and integrates a visualization task taxonomy to account for the different actions that can be performed with information dashboards. This metamodel may be used to design a domain-specific language to specify dashboards' requirements in a structured way [34]. Grivokostopoulou et al. [35] model 3D virtual worlds the domain of environmental engineering and energy generation, including intelligent pedagogical agents, to enhance students' interaction and improve their overall learning experience. Authors want to examine and deeply understand the effect that embodied pedagogical agents have on students' learning experience and their performance.

To personalize learning [36], it is mandatory to characterize activities for further recognition and make models of the learners [37]. Real-Fernández et al. [38] propose that the students are characterized based on their system activity instead of on self-reporting. The vectors are data structures formed by numerical or categorical variables such as learning style, cognitive level, knowledge type, or the history of the learner's actions in the system, which are computed by artificial intelligence algorithms.

Since the early 1980s, researchers have developed intelligent tutoring systems looking for the introduction of the artificial intelligence in education [39]. Subirats et al. [40] introduce a tutoring system that uses three different granularities to help students classify animals from bone fragments in zooarchaeology. The 3406 bone remains, which have 64 attributes, were obtained from an excavation of the Middle Paleolithic. The research done demonstrated the usefulness of the tutoring system for students when facing their first classification activities and seniors since the tutoring system gives them valuable clues for helping in difficult classification problems. Schez-Sobrino et al. [41] develop an intelligent tutoring system for support students on learning programming by using a notation based on a metaphor of roads and traffic signs represented by 3D graphics in an augmented reality environment.

Nevertheless, intelligent tutoring systems are not the only intelligent systems that are used in education. There many more kinds of intelligent platforms that might be considered as smart learning environments [42]. Nieto-Márquez et al. [43] explore the Smile and Learn intelligent platform's usage in three pilot groups schools from different regions of Spain, outlining future directions in the design of digital materials. The results show high use of STEM (Science, Technology, Engineering, and Maths) activities [44] among all the activities that could be chosen.

Assessment is one of the most complex online education activities [45,46]; thus, smart services that support teachers' evaluation processes are needed. The contribution of Ramanauskaite and Slotkiene [47] is devoted to making an empirical study to adapt the competency tree design and application for competencies e-evaluation method, based on flexibility, adaptability, and granularity of learning material. Guerrero-Higueras et al. [48] show a methodology that uses several machine learning models' performances to select the appropriate predicting model for assessing the students' achievements based on their interactions with a version control system in computer science subjects. Melesko and Novickij [49] tackle the formative assessment defining an approach based on a Multi-Armed bandit problem that uses the Upper-Confidence Bound algorithm in adaptive tests.

Cloud services are expandable and on-demand that are served via the Internet from specialized data centers. Cloud service delivery is usually represented by three classifications that are often referred to as the SPI Model, where SPI refers to Software, Platform or Infrastructure (as a Service), denoted in the literature as the acronyms SaaS, PaaS, and IaaS, respectively. Cloud services have a significant and growing presence in educational institutions seeking to reduce their information technology and maintenance budgets as well as increasing the number of quality services with easier accessibility and more user experience [50], which is translated into higher levels of perceived usefulness of faculty and students [51]. Tobarra et al. [52] present and evaluate a virtual laboratory based on Linux Docker virtualization technology, which allows us to create consistent realistic scenarios with lower configuration requirements for the students about the cybersecurity topic.

Internet of Things technologies are motivating institutions for digital transformation [53]. In the NMC Horizon Report, the impact of current and future technologies on education, mentioned the Internet of Things the first time in its 2012 edition [54]. Fernández-Caramés and Fraga-Lamas [55] review the state of the start on the application of the Blockchain [56], Internet of Things [57], Fog [58], and Edge Computing [59] technologies to develop smart campuses and universities. Sretenovic et al. [60] introduces a laboratory for biometric engineering education, which allows students to learn more about fingerprint acquisition and analyze the impact of the acquisition on other parts of the biometric authentication process with an Internet of Things approach. Santos Pereira et al. [61] evaluate and compare the current state of digital adoption in terms of the preparation according to the prevailing technological categories (pillars and innovation accelerators) and future priorities of organizations in the implementation of digital transformation in Portuguese organizations.

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