Heliyon 10 (2024) e26191

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Review article

Thematic evolution of smart learning environments, insights and directions from a 20-year research milestones: A bibliometric analysis

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A R T I C L E I N F O

Keywords:
Adaptive learning
Bibliometric analysis
Personalized learning
Smart learning environments
Thematic evolution

A B S T R A C T

Smart learning environments (SLEs) have been developed to create an effective learning environment gradually and sustainably by applying technology. Given the growing dependence on technology daily, SLE will inevitably be incorporated into the teaching and learning process. Without transforming technology-enhanced learning environments into SLE, they are restricted to adding sophistication and lack pedagogical benefits, leading to wasteful educational investments. SLE research has grown over time, particularly during the COVID-19 pandemic in 2020–2021, which fundamentally altered the "landscape" of technology use in education. This study aims to discover how the stages of SLE transform from time to time by applying two bibliometric analysis approaches: publication performance analysis and science mapping. The dataset was created by extracting bibliometric data from Scopus, including 427 articles, 162 publication sources (journals and proceeding), and 1080 authors from 2002 to 2022. Three kinds of SLE research subjects were identified by keyword synthesis: SLE features, technological innovation, and adaptive learning systems. Adaptive learning and personalized learning are consistently used interchangeably to demonstrate the significance of supporting the diversity of student and teacher conditions. Learning analytics, essential to employing big data technology for educational data mining, is a new theme being considered increasingly in the future to achieve adaptive and personalized learning. The 20-year SLE research milestone, broken down into five stages with various focuses on goals and served as the foundation for creating a maturity model of SLE.

1. Introduction

In the digital age, the organizational environment is changing faster and becoming more volatile, uncertain, and complex than in the past [1]. It also occurs in educational organizations and individual learning environments: digital integration, adoption, and transformation support teaching and learning [2,3]. A learning environment nowadays could be a classroom, computer workstation at home, in the workplace, at any place, or virtual learning with a teacher, students, situation, context, and various tools and technologies

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https://doi.org/10.1016/j.heliyon.2024.e26191
Received 9 May 2023; Received in revised form 31 January 2024; Accepted 8 February 2024
Available online 23 February 2024
2405-8440/

to support learning. Technology-enabled learning environments attract educators in all areas of education to provide new learning opportunities, implement new teaching methods, and apply innovative approaches [4,5]. According to Kinshuk, Chen, Cheng, and Chew [6], the availability of technology and the existence of digital transformation have changed behavior, habits, and teaching and learning processes to encourage the transformation of the learning environment into a smart learning environment (SLE).

Digital transformation is a continuous adoption process [1], resulting in the transformation towards SLE that also occurs sustainably. Implementing an online learning policy during the COVID-19 pandemic, which lasted from 2020 to 2021, accelerated the transformation process. The transition from face-to-face learning to online learning ensured that learning does not stop even if educational institutions are forced to close classrooms [7]. The policy ensures that during the period of social restriction, the community would still have access to technology-based learning opportunities. The policy forces students, teachers, educational institutions, and communities to become accustomed to optimizing technology for learning and sharing information. However, the policy given is of an emergency nature, so many essential aspects of the objectives and the teaching and learning process may be overlooked. Learning from this experience, the development of a technology-enriched learning environment (TELE) is a necessity, but its development needs to consider aspects of integrating technology and pedagogy [6]. Therefore, SLE was developed to create an effective learning environment gradually and sustainably by applying technology based on a student-centered learning environment (SCLE) paradigm [8]. The goal of shifting the learning environment toward SLE, according to Spector [8], is to improve learning and teaching in a positive and desirable way by maximizing technological potential.

Various studies in the field of SLE are carried out by optimizing TELE to improve learning processes and outcomes. The term "smart learning environment" emerged in the early 2000s with the increasing use of new technologies in education. The term smart learning environment is defined by researchers from different perspectives.

Some SLE studies focus on aspects of the physical environment and technology, while other researchers consider aspects of learning, teaching and educational management [9]. Kinshuk et al. stated the study of the technical approach in SLE encompasses at least three aspects: the emergence of new technologies, the inventive application of established technologies, and new technological paradigms for learning and teaching [6]. For instance, Hwang defined SLE based on the perspective of context-aware ubiquitous learning that emerges as a result of the presence of mobile technology, wireless communication, and sensing technology in the learning environment [10]. The use of digital gadgets in the learning environment, or their absence, is considered by Koper to be a criterion for determining of SLE [11]. Meanwhile, Spector offers an overview of how to operationalize SLE based on at least six of the twelve indicators of effectiveness, efficiency, engagement, flexibility, adaptivity, and reflectivity [8]. The aspect of education management is implicitly stated by Spector [8] in the self-organizing indicators. These four studies serve as a starting point for SLE creation and can be expanded upon to generate guidelines for designing, implementing, and assessing learning environments toward SLE. Although they may appear to be distinct, the aforementioned definitions have one thing in common. They defined SLE in terms of a set of traits, including context-awareness, adaptability, personalization, engagement, effectiveness, efficiency, and promotion of better and faster learning, fusion of technology and pedagogy, and real-time availability.

SLE research has progressed over the past two decades, as evidenced by the many articles published. A large amount of data available can be used to identify state-of-the-art and explore topic trends and changes over time in the SLE research area. One of the methods used to do that is bibliometric analysis. A bibliometrics analysis is a set of methods used to study or measure texts and information, especially in big datasets from research articles [12,13].

An in-depth exploration of developments and yearly topic changes is necessary to gain insight into how the focus of SLE research has changed over time. This is important as one of the basics for formulating the level of smartness in the learning environment to increase its effectiveness gradually and continuously. It also could describe how the learning environment changes from time to time to SLE.

The remainder of the paper is structured as follows: Section 2 focuses on the procedure of bibliometric analysis. Section 3 presents the results, while Section 4 discusses the results and implications of the study. Finally, section 5 draws the conclusions.

2. Method

Bibliometric analysis is the statistical analysis of publications and citations to evaluate their impact and learn about the past, present, and future directions of an area of research. It helps identify essential structures of the research field, such as research networks, topics, journals, main themes, and emerging research topics [14,15]. The bibliometric analysis, as stated by Khare and Jain [15], evaluates the literature objectively such as by exploring authors, documents, or sources that have had a significant influence on the academic field, identifying the main themes, subthemes, and patterns of the area, and interactions and collaborations among authors. Unlike systematic literature reviews, which tend to rely on qualitative techniques, which the interpretive bias of the researchers can undermine, Donthu et al. [14] mentioned that bibliometric analysis relies on quantitative methods to avoid or reduce this bias. It is also valuable for identifying historical trends and the most influential researchers [16,17]. Thus, bibliometric analysis is an appropriate method to reveal the knowledge structure of SLE.

Performance in SLE research has been reviewed by some studies, including [18–20]. The studies used different database sources with varying ranges of years. The three reviews conducted studies to produce publications based on sources, authors, research collaborations, most cited articles, focused themes, trending topics, and thematic analysis based on keywords. However, they did not explore the thematic evolution of SLE's research.

The procedure of Aria and Cuccurullo [13] is adopted to perform bibliometric analysis with the help of the Biblioshiny web application, a bibliometrix-R package. It has robust statistical methods and built-in data visualization capabilities [12] and provides visualization techniques to demonstrate the conceptual knowledge structure. The procedure of bibliometric analysis in this research consist of four stages: 1) define review questions, 2) data search and collection, 3) data extraction, and 4) data synthesize and visualizations. Each stage is described in the following subsections.

2.1. Define review questions

The bibliometric study's aim and scope must be established before choosing the analytic method and beginning data gathering [14], which is determined based on a review of articles reviewing previous SLE research. Specifically, there are three review questions (RQs).

RQ1. What are the most influential SLE publications over the past 20 years?

RQ2. What are SLE topic models over 20 years?

RQ3. How has the topic of SLE research changed yearly?

This study conducted a review of SLE research to explore changes in the topic not only to gain insight into how the focus of SLE research has changed over time. This research also considers potential changes in the topic of technology use in education to describe the transformation of the learning environment which can be the basis for formulating SLE maturity levels.

2.2. Data search and collection

Data was searched and collected from Scopus. It contains a sizable number of pertinent publications and proceedings of reputable journals in the field of SLE. Scopus offers downloadable metadata in BibTex format. Therefore, the authors conducted a bibliometric analysis by specifying the scope of the search with the keyword "smart learning environment*" based on the title, abstract, and publication source. The data is searched for all publications published until July 2022 with the search keywords in the form of Boolean Search as follows (see Table 1).

The scope of the study should generally be large enough to warrant that bibliometric analysis handles large volumes of data. At least 300 papers are required for the research scope of bibliometric analysis to be sufficiently broad [14]. During the initial search, 496 articles were found and 427 papers after the second selection phase (see Table 1). This amount was determined to be adequate for the bibliometric analysis of SLE. As Mostafa did, only journal articles and proceedings were used for bibliometric analysis because the articles usually undergo a rigorous peer-review process and are generally of high quality [21].

2.3. Data extraction

Next, the bibliometric data is saved in a BibTex file and imported into the Biblioshiny application. Automatically, Biblioshiny converts Bibtex data into an R data frame, namely a bibliographic data frame with cases that match documents and variables with tag fields in the original export file [16]. Each document element is checked for adequacy, including the author's name, title, keywords, and other bibliographic attributes (metadata). The extraction results were used to determine synthesis and visualization methods to answer the three review questions.

At this stage, the research team also extracted the frequency of keywords, which were then analyzed and found terms with the same meaning but written differently. Therefore, a preprocessing stage is needed, namely adding a list of synonym words and a list of stop words based on a list of terms extracted from bibliometric data. According to Donthu et al. [11], removing duplicates and incorrect entries is crucial to avoid misrepresentation in the preprocessing stage of the bibliometric analysis stage. Aria and Cuccurullo [16] explained that the most frequent words or terms are ignored because they consist of a collection of terms used to build a search query on the original data source. This result is relevant to the Luhn distribution, where the query term is included in the "upper cut-off" category, which can be removed because it includes non-significant words that do not contribute significantly to the article's content. This extraction creates a list of synonyms and stopwords used in the next stage.

2.4. Data synthesize and visualizations

Bibliometric analysis is realized in performance analysis and science mapping [13,14]. In this research, the performance analysis is used to answers the first question. The last two review questions above are formulated explicitly to discover how the stages of SLE transform from time to time. The conceptual structure of SLE publications is used to answer the last two questions because it can provide an understanding of the topics covered by the journal, determine the most important and newest topics, and study the evolution of research topics over time [12].

2.4.1. Performance analysis

Performance analysis describes the performance of authors, institutions, countries, and journals as a field's background or research profile [13,14,16]. This study uses the number of publications as a productivity indicator and the number of citations as an impact indicator to describe an overview of the performance of SLE publications [17]. This study also analyzes the interrelationships of keywords to the author and the country by utilizing the three-field plot feature in the Biblioshiny which is visualized using the Sankey Diagram to represent the relationships between each plot [21].

2.4.2. Science mapping

On the other hand, science mapping is concerned with intellectual interactions and structural relationships between research constituents using citation analysis [13,14]. This research focused on identifying topics and their changes every year for 20 years, so the co-word analysis was chosen from the author's keywords. Keywords in academic publications express the thematic concept of the document, where the author's keywords are considered essential terms of the text and represent the author's intent [14,22]. As Cobo et al. [1013] stated, co-word analysis is more suitable for discovering the conceptual evolution of a research field. Co-word analysis is a content analysis technique that deals with a collection of terms shared by documents and maps literature to the interaction of key terms [9,10] by assuming that words that frequently appear together have a thematic relationship [14]. Data synthesis uses co-word analysis to answer RQ2 and RQ3.

This study uses two conceptual structural approaches, namely factorial analysis as a factorial approach and thematic evolution and maps as a network approach. The Biblioshiny allows the use of the conceptual structure function to perform Multiple Correspondence Analysis (MCA) to visualize conceptual structures. MCA analyzes categorical variables to find the relationships between categorical variables in general. Homogeneity analysis of an indicator matrix is performed by MCA, an exploratory multivariate technique for the graphical and numerical analysis of multivariate categorical data, in order to provide a low-dimensional Euclidean representation of the original data [13]. The words are plotted on a two-dimensional map and interpreted based on the relative positions of the points and their distribution along the dimensions. The MCA graph demonstrates that the closer the dots are together, the more similar a profile they represent, whereas each cluster of dots denotes a different type of profile [21,23].

Finding the key themes and subfields of a research field and mapping these themes on a bi-dimensional matrix are the next phases in deconstructing a conceptual structure [15]. The conceptual structure of a research domain was explored using thematic analysis to enhance topic visualization and interpretation and track topical trends over time [24].

Thematic maps show the clusters identified by the co-occurrence network and divided into four topological regions mapped in strategic diagram, which is built by plotting themes according to their centrality and density ratings [13,24]. The X-axis (horizontal axis) represents centrality, that is, the degree of interaction of network clusters compared to other clusters, and provides information about the importance of the theme. The Y-axis (vertical axis) represents density, which measures the internal strength of the cluster network, and can be assumed as a measure of theme development. Thus, according to Cobo et al. [13], the four quadrants formed consist of: motor themes, niche themes, emerging or declining themes, and basic themes. The first quadrant in the upper-right quadrant is known as the motor themes, characterized by high centrality and high density, meaning they are developed and essential for the research field. The second quadrant in the lower-right quadrant includes basic and transverse themes (basic themes) about general topics that are transverse to different research areas in the field, characterized by high centrality and low density. The third quadrant in the lower-left quadrant contains emerging or declining themes that are underdeveloped and marginalized, with low centrality and low density. The fourth quadrant in the upper-left quadrant plots highly developed and isolated themes (niche themes); with highly developed internal links (high density) but minor outward links, those themes are not particularly significant for the subject (low centrality). Thematic analysis is used, in this study, to extract the various topics related to SLE and highlight the development of the discourse about transforming the learning environment into SLE.

3. Results

The extraction of bibliometric data from Scopus shows that 427 documents, 162 publication sources, and 1080 authors are stored in the dataset.

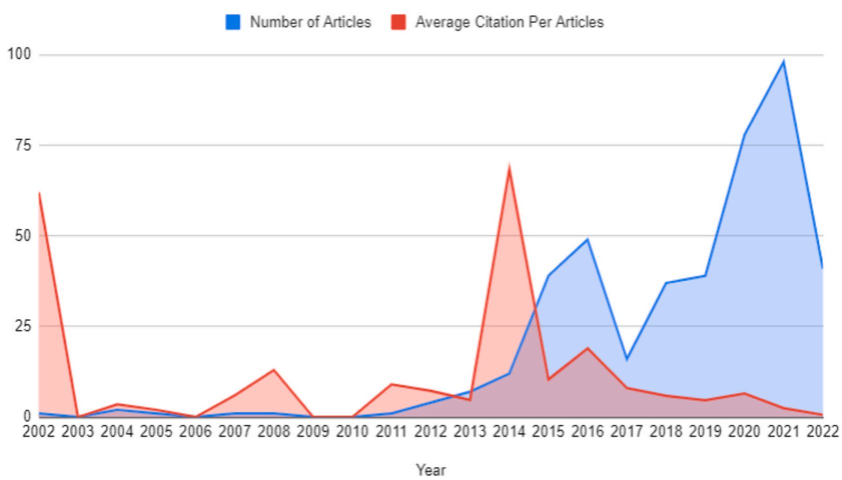

Fig. 1. Scopus indexed growth chart of SLE publications for January 2002–2022.

3.1. Addressing RQ1. What are the most influential SLE publications over the past 20 years?

3.1.1. Annual scientific production

The annual scientific production and average citation per articles from 2002 to 2022 displays a growth graph in Fig. 1.

The calculation result of the annual growth rate of 20.4% shows positive growth for the publication of SLE research every year for 20 years. The graph in Fig. 1 shows that researcher's interest in the SLE field is still relatively high, but this rate is not evenly distributed. For example, in 2003, 2006, 2009, and 2010 there were no SLE's publications on which Scopus index. Additionally, the number of publications decreased from 49 articles the year before to 16 in 2017 and then increased to 37 in 2018. Future trends are probably going to follow the annual growth rate and it is estimated that publications in 2022 will reach around 120 articles by the end of year.

Citation of articles published from 2002 to 2022 fluctuated. The articles that received the most citations were those published in 2002 and 2014. Only one article published in 2002 was written by Sosteric et al. [34]. This article mentioned learning objects as the next hot topic in distance education research that seeks to create SLE to enter the broader education market. Fig. 2 shows a graph of the average total citations per article each year, where the 12 published in 2014 were cited at most, reaching an average of 68.42. The following Table 2 presents a list of Scopus-indexed SLE publications in 2014.

The information in Table 2 reveals that the five most-cited publications were those that were published in Smart Learning Environments Journals. The article by Hwang [30] received the most citations across the board in the dataset, the article by de Jong et al. [32] being the second, and the work by Spector [8] coming in third. Although identifying the conditions for the development of effective smart learning environments by enriching physical environments with digital, context-aware, and adaptive devices, article written by Koper [11] received fewer citations than the other three articles. Whereas, the work of Zhu et al. [5], which had 232 citations, was the second-most-cited publication, according to a closer look at the graph in Fig. 2. For many SLE researchers, the works of Hwang [10], Koper [11], Spector [8], Zhu et al. [5], and de Jong et al. [32]became fundamentals.

On the other hand, there have been publications during the COVID-19 pandemic that offer fresh perspectives that are beneficial to the emergence of SLE. The number of citations, which has increased by over 15 times after publication (Table 3), confirms it (Table 3). Explicitly, the titles of the articles illustrate the expansion of the topic of SLE.

A number of articles have covered both cognitive [42] and affective [35] aspects of assessment. The merging of ideas from the perspectives of education, technology and psychology as proposed by Spector [8] has also been a focus of SLE development [36,37, 39–41]. The potential of advanced technologies such as the Internet-of-things (IoT), artificial intelligence (AI), and blockchain, has received serious attention from SLE researchers [38,39,43]. This broadening of topics reveals a change in the SLE's course of development.

3.1.2. Three-field plots of authors, keywords and countries

The following general information is provided by three-field plots (Fig. 3) to show the links between authors, keywords, and countries, with gray links indicating how these three components are related. The first element, on the left, is authors. Each author is linked to a topic on the right with frequently used keywords. The chart shows that Alario-Hoyos, Bote-Lorenzo, Huang, Kinshuk, Gomez-Sanchez, and Oyelere are the authors who contributed the most to the use of keywords. The second element includes the topic keywords that were used in papers the most. Each subject has authors who have written substantially on it. The third component is the country indicating the author's country of origin.

Each list's rectangle sizes in Sankey Diagram correspond to the number of papers related to each element. In Fig. 3, the "Kinshuk" box on the author side is the tallest, indicating that he produced the most articles, while the "e-learning" box on the keywords side and "Japan" on the nation side are the two that are the smallest, indicating that they include the fewest articles. The bands represent the link between the components. The smaller the band, the less significant the relationship between the two connected boxes. For instance, the "smart learning" box in the middle of the Sankey diagram receives eight input bands from the author box, and nine output bands go to the country box. In this example, the widest band is shown between "smart learning" and "korean", meaning that research with these keywords comes mostly from Korean researchers.

Fig. 2 confirms that although "smart education" and "e-learning" were not found as keywords used by the top ten authors, the researchers' interest in them was very high. For example, "smart education" was used the most by other authors from the United States and Spain, while "e-learning" was the keyword most used by authors from China and Korea. These results also show research developments in three continents: Asia, Europe, and America influence the scope of SLE topics.

Table 1
Search and select articles on Scopus for bibliometric analysis.

Phase	Criteria	Total articles
Initial search	(TITLE-ABS-KEY ("smart learning environment*") OR SRCTITLE ("smart learning environments"))	496
First selection	(TITLE-ABS-KEY ("smart learning environment*") OR SRCTITLE ("smart learning environments")) AND (LIMIT-TO (PUBSTAGE, "final")) AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "ch")) AND (LIMIT-TO (LANGUAGE, "English")) AND (EXCLUDE (LANGUAGE, "Italian"))	444
Second selection	Inclusion criteria: selected articles where the title or abstract of the article contained the keywords 'smart learning environment' or relevant keywords such as 'smart education', 'smart educational learning', 'smart classroom' and others. Exclusion criteria: articles that met any of the following criteria were removed: 1) bibliometric analysis; 2) abstract not available; 3) duplicates.	427

Table 2
List of Scopus-indexed SLE publications in 2014.

Title and references	Sources	Cited
A pilot study comparing secondary school students' perception of smart classrooms in Hong Kong and Beijing [25]	Proceedings of the 22nd International Conference on Computers in Education, ICCE 2014	0
Educational affordances of smart learning applications in science education [26]	Proceedings of the 22nd International Conference on Computers in Education, ICCE 2014	0
A peer-assessment system connecting on-line and a face-to-face smart classroom [27]	Life Science Journal	3
Automated tutoring system: Mobile collaborative experiential learning (MCEL) [28]	Proceedings - IEEE 14th International Conference on Advanced Learning Technologies, ICALT 2014	2
Smart learning for the next generation education environment [29]	Proceedings - 2014 International Conference on Intelligent Environments, IE 2014	11
Designing and experiencing smart objects based learning scenarios: An approach combining IMS LD, XAPI and IoT [30]	ACM International Conference Proceeding Series	8
The effectiveness of digital storytelling in the classrooms: a comprehensive study [31]	Smart Learning Environments	91
Innovations in STEM education: the Go-Lab federation of online labs [32]	Smart Learning Environments	163
Conditions for effective smart learning environments [11]	Smart Learning Environments	91
Conceptualizing the emerging field of smart learning environments [8]	Smart Learning Environments	168
Definition, framework and research issues of smart learning environments - a context-aware ubiquitous learning perspective [10]	Smart Learning Environments	281
Conceptualizing and supporting the learning process by conceptual mapping [33]	Smart Learning Environments	3

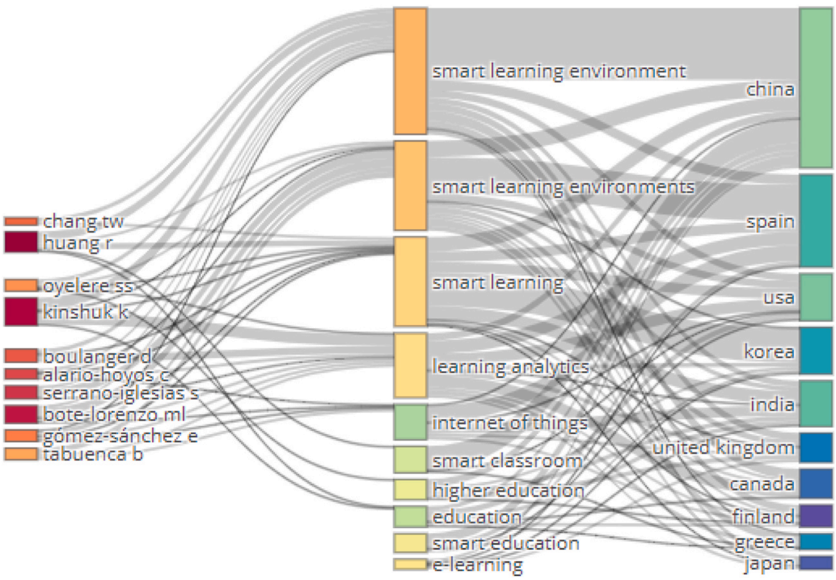

Fig. 2. Three-field plots between authors, keywords and countries in SLE publications.

3.2. Addressing RQ2. What are SLE topic models over 20 years?

The following subsections analyze and discuss a review of current research in the field of SLE based on word frequency and conceptual structure of scientific mapping utilizing keywords.

3.2.1. Factorial analysis using Multiple Correspondence Analysis

Fig. 3 shows the conceptual evolution of SLE over twenty years. Based on the author's keywords, MCA sorted the SLE's keywords into three groups of clusters. The largest red cluster contains the most keywords and is more broadly scattered and closer to the map's center, which means have received more attention in recent years [23]. As illustrations, there are 74 articles related to "smart learning, " 40 articles discussing "learning analytics," and 25 articles analyzing "e-learning" and "personalized learning" in SLE's context. The largest red cluster contains the most keywords that describe the breadth of the scope of SLE.

In contrast, the less-discussed study topics are associated with the more equally distributed terms [23], as shown in the blue and green clusters. At the upper right, the term "technology-enhanced learning" has been studied more in SLE (20 articles) than "ubiquitous learning" (12), "big data" (9), and "video-based learning" (2). The four keywords have the same idea of a technological approach to SLE. If seen from its position in the MCA conceptual map, the four words in the blue cluster have received the attention of

Table 3
Most cited articles published in 2019–2021.

Title and references	Sources	Years	Cited
Assessment in smart learning environments: psychological factors affecting perceived learning [35]	Computers in Human Behavior	2019	17
Personalized adaptive learning: an emerging pedagogical approach enabled by a smart learning environment [36]	Smart Learning Environments	2019	19
The impact of gamification on students' learning, engagement and behavior based on their personality traits [37]	Smart Learning Environments	2020	24
A blended learning model with IoT-based technology: effectively used when the Covid-19 pandemic? [38]	Journal for the Education of Gifted Young Scientists	2020	25
Eye-tracking and artificial intelligence to enhance motivation and learning [39]	Smart Learning Environments	2020	25
Exploring the role of social media in collaborative learning the new domain of learning [40]	Smart Learning Environments	2020	54
Disrupted classes, undisrupted learning during covid-19 outbreak in china: application of open educational practices and resources [41]	Smart Learning Environments	2020	91
Examining the key influencing factors on college students' higher-order thinking skills in the smart classroom environment [42]	International Journal of Educational Technology in Higher Education	2021	19
Blockchain technology adoption in smart learning environments [43]	Sustainability	2021	27

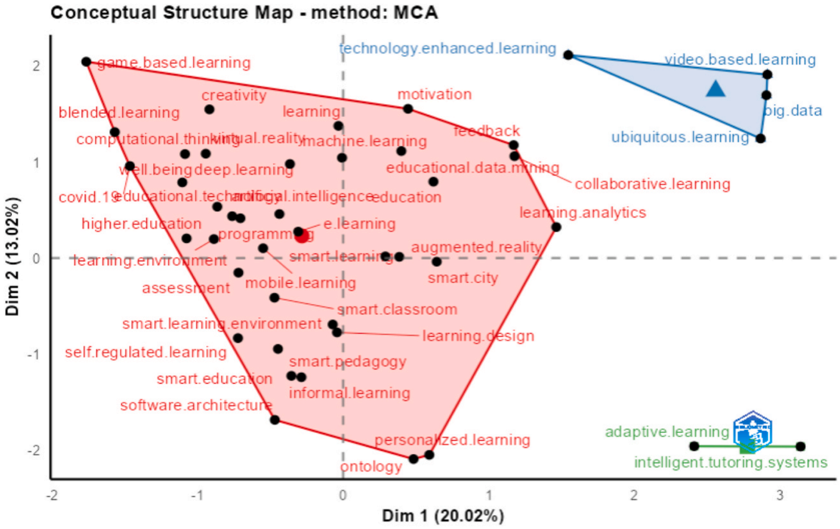

Fig. 3. Conceptual map and keyword clusters of SLE's research.

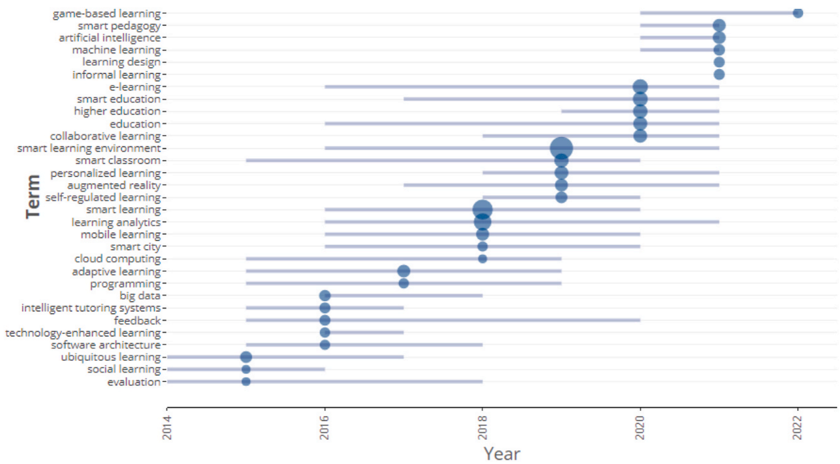

Fig. 4. Trend of SLE's topics yearly 2004–2022 based on author's keywords.

SLE researchers but still have the potential to be studied in more depth. Likewise, the two keywords in the green cluster are “adaptive learning” (15 articles) and “intelligent tutoring system” (10 articles). These two words are ideas that have been around for a long time and are still interesting to study regarding the ability of SLE to facilitate learner diversity. However, their correspondence with other more widely-discussed topics still needs to be clarified. The MCA concludes that the conceptual structure of SLE consists of three clusters: the scope of SLE, technological approaches, and adaptive learning systems.

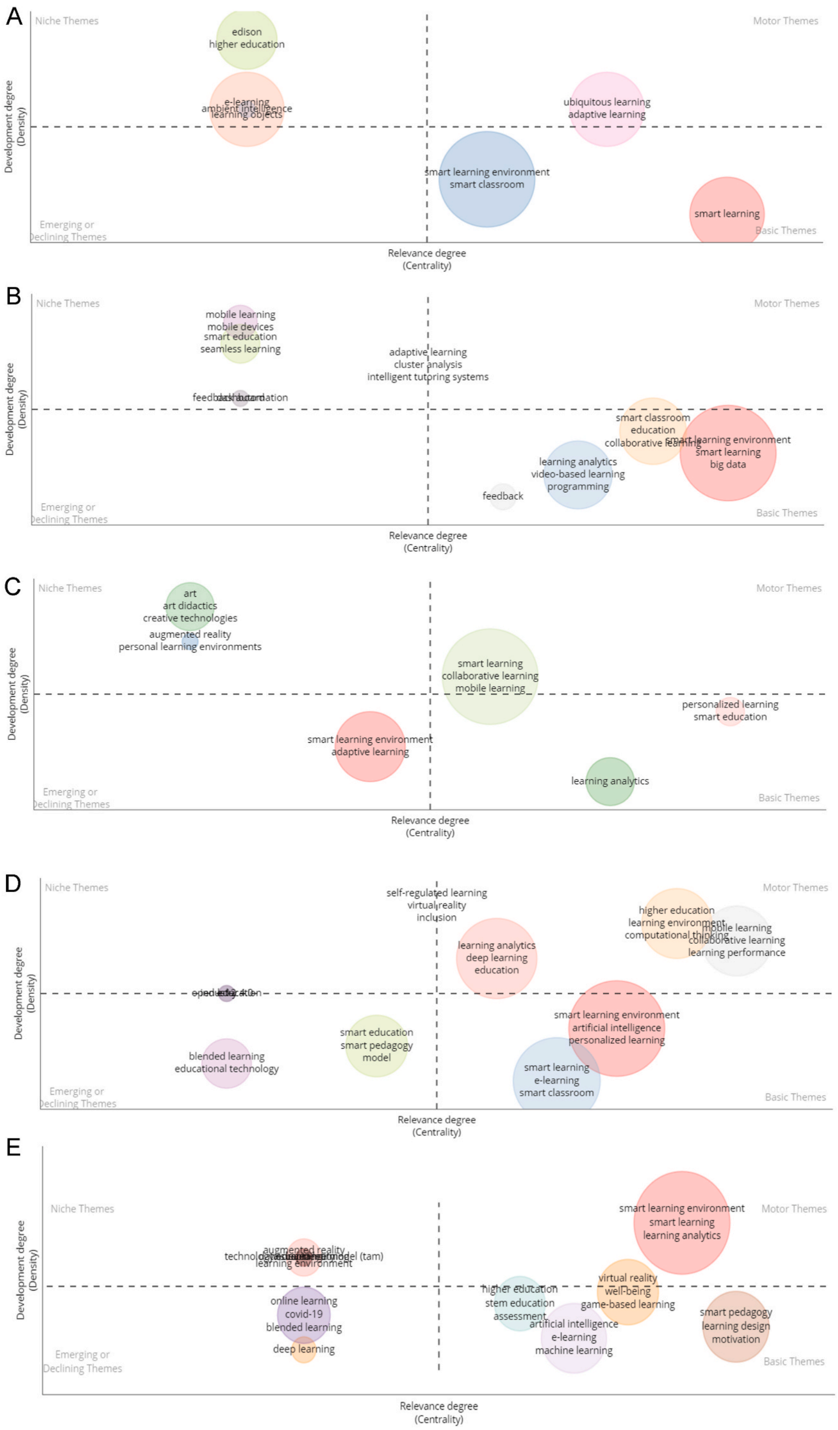

Fig. 5. 5a Thematic map of SLE between 2002 and 2014: Fig. 5b Thematic map of SLE between 2015 and 2016: Fig. 5c Thematic map of SLE between 2017 and 2018: Fig. 5d Thematic map of SLE between 2019 and 2020: Fig. 5e Thematic map of SLE between 2021 and 2022.

3.2.2. Topics trend

To get information on the major trending topics from year to year, Biblioshiny provides a visualization based on the parameters of the minimum frequency per year and the number of keyword that be displayed. In this study, the parameters used are the frequency of terms at least three and the number of terms per year equal five. The topic trend visualization in Fig. 4 shows 31 keywords that meet the parameters, which appear from 2014 to 2022. These results show that keywords that became trending topics during 2002–2013 had frequency less than three. The graphs describing topics that are trending each year vary. For example, in 2014, the keywords "ubiquitous learning", "social learning", and "evaluation" became hot topics, but since 2016 the issue of "social learning" began to be abandoned in SLE research.

Some keywords became trending topics in the SLE field for a relatively long period of about five years or more during the 2015–2021 range, namely "e-learning", "smart education", "education", "smart classroom", "augmented reality", "smart learning", "learning analytics", "mobile learning", "smart city", "cloud computing", "adaptive learning", "programming", and "feedback". The new hot topic is "game-based learning" which has attracted the interest of SLE researchers from 2020 until now. The subject of "big data" was widely discussed in SLE research in the 2016–2018 period, which seems to be implicitly discussed again starting in 2020 through the topics of "smart pedagogy", "artificial intelligence", and "machine learning". Because the body of knowledge in a particular area might be organized as a series of themes that arise, grow in prominence for a specific amount of time, and then disappear, an unexpected burst or spike in keywords may also be a sign of possible trends [21].

Despite having the possibility for future SLE study, several keywords halted in 2021 and did not return in 2022 since they did not match the visualization parameter. Thematic evolution could be used to continue the research of popular topics over time. The outcomes of the co-word analysis procedure to identify theme progression are described in the following subsection.

3.3. Addressing RQ3. How has the topic of SLE research changed yearly?

3.3.1. Thematic evolution and maps

This study divides the period into time slices so that bibliometric analysis is carried out at a certain point to represent a static picture of the field to capture the development of research through time [16]. The cutting years is determined by the distribution of the number of articles published and the results of the topic trend graph shown in Fig. 5. Parameters of time slices are four points with cutting years: 2014, 2016, 2018, and 2020. Each period consists of some clusters formed by a set of keywords and visualized in bi-dimensional thematic maps, namely strategic diagram.

Five thematic maps for the periods 2002–2014, 2015–2016, 2017–2018, 2019–2020, and 2021–2022 are shown in Figs. 5a–5e, respectively. This research used a minimum threshold of three occurrences to filter only the most frequent [12]. A better understanding of the keywords in the time-sliced themed maps is obtained by using the top three words in each group of maps. The theme "smart learning" and "smart learning environment," including the sub-theme "smart classroom," are fundamental themes for the SLE area; however, they have not yet matured between 2002 and 2014.

The concepts of "e-learning" and "higher education" emerged but were not essential to SLE study. The concept of "ubiquitous learning," along with its sub-theme of "adaptive learning," was extensively developed during this time. The fact that these two keywords are in a bubble that crosses the X-axis suggests that the theme is transitioning from a basic theme to a motor or vice versa. The topic of "e-learning" is between niche and emerging/declining themes. Therefore, it is necessary to examine where these issues will stand in the upcoming time.

The second period of the thematic evolution of SLE is from 2015 to 2016 (Fig. 5b), where there are no themes in the emerging/declining and motor themes quadrant. In this period, it can be seen that the "smart learning environment" cluster contains "smart learning" which was initially in a different and separate cluster from the "smart classroom". From the position, these three themes are still the basic themes that are slowly moving toward the motor theme becoming a hot topic. Meanwhile, themes containing the keyword "adaptive learning" move towards niche themes considered underdeveloped in SLE research.

One interesting thing from the evolution of the theme is seen in the third period (Fig. 5c), 2017–2018, where the quantity of SLE publications decreased and caused a shift in the "smart learning environment" theme to the emerging/declining quadrant. On the other

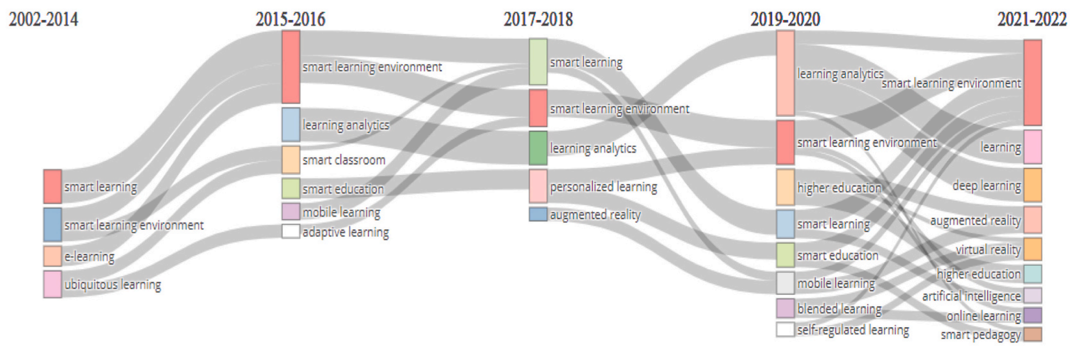

Fig. 6. SLE's thematic evolution over five periods from January 2021–2022.

hand, the "smart education" theme has moved from a niche to a basic theme as part of the "personalized learning" topic. The "smart learning" cluster in the third period became a hot topic by covering the keywords "collaborative learning" and "mobile learning".

The 2019–2020 time slice shows more clusters than the previous three periods, but no clusters are in the exact middle of the niche quadrant. There are two clusters in the emerging/declining theme quadrant: "blended learning" and "smart education." In this fourth period (Fig. 5d), the "smart learning environment" cluster, which includes the keywords "artificial intelligence" and "personalized learning," is again the basic theme of the "smart learning" cluster. The clusters "learning analytics," "higher education," and "mobile learning" were among the current hot themes. Theme "self-regulated learning," a new theme that arose, was in the middle of the centrality and density axis, indicating the importance of this theme as a hot topic in SLE research.

The last period of theme evolution is 2021–2022, which shows the four quadrants containing some clusters. Fig. 5e depicts a thematic map containing nine clusters. Several clusters initially in the niche, motor, or emerging/declining quadrant, in this period are in the basic theme or mid-density axis between the basic and the motor theme. In this time slice (Fig. 5e), the "smart learning environment" cluster has moved from the basic quadrant to the motor quadrant and has become a hot topic. The position of each cluster in each quadrant shows the value of centrality and density. The further away from the center axis indicates cluster's role in the quadrant is weakened.

After examining each sub-period, it is possible to understand how the study themes on SLE have changed through time. Fig. 6 shows the Sankey diagram for five periods of SLE theme evolution, showing the flow of theme changes represented by the box cluster over time. The flow band shows the movement of themes from one period to another, and there are two types of flow, namely: "incoming flow" and "outgoing flow." For example, the "smart learning" cluster in 2002–2014 has one band that exits to the "smart learning environment" cluster in 2015–2016. However, the "smart learning environment" cluster in that period has three "incoming flow" bands originating from "smart learning", "smart learning environment," and "e-learning." In addition, the cluster also has two "outgoing flow" bands towards "smart learning" and "smart learning environment" in the 2017–2018 period. Meanwhile, the "augmented reality" cluster in the 2017–2018 period and "blended learning" and "self-regulated learning" in 2019–2020 only had an "outcoming flow" band, even though all three were in the middle of the SLE research period. These streams show that themes emerged from the development of themes in the previous period, disappeared with the emergence of new themes, or just appeared as other relevant themes emerged.

Each period has many keywords (terms) from a set of articles published on that time slice.

4. Interpretation and discussion

The extraction and visualization results from performance analysis and conceptual structure are then synthesized, analyzed, and discussed in the following sections.

4.1. The most impactful SLE publications

The first review question about the most influential SLE publications over the past 20 years was answered based on performance analysis as follows. Information obtained from annual scientific production shows an increase in the quantity of SLE publications, especially after 2018. The publications of the most influential research in the SLE field are the works of [5,8,10], shown from the total citations. Epistemology, psychology, and technology are three primary areas that provide meaningful input for the design, development, and implementation of SLE [8]. Meanwhile, SLE framework with a ubiquitous technology approach could support online and real-world learning activities for any student in the right place at the right time and in smart ways [10]. Their approach to SLE had a distinct perspective.

The terms "activity systems", "adaptive learning", "epistemology", "human factors", "personalized learning", and "learning psychology" to represent the SLE as an effective, efficient, and engaging (3E) learning environment [8]. An effective learning environment could produce generally acceptable or desirable learning outcomes if it applies the Student-Centered Learning Environment (SCLE) paradigm which is based on a social constructivist philosophy [8]. This philosophy became a pedagogical foundation that accommodates students' various needs, skills, and interests to fulfill learning objectives [8,36,44]. It helps people become "smart" in different ways, anytime, and under various circumstances through interaction and communication with their environment. Because of this, assessments are an essential component of SLE research from a pedagogical perspective as one of the tools to facilitate student diversity [6,10,35]. Regarding assessment in SLE, Thomas et al. mentioned that the psychological factor of social support affects perceived learning [35].

On the other side, SLE as an engaging learning environment is able to motivate and maintain the interest and ongoing participation of various learners [8]. For example by implementing pedagogical innovation through digital storytelling which can engage students in deep and meaningful learning in a constructivist learning environment [31]. Efforts to increase student motivation and engagement are currently growing through the utilization of AI potential [39] and gamification [37]. Technological support enables communication and interactive processes that create opportunities to increase student and teacher engagement for personalized and adaptive learning [33,36].

Therefore, efforts to provide individualized pedagogical support for varied motivations, competencies, learning styles, interests, assessments, and feedback are considered when developing a learning environment toward SLE [44]. Personalization of learning that considers student requirements and goals results in a complex activity method called personalized learning [45]. These systems include adaptive and context-aware ubiquitous learning systems designed to offer students personalized learning support based on their preferences, learning status, and learning environments and materials characteristics [10]. Designing adaptive learning systems requires taking emotions and personality into account because they are fundamental components of human characteristics and substantially impact aspects of adaptive systems like implicit feedback [36,46].

In the meantime, Hwang [10] puts forth the definition and framework of SLE from the perspective of technological innovation for learning, specifically context-aware ubiquitous learning. The terms "smart learning," "ubiquitous learning," "context awareness," "adaptive learning," "intelligent tutoring systems," "google glass," "augmented reality," and "seamless learning" were chosen by Hwang to emphasize on a technological approach. In 2014, the idea of "smart learning" was also discussed by Cho et al. [23] and Ng et al. [29]. Cho et al. [26] focused on exploring the capabilities of intelligent learning applications in terms of information acquisition, investigation, modeling, and collaboration that support meaningful learning in science education. On the other hand, Ng et al. [29] proposed the iCampus framework as self-organized peer-to-peer learning as implementing smart learning in formal and informal learning environments. Both of the studies carry technological innovation for learning, as proposed by Hwang [10].

Another technological approach suggested for the SLE framework is an "intelligent tutoring system" [10]. This concept is also used to develop an automated tutoring system that is implemented as mobile collaborative-experiential learning (MCEL) to provide personalized formative assessments [28]. Song and Bhati [28] found that the assessment aspect is one of the gaps in SLE research and proposed MCEL as a solution.

The development of context-aware ubiquitous learning environments has been made possible by the rapid development of cellular and wireless communication technologies [10]. On the other hand, the ease of communication through the internet shows the new potential of social media as a new way through collaborative learning [40]. These environments facilitate seamless interaction between real-world and digital materials and provide personalized learning opportunities [4]. The latest methods can take advantage of ubiquitous technology to enhance learning activities [4,10], becoming one of the ways to realize SLE in universities. SLE research at the higher education level has increased interest, as shown in Fig. 3.

In addition to the conceptual ideas of SLE above, the Go-Lab by de Jong et al. [32] and Human Learning Interfaces (HLI) by Koper [11] are also quite influential in terms of the number of citations. Go-Lab offers the opportunity to conduct scientific experiments with online laboratories in pedagogically structured inquiry learning spaces [32] by combining technology and pedagogy for personalization. Like model's Spector [8], HLI-based SLE's model is also based on psychology and pedagogy, where SLE facilitates the physical environment to provide appropriate input and integrates output to stimulate or accelerate the learning process through adaptive technology enrichment [11]. Each of these studies has one of the characteristics of SLE: personalized and adaptive learning, which is still the focus of SLE development until 2022 [36,47].

The three-field plot demonstrates that the results of SLE studies from Asia, Europe, and America may be utilized to prove that regulation is also essential for the learning environment's maturity. In South Korea, the government reformed the education system and improved the education infrastructure to achieve the main objectives of the SMART (Self-directed, Adaptive, Motivated, Resource-Free, Technology) education project [5]. Since launching the Education Informatization 2.0 Action Plan in April 2018, Chinese education has systematically transitioned towards education 2.0 through research and implementation of SLE [16]. Likewise, in Europe and the United States, the Open Education Movement, which began in the 2000s, is a way to reduce the gap between people who have access to information and people who have difficulty accessing it [48]. This movement relates to SLE's mission to facilitate adaptive and personalized learning. The circumstances above demonstrate that new educational policies are necessary for developing SLE because, as stated by Ref. [6], outdated educational policies can undermine the effectiveness and efficiency of learning environments.

The early concept of SLE proposed by Hwang [10], Kinshuk et al. [6], Koper [11], Spector [8], Zhu et al. [5], and de Jong et al. [32] are the basis of current SLE research. New models or frameworks such as those proposed by Garcia-Tudela et al. [49], Liu et al. [50], Maulidiya et al. [9], Rosmansyah et al. [51], and Yusufu and Nathan [52] generally use one or more of these initial concepts. Nevertheless, it has expanded significantly to include various perspectives in response to societal changes accompanied by government regulatory support.

4.2. SLE's topics in 20- years publications

The following explanations respond to RQ2. A major part of SLE research has developed a broad conceptual framework for fusing technology and pedagogical techniques. Others created SLE using adaptive learning systems and technology-enhanced learning methodologies. The three research clusters mainly referred to Hwang [10] and Spector [8] for their inspiration. Hwang's framework was adapted by Siripongdee et al. [38] to develop SLE by adding IoT technology. Maulidiya et al. [9] used Spector's ideas as an initial reference to create a multi-dimensional conceptual model of SLE. Their ideas also has motivated Garcia-Tudela et al. [49] to create a new definition of SLE by adding new elements such as ergonomics and learning analytics. The three studies that were published between 2019 and 2021 are only a few examples of using early SLE concepts.

The terms 'personalized learning' and 'adaptive learning' are different. The concept of adaptive learning is very closely related to ubiquitous technology, and personalized learning is related to the use of technology to innovate pedagogy. However, Shemshack et al. [45] have shown that adaptive learning has been used interchangeably with personalized learning when developing the most suitable sequence of learning units for each learner. Regardless of the definition of the two, adaptive learning or personalization has become a fundamental learning paradigm in the educational technology research community, especially SLE. Adaptive and personalized learning as the SLE characteristics were developed utilizing an assessment instrument to discover motivations, competencies, learning preferences, and interests before processing the data to generate feedback. The term "feedback" refers to the data provided by the SLE based on how instructors and students carry out learning activities [53]. The need for feedback is one of the critical elements driving learning analytics research in SLE. The term "learning analytics" has become a new focus in SLE research which extends the concept of adaptive and personalized learning.

In SLE, large amounts of student data from various sources can be collected, combined, and analyzed using learning analytics to generate data reports about students and their context that can provide a better understanding of the learning process [54–56]. Zhu et al. [5] reveal SLE as one of the key elements of smart education, besides smart pedagogy and smart learner by reviewing how learning analytics will support student progress. Learning analytics is rooted in data science, artificial intelligence, and practices of recommendation systems, online marketing, and business intelligence integrated with learning science, making it possible to identify trends and patterns based on data mining in education [55,56]. Learning analytic results used as cognitive feedback have been shown to reduce learning gaps between students and increase motivation [54]. As a result, it is acknowledged as having the ability to enhance instructional practices, promote student achievement, and predict student achievement in a learning environment [57]. Learning profiles created by learning analytics based on student and learning pattern data sets enable personalized and dynamic learning environments [45].

4.3. The change of SLE's topics over 2002–2022

The third review question (RQ3) was answered by analyzing trending topics in SLE research divided into five periods. The division of the period is based on the frequency distribution of topics for 20 years, as shown in Fig. 5. In each period, the keywords are not necessarily the same, except for "smart learning environment," which is the search keyword in the database.

Thematic analysis was used to facilitate the analysis and interpretation of results by adopting the theme groupings conducted by Garcia-Tudela et al. [49], Liu et al. [50], and Maulidiya et al. [9]. Garcia-Tudela et al. [49] used ten SLE themes, namely smart assessment, smart technology, combination of physical and virtual environments, educational process optimization, educational roles, ergonomic and inclusive experience, learning alternatives or paths, physical environments enriched with technology, smart education or pedagogies, and virtual teaching environments. Meanwhile, Liu et al. [50] used four groups of themes: learning activity, teaching activity, learning content, and learning space. Maulidiya et al. [9] used four SLE's themes: physical environment, technology, learner aspects, and teaching aspects. The study of the three themes became the basis for grouping the research themes in the bibliometric analysis of this study as follows: 1) technology; 2) development of virtual or digital learning environments; 3) enrichment of physical learning environments; and 4) improvement of pedagogy (teaching and learning).

4.3.1. The initial period of SLE

The range of 2002–2014 was the beginning of the emergence of SLE research that focused on smart classrooms with hot topics on ubiquitous learning that Hwang used to create a framework with adaptive characteristics, while e-learning was considered a common theme for SLE development [30]. Two years prior, Dekdouk [58] showed that cloud-based e-learning enhances the classroom using ubiquitous technology.

According to Fig. 5a, a "smart learning environment" refers to the concept of a "smart classroom," as in the work of Huang et al. [59] in 2012 which enhancing the physical learning space with smart technology. Smart classroom as an SLE with three sorts of characteristics: "high definition," "deep experience," and "rich interactivity" by merging sensor technology, artificial intelligence, rich media technology, and communication technology into the classroom [59]. Two years following Huang et al. [59], the "smart classroom" was covered in two publications from different angles. Li and Kong [25] evaluated physically smart classrooms in Beijing and Hong Kong based on student views. Park and Hyun [27] addressed peer-assessment systems in smart classrooms, both in the online and face-to-face learning which expanded the smart classroom towards SLE by integrating assessment across two different learning modes. At this time, the topics of "smart learning" and "smart learning environment", although not within the exact scope of the study, have become the primary topics for SLE research. No publication in recent years has used these two keywords together.

The above review shows that the first period of research theme mapping focuses on ubiquitous technology that is aligned with the development of virtual/digital learning environments in the form of e-learning. The development of e-learning is part of smart learning as a digital learning environment that aims to create a smart classroom as a technology-enriched physical environment. As for pedagogy-related themes, most researches in this period focused on learning objects and learning scenarios, and few discussed assessments.

4.3.2. The second period of SLE

In the second period, 2015–2016, a total of 88 articles were published in which quite many researchers used the basic theme keywords: "smart learning environment," "smart classroom," and "learning analytics." At this time, there seems to be a shift in the topic of "smart learning environment," which discusses the development of smart learning and the use of big data, as done by Hammad and Ludlow [2]. SLE could utilize big data technology to process information in smart cities and provide learning services in the form of learning analytics [2]. On the other hand, Giannakos, Sampson, and Kidziński [60] describe the topic of "learning analytics" that supports smart learning features and processes by demonstrating the use of video assignments in SLE. The two studies show a shift in SLE's focus from enriching physical spaces with hardware to big data technologies.

Research related to smart classrooms is a separate study focusing on pedagogical innovations, namely collaborative learning, as carried out by Sung [61] which design smart learning in a collaborative environment based on components of SLE such as mobile technology, wireless network, and sensors. The topic of "mobile learning" in a niche area demonstrates how well-developed it is, but its significance for SLE research is limited. Lin and Liu [62] are another study in the "mobile learning" cluster that looks at teachers' demands utilizing e-textbooks. The study illustrates how and why SLE also has teacher-related characteristics.

The topic of adaptive learning has changed in this second period from a motor theme area to a niche theme, demonstrating that it is still crucial to SLE research but is losing its interest in academics. However, Kinshuk et al. [6] emphasized the importance of building an autonomous adaptive learning environment so that SLE can engage and integrate formal and informal learning that provides a smooth and real-time learning experience anywhere for students.

Thus, the focus of SLE development in the second period is still on enriching the physical environment (smart classroom) but with big data technology innovation to enhance the features of digital learning environment with learning analytic capabilities in both e-learning and mobile learning. On the other hand, in the pedagogical aspect, the use of e-textbooks is used to improve the quality of teaching.

4.3.3. The third period of SLE

There were fewer SLE publications in 2017 and more in 2018, with 53 articles published over these two years. At this time, the topic of "smart learning" shifted from a basic topic to a hot topic and left the "smart learning environment" cluster. In the third period, smart learning research was developed using collaborative learning [63] and mobile learning [64]. The combination of smart learning and constructivism learning theory as smart constructivist learning systems could be used to figure out how students understand things by implementing collaborative learning in SLE [63]. Mobile phones are described as highly useful instruments in SLE to increase student learning behavior by offering smart motivation and personalization [64]. Meanwhile, research on the topic of "smart learning environment" moves from basic topics to emerging/declining topics in the third period, that are developing weak and marginal, especially about adaptive learning. Adnan et al. [64] merely described the application as having one of feature—adaptive, which enables the system to inform students of the current class status—while providing a little brief justification for this characteristic.

On the other hand, "learning analytics" has shifted to become an essential basic theme in SLE research, together with the new basic topic "personalized learning". The research of [65] conducted a case study on the application of smart learning analytics for promoting personalized and self-regulated learning through giving remediation and recommending materials and pedagogy for remediation through integrating learning analytics technology (big data), domain knowledge, and locale-based information. Using augmented reality as a collaborative activity [65], examine the capacity of smart learning analytics to offer feedback and remediation.

As shown in Fig. 5c, the niche theme area includes "augmented reality," which, despite not being particularly significant for SLE research, is still expanding. SLE studies related to augmented reality, such as those conducted by Azhar et al. [66], are still developing but can be considered not to have a significant impact. Augmented reality combined with the Internet of Things (IoT) would transform future classrooms into highly immersive and collaborative learning spaces [66]. Applying IoT to learning has been an issue since the early development of SLE. For example, research of Taamallah and Maha [30] proposed learning scenarios using IoT-based smart objects to detect learner contextual information, strategy adaptation, and pedagogical services. However, its application needs to pay attention to the readiness and maturity of the learning environment which includes institutions, teachers, students, and the necessary interactions [7].

The third period of SLE development shows the theme of advanced technology, especially augmented reality (AR) and IoT, becoming a new topic of considerable attention. These technologies are optimized for the development of learning analytics which becomes a feature of personalized digital learning environment. While in the pedagogical aspect, the issue of learning scenarios, motivation and feedback for remedial has received enough attention especially in the development of learning analytics. Education support especially standards or regulation is still not a concern, similar to in the first and second phases.

4.3.4. The fourth period of SLE

In the 2019–2020 period, during the early days of the COVID-19 pandemic, SLE publications increased rapidly with the hot topics of "learning analytics," "higher education," "mobile learning," and, albeit slightly, "self-regulated learning." For example, research by Spiliotopoulos et al. [67] presents an adaptive SLE framework in a digital environment by integrating interactive, mixed (augmented and virtual) reality technologies and mobile learning to facilitate the development of self-regulated skills. Therefore, Spiliotopoulos et al. add learning analytics and artificial intelligence to this environment [67]. The research examines the relationship between keywords by integrating constructivist pedagogy and technological innovation.

Topics "smart learning" and "smart learning environment" become the basis and intersect, where some of the exact keywords are relevant for both topics. In this period, SLE research that discusses "smart education" and "blended learning" still seems attractive, despite the small impact. The pandemic conditions that need fully or partially online learning during this time are a major driving force behind blended learning research in the fourth periode. However, encouraging innovation to utilize advanced technology is the positive outcome of this period. Although blended learning has been a concept for many years, Siripongdee et al. [38] demonstrate how innovation can be achieved by involving IoT.

The work of [51] is an example of a publication that focuses on developing a smart education model as a learning environment that supports adaptive, personalized, collaborative, and self-learning processes. SLE become a component of smart education related to smart pedagogy, smart technologies, and smart learners [51]. It is natural if the "smart education" topic shifts away from the "smart learning environment" cluster because education is assumed to be broader than the learning environment [5,16].

The development of the digital learning environment is accelerating in this fourth period, particularly in relation to learning analytics, mobile learning, blended learning, and self-regulated learning. There are few new discoveries in the field of pedagogy, but there are numerous initiatives to combine psychological components such as motivation and habits into the use of advanced technology for learning. Researchers are particularly concerned about the education support aspect, as evidenced by online learning policies implemented during the pandemic.

4.3.5. The fifth period of SLE

The last cut, 2021–2022, where many publications are research results in 2020 when online learning is the only formal learning option. As the only choice of educational institutions during COVID-19, online learning is organized through various digital platforms and tools to ensure the continuity of education [7]. This phenomenon is also illustrated in SLE research in this period.

Most clusters are gathered in the middle of the density and centrality axis between the motor area and the basic theme. The topic of "smart learning environments" became a hot topic with the keywords "smart learning" and "learning analytics" in it. The one of fundamental topics are AI. Intelligent tutoring system (ITS) is one of the ways AI is being used for personalized learning, and researchers like AlShaikh and Hewahi [68] and Rosmansyah et al. [51] are investigated how it may be used for personalized learning in SLE. The development of artificial intelligence for personalized learning in SLE in the form of multimodal technologies will enable more sophisticated digital learning tools, precision-based learning approaches, and evaluation measures [69]. Another way of using AI is as a device to detect students' eye movements as input to provide motivation [39]. Learning analytics innovation in this period was demonstrated by Mbunge et al. [70] which explored deep learning models to predict student performance in SLE. In this period, SLE development increasingly relies on AI and deep learning technology.

Cluster "virtual reality" can be said to be a basic topic and important to SLE research. Luo and Du showed that the use of virtual reality desktop technology was significantly correlated with self-efficacy to apply theoretical knowledge in a real environment [71]. Although virtual reality and augmented reality are different technologies, the similarity of functions to create interactive experiences is the choice of pedogical innovation in the fifth period. SLE studies related to augmented reality, such as those conducted by Azhar et al. [66], are still developing but can be considered not to have a significant impact. Augmented reality combined with the Internet of Things (IoT) would transform future classrooms into highly immersive and collaborative learning spaces [66]. Applying IoT to learning has been an issue since the early development of SLE. For example, research of Taamalah et al. [30] proposed learning scenarios using IoT-based smart objects to detect learner contextual information, strategy adaptation, and pedagogical services. Likewise, research focusing on online learning and deep learning, although a marginal topic, is still relevant in the post-pandemic period [66]. However, its application needs to pay attention to the readiness and maturity of the learning environment which includes institutions, teachers, students, and the necessary interactions [7].

The above review shows the enthusiastic trend of using advanced technology, especially AI, augmented and virtual reality for fully online or blended learning, is increasing. This aspect of technology is also starting to become a focus of pedagogical development where there is potential for automation of teaching and learning data collection and processing. Related to this, educational support in the form of regulations and policy standards is one of the areas reviewed in a number of studies in this period.

5. Main contributions: the milestone of SLE's development

The review presented above is summarized in the form of a timeline showing the focus of SLE development over time. A brief review of the five periods of SLE development using thematic analysis is presented in the following Table 4.

Almost 20 years of publication demonstrates a change in the goals of SLE research, which were previously more focused on integrating technology into the physical environment have changed to utilize big data technology and smart pedagogy to enable learning optimization in multiple contexts. The following SLE's research milestone (Fig. 7) can be described by looking at recurring shifts in topics.

The milestones show the evolution of the SLE development process from time to time which shows digital transformation efforts in the learning environment. Integration, adoption and digital transformation are considered to have become assets that support the teaching and learning process [20]. Digital transformation is a continuous adoption process [1], meaning that the transformation towards SLE also occurs continuously. Systematic procedures are needed to make changes towards a SLE through the integration of technology and pedagogical approaches starting from planning, implementation and evaluation [6,20].

Maturity models can be seen as tools that allow assessing the maturity of technology use in certain circumstances over time [72]. Thus, the maturity model can be used as a model for assessing the intelligence of the learning environment. As Mettler [72] revealed, maturity assessment in social systems such as SLE could focus on process, people, and technology. Two early concepts of SLE that are relevant to assessing learning environments are those proposed by Koper [11] and Spector [8]. Koper differentiates learning environments based on the availability of digital devices [11]. As a set of measures of a learning environment's smartness, Spector proposed three types of SLE's categories [8]. The elaboration of these two concepts into SLE milestones is presented in the following diagram.

Table 4
Theme mapping of five periods of SLE development.

Period	Technology	Development virtual or digital learning environment	Enrichment of physical learning environment	Improvement of pedagogy
First	Ubiquitous technologies	E-learning; ubiquitous learning	Smart classroom	Learning objects; learning scenarios; assessments
Second	Big data	E-learning; mobile learning; adaptive learning	Smart classroom	Learning analytics; e-textbooks
Third	AR, IoT, Big data	Personalized learning	Smart classroom	Learning analytics
Fouth	AR, IoT, Big data	Mobile learning	Smart education	Learning analytic; self-regulated learning; blended learning
Fifth	AI, AR/VR, IoT, Big data, deep learning	Personalized and adaptive learning	Smart education	Learning analytic; self-regulated learning; blended learning

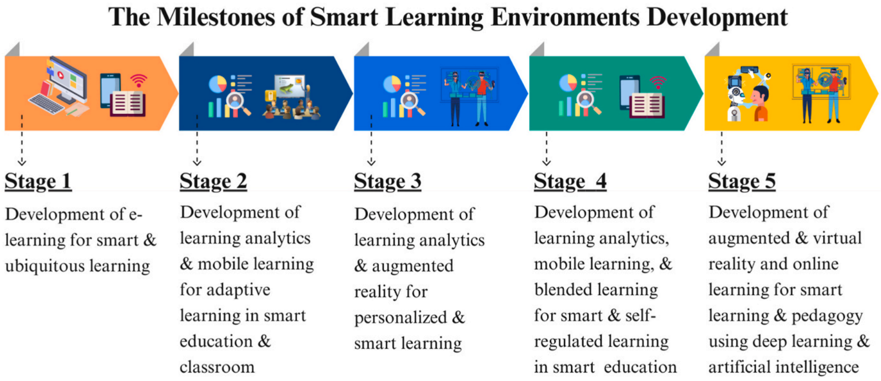

Fig. 7. Milestone of SLE's development.

In Fig. 8, SLE milestone serves as the foundation for defining process maturity, which expresses how well the SLE development process is clearly defined, managed, measured, and controlled [72]. The illustration serves as a preliminary recommendation for maturity levels that will support the future proposed SLE maturity model.

6. Conclusion and future works

In addition to describing the shift in SLE development's focus into five phases, this research has identified the most significant early studies on SLE, issues that have been the focus of development over the past 20 years. The keyword synthesis revealed three groups of SLE research topics: characteristics of SLE, technological innovation, and pedagogical innovation. These three topics are crucial factors to design, development, and implementation of SLE [6]. Although the SLE concepts have a distinct strategy or focus, their traits, particularly adaptive learning and personalized learning, are similar. As said by Fatahi [36], an adaptive learning system produces the most appropriate behavior for interaction for each learner to improve the individual learning process. Any evidence relating to each learner must be considered, in particular, because SLE is personalized to fulfill the needs of individual learners in all types of scenarios [6]. An environment that adapts to learners and personalizes learning assistance makes a learning environment successful, efficient, and appealing to students with varying levels of prior knowledge, backgrounds, and interests [45].

This research also finds out how e-learning is one of the first steps towards SLE where its features can be supplemented with various capabilities such as learning analytics, adaptive system, automated feedback, and others. To make learning sessions more personalized and, as a result, more engaging, SLEs should provide appropriate adaptations based on students' profiles [38]. Student profiles and their learning environment include vast amounts of data that need to be processed using sophisticated algorithms and technologies. It encourages SLE researchers' interest in applying learning analytics as an innovation in the assessment paradigm to provide personalized and adaptive learning through leveraging AI, IoT, and deep learning.

The analysis of thematic evolution reveals a shift in the topic of SLE related to the focus of research objectives relevant to advancing or renewing technology, pedagogical innovation, and real-world situations. The COVID-19 pandemic from the end of 2019–2021 demonstrates how crucial it is to expand and be flexible with the space, structure, and range of teaching and learning processes. This expansion and flexibility are not limited to technology that enriches the learning environment and needs to be integrated with smart pedagogy. The bibliometric analysis above also shows that government policy plays a role in the transformation towards SLE.

On the other hand, the milestones presented in the review also show the gradual transformation of the learning environment. This research indicates that the thematic evolution obtained from the bibliometric analysis has resulted in milestones of changing focus in SLE development from time to time. These results formulate the SLE process's maturity in five stages, which will be expanded by considering maturity factors relevant to people, culture, and technology. Changes or shifts in the learning environment need to be evaluated and directed to achieve the goal of SLE as an effective learning environment. As a result, future research will draw on the insights of this review to develop an instrument for assessing the maturity of a learning environment that has the potential to be "smart" under specific circumstances.

The use of only journal articles and proceedings, the use of text data from Scopus, and the processing of only author keywords are some of the limitations of this study. Therefore, the entire content of the document needs to be considered by using a topic modeling technique that can synthesize hidden topics more thoroughly to derive the SLE maturity factor construct.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

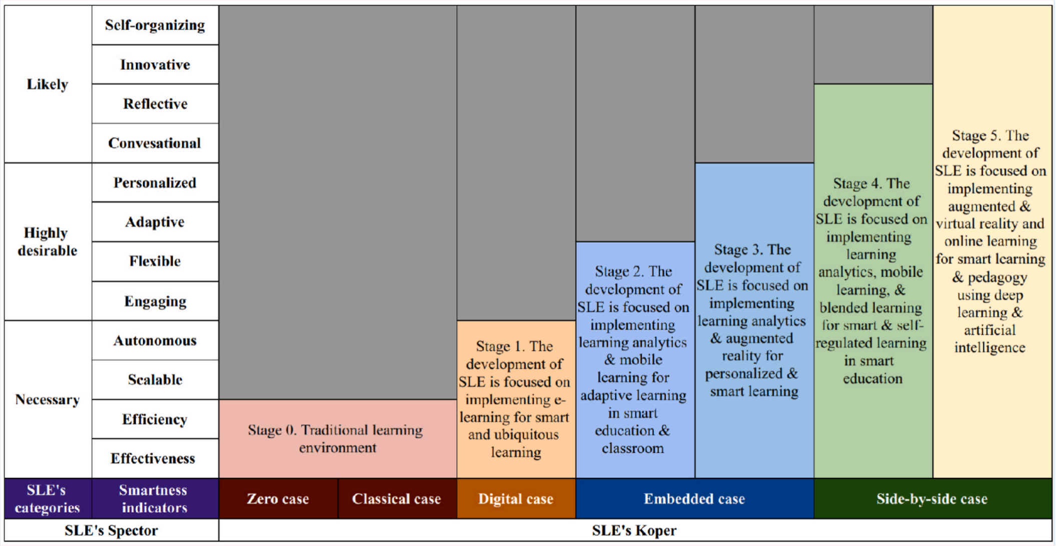

Fig. 8. Elaboration of categories, indicators, types and milestones in SLE development.

Fundings

This research was supported by Direktorat Riset dan Pengembangan (Risbang) Universitas Indonesia through Hibah Publikasi Terindeks Internasional (PUTI) Q1 2022 (Grant Number: NKB-393/UN2.RST/HKP.05.00/2022).

CRediT authorship contribution statement

Della Maulidiya: Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Budi Nugroho:** Writing – review & editing, Supervision, Resources, Methodology, Formal analysis, Conceptualization. **Harry B. Santoso:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Zainal A. Hasibuan:** Writing – review & editing, Supervision, Resources, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e26191.

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