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

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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 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.

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. 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 COVID-19 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 (ICLSE) 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.” Alternately, 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

There exist some works in which relevant publications on SLEs are reviewed. Pappamissis 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 feedback services, 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 by Potuo 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-of-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 (ICSLIE), 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 (SLERD). 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 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 mentioned in the title, keywords or slightly in the text without discussing its “smart” characteristics 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].

### Table I

<table>
<thead>
<tr>
<th>Inclusion criteria</th>
<th>Exclusion criteria</th>
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<tbody>
<tr>
<td>Empirical work. Tools that are evaluated in case studies. Papers describing framework/architectures including a final solution contextualized in a pedagogical approach and using technology.</td>
<td>Off-topic papers. Publications were excluded if their main focus was not on the use of technology for learning/teaching, OR.</td>
</tr>
<tr>
<td>Surveys were discarded. Technological proposals that were not described within a pedagogical context were also discarded.</td>
<td>Publications focused exclusively on theories, philosophical aspects, concepts, visions, or ideas. Surveys on these aspects are not considered as empirical papers. OR.</td>
</tr>
<tr>
<td>In case of multiple articles reporting the same study, all but the most recent one are discarded. OR.</td>
<td>Papers where the term smart was only mentioned in the title, keywords or slightly in the text without discussing its “smart” characteristics were discarded. All these restrictions were formulated as inclusion and exclusion criteria (IC/EC), as shown in Table I.</td>
</tr>
<tr>
<td>Publications exploring organizational aspects in educational institutions. OR</td>
<td>Publications not written in English.</td>
</tr>
</tbody>
</table>

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. The concepts are extracted from the papers as mentioned by the authors, i.e. it is possible that synonymous concepts may be treated differently if the authors do not contemplate it.

Regarding the extraction of affordances, the review process included an item in which reviewers had to identify the affordances that were highlighted by authors regarding their SLEs. 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. The questions related with the pedagogical approaches, learning strategies and learning domains, reviewers were presented with items extracted from the previous review. Nevertheless, reviewers were encouraged to include any additional classification as stated by the authors of the corresponding paper.
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. The most relevant journals were the Smart Learning Environments journal (n = 31) and the International Journal of Web-Based Learning and Teaching Technologies (n = 2). The most relevant conference was the International Conference on Smart Learning Environments (n = 8).

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 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, Dukich 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. To make the tables easier to read, only the most frequent concepts are shown.

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 Bidiwi 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, 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
TABLE II

<table>
<thead>
<tr>
<th>Concepts Associated with the Term “Smart”</th>
<th># Papers (%)</th>
<th>Articles</th>
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<tbody>
<tr>
<td>Smart phone</td>
<td>12 (17.6%)</td>
<td>[26], [32], [34], [38], [41], [49], [51]</td>
</tr>
<tr>
<td>Smart classroom</td>
<td>9 (13.2%)</td>
<td>[20], [33], [34], [44], [48], [52], [55]</td>
</tr>
<tr>
<td>Smart devices</td>
<td>3 (4.4%)</td>
<td>[32], [45], [56]</td>
</tr>
<tr>
<td>Smart teacher</td>
<td>2 (2.9%)</td>
<td>[46], [57]</td>
</tr>
<tr>
<td>Smart workspace</td>
<td>2 (2.9%)</td>
<td>[20], [34]</td>
</tr>
<tr>
<td>Smart lab</td>
<td>2 (2.9%)</td>
<td>[20], [47]</td>
</tr>
<tr>
<td>Smart education</td>
<td>2 (2.9%)</td>
<td>[48], [53]</td>
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</table>

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 consisting 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, Bidiwi 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, Lal-ingkar 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. [29] 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 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, Kifteodimos 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.

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. Chou 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.

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), process data (analyze onwards), and output data (react onwards). Here technologies are classified and listed following these processes.

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...
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., RFID); (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, hand-held 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 chatbot that collects frequently asked questions by students.

Learning management systems (LMSs) were referenced in 20% of the selected publications. LMSs are commonly used in e-learning environments. The work from Koulouchari 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 provide 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.
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 Savos et al. [66], machine learning was used within a system that inferred students’ level of attention and enriched the description.

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 environments 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 Trivonen 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 “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, handeld devices, and tablets were referenced in 27% of the selected publications. The work of Lytridis et al. [43] shows a mobile tool that responds to the identification of a problem in SLEs. For example, the work of Lytridis et al. [43] shows a mobile tool that responds to the identification of a problem in SLEs.

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 reacted 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 Kishuk [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 reacts displaying recommendations on how students should behave onwards to reduce the risks of contamination.

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/RUBAR) 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, Bidoni 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. Seanoisky et al. [21] relied on a system (SCALE) to evaluate the skills of the workers in a company on emergency procedures. Bardama 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 Moodle, reducing the number of dropouts. Pesare et al. [26] supported health professional 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], [29], [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, Angello 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.

On the other hand, 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]. Temudee [51] implemented a mobile application to enhance digital literacy on ethnic minority groups in Thailand. Due to the disparate type of logs collected by mobile phones (e.g., sensors, chat interactions), different approaches adopted a LA perspective to understand how students learn (e.g., using facial recognition [49], or exploring chat interventions [40]). Additionally, some authors attempt to support virtual laboratories by means of
TABLE VIII
LEARNING DOMAINS IN SLEs

<table>
<thead>
<tr>
<th>Learning domains</th>
<th># Papers (%)</th>
<th>Articles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engineering</td>
<td>15 (22.06%)</td>
<td>[21], [22], [27], [33], [34], [42], [47], [48], [53], [61], [67], [69], [80], [84], [86], [88]</td>
</tr>
<tr>
<td>Technology</td>
<td>10 (14.70%)</td>
<td>[35], [63], [67], [71], [78], [82]</td>
</tr>
<tr>
<td>Science</td>
<td>8 (11.76%)</td>
<td>[23], [33], [36], [40], [47], [67], [73], [74]</td>
</tr>
<tr>
<td>Foreign language</td>
<td>6 (8.82%)</td>
<td>[28], [38], [39], [46], [76], [88]</td>
</tr>
<tr>
<td>Mathematics</td>
<td>4 (5.88%)</td>
<td>[29], [60], [62], [67]</td>
</tr>
<tr>
<td>Biology</td>
<td>3 (4.41%)</td>
<td>[47], [73], [75]</td>
</tr>
<tr>
<td>Computer science</td>
<td>2 (2.94%)</td>
<td>[23], [36]</td>
</tr>
<tr>
<td>Education</td>
<td>2 (2.94%)</td>
<td>[39], [81]</td>
</tr>
<tr>
<td>Health</td>
<td>2 (2.94%)</td>
<td>[26], [59]</td>
</tr>
<tr>
<td>Medicine</td>
<td>2 (2.94%)</td>
<td>[66], [75]</td>
</tr>
<tr>
<td>Chemistry</td>
<td>1 (1.47%)</td>
<td>[73]</td>
</tr>
<tr>
<td>Commerce</td>
<td>1 (1.47%)</td>
<td>[52]</td>
</tr>
<tr>
<td>Economics</td>
<td>1 (1.47%)</td>
<td>[77]</td>
</tr>
<tr>
<td>Environmental education</td>
<td>1 (1.47%)</td>
<td>[41]</td>
</tr>
<tr>
<td>Geography</td>
<td>1 (1.47%)</td>
<td>[57]</td>
</tr>
<tr>
<td>Music</td>
<td>1 (1.47%)</td>
<td>[79]</td>
</tr>
<tr>
<td>Nursing</td>
<td>1 (1.47%)</td>
<td>[65]</td>
</tr>
<tr>
<td>Psychology</td>
<td>1 (1.47%)</td>
<td>[64]</td>
</tr>
</tbody>
</table>

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.

VI. DISCUSSION

Multiple definitions of SLEs have been given in recent years while none of them has been widely accepted. The reviews that have been conducted so far have not focused on providing a better understanding of SLEs, but rather on some characteristics that may be associated with them. In Papatmotsiou and Economides [3] the work focuses on the potential of learning analytics. In Putro et al. [11] the review focuses on AI learning in groups, a feature that need not always be supported by SLEs. On the other hand, other reviews have focused on theoretical proposals, such as the one in Heinemann and Uskov [12]. However, we have conducted a review of the literature with a focus on empirical studies. This may help to better understand the specific characteristics of existing SLEs, as well as the technologies and educational contexts where they have been used, and the current limitations of the field. In addition, our literature review has been carried out in a rigorous manner, with a strong methodology. To the best of our knowledge, no systematic review of the literature on SLEs has been conducted previously.

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 show that this research area is in an initial state (see Section IV).

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, ubiquity, etc.) 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 IJSE) 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.” Coherently with [7], [9], [10],
Table 3 shows that adaptability (adaptation, customization, and personalization) is the most commonly used affordance to describe SLEs. Nonetheless, 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 SLEs. 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).

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-B.1.

- **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 future 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.

According to the number of papers found, most aspects that arouse the interest of the community are still poorly developed. Researchers should further consider the support provided to teachers in SLEs for a wider adoption of these environments, as well, the connection between formal, non-formal and informal learning experiences. Another aspect to consider is to work more on different affordances in SLEs. Hardly any papers have been found with the affordance assessment [20], [38], [40], motivation [33] or sustainable [56]. Further research should investigate these issues implementing SLEs that consider the three core functions.

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 bandwidth), 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.

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