Affordances and Core Functions of Smart Learning Environments: A Systematic Literature Review

Bernardo Tabuenca *Senior Member, IEEE*, Sergio Serrano-Iglesias, Adrián Carruana Martín, Cristina Villa-Torrano, Yannis Dimitriadis, Juan I. Asensio-Pérez, Carlos Alario-Hoyos, Eduardo Gómez-Sánchez, Miguel L. Bote-Lorenzo, Alejandra Martínez-Monés, and Carlos Delgado Kloos

***Abstract*—Smart learning environments (SLEs) have gained considerable momentum in the last 20 years. The term SLE has emerged to encompass a set of recent trends in the field of educational technology, heavily influenced by the growing impact of technologies such as cloud services, mobile devices, and interconnected objects. However, the term SLE has been used inconsistently by the technology-enhanced learning (TEL) community, since different research works employ the adjective "smart" to refer to different aspects of novel learning environments. Previous surveys on SLEs are narrowly focused on specific technologies, or remain at a theoretical level that does not discuss practical implications found in empirical studies. To address this inconsistency, and also to contribute to a common understanding of the SLE concept, this paper presents a systematic literature review (SLR) of papers published between 2000 and 2019 discussing SLEs in empirical studies. Sixty eight papers out of an initial list of 1,341 papers were analyzed to identify: 1) what affordances make a learning environment smart; 2) which technologies are used in SLEs; and 3) in what pedagogical contexts are SLEs used. Considering the limitations of previous surveys, and the inconsistent use of the SLE concept in the TEL community, this paper presents a comprehensive characterization to describe SLEs through their affordances, the technologies used and pedagogical approaches considered in the selected papers. As a result, specific core functions of SLEs are identified and explained. This work aims at ensuring a relevant knowledge base and reference towards the implementation of future SLEs.**

***Index Terms*—Systematic literature review, smart learning environments, technology-enhanced learning.**

Manuscript sent for review July 30, 2020. Revised month day, year; Accepted month day, year. Date of publication month day, year. (*Corresponding author: Bernardo Tabuenca*)

This work was partially funded by the European Regional Development Fund as well as by the National Research Agency of the Spanish Ministry of Science, Innovations and Universities through the SmartLet project under grant numbers TIN2017-85179-C3-1-R and TIN2017-85179-C3-2-R, by the Madrid Regional Government through the e-Madrid-CM Project under grant S2018/TCS-4307, a project which is co-funded by the European Structural Funds (FSE and FEDER) and by the European Regional Development Fund as well as the Regional Council of Education of Castile and Leon through CasualLearn project under grant number VA257P18. Partial support has also been received from the European Commission through Erasmus+ Capacity Building in the Field of Higher Education projects LALA (586120-EPP-1-2017-1-ES-EPPKA2-CBHE-JP), InnovaT (5898758-EPP-1-2018-1-AT-EPPKA2-CBHE-JP), PROF-XXI (609767-EPP-1-2019-1-ES-EPPKA2-CBHE-JP), through the Erasmus+ Knowledge Alliances project ColMOOC (588438-EPP-1-2017-1-EL-EPPKA2-KA), and through the Erasmus+ Strategic Partnerships for higher education project TEASPILS (2020-1-ES01-KA203-082258). This publication reflects the views only of the authors and funders cannot be held responsible for any use which may be made of the information contained therein.

B. Tabuenca is with the Information Systems Department, Universidad Politécnica de Madrid, Calle Alan Turing s/n, 28031 Madrid, Spain (e-mail:bernardo.tabuenca@upm.es).

S. Serrano-Iglesias, C. Villa-Torrano, Y. Dimitriadis, J.I. Asensio-Pérez, E. Gómez-Sánchez, M.L. Bote-Lorenzo, and A. Martínez-Monés are with the Cooperative and Ingeligent Systems Group, Universidad de Valladolid, Valladolid, Spain (e-mail: sergio@gsic.uva.es, crsitina@gsic.uva.es, yannis@tel.uva.es, juaase@tel.uva.es, edugom@tel.uva.es, migbot@tel.uva.es, amartine@infor.uva.es).

A. Carruana Martín, C. Alario-Hoyos, and C. Delgado Kloos are with the Telematic Engineering Department, Universidad Carlos III de Madrid, Madrid, Spain (e-mail: acarruan@inf.uc3m.es, calario@it.uc3m.es, cdk@it.uc3m.es).

Digital Object Identifier XX.XXXXX/TLT.YEAR.XXXXXX

I. Introduction

In recent years, educational technology has evolved in response to new educational needs with affordances that offer new opportunities for teaching and learning. The technological changes unleashed since the universalization of the Internet and the later popularization of smartphones have facilitated ubiquitous access to multiple formal, informal, and non-formal learning options. Learning and teaching have evolved enormously thanks to the adoption of software tools for improved collaboration between people (e.g., open source software, video-conferencing tools, chats, MOOC platforms), or information technologies (IT) that are helping to understand what happens in our environment (e.g., cloud services, sensors, artificial intelligence, data algorithms). In addition, new modalities of educational environments have emerged, in face-to-face, online (e-learning) and mobile environments where learning occurs anytime and anywhere (m-learning). The recent pandemic and its effect on teaching and learning provides an illustrative example of the new opportunities and challenges of recent advances in educational technology.

Additionally, the combination of mobility with improved connectivity and cloud computing have facilitated the creation of environments where multiple physical and virtual objects, as well as people, are interconnected to support the so-called ubiquitous learning situations [1], [2]. The combination of ubiquitous learning with recent trends in social learning and learning analytics has led the focus of this paper: smart learning [3]. Broadly speaking, smart learning can be regarded as learning in interactive, intelligent, and tailored environments, supported by advanced digital technologies and services [4]. In the context of these learning environments, students may adopt different learning patterns depending on their daily activity, the device in their hands, their connectivity, time availability, location, and needs for interaction with objects or colleagues [5]. Students can benefit from learning environments like these, which may efficiently fit into their daily routine, and seamlessly integrate formal and informal learning [5].

In recent years, new associations like the International Association for Smart Learning Environments (IASLE), conferences like the International Conference on Smart Learning Environments (ICLSLE) or the International Conference on Smart Learning Ecosystems and Regional Developments (ICSLERD), and journals like the *Smart Learning Environments journal* (SLE journal) or *Interactive Technology and Smart Education journal* (ITSE) have clustered research efforts attempting to define, assimilate, and integrate emerging technologies in educational environments aimed at improving learning performance, the so-called smart learning environments (SLEs). All this swarm of research activity suggests that SLEs are progressively becoming the focus of a distinct subcommunity within the wider technology-enhanced learning (TEL) research field. However, the initial development of this community, as usual [6], leaves many questions that need further investigation.

Within this new evolving landscape several relevant proposals have been made with the aim to delimitate the definition, features, and scope of SLEs. Kinshuk [7] defined SLEs as ecosystems that enable the fusion of technology and pedagogy to provide real-time and ongoing evidence of changes in knowledge and skills, which are seamlessly assimilated by learners as they move from one learning context to another. Spector [8] identified ten affordances that are necessary (effective, efficient, and scalable), highly desirable (engaging, flexible, adaptive, and personalized), and likely (conversational, reflective, and innovative) "to develop thoughtful, productive, and responsible members of society using SLEs". Spector's general claim is that the extent to which these affordances are present determines whether and to what extent a particular learning environment should be considered "smart". Alternatively, Hwang [9] summarized the potential of SLEs into three key capabilities: 1) SLEs are aware of learners' situation or their context, meaning that the system is able to provide learning support based on the learners' status; 2) SLEs are able to offer instant and adaptive support to learners by analyzing their individual needs, and considering different perspectives (e.g., learning performance, learning behaviors, profiles, personal factors); and 3) SLEs are able to adapt the user interface and the subject contents to meet the personal characteristics (e.g., learning styles and preferences) and learning status (e.g., learning progress, learning performance) of individual learners [9]. Last but not least, Koper [10] focused on the efficiency to describe SLEs as improved environments to promote "better and faster" learning.

As shown above, multiple definitions of SLEs and their scope have been proposed, while no single definition has been widely accepted and used in the literature. Moreover, existing literature reviews are either very narrowly focused, or are limited to theoretical primary studies that do not discuss practical implications as in empirical studies. Additionally, despite the relevant role that technology plays in SLEs, it has not been considered a core topic in any of those previous literature reviews. Empirical results from case studies help to analyze the consistency and the evolution of a research area over time. Therefore, a review of empirical research on SLEs could help to better understand the specific features of existing SLEs, as well as the particular technologies they use and the educational contexts in which they have been tested. By understanding those three ingredients, which are much harder to grasp from theoretical proposals, it is more likely to obtain a clearer delimitation of the SLE concept. Based on the understanding of those ingredients, this work investigates a convergent vision of SLE that aims at providing consistency of the term SLE in further research.

In this paper, a systematic literature review is carried out to characterize SLEs in three dimensions: 1) what affordances make a learning environment "smart"; 2) which technologies are used in SLEs; 3) in what pedagogical contexts are SLEs used. Based on this characterization, we propose a definition of SLE, discuss the results of the literature review, and suggest research opportunities in the field of SLEs.

This paper is structured as follows. Section II presents and compares existing literature reviews related with SLEs. Section III describes the methodology applied to perform the literature review. Next, Section IV describes the results of the analysis of relevant publications presenting the evolution of the topic within the last two decades, and identifying the key authors and publications. SLEs are characterized in Section V. Then, in Section VI, gaps for further research in the field of SLEs are discussed.

II. Related Work

The scientific literature includes relevant reviews in which publications on SLEs are explored. Papamitsiou and Economides [3] performed a meta-analysis quantifying empirical findings for publications between 2009 and 2015 in the intersection of two research areas: SLEs and learning analytics. The results of their analysis suggested that the main pedagogical objectives consisted in predicting learning performance, modeling student behavior, improving assessment, and anticipating dropouts. However, this review targeted the potential of learning analytics, rather than a better understanding of the affordances of an SLE. Moreover, it covered a period in which research on SLEs was still incipient. A more recent work work by Putro *et al.* [11] reviews the scientific literature to explore alternative options for group formation in SLEs. Although the authors considered Hwang's definition to contextualize their work within group organization issues towards learning, the review is narrowly focused on one specific feature (learning in groups), which is in fact not always supported or even needed in many SLEs that only support individual learning. Moreover, the characteristics of SLEs, as defined by Hwang, were not discussed in the presentation of the results. Heinemann and Uskov [12] also presented a literature review to explore key concepts with regard to the implementation of smart universities and identified several key concepts, such as smart campus, smart learning environments, smart teacher, smart classrooms, and smart education. The authors of this last review identified 4 key features of SLEs inspired by Hwang's vision: ubiquitous computing, context-aware systems, adaptive teaching, and seamless learning. However, their findings are based solely on theoretical proposals, rather than on analysis of empirical studies involving SLEs.

All in all, previous literature surveys have focused on quite specific issues (e.g., the role of learning analytics in SLEs, or group formation in SLEs) or have paid attention to the affordances of SLEs in specific educational contexts (e.g., higher education), and they have not analyzed the empirical results of the use of SLEs. From a conceptual perspective, it remains unclear what are the affordances of an SLE that make it smart. From a practical perspective, the implications of different technologies have not been studied. Finally, with regard to the experience of learning in SLEs, to the best of our knowledge, existing literature has not systematically analyzed the different pedagogical approaches and educational settings in which SLEs have been used.

III. Method

This systematic literature review (SLR) has been carried out following the method specified by Kitchenham and Charters [13]. This method was initially conceived for the field of software engineering. However, its use has spread to multiple research areas, including technology-enhanced learning (TEL) [1], [14], [15].

A. Research Questions

The following research questions guided the study:

1) Research question 1 (RQ1). What affordances make a learning environment "smart"?: Existing models provide multiple working definitions for SLEs using specific affordances of adaptability, efficiency, effectiveness, sustainability, or intelligence [7]–[10]. It is worth studying how these definitions and affordances have been used in real settings, in order to converge towards a more consistent characterization. Here we focus our exploration on previous works that have evaluated the impact of SLEs in real learning settings. We believe that research findings based on empirical evidence, instead of analyses that are theoretical in nature, can better explain the impact of the SLEs main features in real situations in which different pedagogical approaches, technological tools, and roles (teachers, students, institutions, etc.) are involved.

2) Research question 2 (RQ2). Which technologies are used in SLEs?: SLEs are used in face-to-face (e.g., physical classrooms), online (e.g., learning management systems), or hybrid [16] (e.g., physical and digital artefacts, physical spaces with augmented reality, web-based with 3D worlds, etc.) learning contexts. From a different perspective, SLEs are employed in classroom, out-classroom learning situations. With respect to time, SLEs involve synchronous or asynchronous interactions. Technology plays a key role in assisting stakeholders across these learning contexts, situations, and interactions. This study investigates how these enabling-technologies are organized and what ecologies are usually formed.

3) Research question 3 (RQ3). In what pedagogical contexts are SLEs used?: The introduction of advanced functionalities in environments can be applied in various pedagogical contexts (e.g., problem-based learning, immersive education, inquiry-based learning), educational settings (formal learning, informal learning, or non-formal learning), educational levels (e.g., primary, secondary, higher education, etc.), and domains (e.g., workplace, wellness, health and fitness). This SLR explores and systematizes the literature considering these contexts.

B. Review Methodology

The literature review was accomplished following Kitchenham's guidelines for SLRs [13]. Nine researchers participated in the review. An overview of the process is graphically depicted in Fig. 1, where search, selection of studies, and data extraction processes are described. The full dataset including the results of the complete process is shared in open access.

1) Search: The search phase spanned from September 2019 to November 2019. As illustrated in Fig. 1, the search was performed using three different sources to identify relevant articles:

- Digital libraries. An automatic search of the query string "smart learning environment" was carried out in digital libraries within the fields (Title or abstract or keywords or body). The search was performed using the databases considered most relevant to cover the scope of this research: ACM Digital Library, IEEE Xplore Digital Library, Web of Science, Scopus, SpringerLink, and ScienceDirect.
- Journals with a specific focus on SLEs. A manual search for journals referencing SLEs in their journal name, scope, or issue name was done. Two specific journals were identified: 1) the *SLE journal*, released in 2014, which has published approximately 30 articles per year in open access; and 2) the *ITSE journal*, released in 2004, which has published approximately 24 articles per year in Open Access.
- Conferences with a specific focus on SLEs. A manual search for conferences including "SLE" in their name, scope, or proceedings title was done. Two conferences were shortlisted. The first conference is the International Conference on Smart Learning Environments (ICSLE), which was first organized in 2012 as the International Symposium on Smart Learning Environments. Its second edition (now as a conference) was held in 2015. Since then it has been held annually with the exception of 2017. The second conference is the ICSLERD, which was first organized in 2016. Since then, it has been held every year. Moreover, conferences with a focus on educational technology were manually scanned to identify special tracks including "SLE" in their title. Therefore, publications from the SLE special track at the IEEE International Conference on Advanced Learning Technologies (ICALT) were included in the initial dataset.

Duplicated papers or preliminary versions of publications were removed. This phase resulted in a set of 1,341 articles.

2) Selection of studies: In order to let the formulated RQs guide the literature selection, the search targeted publications in which one or several technological tools were used in the context of an SLE. As noted above, this review aims to fill a research gap: explore publications in which SLEs are empirically presented. Therefore, the description of technological tools should include their specific components, and it

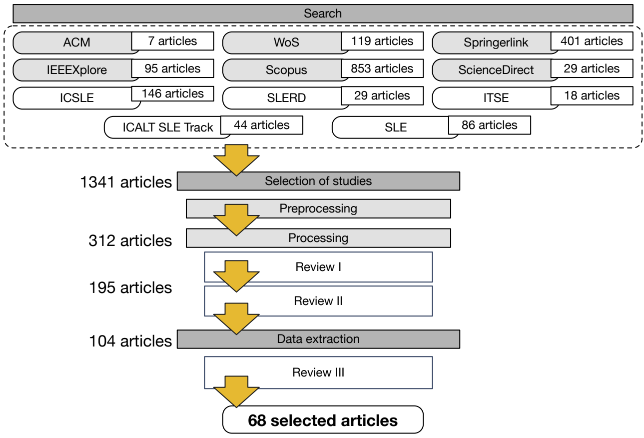


Fig. 1. Methodology used in this systematic literature review.

TABLE I
INCLUSION AND EXCLUSION CRITERIA

Inclusion criteria	**Exclusion criteria**
• Empirical work. Tools that are evaluated in case studies. Papers describing frameworks/architectures including a final solution contextualized in a pedagogical approach, and using technology.	• Off-topic papers. Publications were excluded if their main focus was not on the use of technology for learning/teaching, OR • Publications focused exclusively on theories, philosophical aspects, concepts, visions, or ideas. Surveys on these aspects are not considered as empirical papers, OR • In case of multiple articles reporting the same study, all but the most recent one are discarded, OR • Publications exploring organizational aspects in educational institutions, OR • Publications not written in English.

should be shown that such tools have achieved, at least, the level of functional prototype, capable of being used by real stakeholders (teachers, students, etc.). Likewise, publications should provide enough evidence (e.g., evaluation, pictures, detailed architecture schemas) to corroborate that the SLE had indeed been used by real teachers and/or students (i.e., they were not just yet-to-be-developed tools). Articles describing only ideas, theories, or models to be implemented in the future were considered outside the scope of this review. Surveys were discarded. Technological proposals that were not described within a pedagogical context were also discarded. Papers where the term "smart" was only stated in the title, keywords or slightly in the text without justifying its "smartness" were discarded. All these restrictions were formulated as inclusion and exclusion criteria (IC/EC), as shown in Table I:

The papers were independently reviewed by four researchers with respect to the inclusion and exclusion criteria as suggested by Breton *et al.* [17]. In all reviews, the disagreements were negotiated refining the IC/EC criteria or accordingly adapting the RQs. The selection process was performed to filter out-of-scope publications in two steps:

- Preprocessing. Two researchers reviewed the titles, keywords and publication scope of the studies found in the search process, and irrelevant papers were discarded according to the IC/EC. The set of primary studies was reduced to 312 publications.
- Processing. The same two researchers independently reviewed titles, abstracts, and keywords against the IC/EC in two iterations. In the first review, the set of primary studies was reduced to 195 publications. Kitchenham and Charters proposed using Cohen's Kappa statistic to measure the agreement between two judges during the study selection process [13]. The value of Kappa in the first review resulted (κ = 0.58) in a moderate agreement according to Landis and Koch [18]. The second review was performed including two new researchers with the aim of considering alternative points of view. The set of primary studies was reduced to 104 publications in the second review whereas the value of Kappa resulted (κ = 0.93) in an almost *perfect agreement* [18].

3) Data extraction: In the third phase, nine researchers reviewed the papers to extract data that will be further analyzed with respect to the RQs. The researchers had to read the full text and then fill out a structured questionnaire.

Reviewers were requested to classify each article according to the type of publication, authors, number of citations, the way authors had approached the concept of SLE, and the pedagogical context in which the SLE was introduced.

Reviewers extracted "smart" concepts (e.g., artifacts, spaces, or approaches) associated with the SLEs that were presented in the articles. Hence, they could select these concepts from a given list (8 concepts shortlisted during the selection of studies), or even introduce concepts that had not been shortlisted. These concepts were extracted from the articles as literally stated by their authors. Hence, reviewers categorized articles considering authors' perspectives on what might be qualified as "smart" in their own publication. The reviewers did not make interpretations aggregating similar concepts nor separating disparate concepts because the "smartness" was not always sufficiently justified in the texts.

Similarly, the identification of affordances was performed in two steps: Firstly, in the preprocessing reviewers shortlisted the most frequent affordances of SLEs; Secondly, in the data extraction process reviewers classified SLEs considering these affordances. Optionally, reviewers could suggest additional affordances that had not been shortlisted.

With respect to technologies, the review process included an item in which reviewers should identify technologies used in the SLEs that were used in the papers. As a result of the initial review, 21 technologies were previously shortlisted. The questionnaire offered a choice of these technologies, allowing for multiple selection. Likewise, reviewers had the option to propose additional technologies.

With regard to the pedagogical contexts, an analysis of the pedagogical approaches involved in the contributions from a TEL perspective was performed. Hence, reviewers had to classify the publications considering the list of 13 topics included in the scope of the European Conference on Technology-Enhanced Learning 2019 (EC-TEL). The usage of these topics in the review process was considered due to the high relevance of this conference in the area. The review process included 10 questions to investigate the pedagogical context in SLEs. Questions referring to pedagogical approaches and learning strategies, and learning domains presented a set of items extracted from the previous phase. Reviewers were encouraged to identify the most suitable one for the reviewed paper. Nevertheless, reviewers could add any additional category as they see fit.

In addition, a question was included to filter articles that were not sufficiently detailed, or that were outside the scope of educational technology.

Finally, the set of primary studies was reduced to 68 publications in the third phase. The value of Kappa resulted (κ = 0.85) in an *almost perfect agreement* [18] against the IC/EC.

IV. Analysis of Publications Included in the SLR

Fig. 2 shows the evolution in the number of papers published per year, escalating notably in the last 5 years. The rapid growth in the number of publications in recent years coincides with the time when the *Smart Learning Environments journal* was first released (2014). Likewise, the International Conference on Smart Learning Environments and the International Conference on Smart Learning Ecosystems and Regional Developments were organized for the first time in 2015 and 2016 respectively. The low peak in 2017 can be attributed to the cancellation of the 2017 International Conference on Smart Learning Environments and the subsequent lack of publication (within the same year) of extended versions in the partner journal *Smart Learning Environments*. It stands out that prior to the peak in 2015, two articles presenting SLEs were published [19], [20] in 2003 and 2008 respectively. As specified in Section III-B1, it should be noted that the search process did not include all publications in 2019 (the search was performed in September 2019) justifying the slight decrease in the last year.

Regarding the distribution of papers by publication type, the fact that only rather mature papers with empirical articles are considered, justifies that most of the selected articles come from journals: 59% (n = 40) were published in journals, 40% (n = 27) were published in conference proceedings, and less than 1% (n = 1) were published as book chapters. Considering the number of articles selected, the *Smart Learning Environments journal* (n = 31) and the *International Journal of Web-Based Learning and Teaching Technologies* (n = 2) were the most relevant journals, whereas the International Conference on Smart Learning Environments (n = 8) was the most relevant conference.

The 68 publications extracted in the SLR were written by 222 different authors. Only 20 authors have 3 or more publications. According to this classification, Kinshuk (n = 8), Kumar (n = 3), Boulanger (n = 3) and Seanosky (n = 3) are the most relevant authors. Kinshuk, Boulanger, and Seanosky have co-authored 3 publications [21]–[23], whereas Kumar has also

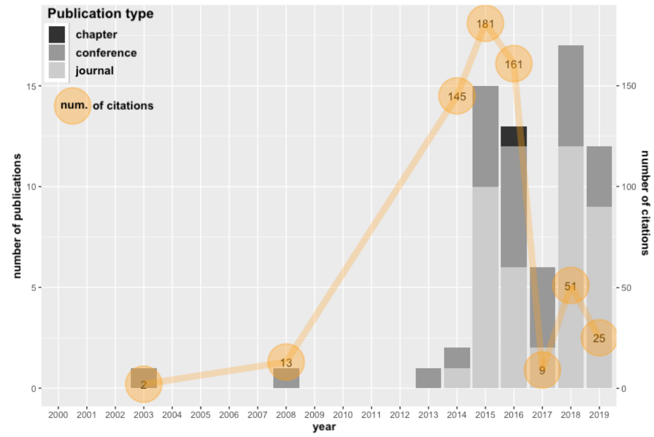


Fig. 2. Evolution in the number of empirical papers published between 2000 and 2019 (September).

co-authored 2 publications with them [21], [22]. Exploring the number of citations in Google Scholar (see right vertical axis in Fig. 2), the most highly cited publications were [24] (n = 130 citations), [25]–[28] (30 < n < 40 citations), and [29]–[33] (15 < n < 30 citations). The highest number of citations occurs between 2014 and 2016. Regarding the number of cites per year, again [24] obtained the higher rate (n = 21), followed by [25]–[29], [34]–[36] (5 > n > 10 cites per paper). Smeda, Dakich and Sharda [24] present a special software where students go through the complete lifecycle of digital storytelling under the guidance of teachers.

V. Characterization of SLEs

This section aims at characterizing the SLEs by means of investigating "smart" concepts that are associated with SLEs (what is smart in SLEs?), their affordances, the technologies used, and the pedagogical contexts as they are described in the selected studies. The analysis and interpretation of the results are reported in the conclusions section. For the sake of readability, tables presented in this section only illustrate the most frequently used concepts to characterize SLEs.

The results presented in Table II show that SLEs are usually implemented considering *smartphones* within the environment [37]. Smartphones play a key role in SLEs as they embed multiple sensors and actuators in just one device. For example, *smartphones* are used as clickers to complete questionnaires and assignments [26], [38]–[41]. Alternatively, *smartphones* are used to visualize learning contents [32], [42], [43].

SLEs are usually implemented in *smart classrooms* that combine the physical and virtual spaces. Burghardt *et al.* [20] designed a smart meeting room equipped with multiple cameras and projection surfaces for learning purposes. The teacher speaks and moves along a room while a set of cameras capture the most relevant view which is projected on screens. Similarly, in the work of Bdiwi *et al.* [34], classrooms were equipped with cameras, screens, tablets, and RFID (radio frequency identification) tags to investigate the impact of the presence of the teacher in working groups. The results indicated that the presence of the teacher increased learners' motivation, engagement, and effective learning. Finally,

TABLE II
CONCEPTS ASSOCIATED WITH THE TERM "SMART"

Concepts	**# Papers (%)**	**Articles**
Smart phone	12 (17.65%)	[26], [32], [34], [38]–[43], [49]–[51]
Smart classroom	9 (13.24%)	[20], [33], [34], [44], [48], [52]–[55]
Smart devices	3 (4.41%)	[32], [45], [56]
Smart teacher	2 (2.94%)	[46], [57]
Smart workspace	2 (2.94%)	[20], [34]
Smart lab	2 (2.94%)	[20], [47]
Smart education	2 (2.94%)	[48], [53]

Chaczko *et al.* [44] presented an architecture in the context of a smart classroom featuring gesture recognition, haptic devices, speech recognition, and ambient sensors to enhance collaborative learning.

Regarding the use of *smart devices*, Augello *et al.* [45] presented a system (Personal Intelligent Coach) to manage learning tasks and interactions within a complex SLE. This system featured two alternative embodiments: 1) a humanoid robot; and 2) an avatar running on a mobile application. This system adapted the learning contents based on students' needs along the learning process.

With respect to the concept of *smart teacher*, Preston *et al.* [46] presented a kitchen equipped with cookware (smart objects), and high resolution screens. An avatar guided the user with audio messages to cook while learning the vocabulary in the selected foreign language. Tan *et al.* [47] presented a *smart lab* that supports students to perform assignments remotely using robotics, internet of things (IoT) devices, learning analytics, cloud services, and virtual reality.

Finally, the concept of *smart education* is used in the context of electrical engineering education to train students supported by an autonomous robotic system [48]. The authors justified the smartness of the system considering adaptation, autonomy, and self-organization features.

A. Affordances of SLEs

The results summarized in Table III show that many SLEs adapt to stakeholders' (i.e. learners and teachers) context to support them to perform learning activities. *Adaptation, customization, and personalization* (*adaptable* onwards) are the most frequently referred (62%) affordances when defining SLEs. *Adaptable* refers to adjusting the learning environment considering stakeholders' context. In the context of clinical care, Pesare *et al.* [26] developed serious games for symptom identification and therapeutic interventions. In these serious games, students make decisions and are scored depending on their performance. In addition, the game becomes more complicated as the student progresses. Hence, the authors managed to create an adaptive and personalized environment for each student. Similarly, Paquette *et al.* [25] presented a method for computing the relationships between students' competencies to personalize their MOOC. Thus, the system adapted the learning environment considering the profile of each student.

SLEs record data from stakeholders' context throughout learning activities using sensors installed in the environment [58], or in embedded systems [34], [44], [52], [59], such as smartphones and wearables. The results of the analysis show that *tracking and monitoring* affordances (*traceable* onwards) were identified in 31% of the publications. In the context of language learning, Mouri *et al.* [28] designed a methodology for learning Japanese as a foreign language. Similarly, Bdiwi *et al.* [34] defined a collaborative learning environment aimed at learning how to make a joystick using an Arduino microcontroller. Teachers could track and provide support to different groups of students using sensors and cameras.

Feedback and recommendations (*recommendation* onwards) refers to information provided by the SLE based on stakeholders' actions performing learning activities. The results show that the *recommendation* affordance was recognized by 29% of the publications. In the context of tutoring systems, Lalingkar *et al.* [60] developed a system that provided corrective feedback clues just after answering the question. The difficulty level of the questions could be configured by the teacher.

SLEs usually analyze the collected data, and identify patterns related to stakeholders' behavior and their context when carrying out learning activities. The results of the analysis show that *patterns, activity, and behavior identification* affordances (*pattern recognition* onwards) were identified in 23% of the publications. In the context of presentation training, Burghardt *et al.* [20] proposed a system that recorded a speaker making a presentation in public, recognized the presenter's behaviors, and provided suitable guidance to improve it. Similarly, Denden *et al.* [61] developed a role-playing game to teach the subject of computer architecture. Their system used data analysis techniques to identify behaviors within the game. Consequently, the system sketched out the personality of the students considering these patterns.

SLEs offer appropriate adaptations based on stakeholders' profile to personalize their learning activities and consequently to provide a more engaging learning experience. The analysis shows that the *engaging* affordance was recognized in 21% of the publications. In the context of video-based learning, Kleftodimos *et al.* [30] designed a tool for teachers to add interactive features to videos, such as question answering, extra information, jokes, etc. Thus, learning became more fun and attractive to students.

Efficient in SLEs refers to how well is education performed with respect to the required effort. The results show that the *efficiency* affordance was identified by 21% of the publications. In the context of primary education, Smeda *et al.* [24] investigated the *efficiency* of digital storytelling in a physical classroom considering learning performance and students' engagement.

Effective learning in SLEs is considered when stakeholders perform their learning activities successfully obtaining the intended result. The results show that the *effective* affordance was recognized by 16% of the publications. Choi *et al.* [29] analyzed the impact of the light intensity in the effectiveness of resolving arithmetic problems. The authors found a small increase in the academic performance when light had a higher intensity.

TABLE III
AFFORDANCES ASSOCIATED WITH SLES

Affordances	# Papers (%)	Articles
Adaptable (adaptation, customization, and personalization)	42 (61.76%)	[19]–[22], [25]–[32], [38], [40], [41], [45]–[47], [49], [51], [53], [54], [56]–[60], [62]–[76]
Traceable (tracking and monitoring features)	21 (30.88%)	[19], [21], [22], [26], [28], [31], [34], [40], [41], [44], [46], [47], [50], [52], [53], [58], [59], [66], [71], [73], [76]
Recommender (feedback and recommendation affordances)	20 (29.41%)	[19], [25], [26], [31], [38], [40], [46], [56], [58]–[60], [66], [69], [70], [73]–[75], [77]–[79]
Pattern recognizer (emotion, face, activity, and behaviour identification affordances)	19 (27.94%)	[20]–[22], [25], [31], [34], [45], [46], [49], [50], [52], [61], [62], [64], [66], [69], [77], [80], [81]
Engaging	14 (20.59%)	[23], [24], [26], [27], [30], [33], [46], [48], [55], [56], [64], [73]–[75]
Efficient	14 (20.59%)	[23], [24], [28], [31], [33]–[35], [38], [54], [57], [74], [79], [82], [83]
Effective	11 (16.18%)	[20], [22], [26], [29], [31], [33], [35], [40], [54], [76], [78]
Real time interaction	8 (11.76%)	[31], [32], [40], [44], [46], [47], [62], [63]
Collaborative	7 (10.29%)	[34], [35], [39], [52], [62], [74], [84]

B. Technologies Involved in SLEs

The analysis of the technologies identified in the review suggests that technology is used in three well-differentiated processes of the SLE: input data (*sense* onwards, such as computers, smartphones, microcontollers, biometric sensors, ...), process data (*analyze* onwards, such as machine learning, ontologies, process mining, ...), and output data (*react* onwards, such as smartphones, computers, data visualizations, ...). Here technologies are classified and listed considering these core functions.

1) Collecting contextual information. Sense: SLEs collect specific information about stakeholders' context, in order to prepare personalized adaptations. Likewise, SLEs might collect multiple samples along the learning activity to trace stakeholders' actions and reactions. Technology plays a key role in SLEs collecting contextual information, which could refer to [85]: (i) identification of the stakeholder (e.g., through face recognition, person identification) or an object (e.g., near field communication - NFC); (ii) timestamp when learning activities are performed, to record the time where the learning activity is performed; (iii) who collaborates with the stakeholder within the SLE; and (iv) the conditions in which the learning activity is carried out (e.g., environmental, physical, or biometric conditions); Table IV lists technologies found in the review that are used to sense information in SLEs.

The most frequently used technologies on SLEs were *smartphones, handheld devices, and tablets*. These devices usually comprised multiple sensors and interfaces that facilitated retrieving data from them. For example, the work of Bacca *et al.* [38] shows an architecture for customizing the way English is learnt as a foreign language. This architecture included a mobile application, in which the student answered questions that were prompted considering the data collected from his/her profile.

Desktop computers were used in 25% of the selected publications. For example, Hien *et al.* [78] presents a messenger chatbot that collects frequently asked questions by students. The teacher progressively improves the chatbot including answers to the questions.

Learning management systems (LMSs) were referenced in 20% of the selected publications. LMSs are commonly used in e-learning environments. The work from Koulocheri *et al.* [86] presents a LMS that collects information from students' social activity in forums to provide customized assistance.

In recent years, *cameras* featuring new functionalities are showing a great potential for application in the educational field (e.g., GoPro cameras, 360-degree cameras, super slow motion cameras, or cameras with facial/motion recognition). Cameras enable identification of stakeholders, and track them in the sense process. In the context of nursing education, Herault *et al.* [65] used videos recorded with a 360-degrees camera in real medical operations. Later on, these videos were used to promote discussion among students in authentic scenarios.

Nowadays, *wearables* sense data on sleeping patterns or *biometrics*. In the context of smart cities, Kadar [53] developed an early-warning system that collected biometric and environmental conditions to monitor critical processes on a smart campus.

Overall, the results presented in this section help to understand how technology can help to sense data in SLEs. In the next section, alternative techniques for analyzing data using technologies are described.

2) Interpreting the context using data processing techniques. Analyze: The proliferation of sensors, wireless networks, and cloud data systems (the so-called big data) has favored the inclusion of data processing and analysis techniques in SLEs (see Table V). The results of the analysis are presented considering that some of these data processing techniques might overlap in specific taxonomies.

The most frequently used technique to analyze data was *machine learning* (ML) (26%). ML is a set of data processing techniques usually seen as a subset of artificial intelligence [89]. ML studies computer algorithms to improve them through experience. In Savov *et al.* [66], *machine learning* was used within a system that inferred students' level of attention analysing their expressions towards improved engagement.

Learning analytics (LA) were referenced in 25% of the selected publications. LA are driven by the collection and analysis of learners' traces while interacting with the learning environment [90]. In SLEs, *learning analytics* can help to understand and optimize the learning process and the envi-

TABLE IV
TECHNOLOGIES USED TO COLLECT CONTEXTUAL INFORMATION IN SLEs (SENSE)

Technologies	# Papers (%)	Articles
Smartphones, handheld devices, and tablets	19 (27.94%)	[28], [29], [35], [38], [39], [42]–[46], [49], [50], [53], [58], [59], [62], [63], [87], [88]
Desktop computers	17 (25%)	[19], [21], [22], [24], [31], [33], [40], [42], [43], [60], [63], [64], [67], [73], [77], [78], [87]
Learning management system	14 (20.59%)	[21]–[23], [39], [50], [55], [62], [69]–[72], [79], [80], [86]
Cameras	11 (13.41%)	[20], [34], [35], [43], [44], [47], [49], [52], [63], [65], [66]
Microcontrollers	7 (10.29%)	[34], [47], [48], [58], [59], [66], [67]
Virtual/remote laboratories	6 (8.82%)	[20], [47], [53], [73], [74], [82]
Biometric sensors	5 (7.35%)	[34], [52], [66], [67], [71]
Environmental sensors	5 (7.35%)	[41], [53], [59], [66], [67]
Conversational agents	4 (5.88%)	[40], [45], [64], [78]
RFID/NFC	3 (4.41%)	[34], [46], [58]
Microphones	3 (4.41%)	[20], [33], [35]
Robotics	3 (4.41%)	[45], [47], [48]
Social networks	3 (4.41%)	[39], [84], [86]
Infrared motion sensors	2 (2.94%)	[48], [66]
Wearables	2 (2.94%)	[44], [59]
Digital tables	2 (2.94%)	[20], [57]
Digital posters	2 (2.94%)	[20], [44]

TABLE V
TECHNOLOGIES USED TO INTERPRET THE CONTEXT WITH DATA PROCESSING TECHNIQUES IN SLEs (ANALYZE)

Techniques	# Papers (%)	Articles
Machine learning	18 (26.47%)	[20], [23], [27], [36], [49], [54], [61], [64], [66]–[69], [77]–[80], [83]
Learning analytics	17 (25%)	[21]–[23], [30], [31], [36], [38], [41], [50], [53], [57], [61], [68], [70], [71], [79], [80]
Data mining	9 (13.24%)	[22], [27], [31], [36], [54], [67], [69], [72], [80]
Ontologies	6 (8.82%)	[21], [22], [25], [32], [60], [62]
Artificial intelligence	6 (8.82%)	[19], [54], [59], [66], [75], [78]
Cloud computing	5 (7.35%)	[34], [44], [55], [56], [88]
Computer vision	3 (4.41%)	[20], [49], [66]
Process mining	2 (2.94%)	[31], [77]
Text mining	2 (2.94%)	[54], [81]
Multimodal learning analytics	2 (2.94%)	[23], [52]
Big data	2 (2.94%)	[21], [22]

ronments in which this process occurs [91]. For example, the work of Khousa *et al.* [68] presented a SLE career prediction system that analysed the data collected from students in a questionnaire. Based on the results of the analysis, the system aimed at building self confidence on the student within a specific field of employment.

Data mining was referenced in 13% of the selected publications. *Data mining* techniques in education are mostly used to extract and analyze information collected by educational institutions. The work of Toivonen *et al.* [67] showed a SLE for 3D design in which data was collected from students' digital trails. The system analysed data from different learning activities (brainstorming, design, 3D printing, programming, and sharing) and unified the results into a single dashboard.

Ontologies were referenced in 9% of the selected publications. *Ontologies* are frequently used in educational contexts to formulate models of knowledge that can be understood by both humans and machines. For example, the work by Lalingkar *et al.* [60] showed a problem-solving system in which all the interactions of the student were stored in the student model ontology, and displayed the student's learning profile together with a list of missing concepts and misconceptions. Additionally, the system analysed the profile data to provide customized feedback via links to resources to study some concepts in depth.

The results presented in this section showcase how technology can help to improve the analysis of data generated in SLEs. The next step, tackled by the next section, is to understand how technology can also help to "react" and make use of the results of those data analysis with the ultimate goal of improving the learning processes supported by SLEs.

3) Providing customized cues for action. React: SLEs provide customized feedback and recommendation cues for stakeholders based on the interpretation of the data analyzed during the *analysis* process. Table VI summarizes the technologies that are employed to facilitate reaction through suitable recommendations to stakeholders in SLEs. These reactions can be directly produced by the SLE based on the analysis of the data, or indirectly produced by stakeholders based on the recommendations suggested by the SLE (actionable feedback).

Smartphones, handheld devices, and tablets are equipped with useful features to provide feedback or display information: sending messages, displaying multimedia content, or extracting data from Internet services (e.g., repositories or cloud services). For example, the work of Lytridis *et al.* [43] shows a mobile tool that responds to the identification of a specific page in a book, presenting augmented 3D objects to enrich the description.

Similarly, *desktop computers* can react by displaying customized information. Thomas *et al.* [35] presented a simulation tool in which students were posed a problem. Students had to deal with alternative choices, provided by the tool in reaction to their answers, to learn how to solve the problem.

Data visualizations were referenced in 17% of the selected publications. *Data visualizations* comprise charts, representations, or dashboards whose interpretation can be translated into meaningful actionable recommendations to guide stakeholders in their learning [15]. In the context of software engineering [31], students worked individually in conceptual design tasks (i.e. create UML class and interaction diagrams). The tool re-

TABLE VI
TECHNOLOGIES USED TO PROVIDE CUSTOMIZED CUES FOR ACTION IN SLES (REACT)

Technologies	**# Papers (%)**	**Articles**
Smartphones, handheld devices, and tablets	19 (27.94%)	[28], [29], [35], [38], [39], [42]–[46], [49], [50], [53], [58], [59], [62], [63], [87], [88]
Desktop computers	17 (25%)	[19], [21], [22], [24], [31], [33], [40], [42], [43], [60], [63], [64], [67], [73], [77], [78], [87]
Data visualizations	12 (17.65%)	[21], [28], [41], [50], [53], [55], [58], [70], [71], [73], [80], [84]
Videos	7 (10.29%)	[30], [34], [43], [46], [63], [65], [87]
Microcontrollers	7 (10.29%)	[34], [47], [48], [58], [59], [66], [67]
Displays	5 (7.35%)	[20], [24], [35], [58], [59]
Conversational agents	4 (5.88%)	[40], [45], [64], [78]
Robotics	3 (4.41%)	[45], [47], [48]
Social networks	3 (4.41%)	[39], [84], [86]
3D printers	2 (2.94%)	[67], [82]
Wearables	2 (2.94%)	[44], [59]
Digital tables	2 (2.94%)	[20], [57]
Digital posters	2 (2.94%)	[20], [44]

acted providing customized visualizations for improved design considering students' traces.

Videos were referenced in 10% of the selected publications. *Videos* are frequently used in online education as embedded resources in LMSs or in *social networks*. In the context of SLEs, Herault *et al.* [65] present an interactive video-based learning system for nursing education. The system reacts to the decisions taken by the student prompting contextualized questions in a simulated scenario.

Microcontrollers and actuators were used in 7% of the selected publications. The results reported in this review show different SLEs in which IoT systems use sensors (See table 6: biometric, environmental) to collect data, use a *microcontroller* to process the data (Arduino [34], [58], ARM Cortex A7 [48], Dragonboard [66], Raspberry [47], [59], [67]), and coherently use actuators to trigger an action to provide *feedback*. For example, the Feedback Cube [58] includes both visual and acoustic actuators. A ring of 16 LEDs can be programmed to respond displaying effects such as fading, blinking, or color transitions. The mini speaker used can reproduce audio effects such as single tones, complex melodies, or encoded audio files. The actuators of the system can be configured by the student to provide customized alerts based on his/her learning patterns.

Displays were referenced in 7% of all publications. Most displays show information visually and acoustically. The publications included in this cluster also include *digital posters* [44] and *digital tables* [57]. The work by Tortorella and Kinshuk [59] presents a medical training system that uses different displays to alert students about potential invisible risks and pathogen contamination usually found in specific spaces (e.g., bathroom, sink, toilet). The system reacted displaying recommendations on how students should behave onwards to reduce the risks of contamination.

TABLE VII
PEDAGOGICAL APPROACHES AND LEARNING STRATEGIES IN SLES

Pedagogical approaches	**# Papers (%)**	**Articles**
Communities of learners	9 (13.23%)	[28], [41], [62], [67], [69], [72], [73], [81], [84]
Competency-based education	9 (13.23%)	[21]–[23], [25], [38], [46], [51], [67], [83]
Problem-based learning	8 (11.76%)	[26], [40], [47], [48], [73], [75], [76], [82]
Project-based learning	8 (11.76%)	[23], [35], [47], [59], [67], [76], [82], [84]
Active learning	7 (10.29%)	[28], [38], [42], [46], [57], [62], [65]
Exploratory and discovery learning	6 (8.82%)	[28], [41], [43], [46], [47], [67]
Simulation-based learning	6 (8.82%)	[26], [31], [35], [65], [73], [74]
Communities of practice	3 (4.41%)	[67], [68], [73]
Computer supported cooperative work	3 (4.41%)	[20], [47], [57]
Game-based learning	3 (4.41%)	[26], [61], [75]
Reflection-based learning	3 (4.41%)	[31], [41], [71]
Storytelling	3 (4.41%)	[24], [45], [73]
Gamification	2 (2.94%)	[27], [75]
Face to face learning	2 (2.94%)	[34], [66]
Differentiated instruction	1 (1.47%)	[25]
Collaborative learning	1 (1.47%)	[34]
Learner-centered pedagogy	1 (1.47%)	[70]
Self-regulated learning	1 (1.47%)	[58]
Task based language learning	1 (1.47%)	[46]
Traditional lectures	1 (1.47%)	[33]
Video-based learning	1 (1.47%)	[30]

C. Pedagogical Contexts in SLEs

In this section we explore RQ3, dealing with the educational settings the SLEs were designed for. An analysis of the conditions of the supported settings helped to understand the rationale of the contributions. The results of this analysis are presented in Table VII. These results show no predominant pedagogical approach or learning strategies tied to SLEs. Such diversity suggests that SLEs do not intrinsically restrict the pedagogical approach to be used.

From the previous results, it can be observed that the supported pedagogical approaches are mostly student-centered. This focus on students is reflected on the stakeholders considered throughout the different papers. From 68 papers reviewed, 39 focused exclusively on supporting learners whereas 3 papers supported exclusively teachers. This interest in supporting learners is consistent with the affordances reported in Section V-A., which are tightly related to the learning experience and sustain the student-centered perspective of SLEs. The support for teachers is mostly aimed at providing reports and visualization of analytics with regard to learners' activity [70], [84]. Imran *et al.* [70] introduced an analytical and visualization tool (rule-based recommender system: VAT-RUBARS) to provide support for teachers in learner-centered courses towards improved performance of their learners. On the other hand, Bechreu *et al.* [84] presented a tool (StudentViz) to help teachers visualize and understand the collaboration patterns among students.

Nonetheless, 23 papers attempted to support both learners and teachers simultaneously. In these contributions, there is a special interest in the adoption of new technologies for enhanced learning practice: with the inclusion of sensors and pervasive devices [29], [33], [44], [52], [53], [57], [79]; enabling the generation and deployment of new learning resources such as documents [30], videos [19], enriching contents with augmented reality (AR) [43], or enabling access to resources from anywhere [56]; facilitating the learning process across spaces [20], [39], [47], [63]]; or exploring its influence of its adoption in practice [24], [82], [83]. Different publications presented systems that aimed at modelling students' actions and behavior [40], [50], [52], [61], [71], [76]. Likewise, Bdiwi *et al.* [34] monitored teacher's interactions with the different groups of students in a classroom with an RFID-based location system to analyze how those interactions affected students' performance.

Beyond the support in educational institutions, some of the papers explored the support to learners in professional settings. Three articles aimed at supporting trainees in the industry where the main goal is to sharpen their professional skills. Seanosky *et al.* [21] relied on a system (SCALE) to evaluate the skills of the workers in a company on emergency procedures. Barmada and Baghaei [87] presented an interactive training platform (Train-for-life) for workers in the area of transport, logistics, security and safety industry. This platform helped the workers of the company to carry out their professional training in MOOCs, reducing the number of dropouts. Pesare *et al.* [26] supported health professionals with the provision of two serious games for sustaining engagement and motivation in medical contexts.

One of the most prominent features of SLEs, according to seminal definitions, refers to the opportunity to bridge formal and informal learning contexts [9], [92]. Most papers focused on formal learning (57 out of 68), nine focused on non-formal [26], [28], [40], [54], [58], [59], [62], [68], [75] and six focused on informal learning [46], [54], [56], [58], [62], [63]. Nevertheless, non-formal and informal learning studies attempt to enable learning in unconventional settings that offer new opportunities to learners, with a major concern on the actions that can be performed or the development of the learning resources. Preston *et al.* [46] encouraged students to learn languages while they are cooking, with the provision of embedded devices and interfaces among the kitchenware. Tortorella and Kinshuk [59] proposed a mobile learning system that provides contextual information about potential pathogens present in the current environment and suitable alternatives to deal with them. Leonidis *et al.* [56] presented an extensible software infrastructure that empowers teachers to design and program purposeful and engaging learning activities for formal and informal learning environments, by combining and orchestrating cloud-based, ambient and pervasive facilities, and services. Still, some contributions attempt to combine these types of learning. Tabuenca *et al.* [58] presented an IoT system based on NFC (near-field communication) tags and audio/visual feedback that learners could use to configure customized alerts, aimed at fostering self-awareness on the time devoted to learning across contexts. Bravo-Torres *et al.* [62] presented a platform (OPPIA) which deploys sporadic learning networks among students with similar learning needs to systematically encourage the interaction among them independently on where they are located.

Regarding the learning spaces, the results of the analysis show that SLEs are implemented for virtual (43%), physical (32%) and blended spaces (25%). Through this analysis, it was found that the objective of the SLEs depends on the supported space. In the physical space, most proposals attempt to enhance the facilities provided by the educational institution in classrooms [24], [29], [30], [33], [35], [41], [43], [45], [57], [63], [65], [66] and laboratories [30], [31], [34], [35], [48], [52], [68], [82]. In these cases, the major interest of the authors is to exploit the integration of technologies in these kinds of environments to provide new types of resources or ways of interaction. In the context of physical classrooms, Augello *et al.* [45] presented the architecture of PICo (Personal Intelligent Coach), an intelligent agent in the form of a storyteller robot that creates personalized learning paths according to the student's needs. Other authors attempted to adapt the classroom to promote convenient conditions for learning. Choi and Suk [29] presented a dynamic lighting system to adapt the light of the classroom, and to investigate the effect of lighting color and temperature on students' performance. Chen *et al.* [33] developed SDPPT (Speech-Driven PowerPoint) to support the presentation of slides through the detection of spoken keywords. In regards of physical laboratories, some researchers explore the acquisition of data from the actions performed by learners in such environments [30], [31], [34], [52] through the usage of the tools and systems involved (e.g., video based learning [30]) or by means of wearable biometric sensors to explore how students interact (e.g., collaborative learning [52]). Nevertheless, other contributions introduce SLEs to foster new interactions in the learning situations. Martinez *et al.* [48] used a robotic platform to guide a problem-based learning approach. Overall, the main focus was to provide alternative resources and strategies to interact using technology [24], [30], [35], [41], [43], [57], [63], [65], [66], [68], [82]. For example, Toivonen *et al.* [68] used a 3D printer in the context of K-12 studies to promote the adoption of the so-called maker movement. Following a similar approach, some publications explored the use of mobile phones (and applications) to facilitate ubiquitous access [43], [63], and to foster awareness of the individual time devoted to learning [58]. Beyond the walls of the classroom, Preston *et al.* [46] considered SLEs at home by installing HDMI (high-definition multimedia interface) displays and tagging cookware in the kitchen for language learning purposes while cooking a recipe.

In addition, the work done on SLEs in the virtual space benefits from the diversity of learning environments and systems available. Among these systems, we found SLEs that build on intelligent tutoring systems (ITSs) [40], [71], personal learning environments (PLEs) [58], [86], serious games [26], [61], blogs and forums [76], and chat rooms supported with conversational agents [64]. Nevertheless, the most prominent environments in this set are learning management systems (LMS). Most publications proposed SLEs deployed in LMSs for the support of online courses and the activities of traditional courses performed in the virtual space [19], [25], [51], [69], [70], [77], [80], [87]. In an online course on competency-based education, Paquette *et al.* [25] presented an LMS feature that dynamically configured the contents provided to students based on their individual profile within the platform. Likewise, the adoption of mobile devices plays a key role in the virtual space [39], [40], [49], [51]. Temdee [51] implemented a mobile application to enhance digital literacy on ethnic minority groups in Thailand. LA is useful to understand how students learn by analysing the logs collected by mobile phones (e.g., facial recognition [49], or chat interventions [40]). Additionally, some authors attempt to support virtual laboratories by means of SLEs [20], [47], [53], [73], [74]. Kuo *et al.* [73] presented a virtual laboratory for students practicing science process skills in chemistry and biology modules. Tan *et al.* [47] presented a telepresence robot equipped with a camera that students could operate remotely to physically perform activities in a real lab.

Finally, the educational levels covered through the different papers were analyzed. In general, higher education has got more attention (38) as compared to primary (6) and secondary (12) education. This preference might be due to convenience for the researchers for the enactment of the experiments, as well as for the availability of the appropriate infrastructure. This reflection might also apply with respect to the support to learning domains. There seems to be a special interest in STEM (science, technology, engineering, mathematics) (32), specially in engineering (15) and technology (10) domains, compared to social sciences (12), or health and medicine (7) as illustrated in Table VIII. In the case of social sciences, it is relevant the amount of papers supporting Foreign languages courses (6), where SLEs facilitated papers related with foreign languages (6), facilitating the interaction with other learners and applying the vocabulary in real-life scenarios. As well, in the case of health and medicine courses, the scenarios generally involved the preparation of learners towards the professional practice, with the provision of new kinds of resources or keeping track of their actions during simulations and games. As a final comment, it is worth noticing that the majority of the contributions were designed to be generally applicable in a broader set of scenarios. Only 20 of the 68 total papers offered an ad-hoc proposal that could not be used in a different learning scenario.

TABLE VIII
LEARNING DOMAINS IN SLES

Learning domains	# Papers (%)	Articles
Engineering	15 (22.06%)	[21], [22], [27], [31], [34], [42], [47], [48], [53], [61], [67], [69], [80], [84], [86]
Technology	10 (14.70%)	[30], [31], [47], [48], [55], [63], [67], [71], [78], [82]
Science	8 (11.76%)	[23], [33], [36], [40], [47], [67], [73], [74]
Foreign language	6 (8.82%)	[28], [38], [39], [46], [76], [88]
Mathematics	4 (5.88%)	[29], [60], [62], [67]
Biology	3 (4.41%)	[47], [73], [75]
Computer science	2 (2.94%)	[23], [36]
Education	2 (2.94%)	[30], [81]
Health	2 (2.94%)	[26], [59]
Medicine	2 (2.94%)	[68], [75]
Chemistry	1 (1.47%)	[73]
Commerce	1 (1.47%)	[52]
Economics	1 (1.47%)	[77]
Environmental education	1 (1.47%)	[41]
Geography	1 (1.47%)	[57]
Music	1 (1.47%)	[79]
Nursing	1 (1.47%)	[65]
Psychology	1 (1.47%)	[64]

VI. DISCUSSION

The results of this review show that the term SLE is used inconsistently in the technology-enhanced learning literature. The systematic literature review reported in this paper aimed at better understanding the specific affordances of existing SLEs, including the particular technologies they use as well as the educational contexts in which they have been evaluated. In this work, 68 articles (out of 1,341) were shortlisted and analyzed to shed some light on what affordances of an SLE make it smart, what technologies are used in SLEs, and in which pedagogical contexts SLEs are used. The results of this review suggest that this research area is in an initial state (see Section IV).

The following aspects differentiate this work from previous reviews. Firstly, we have conducted a review of the literature with a focus on empirical studies. Secondly, we have followed a well-accepted methodology for systematic literature reviews [13] considering the inter–rater reliability to facilitate future iterations. Thirdly, eleven researchers were involved in most phases of the review to ensure the quality of the results. Lastly, an overall synthesized composition of a smart learning environment is presented specifying its core functions and affordances (Fig. 3).

Regarding the distinctive affordances of SLEs identified in the literature review, seminal articles on SLEs pinpoint to features such as adaptive and personalized [7], [9], [10], efficient [8], [10], effective, scalable, engaging, flexible, conversational, reflective, and innovative [8], or, better and faster [10] to characterize SLEs. The results from the literature review suggest that SLEs merge trends of technological innovations (e.g., widespread use of smartphones, learning analytics, or ubiquity) with pedagogical advances mostly focused on the implications of learning in different contexts (being the so-called "seamless learning" one prominent example). SLEs seem also to provide a more interactive, intelligent, and tailored support using advanced digital technologies and services, to learn across multiple physical, virtual, or hybrid spaces [4].

The systematic literature review has also provided some very interesting bibliometric results. On the one hand, the surge of the number of publications about SLEs happened around 2015, together with the creation of key associations (IASLE), conferences (ICSLE and ICSLERD), and journals (*SLE* and *ITSE*) about the topic. On the other hand it looks like not many authors have stood out among the rest regarding the number of publications about SLEs, being Kinshuk the only exception we found.

With **RQ1**, we aimed at investigating what affordances make a learning environment "smart". The classification presented in Table III shows the most frequent affordances in empirical articles. Several correspondences were found with regard to previous SLE definitions in theoretical articles [7]–[10]. Coherently with Kinshuk [7], Hwang [9], and Koper [10], Table III shows that adaptability (adaptation, customization, and personalization) is the most commonly used affordance to describe SLEs. Additionally, several articles were consistent with Spector's vision [8] who used affordances such as engaging, efficiency, and effectiveness to define SLEs. Tracking and monitoring, feedback and recommendation, and pattern recognition affordances are also quite common in SLE.

The smartness of SLEs is usually justified arguing that the system includes a smart component. The results presented in Section V show that *smart classrooms* and *smartphones* are frequently included in SLEs. Classrooms (physical or online) are characterized as smart when they are equipped with some technology that facilitates learning. For example, *smart classrooms* are usually presented as spaces equipped with technology to remotely perform tasks that were usually performed in person (e.g., remote labs). Smartphones are usually presented in SLEs as devices that facilitate learners' ubiquitous access to learning resources, or to track students' learning activities.

Nonetheless, there are many publications that label their learning environment as "smart", but their authors do not provide arguments to justify it. The results of this review suggest that the adjective "smart" is sometimes used to characterize learning environments when they feature a technology or put into practice a pedagogical approach, which is not aligned with the most traditional vision of learning environments.

All in all, SLEs can be characterized as stakeholder-centered (student or teacher) learning ecologies [37], [93]. Luckin [37] proposed the ecology of resources (EoR) model to consider a broader spectrum of learning resources beyond the students' usual learning environment. This model is used to represent how existing tools in the students' context can offer new ways of assistance [94]. Luckin distinguishes three resources in ecology: *knowledge, environment, and technology*. From our perspective, the results are aligned with this model considering stakeholders in the centre of the ecology. To support learning, it is necessary to explore the manner in which the interactions of a learner with resources (*knowledge, environment, and technology*) might be constrained (*filters* or barriers) [37]. The smartness in SLEs is the quality of a system to provide forms of assistance for stakeholders considering their barriers for learning. SLEs are equipped with adaptable, traceable, or engaging features (See Table 3). Reflecting on the results reported in Section V, Fig. 3 illustrates our overall perspective of an SLE. The synthesized results suggest that SLEs are ecologies comprising four key components:

1) *Stakeholder.* Students that generally perform learning activities, or teachers that generally define learning activities (learning designs).

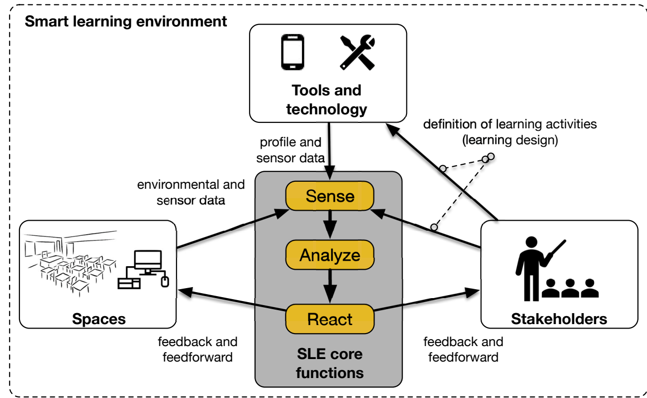


Fig. 3. Overall synthesized composition of a smart learning environment.

2) *Space.* Physical or virtual environment where learning occurs. The classroom, or the desktop where the stakeholder normally performs learning activities. Frequently cited environments in the literature are smart classrooms [20], [33], [34], [44], [48], [52]–[55], smart labs [20], [47], smart workspaces [20], [34], smart homes [46], [58], or smart campuses [53].
3) *System.* SLE core functions that provide smartness to the SLE. The system collects data from the learning context (*sense*), decodes, processes the data collected (*analyze*), and coherently suggests actions to ease learning constraints towards improved learning performance (*react*). These functions are usually performed with the help of technology (see Section V-B).
4) *Tools and technology.* Tools that are added to the usual environment to facilitate student learning. In SLEs, tools and technology are configured to assist stakeholders. Data processing techniques (e.g., machine learning and computer vision) techniques, or IoT systems (e.g. sensors, microprocessors, and actuators) are examples of technologies included in SLEs to assist stakeholders.

With **RQ2**, we aimed at investigating which technologies are used in SLEs. SLEs are equipped with technology to assist students (or teachers) to perform learning (or teaching) activities. Considering the technologies reported in Section V-B, here we describe the SLE core functions performed by the system as illustrated in Fig. 3:

- **Sense.** SLEs are capable of collecting information from the context in which they are introduced. For example, SLEs can sense ambient conditions using environmental sensors [41], [53], [59], [66], [67]. Likewise, SLEs are capable of collecting information from stakeholders when performing teaching and learning activities. For example, SLEs can sense students' patterns both in online classrooms using LMSs [21]–[23], [39], [50], [55], [62], [69]–[72], [79], [80], [86], and physical classrooms using cameras [35], [43], [44], [47], [49], [52], [63]. In addition, technology can sense specific profile information on the stakeholder using sensors (e.g., via smartphone [28], [29], [35], [38], [39], [42]–[46], [49], [50], [53], [58], [59], [62], [63], [87], [88]). In SLEs, the most frequently used technologies to sense data are summarized in Section V-B1.

- **Analyze.** SLEs are able to generate higher-level indicators from the data collected in the sense process using data analysis techniques. The expansion of data generated by increasingly integrated digital learning environments, together with emerging open standards for learning data, offer new opportunities to assess, measure, and document learning [95]. The capacity to analyse digital learning data is a relatively new research field. Therefore, teachers and students are not always sufficiently prepared, or do not have suitable tools, to exploit this data towards improved learning performance. SLEs assist stakeholders by including complex data analysis techniques that help understand how students learn, and consequently facilitate intervention. Indeed, data analysis techniques imply an essential tool for SLEs to configure automatic interventions (performed by the system) that identify actionable insights for both teachers and students. In SLEs, the most frequently used techniques to analyse data are summarized in Table 5.
- **React.** SLEs are able to provide customized recommendations for stakeholders based on the data collected during the sense process, and its interpretation performed during the analysis process. In this review, various technology actuators have been identified that present visual (data visualizations, videos, displays), auditory (chatbots), or tangible (3D printers, wearables, interactive posters) recommendations to stakeholders. Reactions (e.g., mobile notifications, contextual recommendations in LMS, alerts) are usually configured to be triggered after identifying actionable insights in the analysis process (e.g., lack of activity within an assignment, increase of dropouts). In SLEs, the most frequently used technologies are described in Section V-B3.

With **RQ3**, we aimed at investigating in which types of pedagogical contexts are SLEs used. Student-centered support is the core of SLEs. SLEs support a wide variety of pedagogical approaches that keep students in the main focus. Nevertheless, teachers are still considered in these environments, both for the provision of reports and analytics, and the enactment and provision of learning activities in these environments. We have not been able to deduce that SLEs are conditioned by a specific type of pedagogy or learning context. Indeed, it seems they are not necessarily associated with instructional technologies. Therefore, SLEs put more emphasis on learning activities, revealing a certain tendency to student-centered approaches. SLEs are flexible enough to support a wide variety of pedagogical approaches, learning domains and spaces, involving physical and virtual spaces. Some researchers have explored the connection between formal, non-formal and informal learning. These studies not only attempted to extend the learning situation to unconventional learning settings, but also considered how the conditions of those settings can promote different learning activities and interactions among students. However, these papers are a minority compared to the ones focused on formal learning and should be covered in further research.

VII. Conclusions

From this review, we can conclude that an SLE comprises a space in which stakeholders (students or teachers) carry out their activities with the assistance of technology to face learning barriers. The SLE performs three core functions that provide smartness to the SLE: sensing, analyzing, reacting. There are works that place more emphasis on some functions than others, but this would be the common denominator. This definition is not intended to be normative, but rather a way of synthesizing all the work done so far, and which will continue in future research.

The survey of papers reporting innovative contributions in the field of SLEs show that most aspects that triggered the interest of the community are still poorly developed. Due to the student-centered nature of SLEs, many researchers have explored how learners use these new environments in the classroom. However, teachers should not be left behind, and research should explore how to involve them in the design of SLEs. The demand for a higher involvement of learners and teachers can be observed in related fields, such as learning analytics, that are progressively incorporating human-centered approaches in their design processes [96], [97]. In order to exploit the possibilities offered by SLEs, further work has to be done to support teachers in designing appropriate learning situations that can take advantage of their main affordances, specially on the assessment and motivation of learners, and the connection of formal and informal learning experiences. For example, SLEs can support learning situations in real-life settings that can motivate learners to further reflect on the concepts explored during the lessons. These affordances should be evaluated not only in controlled laboratory settings, but also during real-world experiments over longer periods of time in order to evaluate the impact on stakeholders. Further research should investigate these issues implementing SLEs that consider the sense, analyze and react functions. Finally, ethics and privacy concerns should be taken into account, specially with the sensitive information collected from learners. In this regard, more work should be done to make analytics transparent and understandable for teachers and students, in line with global calls to provide trustworthy artificial intelligence (AI) based systems [98], with a focus on the educational domain [99].

The affordances identified in this review were shortlisted considering empirical articles. Future reviews might classify SLEs not only examining the affordances specified in empirical articles as listed in Table III, but also the affordances as identified in theoretical articles [7]–[10].

The term SLE is usually coined in a vague way in articles where "smart" might have alternative meanings and the smartness of the tool is not specified. This is probably a sign of immaturity. The increase in the number of publications in recent years and the creation of associations, conferences, and specialized journals on this topic, might forecast a significant growth in the near future. We expect this work will help to better define the field toward extended research.

The increase in the number of computer networks (with greater speed and broadband), the universalization in the use of smartphones (which include information on the profile of the stakeholder), and the increased availability of internet services (e.g., cloud services, IoT platforms) might facilitate the growth in this research field in the coming years.

This work is limited by the restrictions of the keyword search. Therefore, it is possible that relevant articles in the field of SLE have not been considered in the review process. Nonetheless, we believe that the conclusions obtained from a systematic review in which 1,341 papers were screened and 11 researchers were involved will contribute to advance the community and draw attention to academic debates.

REFERENCES

[1] J. A. González-Martínez, M. L. Bote-Lorenzo, E. Gómez-Sánchez, and R. Cano-Parra, "Cloud computing and education: A state-of-the-art survey," *Computers & Education*, vol. 80, pp. 132–151, 2015, doi: 10.1016/j.compedu.2014.08.017.

[2] B. Tabuenca, V. García-Alcántara, C. Gilarranz-Casado, and S. Barrado-Aguirre, "Fostering environmental awareness with smart iot planters in campuses," *Sensors*, vol. 20, no. 8, 2020, doi: 10.3390/s20082227.

[3] Z. Papamitsiou and A. A. Economides, "Learning analytics for smart learning environments: A meta-analysis of empirical research results from 2009 to 2015," *Learning, design, and technology: An international compendium of theory, research, practice, and policy*, pp. 1–23, 2016, doi: 10.1007/978-3-319-17727-4_15-1.

[4] J. Lee, H. Zo, and H. Lee, "Smart learning adoption in employees and hrd managers," *British Journal of Educational Technology*, vol. 45, no. 6, pp. 1082–1096, 2014, doi: 10.1111/bjet.12210.

[5] B. Tabuenca, S. Ternier, and M. Specht, "Supporting lifelong learners to build personal learning ecologies in daily physical spaces," *International Journal of Mobile Learning and Organisation 11*, vol. 7, no. 3-4, pp. 177–196, 2013, doi: 10.1504/IJMLO.2013.057160.

[6] T. S. Kuhn, *The structure of scientific revolutions*. University of Chicago press, 2012.

[7] Kinshuk, *Designing adaptive and personalized learning environments*. Routledge, 2016.

[8] J. M. Spector, "Conceptualizing the emerging field of smart learning environments," *Smart learning environments*, vol. 1, no. 1, pp. 1–10, 2014, doi: 10.1186/s40561-014-0002-7.

[9] G.-J. Hwang, "Definition, framework and research issues of smart learning environments-a context-aware ubiquitous learning perspective," *Smart Learning Environments*, vol. 1, no. 1, p. 4, 2014, doi: 10.1186/s40561-014-0004-5.

[10] R. Koper, "Conditions for effective smart learning environments," *Smart Learning Environments*, vol. 1, no. 1, pp. 1–17, 2014, doi: 10.1186/s40561-014-0005-4.

[11] B. L. Putro, Y. Rosmansyah *et al.*, "Group formation in smart learning environment: A literature review," in *2018 International Conference on Information Technology Systems and Innovation (ICITSI)*. IEEE, 2018, pp. 381–385, doi: 10.1109/ICITSI.2018.8695917.

[12] C. Heinemann and V. L. Uskov, *Smart University: Literature Review and Creative Analysis*. Cham: Springer International Publishing, 2018, pp. 11–46, doi: 10.1007/978-3-319-59454-5_2.

[13] B. Kitchenham, S. Charters *et al.*, "Guidelines for performing systematic literature reviews in software engineering version 2.3," *Engineering*, vol. 45, no. 4ve, p. 1051, 2007.

[14] L. Xia and B. Zhong, "A systematic review on teaching and learning robotics content knowledge in k-12," *Computers & Education*, vol. 127, pp. 267–282, 2018, doi: 10.1016/j.compedu.2018.09.007.

[15] W. Matcha, D. Gašević, A. Pardo *et al.*, "A systematic review of empirical studies on learning analytics dashboards: A self-regulated learning perspective," *IEEE Transactions on Learning Technologies*, vol. 13, no. 2, pp. 226–245, 2020, doi: 10.1109/TLT.2019.2916802.

[16] A. Cohen, R. T. Nørgård, and Y. Mor, "Hybrid learning spaces—-design, data, didactics," *British Journal of Educational Technology*, vol. 51, no. 4, pp. 1039–1044, 2020, doi: 10.1111/bjet.12964.

[17] P. Brereton, B. A. Kitchenham, D. Budgen, M. Turner, and M. Khalil, "Lessons from Applying the Systematic Literature Review Process within the Software Engineering Domain," *Journal of Systems and Software*, vol. 80, no. 4, pp. 571–583, 2007, doi: 10.1016/j.jss.2006.07.009.

[18] J. R. Landis and G. G. Koch, "The measurement of observer agreement for categorical data," *Biometrics*, vol. 33, pp. 159–174, 1977. [Online]. Available: http://www.jstor.org/stable/2529310

[19] J. C. Burguillo and E. Vázquez, "X-learn: An intelligent educational system oriented towards the net," in *Conference on Technology Transfer*, vol. 3040. Springer, 2003, pp. 628–637, doi: 10.1007/978-3-540-25945-9_62.

[20] C. Burghardt, C. Reisse, T. Heider, M. Giersich, and T. Kirste, "Implementing scenarios in a smart learning environment," in *2008 Sixth Annual IEEE International Conference on Pervasive Computing and Communications (PerCom)*. IEEE, 2008, pp. 377–382, doi: 10.1109/PERCOM.2008.96.

[21] J. Seanosky, D. Boulanger, V. Kumar, and Kinshuk, "Unfolding learning analytics for big data," in *Emerging Issues in Smart Learning*. Springer Berlin Heidelberg, 2015, pp. 377–384, doi: 10.1007/978-3-662-44188-6_52.

[22] V. Kumar, T. Somasundaram, S. Harris, D. Boulanger, J. Seanosky, G. Paulmani, K. Panneerselvam *et al.*, "An approach to measure coding competency evolution," in *Smart Learning Environments*. Springer Berlin Heidelberg, 2015, pp. 27–43, doi: 10.1007/978-3-662-44447-4_2.

[23] K. Govindarajan, D. Boulanger, J. Seanosky, J. Bell, C. Pinnell, V. S. Kumar *et al.*, "Assessing learners' progress in a smart learning environment using bio-inspired clustering mechanism," in *Innovations in Smart Learning*. Springer, 2017, pp. 49–58, doi: 10.1007/978-981-10-2419-1_9.

[24] N. Smeda, E. Dakich, and N. Sharda, "The effectiveness of digital storytelling in the classrooms: a comprehensive study," *Smart Learning Environments*, vol. 1, no. 6, pp. 1–21, 2014, doi: 10.1186/s40561-014-0006-3.

[25] G. Paquette, O. Mariño, D. Rogozan, and M. Léonard, "Competency-based personalization for massive online learning," *Smart Learning Environments*, vol. 2, no. 4, pp. 1–19, 2015, doi: 10.1186/s40561-015-0013-z.

[26] E. Pesare, T. Roselli, N. Corriero, and V. Rossano, "Game-based learning and gamification to promote engagement and motivation in medical learning contexts," *Smart Learning Environments*, vol. 3, no. 5, pp. 1–21, 2016, doi: 10.1186/s40561-016-0028-0.

[27] G. Barata, S. Gama, J. Jorge, and D. Gonçalves, "Gamification for smarter learning: tales from the trenches," *Smart Learning Environments*, vol. 2, no. 10, pp. 1–23, 2015, doi:10.1186/s40561-015-0017-8.

[28] K. Mouri and H. Ogata, "Ubiquitous learning analytics in the real-world language learning," *Smart Learning Environments*, vol. 2, no. 15, pp. 1–18, 2015, doi: 10.1186/s40561-015-0023-x.

[29] K. Choi and H.-J. Suk, "Dynamic lighting system for the learning environment: performance of elementary students," *Opt. Express*, vol. 24, no. 10, pp. A907–A916, 2016, doi: 10.1364/OE.24.00A907.

[30] A. Kleftodimos and G. Evangelidis, "Using open source technologies and open internet resources for building an interactive video based learning environment that supports learning analytics," *Smart Learning Environments*, vol. 3, no. 9, pp. 1–23, 2016, doi: 10.1186/s40561-016-0032-4.

[31] E. Serral, J. De Weerdt, G. Sedrakyan, and M. Snoeck, "Automating immediate and personalized feedback taking conceptual modelling education to a next level," in *2016 IEEE 10th Int. Conf. Research Challenges in Information Science (RCIS)*, Grenoble, France, 2016, pp. 1–6, doi: 10.1109/RCIS.2016.7549293.

[32] A. Taamallah and M. Khemaja, "Designing and experiencing smart objects based learning scenarios: An approach combining ims ld, xapi and iot," in *Proc. 2nd Int. Conf. Technological Ecosystems for Enhancing Multiculturality (TEEM '14)*. New York, NY, USA: Association for Computing Machinery, 2014, pp. 373–379, doi: 10.1145/2669711.2669926.

[33] C.-L. D. Chen, Y.-H. Chang, Y.-T. Chien, C. Tijus, and C.-Y. Chang, "Incorporating a smart classroom 2.0 speech-driven powerpoint system (sdppt) into university teaching," *Smart Learning Environments*, vol. 2, no. 7, pp. 1–11, 2015, doi: 10.1186/s40561-015-0010-2.

[34] R. Bdiwi, C. de Runz, S. Faiz, and A. A. Cherif, "Smart learning environment: Teacher's role in assessing classroom attention," *Research in Learning Technology*, vol. 27, pp. 1–14, 2019, doi: 10.25304/rlt.v27.2072.

[35] L. J. Thomas, M. Parsons, and D. Whitcombe, "Assessment in smart learning environments: Psychological factors affecting perceived learning," *Computers in Human Behavior*, vol. 95, pp. 197–207, 2019, doi: 10.1016/j.chb.2018.11.037.

[36] G. Akçapınar, M. N. Hasnine, R. Majumdar, B. Flanagan, and H. Ogata, "Developing an early-warning system for spotting at-risk students by

using ebook interaction logs," *Smart Learning Environments*, vol. 6, no. 4, pp. 1–15, 2019, doi: 10.1186/s40561-019-0083-4.

[37] R. Luckin, "The learner centric ecology of resources: A framework for using technology to scaffold learning," *Computers & Education*, vol. 50, no. 2, pp. 449–462, 2008, doi: 10.1016/j.compedu.2007.09.018.

[38] J. Bacca, Kinshuk, and D. Segovia-Bedoya, "An architecture for mobile-based assessment systems in smart learning environments," in *Proc. 2019 Int. Conf. Smart Learning Environments (ICSLE 2019)*. Denton, TX, USA: Springer, 2019, pp. 25–34, doi: 10.1007/978-981-13-6908-7_4.

[39] X. Huang, "Wechat-based teaching for an immersion cultural exchange program–a case study in cfl," *Smart Learning Environments*, vol. 6, no. 7, pp. 1–21, 2019, doi: 10.1186/s40561-019-0087-0.

[40] V. Rus and D. Ştefănescu, "Non-intrusive assessment of learners' prior knowledge in dialogue-based intelligent tutoring systems," *Smart Learning Environments*, vol. 3, no. 2, pp. 1–18, 2016, doi: 10.1186/s40561-016-0025-3.

[41] I. Jormanainen, T. Toivonen, and V. Nivalainen, "A smart learning environment for environmental education," in *Proc. 2018 Int. Conf. Smart Learning Environments (ICSLE 2018)*. Beijing, China: Springer, 2018, pp. 13–16, doi: 10.1007/978-981-10-8743-1_2.

[42] D. Kohen-Vacs, M. Milrad, M. Ronen, and M. Jansen, "Evaluation of enhanced educational experiences using interactive videos and web technologies: pedagogical and architectural considerations," *Smart Learning Environments*, vol. 3, no. 6, pp. 1–19, 2016, doi: 10.1186/s40561-016-0029-z.

[43] C. Lytridis and A. Tsinakos, "Evaluation of the artutor augmented reality educational platform in tertiary education," *Smart Learning Environments*, vol. 5, no. 6, pp. 1–15, 2018, doi: 10.1186/s40561-018-0058-x.

[44] Z. Chaczko, W. Alenazy, and C. Y. Chan, "Middleware-based software architecture for interactions in the smart learning environment," in *Proc. 26th Int. Business Information Management Association Conf. - Innovation Management and Sustainable Economic Competitive Advantage: From Regional Development to Global Growth (IBIMA 2015)*. Madrid, Spain: IBIMA Publishing, 2015, pp. 699–714.

[45] A. Augello, I. Infantino, A. Manfré, G. Pilato, F. Vella, M. Gentile, G. Città, G. Crifaci, R. Raso, and M. Allegra, "A personal intelligent coach for smart embodied learning environments," in *Proc. 9th KES Int. Conf. Intelligent Interactive Multimedia Systems and Services (IMSS-16)*. Cham: Springer International Publishing, 2016, pp. 629–636, doi: 10.1007/978-3-319-39345-2_56.

[46] A. Preston, M. Balaam, P. Seedhouse, S. Kurhila, L. Kotilainen, A. Rafiev, D. Jackson, and P. Olivier, "Can a kitchen teach languages? linking theory and practice in the design of context-aware language learning environments," *Smart Learning Environments*, vol. 2, no. 9, pp. 1–19, 2015, doi: 10.1186/s40561-015-0016-9.

[47] Q. Tan, M. Denojean-Mairet, H. Wang, X. Zhang, F. C. Pivot, and R. Treu, "Toward a telepresence robot empowered smart lab," *Smart Learning Environments*, vol. 6, no. 5, pp. 1–19, 2019, doi: 10.1186/s40561-019-0084-3.

[48] F. Martínez, H. Montiel, and H. Valderrama, "Using embedded robotic platform and problem-based learning for engineering education," in *Proc. 3rd Int. KES Conf. Smart Education and e-Learning (KES-SEEL-16)*. Tenerife, Spain: Springer, 2016, pp. 435–445.

[49] I. L. Enegi, M. Hamada, and S. A. Adeshina, "Adaptive multimedia learning framework with facial recognition system," in *2017 13th International Conference on Electronics, Computer and Computation (ICECCO)*, 2017, pp. 1–6, doi: 10.1109/ICECCO.2017.8333315.

[50] M. M. El-Bishouty, T.-W. Chang, R. Lima, M. B. Thaha, S. Graf *et al.*, "Analyzing learner characteristics and courses based on cognitive abilities, learning styles, and context," in *Smart Learning Environments*. Springer, 2015, pp. 3–25, doi: 10.1007/978-3-662-44447-4_1.

[51] P. Temdee, "Smart learning environment for enhancing digital literacy of thai youth: A case study of ethnic minority group," *Wireless Personal Communications*, pp. 1–12, 2019, doi: 10.1007/s11277-019-06637-y.

[52] G. Dafoulas, C. C. Maia, J. Samuels-Clarke, A. Ali, and J. C. Augusto, "Investigating the role of biometrics in education–the use of sensor data in collaborative learning," in *IADIS Int. Conf. e-Learning 2018*. IADIS, 2018. [Online]. Available: https://eprints.mdx.ac.uk/id/eprint/24621

[53] M. Kadar, "Smart learning environment for the development of smart city applications," in *2016 IEEE 8th International Conference on Intelligent Systems (IS)*, 2016, pp. 59–64, doi: 10.1109/IS.2016.7737500.

[54] G. Yang, Kinshuk, D. Wen, and E. Sutinen, "A contextual query expansion based multi-document summarizer for smart learning," in *2013 International Conference on Signal-Image Technology Internet-Based Systems*, 2013, pp. 1010–1016, doi: 10.1109/SITIS.2013.163.

[55] K. Simić, M. Despotović-Zrakić, Ž. Bojović, B. Jovanić, and Đ. Knežević, "A platform for a smart learning environment," *Facta universitatis-series: Electronics and Energetics*, vol. 29, no. 3, pp. 407–417, 2016, doi: 10.2298/FUEE1603407S.

[56] A. Leonidis, M. Antona, and C. Stephanidis, "Enabling programmability of smart learning environments by teachers," in *Distributed, Ambient, and Pervasive Interactions*, N. Streitz and P. Markopoulos, Eds. Cham: Springer International Publishing, 2015, pp. 62–73, doi: 10.1007/978-3-319-20804-6_6.

[57] A. Preston, S. Lazem, A. Kharrufa, B. Pursglove, and P. Olivier, "Supporting the smart teacher: an agenda for the use of embedded sensing in novel learning spaces," *Smart Learning Environments*, vol. 5, no. 1, p. 19, 2018, doi: 10.1186/s40561-018-0068-8.

[58] B. Tabuenca, D. Börner, M. Kalz, and M. Specht, "User-modelled ambient feedback for self-regulated learning," in *Design for Teaching and Learning in a Networked World*, G. Conole, T. Klobučar, C. Rensing, J. Konert, and E. Lavoué, Eds. Cham: Springer International Publishing, 2015, pp. 535–539, doi: 10.1007/978-3-319-24258-3_54.

[59] R. Tortorella and Kinshuk, "A mobile context-aware medical training system for the reduction of pathogen transmission," *Smart Learning Environments*, vol. 4, no. 1, pp. 1–13, 2017, doi: 10.1186/s40561-017-0043-9.

[60] A. Lalingkar, C. Ramnathan, and S. Ramani, "Ontology-based smart learning environment for teaching word problems in mathematics," *Journal of Computers in Education*, vol. 1, no. 4, pp. 313–334, 2014, doi: 10.1007/s40692-014-0020-z.

[61] M. Denden, A. Tlili, F. Essalmi, and M. Jemni, "Implicit modeling of learners' personalities in a game-based learning environment using their gaming behaviors," *Smart Learning Environments*, vol. 5, no. 1, pp. 1–19, 2018, doi: 10.1186/s40561-018-0078-6.

[62] J. F. Bravo-Torres, V. E. Robles-Bykbaev, M. L. Nores, E. F. Ordoñez-Morales, Y. Blanco-Fernández, and A. Gil-Solla, "Oppia: A context-aware ubiquitous learning platform to exploit short-lived student networks for collaborative learning." in *Proceedings of the 8th International Conference on Computer Supported Education - Volume 1: CSEDU,*, INSTICC. SciTePress, 2016, pp. 494–498, doi: 10.5220/0005903304940498.

[63] S. Pal, P. K. D. Pramanik, and P. Choudhury, "A step towards smart learning: Designing an interactive video-based m-learning system for educational institutes," *International Journal of Web-Based Learning and Teaching Technologies (IJWLTT)*, vol. 14, no. 4, pp. 26–48, 2019, doi: 10.4018/IJWLTT.2019100102.

[64] M. Procter, F. Lin, and B. Heller, "Intelligent intervention by conversational agent through chatlog analysis," *Smart Learning Environments*, vol. 5, no. 1, p. 30, 2018, doi: 10.1186/s40561-018-0079-5.

[65] R. C. Herault, A. Lincke, M. Milrad, E.-S. Forsgärde, and C. Elmqvist, "Using 360-degrees interactive videos in patient trauma treatment education: design, development and evaluation aspects," *Smart Learning Environments*, vol. 5, no. 1, p. 26, 2018, doi: 10.1186/s40561-018-0074-x.

[66] T. Savov, V. Terzieva, and K. Todorova, "Computer vision and internet of things: Attention system in educational context," in *Proceedings of the 19th International Conference on Computer Systems and Technologies*, ser. CompSysTech'18. New York, NY, USA: Association for Computing Machinery, 2018, pp. 171–177, doi: 10.1145/3274005.3274014.

[67] T. Toivonen, I. Jormanainen, C. S. Montero, and A. Alessandrini, "Innovative maker movement platform for k-12 education as a smart learning environment," in *Challenges and Solutions in Smart Learning*, M. Chang, E. Popescu, Kinshuk, N.-S. Chen, M. Jemni, R. Huang, and J. M. Spector, Eds. Singapore: Springer Singapore, 2018, pp. 61–66, doi: 10.1007/978-981-10-8743-1_9.

[68] E. A. Khousa, Y. Atif, and M. M. Masud, "A social learning analytics approach to cognitive apprenticeship," *Smart Learning Environments*, vol. 2, no. 1, pp. 1–23, 2015, doi: 10.1186/s40561-015-0021-z.

[69] Y. Li, Y. Zheng, J. Kang, and H. Bao, "Designing a learning recommender system by incorporating resource association analysis and social interaction computing," in *State-of-the-Art and Future Directions of Smart Learning*, Y. Li, M. Chang, M. Kravcik, E. Popescu, R. Huang, Kinshuk, and N.-S. Chen, Eds. Singapore: Springer Singapore, 2016, pp. 137–143, doi: 10.1007/978-981-287-868-7_16.

[70] H. Imran, K. Ballance, J. M. C. Da Silva, Kinshuk, and S. Graf, "Vatrubars: A visualization and analytical tool for a rule-based recommender system to support teachers in a learner-centered learning approach," in *State-of-the-Art and Future Directions of Smart Learning*, Y. Li, M. Chang, M. Kravcik, E. Popescu, R. Huang, Kinshuk, and N.-S. Chen, Eds. Singapore: Springer Singapore, 2016, pp. 31–38, doi: 10.1007/978-981-287-868-7_4.

[71] B. Vesin, K. Mangaroska, and M. Giannakos, "Learning in smart environments: user-centered design and analytics of an adaptive learning system," *Smart Learning Environments*, vol. 5, no. 1, p. 24, 2018, doi: 10.1186/s40561-018-0071-0.

[72] H. Elhoseny, M. Elhoseny, S. Abdelrazek, and A. M. Riad, "Evaluating learners' progress in smart learning environment," in *Proceedings of the International Conference on Advanced Intelligent Systems and Informatics 2017*, A. E. Hassanien, K. Shaalan, T. Gaber, and M. F. Tolba, Eds. Cham: Springer International Publishing, 2018, pp. 734–744, doi: 10.1007/978-3-319-64861-3_69.

[73] M.-X. Fan, R. Kuo, M. Chang, and J.-S. Heh, *Story-Based Virtual Experiment Environment*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2015, pp. 175–198, doi: 10.1007/978-3-662-44447-4_10.

[74] K. Aljuhani, M. Sonbul, M. Althabiti, and M. Meccawy, "Creating a virtual science lab (vsl): the adoption of virtual labs in saudi schools," *Smart Learning Environments*, vol. 5, no. 1, pp. 1–13, 2018, doi: 10.1186/s40561-018-0067-9.

[75] S. Johnson and O. R. Zaiane, "Learning to analyze medical images: A smart adaptive learning environment for an ill-defined domain," in *Proc. of Business Process Management Workshops*. Sydney, Australia: Springer, 2018, pp. 56–68, doi: 10.1007/978-981-10-2419-1_15.

[76] S. Li and J. Zheng, "The effect of academic motivation on students' english learning achievement in the eschoolbag-based learning environment," *Smart Learning Environments*, vol. 4, no. 1, pp. 1–14, 2017, doi: 10.1186/s40561-017-0042-x.

[77] G. Deeva and J. De Weerdt, "Understanding automated feedback in learning processes by mining local patterns," in *International Conference on Business Process Management*. Springer, 2018, pp. 56–68, doi: 10.1007/978-3-030-11641-5_5.

[78] H. T. Hien, P.-N. Cuong, L. N. H. Nam, H. L. T. K. Nhung, and L. D. Thang, "Intelligent assistants in higher-education environments: The fitebot, a chatbot for administrative and learning support," in *Proc. of the 9th Int. Symp. on Information and Communication Technology*. New York, NY, USA: Association for Computing Machinery, 2018, pp. 69–76, doi: 10.1145/3287921.3287937.

[79] J. Burrows and V. Kumar, "The objective ear: assessing the progress of a music task," *Smart Learning Environments*, vol. 5, no. 1, 2018, doi: 10.1186/s40561-018-0062-1.

[80] A. Tlili, M. Denden, F. Essalmi, M. Jemni, M. Chang, Kinshuk, and N.-S. Chen, "Automatic modeling learner's personality using learning analytics approach in an intelligent moodle learning platform," *Interactive Learning Environments*, pp. 1–15, 2019, doi: 10.1080/10494820.2019.1636084.

[81] Y. Li, Y. Zheng, H. Bao, and Y. Liu, "Towards better understanding of hot topics in online learning communities," *Smart Learning Environments*, vol. 2, no. 1, pp. 1–14, 2015, doi: 10.1186/s40561-015-0019-6.

[82] T. L. Tyler-Wood, D. Cockerham, and K. R. Johnson, "Implementing new technologies in a middle school curriculum: a rural perspective," *Smart Learning Environments*, vol. 5, no. 1, pp. 1–16, 2018, doi: 10.1186/s40561-018-0073-y.

[83] A. Amigud, J. Arnedo-Moreno, T. Daradoumis, and A. Guerrero-Roldan, "A robust and non-invasive strategy for preserving academic integrity in an open and distance learning environment," in *2017 IEEE 17th Int. Conf. on Advanced Learning Technologies (ICALT)*. Timisoara, Romania: IEEE, 2017, pp. 530–532, doi: 10.1109/ICALT.2017.23.

[84] A. Becheru, A. Calota, and E. Popescu, "Analyzing students' collaboration patterns in a social learning environment using studentviz platform," *Smart Learning Environments*, vol. 5, no. 1, pp. 1–18, 2018, doi: 10.1186/s40561-018-0063-0.

[85] M. Specht, "RTST Trend Report: lead theme Contextualisation," Open Universiteit Netherlands, Tech. Rep., May 2012, accessed: Feb. 24th, 2021. [Online]. Available: https://telearn.archives-ouvertes.fr/hal-00722748

[86] E. Koulocheri and M. Xenos, "Correlating formal assessment with social network activity within a personal learning environment," *International Journal of Web-Based Learning and Teaching Technologies (IJWLTT)*, vol. 14, no. 1, pp. 17–31, 2019, doi: 10.4018/IJWLTT.2019010102.

[87] B. Barmada and N. Baghaei, "Train-for-life (t4l): an interactive learning platform for logistics, safety and security professionals," *Smart Learning Environments*, vol. 5, no. 1, pp. 17–31, 2018, doi: 10.1186/s40561-018-0072-z.

[88] Q. Zhao, "An empirical study on cultivating learners' creativity in smart learning environment," in *Proc. of Int. Conf. on Application of Intelligent Systems in Multi-modal Information Analytics*. Shenyang, China: Springer, 2019, pp. 596–603, doi: 10.1007/978-3-030-15740-1_80.

[89] E. Alpaydin, *Introduction to machine learning*. MIT press, 2020.

[90] W. Greller and H. Drachsler, "Translating learning into numbers: A generic framework for learning analytics," *Journal of Educational Technology & Society*, vol. 15, no. 3, pp. 42–57, 2012, [Online] Available: https://www.jstor.org/stable/10.2307/jeductechsoci.15.3.42.

[91] P. Long and G. Siemens, "Penetrating the fog: analytics in learning and education," *Italian Journal of Educational Technology*, vol. 22, no. 3, pp. 132–137, 2014. [Online]. Available: https://www.learntechlib.org/p/183382

[92] B. Gros, "The design of smart educational environments," *Smart Learning Environments*, vol. 3, no. 1, pp. 1–11, 2016, doi: 10.1186/s40561-016-0039-x.

[93] B. Barron, "Learning ecologies for technological fluency: Gender and experience differences," *Journal of Educational Computing Research*, vol. 31, no. 1, pp. 1–36, 2004, doi: 10.2190/1N20-VV12-4RB5-33VA.

[94] R. Luckin, *Re-designing learning contexts: Technology-rich, learner-centred ecologies*. Routledge, 2010.

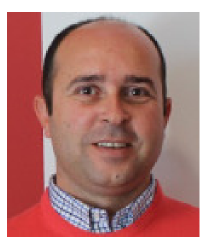
[95] B. Alexander, K. Ashford-Rowe, N. Barajas-Murphy, G. Dobbin, J. Knott, M. McCormack, J. Pomerantz, R. Seilhamer, and N. Weber, "EDUCAUSE Horizon Report: 2019 Higher Education Edition," EDUCAUSE, Louisville, CO, USA, Tech. Rep., 2019, accessed: Feb. 24th, 2021. [Online] Available: http://library.educause.edu/-/media/files/library/2019/4/2019horizonreport.pdf.

[96] X. Ochoa and A. F. Wise, "Supporting the shift to digital with student-centered learning analytics," *Educational Technology Research and Development*, pp. 1–5, nov 2020, doi: 10.1007/s11423-020-09882-2.

[97] S. B. Shum, R. Ferguson, and R. Martinez-Maldonado, "Human-centred learning analytics," *Journal of Learning Analytics*, vol. 6, no. 2, pp. 1–9, 2019, doi: 10.18608/jla.2019.62.1.

[98] High-Level Expert Group on Artificial Intelligence (HLEG-AI), "Ethics Guidelines for Trustworthy AI: Requirements of Trustworthy AI," European Commission, Tech. Rep., April 2019, accessed: Feb. 24th, 2021. [Online] Available: https://ec.europa.eu/digital-single-market/en/news/ethics-guidelines-trustworthy-ai.

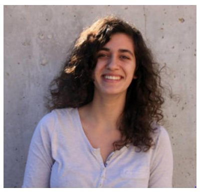
[99] S. Vincent-Lancrin and R. Van der Vlies, "Trustworthy AI in education: promises and challenges," Organisation for Economic Co-operation and Development (OECD), Tech. Rep., February 2020, accessed: Feb. 24th, 2021. [Online] Available: http://www.oecd.org/education/trustworthy-artificial-intelligence-in-education.pdf.



Bernardo Tabuenca is Assistant Professor at Universidad Politécnica de Madrid. He conducted his research at the Research Center for Learning, Teaching, and Technology of the Open University of The Netherlands where he obtained his Ph.D. on the topic "Ubiquitous Technology for Lifelong Learners". His current areas of research include technology-enhanced learning, ubiquitous technology, and smart learning environments.

Sergio Serrano-Iglesias received his BSc and MSc in Telecommunications Engineering from the University of Valladolid, Spain, in 2016 and 2017 respectively. He is currently a PhD candidate in the GSIC-EMIC Research Group at the University of Valladolid. His main research interests include Smart Learning Environments and the application of cloud computing for the support of learning.

Adrián Carruana Martín is currently a PhD candidate in the Department of Telematics Engineering at the Universidad Carlos III de Madrid. He received her BSc and MSc in Computer Science from the Universidad Carlos III de Madrid, in 2015 and 2017. Since then he has been working on research focused on machine learning.



Cristina Villa-Torrano received her BSc and MSc in Computer Science from the University of Murcia, Spain, in 2018 and 2019, respectively. She is currently a PhD candidate in the GSIC-EMIC Research Group at the University of Valladolid. Her main research interests include learning analytics and Smart Learning Environments.

Yannis A. Dimitiradis is currently a full professor of telematics engineering at the University of Valladolid and coordinator of the multidisciplinary research group GSIC/EMIC. His research interests include technological and conceptual support to the design and orchestration of learning and teaching processes in smart learning environments.

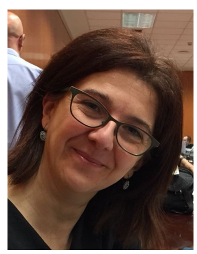
Juan I. Asensio-Pérez is Full Professor of Telematics Engineering at the University of Valladolid, Spain, and member of the multidisciplinary research group GSIC/EMIC. His research interests include the development of technological solutions for ubiquitous learning, learning design support, and learning analytics.

Carlos Alario-Hoyos is Visiting Associate Professor in the Department of Telematics Engineering at the Universidad Carlos III de Madrid. He received M.S. and PhD degrees in Information and Communication Technologies from the Universidad of Valladolid, Spain, in 2007 and 2012, respectively.

His skills and experience include research and development in MOOCs, social networks, collaborative learning, or evaluation of learning experiences.

Eduardo Gómez-Sánchez received his PhD degree in Telecommunications Engineering in 2001. He is currently professor of Telematics Engineering at the University of Valladolid. His main research interests include the design and evaluation of software systems to support collaborative learning, both in formal and informal settings, and connecting them.

Miguel L. Bote-Lorenzo is Associate Professor of Telematics Engineering at the University of Valladolid, Spain, and member of the multidisciplinary research group GSIC/EMIC. His research interests include smart learning environments, learning analytics, and gamification.



Alejandra Martínez-Monés is Associate Professor of Computer Science and Human Computer Interaction at the University of Valladolid, Spain. Her main research interests in the area of technology-enhanced learning include the support to teachers in the design, enactment and evaluation of innovative learning activities using learning analytics approaches.

Carlos Delgado Kloos received the PhD degree in Computer Science from the Technische Universitat Munchen and in Telecommunications Engineering from the Universidad Politecnica de Madrid. He is full professor of Telematics Engineering at the Universidad Carlos III de Madrid, where he is the director of the GAST research group, director of the UNESCO Chair on "Scalable Digital Education for All", and Vice President for Strategy and Digital Education. He is also the Coordinator of the eMadrid research network on Educational Technology in the Region of Madrid. He is the Spanish representative at IFIP TC3 on Education.