Chen *et al. Int J Educ Technol High Educ (2021) 18:2*
https://doi.org/10.1186/s41239-020-00239-6

International Journal of Educational Technology in Higher Education

REVIEW ARTICLE

Open Access

Past, present, and future of smart learning: a topic-based bibliometric analysis

Xieling Chen[1], Di Zou[2*], Haoran Xie[3] and Fu Lee Wang[4]

*Correspondence: dizoudaisy@gmail.com
[2] Department of English Language Education, The Education University of Hong Kong, 10 Lo Ping Road, Tai Po, New Territories, Hong Kong, Hong Kong SAR
Full list of author information is available at the end of the article

Abstract

Innovative information and communication technologies have reformed higher education from the traditional way to smart learning. Smart learning applies technological and social developments and facilitates effective personalized learning with innovative technologies, especially smart devices and online technologies. Smart learning has attracted increasing research interest from the academia. This study aims to comprehensively review the research field of smart learning by conducting a topic modeling analysis of 555 smart learning publications collected from the Scopus database. In particular, it seeks answers to (1) what the major research topics concerning smart learning were, and (2) how these topics evolved. Results demonstrate several major research issues, for example, *Interactive and multimedia learning*, *STEM (science, technology, engineering, and mathematics) education*, *Attendance and attention recognition*, *Blended learning for smart learning*, and *Affective and biometric computing*. Furthermore, several emerging topics were identified, for example, *Smart learning analytics*, *Software engineering for e-learning systems*, *IoT (Internet of things) and cloud computing*, and *STEM education*. Additionally, potential inter-topic directions were highlighted, for instance, *Attendance and attention recognition* and *IoT and cloud computing*, *Semantics and ontology* and *Mobile learning*, *Feedback and assessment* and *MOOCs (massive open online courses) and course content management*, as well as *Blended learning for smart learning* and *Ecosystem and ambient intelligence*.

Keywords: Smart learning, Topic modeling, Research hotspots, Topic evolution

Introduction

Higher education is deeply influenced by the growth of information and communication technologies (ICTs), resulting in the design and construction of smart learning environments (SLEs) globally for educational technology (Alajmi et al. 2020). With the worldwide popularity of mobile learning among learners, it is increasingly common for an authentic learning experience to be realized at any time and in any place (Tatar et al. 2003). The widespread of smart devices like electronic blackboards and intelligent tutoring systems with the combination of innovative online technologies like the Internet of things (IoT) and social networking stimulates mobile learning towards smart learning (Kim et al. 2011). According to Koper (2014), SLEs are "physical environments that are enriched with digital, context-aware, and adaptive devices to promote better and faster learning (p.1)."

Given the increasing popularity of different research domains such as smart learning, learning analytics, and multimodal learning in educational settings (e.g., Molenaaret al. 2020; Siemens 2019; Dawson et al. 2019; Kovanović et al. 2018; Andres et al. 2018; Siemens et al. 2012; Pirahandeh and Kim 2017), as well as their close connection in practical use, it is important to clarify their differences. Learning analytics is "the collection, analysis, use, and appropriate dissemination of student-generated, actionable data with the purpose of creating appropriate cognitive, administrative, and effective support for learners (Slade and Prinsloo 2013, p.3)." It is typically a term used to describe multiplex activities that collect data out of educational contexts to be used to inform and guide the learning processes from which the data come (Piety 2020; Piety and Pea 2018). In this sense, learning analytics is mainly an analytical technique with close interaction with data generated during the process of teaching and learning to "understand, automate, and improve instruction (Behrens et al. 2018, p.230)." According to the European Language Resources Association, multimodal technologies refer to technologies combining features extracted from different modalities (e.g., text, audio, and image). In educational contexts, multimodal learning involves the use of multimodal technologies to enhance learning by engaging various senses, including those from visual and auditory aspects. Smart learning refers to learning in interactive, intelligent, and personalized environments with the support of cutting-edge digital technologies and services (e.g., virtual reality, learning analytics, multimodal technologies, and artificial intelligence) (Lee et al. 2014). Smart learning can be realized through the adoption of diverse technologies, two typical examples of which are learning analytics and multimodal technologies. That is, learning analytics and multimodal technologies are the means of creating SLEs, while smart learning is the purpose and result of the adoption of these two types of technologies. Smart learning is from the dimension of education innovation, and learning analytics and multimodal technologies are from the dimension of technology. This study focuses on smart learning per se rather than the technologies that can be adopted to realize smart learning.

Research on smart learning has received increasing attention from scholars, particularly in educational technology, which can be seen from the growth of scientific output. It is of both importance and need to thoroughly mine the information to explore important issues hidden within these outputs. There are several position papers concerning smart learning and its relevant topics, but they based mostly on qualitative methodologies. Hwang (2014) highlighted that SLEs should be able to detect learning status, assess learning performance, provide adaptive learning tasks/materials and personal support, restore learner profiles and learning portfolios, and determine the "value" of potential learning tasks, strategies, and tools. Several research issues of smart learning were also identified, including (1) development and implementation of SLEs, (2) interpretation and investigation of extant pedagogical theories for SLEs, (3) learning and assessment strategies for smart learning, (4) assessment of learning performance and perception, and (5) analysis of learning behaviors and patterns. However, potential research issues or dimensions concerning smart learning within the above-mentioned reviews, along with other relevant studies (e.g., Spector 2016), were mostly developed or hypothesized based on subjective understanding and judgment, rather than existing literature. In addition, two studies reviewed smart learning literature with the involvement of quantitative methods. Specifically, Papamitsiou and Economides (2016) conducted a meta-analysis to synthesize research on the effectiveness of learning analytics and explore whether research findings on learning analytics could serve as guidance for the construction of SLEs. Their study indicated that computer- and web-based education were the most common settings where smart learning took place with the involvement of learning analytics. Furthermore, in the smart learning context, learning analytics was commonly used for the prediction of performance and student behavior modeling. In addition, classification and statistics were the most used methodologies in smart learning studies. Based on 47 research articles concerning smart learning from 2007 to 2014, Ha and Kim (2014) investigated the research trend of smart learning. The 47 articles were analyzed to explore the major fields of authors, their institutions and countries, the major topics, and authors' opinions about the adoption of smart tools. Their study identified several trends in smart education research, for example, the popularity of smart learning in higher education and the wide adoption of mobile devices and personal computers. With the basis of 108 articles in the journal *Smart Learning Environments* (*SLE*), Chen et al. (2020f) presented a systematic review using bibliometrics to (1) investigate annual trends in the SLE articles, (2) recognize top contributors, (3) list the top SLE articles, and (4) uncover major research issues. Through their analyses, it was found that issues such as learning analytics, learning environments, learning processes, and learning performance were commonly explored. Additional file 1: Table S1 provides a summary of previous reviews or position papers concerning smart learning. Based on the investigation of previous reviews, there are several deficiencies. First, in most of the recent studies except the study by Chen et al. (2020f), articles being published after 2014 have not been quantitatively analyzed. Second, for the exploration of research topics, none of the existing reviews adopted topic modeling, which is a natural language processing technique that has been proven effective in topic detecting and tracking. Additionally, none of the current reviews investigated the evolution of research topics to demonstrate the shifting trend concerning research foci in smart learning.

Therefore, this study quantitatively analyzes the smart learning publications published until the end of 2019 to thoroughly investigate the research landscape, particularly the thematic structure by using topic modeling. Topic modeling is a type of machine learning and dimension reduction technique for the extraction of latent topics from sizable textual data (Lester et al. 2019). Bibliometrics is a statistical technique for assessing and quantifying the number and growing trend in a particular research field (Chen et al. 2018b, 2019c; Hao et al. 2018). Bibliometrics and topic modeling have been widely implemented to evaluate academic outputs of various research fields (e.g., Chen et al. 2018a, 2019b). In particular, they have also been widely used for the evaluation of educational research fields. For example, based on 3914 articles collected from Web of Science (WoS), Song et al. (2019) comprehensively analyzed the status, trends, and the intellectual structure of classroom dialogue research by identifying top contributors and journals, as well as visualizing the scientific collaborations. Chen et al. (2020b) also analyzed the publications in *Computers and Education* quantitatively in terms of research topics, author profiles, and scientific collaborations.

Specifically, this study is conducted based on the following reasons. Firstly, as smart learning has now developed into an active field of research with increasing scientific studies, it is necessary to explore the thematic structure of this research field by using a rigorous machine learning technique that can analyze sizeable textual literature data automatically. Secondly, this study is conducted to facilitate the understanding of what has been concerned and what is being concerned, as well as what might be the future of smart learning research. Such purpose is pursued by the analyses of the shifts in significant patterns of topical prominence and the evolving research areas. In addition, insights and implications related to the future research directions obtained by our analyses are insightful in facilitating scholars in terms of making decisions about what types of research topics to choose.

To that end, this study aims to analyze the smart learning publications indexed in Scopus by using topic modeling and bibliometrics. It should be noted that it is an extension of previous research (Chen et al. 2020f) in terms of the following aspects. First, in the previous study, only publications of the journal *SLE* were adopted for analysis. However, in this study, we collected data from Scopus, the largest abstract and citation database of peer-reviewed literature. Hence, the data analyzed in this study covered a wide range of sources of both types of journals and conferences. Second, in the previous study, the focus was to provide an overview of the *SLE* research in terms of article trends, major contributors, top influential articles, and frequently used key phrases. However, this study mainly focused on the thematic structure of the field of smart learning, including the major issues and their evolutions, as well as their distributions across top contributors. Thirdly, although the analysis of the frequently used key phrases in the previous study could partially reflect issues concerned by authors, such methodology was simple as compared to the topic modeling we used in this study, which has been proven effective and valuable in detecting research topics in a given field (e.g., Chen et al. 2020c). Furthermore, this study further explored the evolution of research topics by using the Mann–Kendall (MK) (Mann 1945) trend test. Such analysis allowed us to see how the research interests concerning smart learning changed with time. In addition, this study also explored and visualized the scientific collaborations between top contributors, which was not available in the previous study. Specifically, we aimed to answer the following seven questions:

RQ1: What was the annual trend of smart learning publications?

RQ2: What were the most prolific publication sources, countries/regions, and institutions?

RQ3: What were the collaborative relations among prolific countries/regions and institutions?

RQ4: What were the major research topics?

RQ5: How did these topics evolve?

RQ6: What were the potential inter-topic research directions?

RQ7: What were the topic distributions of prolific countries/regions and institutions?

Materials and methods

Figure 1 depicts the framework of data collection and analysis, which includes data retrieval and screening, descriptive statistical analysis, topic modeling, the MK trend test, and hierarchical clustering.

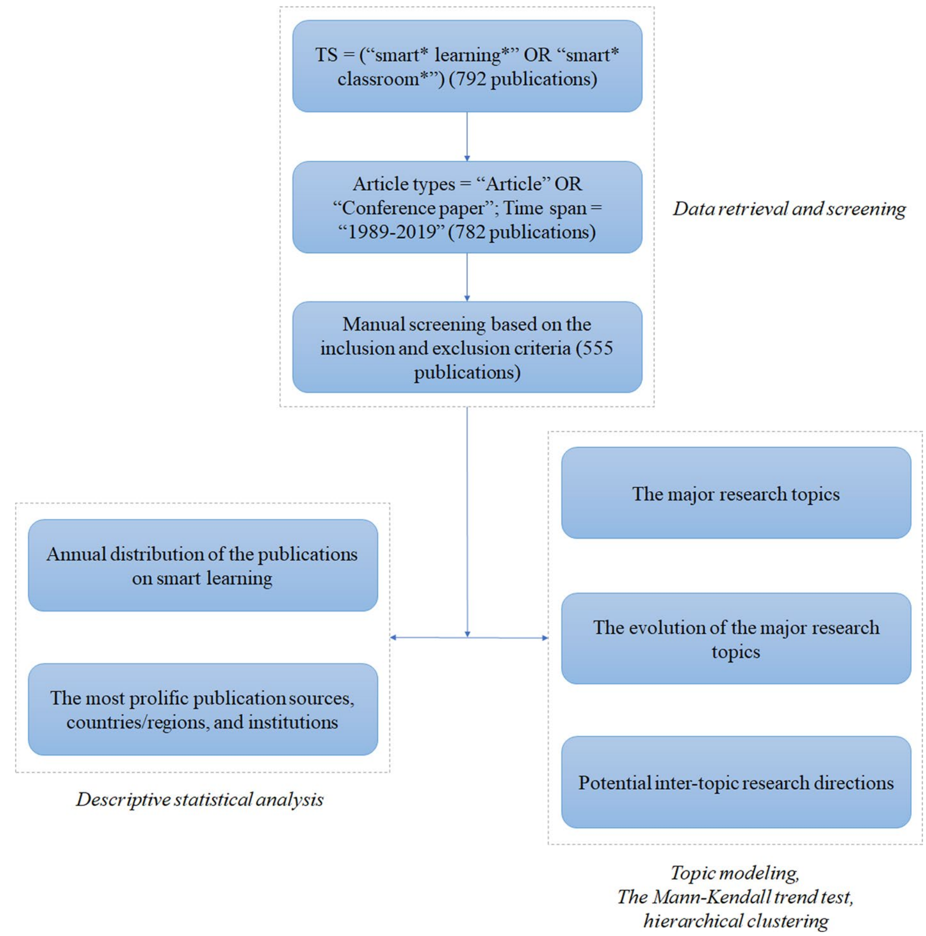

Fig. 1 Framework of data collection and analysis

Data retrieval and screening

In this study, Scopus was used to retrieve smart learning publications since it features smart tools to track, analyze, and visualize research output in various fields such as science, technology, and humanities (Agapiou and Lysandrou 2015; Tober 2011). On 10 January 2020, we conducted the literature search by entering the words "smart* learning*" and "smart* classroom*." With a further restriction to research articles and conference papers, a total of 792 publications were collected. By setting the time span ranging from 1989 to 2019, we obtained 782 publications. In addition, in order to ensure the close relevance of the analyzed articles to smart learning, we conducted manual screening to exclude irrelevant ones according to the criteria displayed in Table 1. In this way, 555 publications remained for further analysis.

Descriptive statistical analysis

With the selected 555 publications, we first analyzed the annual trend using regression analysis. The top prolific publication sources, countries/regions, and institutions were then identified using bibliometric indicators such as the publication count, citation

Table 1 Inclusion and exclusion criteria for data screening

Inclusion criteria	I1	Smart learning supported by mobile technologies, web/online technologies, flipped classroom, smart devices, intelligent devices, Internet of Things, cloud computing, ubiquitous learning, and blended learning approach
	I2	Analysis of behaviors in smart learning environments
	I3	Technology use and instructional strategies in smart classrooms
	I4	Design of smart learning analytics systems
	I5	Development of smart learning frameworks and models
	I6	Design of smart classrooms and smart learning systems
Exclusion criteria	E1	Smart technologies in artificial intelligence
	E2	Not used in the education context
	E3	Courses on smart learning
	E4	The abbreviation of specific, measurable, attainable, realistic, and time-bound (SMART)
	E5	Not focused on smart learning
	E6	Surveys or reviews
	E7	Publications without abstract

count, Hirsch index (H-index), and average citations per article (ACP). For the citation information of each publication, we utilized citations provided by Scopus as counted till 10 January 2020.

Topic analysis

The abstracts and titles of the 555 publications were used for topic modeling since it is commonly accepted that titles and abstracts are "suitable for conceptual reviews because they usually represent the noteworthy content of articles" (Chen et al. 2020b, p.4). Before conducting topic analysis using latent Dirichlet allocation (LDA) (Blei et al. 2003), text preprocessing was conducted by using Natural Language Toolkit[1] to improve data quality. Specifically, tokenization (Manning and Schutze 1999) was applied to divide titles and abstracts into word units. After tokenization, word normalization was applied to convert all capital letters to lowercase. Then, numbers, punctuation, symbols, and stop words were removed because they "appear frequently and are insufficiently specific to represent document content (Salton 1991, p.976)." After that, lemmatization was applied. Although lemmatization and stemming are both used to reduce inflected forms and "sometimes derivationally related forms of a word to a common base form (Manning, Schütze, and Raghavan 2008, p.32)," we prefer lemmatization than stemming due to the fact that "stemming commonly collapses derivationally related words, whereas lemmatization commonly only collapses the different inflectional forms of a lemma (Manning et al. 2008, p.32)." For example, the stem and lemma of "organized" are "organ" and "organize." Stemming thus often leads to difficulties in the correct interpretation of word stems. We further used the term frequency-inverse document frequencies (TF-IDF) to exclude words of less importance. To be specific, only words having a TF-IDF value of not less than 0.05 were included. Secondly, 34 topic models were fitted with topic numbers setting as *c (2:30,35,50,100,150)*, respectively, and ten-fold cross-validation was adopted for model performance evaluation. The best topic model was identified using the perplexity criterion (Chen et al. 2019a). Figure 2 shows the perplexity plots by the topic numbers across the ten-fold validation. Following the strategy used in Chen et al. (2018c), by averaging the ten topic numbers with the minimum perplexities, we

[1] https://www.nltk.org/

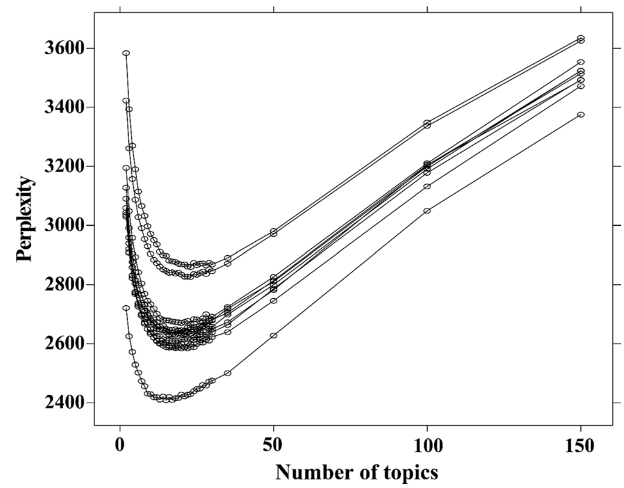

Fig. 2 Perplexity plots by the topic numbers across the ten-fold validation

selected the model with 22 topics as the final, which was estimated by the Gibbs sampling approach.

After modeling, we counted the proportion of each topic to represent their popularities in smart learning research using Eq. (1), where P_k denotes the proportion of the k_{th} topic with $\theta_{d,k}$ being the proportion of the k_{th} topic in the d_{th} publication, and D is 555.

$$P_k = \frac{\sum_d \theta_{d,k}}{D} \tag{1}$$

We then calculated the proportion of the k_{th} topic in year t using Eq. (2). Here, Y_d represents the publication year of the d_{th} publication, and D_t is the number of publications in year t.

$$P_{k,t} = \frac{\sum_{d|Y=t} \theta_{d,k}}{D_t} \tag{2}$$

We employed the MK test to examine whether each of the topics identified by the LDA constantly showed an increasing or decreasing trend in proportion. The MK test is a widely adopted nonparametric test for the detection of trends in time series data (Patakamuri et al. 2020) with a null hypothesis (H_0: no trend) and an alternate hypothesis (H_A: increasing or decreasing monotonic trend).

For a time series $X_i = x_1, x_2, ..., x_n$, the MK test statistic S can be computed using Eq. (3), where n is the number of data points, x_i and x_j are the data values in time series i and j $(j > i)$ respectively, and $sign(x_j - x_i)$ is the sign function expressed as Eq. (4).

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(x_j - x_i) \tag{3}$$

$$sign\left(x_j - x_i\right) = \begin{cases} -1 \;\; if \left(x_j - x_i\right) < 0 \\ 0 \; if \left(x_j - x_i\right) = 0 \\ 1 \; if \left(x_j - x_i\right) > 0 \end{cases} \tag{4}$$

Statistics S follows a normal distribution with parameters $E(S)$ and variance $V(S)$, shown as Eqs. (5) and (6).

$$E(S) = 0 \tag{5}$$

$$V(S) = \frac{n(n-1)(2n+5)}{18} \tag{6}$$

The test statistic Z is then denoted by Eq. (7). If $Z > 0$, it indicates an increasing trend and vice versa. Given a confidence level α, the sequential data is supposed to experience a statistically significant trend if $|Z| > Z(1 - \alpha/2)$, where $Z(1 - \alpha/2)$ is the corresponding value of $p = \alpha/2$ following the standard normal distribution. In this study, the MK test was realized by using an R package *trend*.

$$Z = \begin{cases} \frac{S-1}{\sqrt{V(S)}} \;\; if \;\; S > 0 \\ 0 \;\;\; if \;\; S = 0 \\ \frac{S+1}{\sqrt{V(S)}} \;\; if \;\; S < 0 \end{cases} \tag{7}$$

In addition, with the basis of the document-topic distribution matrix, we further conducted hierarchical cluster analysis using a complete-linkage agglomerative algorithm (Sneath and Sokal 1973) to explore how the identified topics correlated. The document-level similarity was measured using cosine similarity. Assuming A and B are two vectors of attributes, the cosine similarity cos(A, B) is calculated using Eq. (8).

$$similarity = \cos(A, B) = \frac{A \cdot B}{||A||||B||} = \frac{\sum A_i \times B_i}{\sqrt{\sum (A_i)^2} \times \sqrt{\sum (B_i)^2}} \tag{8}$$

In topic modeling, a topic is a document distribution on a corpus. Given D documents, the assignment of topic k to them is represented by a vector $VD = (\theta_{k,1}, \theta_{k,2}, ..., \theta_{k,D})$, where $\theta_{k,i}$ is the proportion of topic k in document i. Then the document-level similarity between topics k and l is computed using Eq. (9).

$$\cos_{document}(k, l) = \frac{\sum_{i=1}^{D} \theta_{k,i} \times \theta_{l,i}}{\sqrt{\sum_{i=1}^{D} (\theta_{k,i})^2} \times \sqrt{\sum_{i=1}^{D} (\theta_{l,i})^2}} \tag{9}$$

We additionally extracted key phrases from abstracts and titles using Natural Language Toolkit by retaining terms that were a singular noun, plural noun, singular propernoun, plural propernoun, verb of baseform, verb of pasttense, verb of gerund/present participle, verb of pastparticiple, present tense verb, third singular present tense verb, adjective, comparative adjective, and superlative adjective. For the extracted key phrases, we conducted analyses in two aspects. For one thing, we identified high frequency used key phrases based on their occurrences in the 555 smart learning publications. For

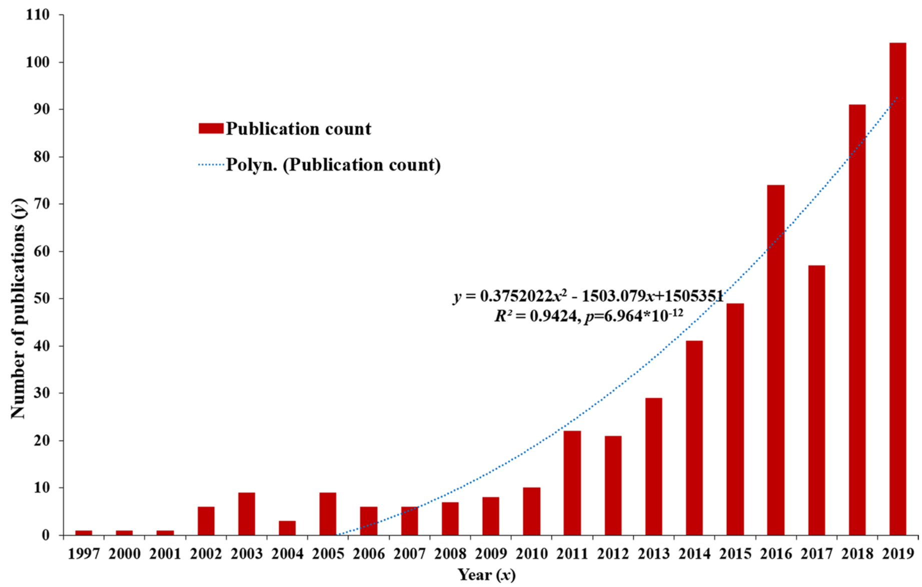

Fig. 3 Annual distribution of the smart learning publications

another thing, we examined the occurrences of the top frequently used key phrases in three sub-periods, that is, 1997–2004, 2005–2012, and 2013–2019.

Results

Annual trend of the smart learning publications

Figure 3 visualizes the annual trend of smart learning publications during the period 1997–2019. The annual number of smart learning publications increased dramatically from only one in 1997 to a total of 104 in 2019, which can also be reflected from the positive coefficient of the estimated equation $y = 0.3752022x^2 — 1503.079x + 1{,}505{,}351$. The regression model has a goodness-of-fit of 0.9424, indicating that the curve fitted the annual trend of smart learning publications well. With the estimated equation, the future number of smart learning publications could be predicted. For instance, the number of smart learning publications for the year 2020 was predicted as 106. From the analysis of the annual distribution of smart learning publications, we can see that the research on smart learning has received a dramatic growth of interest from the academia, showing a flourishing and promising development trend.

Prolific publication sources

The 555 smart learning publications were distributed in 297 publication sources. However, only 22.89% of them had more than one publication, and the top nine prolific ones, as shown in Table 2, contributed to more than 28.29% of the total corpus. The most prolific one was *Lecture Notes in Computer Science* with 34 articles and the highest H-index value of seven. Other prolific publication sources included *Smart Innovation, Systems and Technologies* (32 articles), *ACM International Conference Proceeding Series* (22 articles), and *Lecture Notes in Educational Technology* (22

Table 2 Top prolific publication sources

Publication sources	A	C (R)	ACP	H (R)	A1	A2
Lecture Notes in Computer Science	34	159 (2)	4.68	7 (1)	19	15
Smart Innovation, Systems and Technologies	32	103 (3)	3.22	5 (2)	0	32
ACM International Conference Proceeding Series	22	59 (7)	2.68	4 (3)	4	18
Lecture Notes in Educational Technology	22	47 (11)	2.14	4 (3)	0	22
Communications in Computer and Information Science	14	37 (14)	2.64	4 (3)	6	8
International Conference on Computers in Education	10	4 (87)	0.40	1 (30)	5	5
International Conference of Educational Innovation through Technology	8	2 (123)	0.25	1 (30)	0	8
International Conference on Advanced Learning Technologies	8	11 (42)	1.38	2 (10)	3	5
Computer-Supported Collaborative Learning Conference	7	24 (24)	3.43	3 (7)	6	1

R ranking position, *A, A1, A2* publication counts for periods 1997–2019, 1997–2014, and 2015–2019, *C* citation count, *ACP* average citations per article, *H* H-index

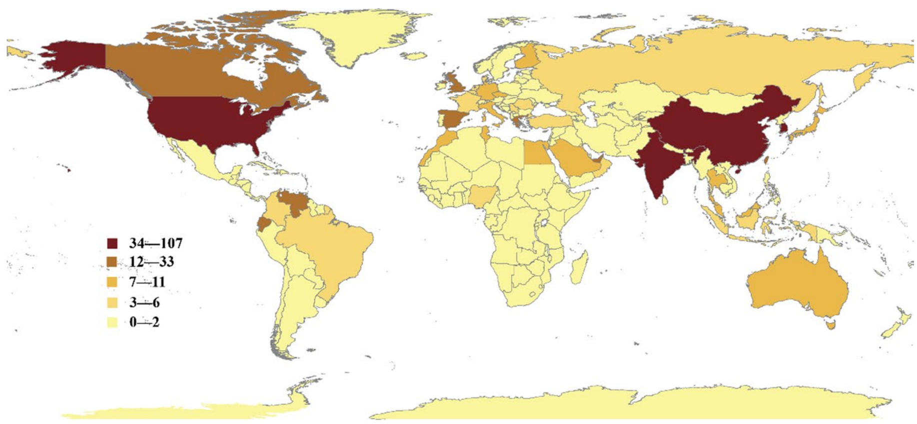

Fig. 4 Geographical distribution of the smart learning publications

articles). It is also worth noting that all listed publication sources were conferences or conference proceedings, which indicates that currently, research studies on smart learning were mainly published by conferences.

Prolific countries/regions and institutions

The geographic distribution of the 555 smart learning publications is shown in Fig. 4. Totally, 70 countries/regions showed interest in research on smart learning. However, only 20% of them had more than 10 publications, and the top 12 prolific ones, as shown in Table 3, contributed to more than 78% of the total corpus. China was the most prolific, with 107 publications and the highest H-index value of 11. Other prolific countries/regions included South Korea (68 articles), the USA (58 articles), and India (50 articles). Moreover, from an H-index perspective, the top three were the same as ranked by the publication count, demonstrating the significant contributions of China, South Korea, and the USA to the field, and their studies had a great impact on academia.

In total, 510 institutions have contributed to the 555 smart learning publications. However, only 12 of them had more than five publications, as depicted in Table 4. Tsinghua University was the most prolific, with 25 publications and the highest H-index

Table 3 Top prolific countries/regions

C/R	A	C (R)	ACP	H (R)	A1	A2
China	107	546 (1)	5.10	11 (1)	40	67
South Korea	68	227 (3)	3.34	8 (3)	36	32
USA	58	399 (2)	6.88	10 (2)	21	37
India	50	66 (10)	1.32	4 (10)	6	44
Canada	33	183 (4)	5.55	6 (4)	15	18
Greece	19	60 (13)	3.16	6 (4)	10	9
Taiwan	18	111 (5)	6.17	5 (7)	9	9
Venezuela	18	84 (7)	4.67	6 (4)	0	18
Ecuador	16	79 (8)	4.94	5 (7)	0	16
Spain	16	63 (11)	3.94	4 (10)	5	11
U Arab Emirates	15	68 (9)	4.53	4 (10)	4	11
UK	15	89 (6)	5.93	5 (7)	4	11

R ranking position, *C/R* country/region, *A, A1, A2* publication counts for periods 1997–2019, 1997–2014, and 2015–2019; *C* citation count, *ACP* average citations per article, *H* H-index

Table 4 Top prolific institutions

Institutions	C/R	A	C (R)	ACP	H (R)	A1	A2
Tsinghua University	China	25	434 (1)	17.36	9 (1)	20	5
University of the Andes	Venezuela	18	84 (5)	4.67	6 (2)	0	18
University of Toronto	Canada	15	93 (3)	6.20	5 (4)	13	2
Bradley University	USA	14	92 (4)	6.57	5 (4)	0	14
Foundation for Research and Technology-Hellas	Greece	14	57 (7)	4.07	6 (2)	10	4
Beijing Normal University	China	13	13 (60)	1.00	2 (18)	2	11
Central China Normal University	China	13	19 (50)	1.46	2 (18)	0	13
Technical University of Loja	Ecuador	12	64 (6)	5.33	5 (4)	0	12
University of Crete	Greece	11	45 (11)	4.09	5 (4)	9	2
Amrita Vishwa Vidyapeetham	India	8	11 (69)	1.38	2 (18)	1	7
Athabasca University	Canada	7	46 (10)	6.57	3 (8)	0	7
University of Hradec Kralove	Czech Republic	7	23 (45)	3.29	3 (8)	3	4

R ranking position, *C/R* country/region, *A, A1, A2* publication counts for periods 1997–2019, 1997–2014, and 2015–2019, *C* citation count, *ACP* average citations per article, *H* H-index

value of nine. Other prolific institutions included University of the Andes (18 articles), University of Toronto (15 articles), Bradley University (14 articles), and Foundation for Research and Technology-Hellas (14 articles).

Scientific collaboration

The scientific collaborations among prolific countries/regions and institutions are visualized in Figs. 5 and 6, respectively. The collaborative network among the 28 countries/regions with a minimal publication count of six is displayed in Fig. 5. The USA, Canada, the UK, Spain, and China were the most collaborative, collaborating with ten, nine, nine, eight, and seven countries/regions respectively. Ecuador and Venezuela were the closest collaborators, followed by the USA and China.

The scientific collaborations among the top prolific institutions with a minimal publication count of three are visualized in Fig. 6. Beijing Normal University, Capital Normal

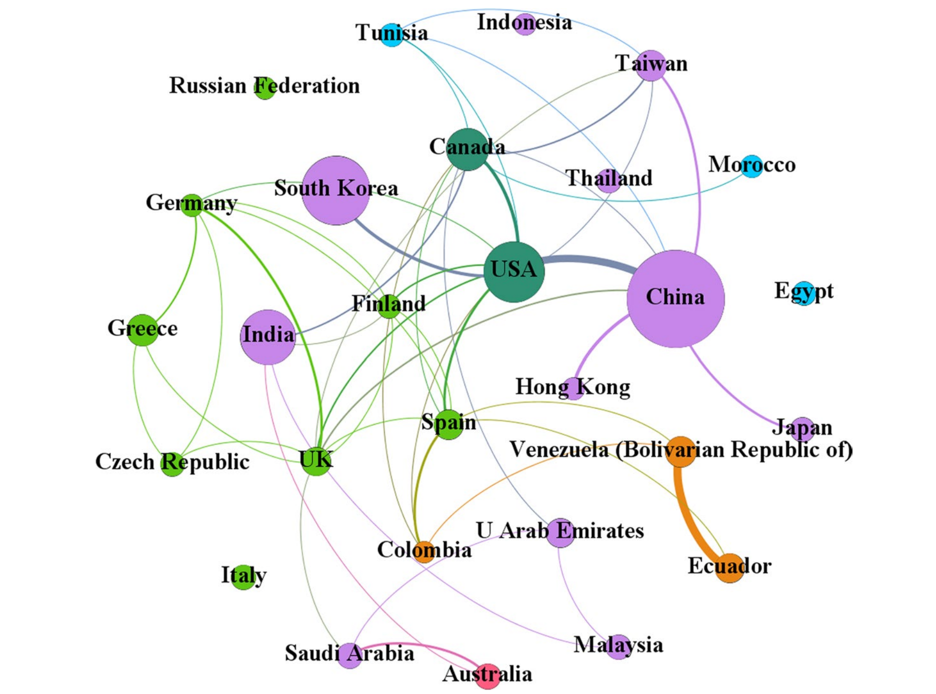

Fig. 5 Collaboration network of top prolific countries/regions (publication count > = six)

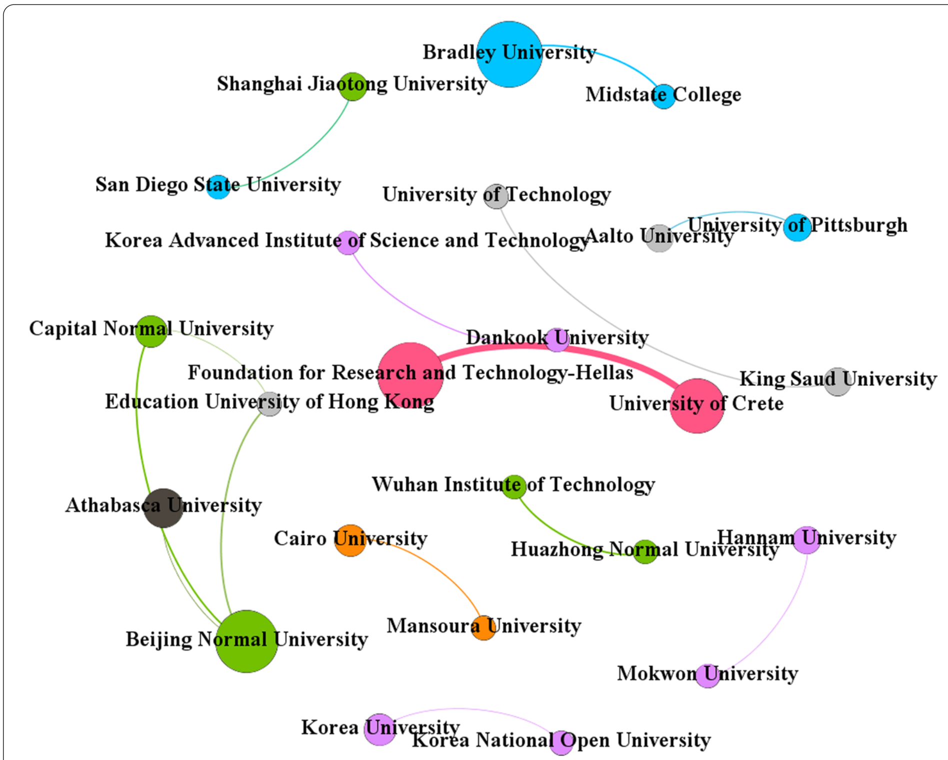

Fig. 6 Collaboration network of top prolific institutions (publication count > = three)

University, and The Education University of Hong Kong were the most collaborative, collaborating with three, two, and two other institutions, respectively. Foundation for Research and Technology-Hellas and University of Crete were the closest collaborators. From the figures, it can be seen that countries/regions from the same continents as well as institutions from the same countries/regions were more likely to conduct collaborative research on smart learning.

Major research topics and topic trends

Through the frequency analysis of the key words used in smart learning studies, several important words were identified. The most frequently used word was "content (appearing in 97 publications, taking a proportion of 17.48%)." Other important words included "learner (96, 17.30%)," "user (87, 15.68%)," "university (86, 15.50%)," "framework (85, 15.32%)," "network (82, 14.77%)," "service (82, 14.77%)," and "mobile (81, 14.59%)." These words could, to a certain degree, reflect important issues concerned by the smart learning scholars. Table 5 lists the top frequently used key phrases. The term "smart classroom" was ranked the first, appearing in 231 publications. Other frequently used phrases included "learning analytics (29 publications)," "e-learning system (21)," "augmented reality (20)," "virtual reality (18)," and "artificial intelligence (14)."

The results of the estimated 22-topic LDA are shown in Table 6, together with assigned labels, topic proportions, and the results of the MK trend test. Representative terms and studies for each topic are listed in Additional file 1: Tables S2 and S3. The five most frequently discussed topics were *Mobile learning* (8.26%), *Blended learning for smart learning* (6.64%), *IoT and cloud computing* (6.28%), *Ecosystem and ambient intelligence* (5.70%), and *MOOCs (massive open online courses) and course content management* (5.43%). First, the topic *Mobile learning* captures issues connected with smart learning in the environment based on mobile devices. The combination of smart devices that are potential in facilitating learning "anytime and anyplace" with innovative online technologies has resulted in the evolution of mobile-based learning into "smart learning" (Kim et al. 2011; Traxler 2007). Second, the strategy of blended learning is considered promising for the inclusion of affective learning into increasingly popular smart learning contexts (Mikulecky 2013). Third, intelligent technologies, for example, cloud computing, learning analytics, big data, and IoT, have the potential to promote the emergence of smart education by facilitating personalized and adaptive learning (Mayer-Schönberger and Cukier 2013; Zhu et al. 2016). Furthermore, ambient intelligence, as "a digital environment that proactively, but sensibly, supports people in their daily lives (Augusto and McCullagh 2007, p.4)," is considered a promising technique in educational domains (Abrami et al. 2006; Cook et al. 2009). Examples of the applications of ambient intelligence in education include smart classrooms (Shi et al. 2003) and ClassMATE (Leonidis et al. 2010). The former can facilitate collaborative learning using pervasive computing technologies, while the latter aims to create robustly and open ubiquitous computing frameworks. In addition, recently, there has been a tendency to develop the "next generation" MOOCs by integrating smart and intelligent learning technologies in MOOCs environments that facilitate rich, challenging, and productive learning experiences for all.

Table 5 Frequently used key phrases

Key phrases	1997–2004		2005–2012		2013–2019		1997–2019	
	A	%	A	%	A	%	A	%
Smart classroom	17	80.95	54	60.67	160	35.96	231	41.62
Smart learning environment	0	0.00	5	5.62	65	14.61	70	12.61
Smart learning	0	0.00	4	4.49	60	13.48	64	11.53
Learning process	1	4.76	2	2.25	54	12.13	57	10.27
Smart device	0	0.00	3	3.37	32	7.19	35	6.31
Mobile device	0	0.00	6	6.74	26	5.84	32	5.77
Learning analytics	0	0.00	0	0.00	29	6.52	29	5.23
Learning experience	0	0.00	3	3.37	26	5.84	29	5.23
Collaborative learning	1	4.76	3	3.37	18	4.04	22	3.96
Smart education	0	0.00	1	1.12	21	4.72	22	3.96
E-learning system	1	4.76	5	5.62	15	3.37	21	3.78
Augmented reality	0	0.00	0	0.00	20	4.49	20	3.60
Information technology	0	0.00	2	2.25	18	4.04	20	3.60
Smart phone	0	0.00	3	3.37	16	3.60	19	3.42
Mobile technology	0	0.00	1	1.12	18	4.04	19	3.42
Virtual reality	0	0.00	1	1.12	17	3.82	18	3.24
Communication technology	0	0.00	5	5.62	12	2.70	17	3.06
Smart learning system	0	0.00	2	2.25	15	3.37	17	3.06
Case study	0	0.00	2	2.25	14	3.15	16	2.88
Artificial intelligence	0	0.00	2	2.25	12	2.70	14	2.52
Cloud computing	0	0.00	2	2.25	12	2.70	14	2.52
Interactive learning	0	0.00	3	3.37	11	2.47	14	2.52
Learning style	0	0.00	0	0.00	14	3.15	14	2.52
Smart technology	0	0.00	1	1.12	13	2.92	14	2.52
Smart university	0	0.00	0	0.00	14	3.15	14	2.52
Learning outcome	0	0.00	1	1.12	11	2.47	12	2.16
Ambient intelligence	0	0.00	3	3.37	8	1.80	11	1.98
Computing technology	2	9.52	0	0.00	8	1.80	10	1.80
Context-aware application	0	0.00	6	6.74	4	0.90	10	1.80
Real time	0	0.00	0	0.00	10	2.25	10	1.80
Virtual classroom	3	14.29	3	3.37	4	0.90	10	1.80
College student	1	4.76	0	0.00	8	1.80	9	1.62
Conceptual model	0	0.00	0	0.00	9	2.02	9	1.62
Flipped classroom	0	0.00	0	0.00	9	2.02	9	1.62
Intelligent classroom	1	4.76	3	3.37	5	1.12	9	1.62
Multi-agent system	2	9.52	1	1.12	6	1.35	9	1.62
Wireless network	0	0.00	2	2.25	7	1.57	9	1.62
Big data	0	0.00	0	0.00	8	1.80	8	1.44
Computer science	0	0.00	0	0.00	8	1.80	8	1.44
Context awareness	0	0.00	5	5.62	3	0.67	8	1.44
Online learning	0	0.00	0	0.00	8	1.80	8	1.44
Primary school	1	4.76	0	0.00	7	1.57	8	1.44
Wireless communication	1	4.76	3	3.37	4	0.90	8	1.44
Active learning	0	0.00	1	1.12	6	1.35	7	1.26
Adaptive learning	0	0.00	1	1.12	6	1.35	7	1.26
Cloud service	0	0.00	1	1.12	6	1.35	7	1.26
Computing device	1	4.76	0	0.00	6	1.35	7	1.26
Deep learning	0	0	0	0	7	1.57	7	1.26

A publication count, *%* proportion

Table 6 Results of the STM model with 22 topics

Topic label	%	*Z*	*p*	*S*	*Trend*
Interactive and multimedia learning	5.38	-0.36	0.7212	-12	↑
STEM education	3.82	2.69	0.0071	84	↑↑↑
Attendance and attention recognition	4.15	1.65	0.0980	52	↑
Blended learning for smart learning	6.64	3.02	0.0026	94	↑↑↑
Affective and biometric computing	3.54	3.15	0.0016	98	↑↑↑
Collaborative inquiry-based learning	5.09	1.52	0.1273	48	↑
Feedback and assessment	3.61	0.94	0.3468	30	↑
Infrastructure for smart learning	3.55	1.52	0.1273	48	↑
Smart learning analytics	3.66	3.47	0.0005	108	↑↑↑↑
Semantics and ontology	3.94	0.42	0.6732	14	↑
Software engineering for e-learning systems	4.50	3.86	0.0001	120	↑↑↑↑
Apps for smart learning	3.01	2.82	0.0048	88	↑↑↑
Augmented and virtual reality	3.95	1.91	0.0556	60	↑
Sensor and wireless	3.17	1.14	0.2561	36	↑
Context-aware services	3.42	0.81	0.4173	26	↑
Mobile learning	8.26	0.29	0.7703	10	↑
MOOCs and course content management	5.43	3.08	0.0021	96	↑↑↑
Smart learning for special needs education	4.81	-2.04	0.0410	-64	↓↓
IoT and cloud computing	6.28	3.93	0.0001	122	↑↑↑↑
Ecosystem and ambient intelligence	5.70	2.95	0.0032	92	↑↑↑
English and language learning	4.54	1.78	0.0744	56	↑
RFID and laser techniques	3.55	-0.49	0.6265	-16	↓

%: topic proportion; *p*: significance level; ↑↑(↓↓), ↑↑↑(↓↓↓), ↑↑↑↑(↓↓↓↓): significantly increasing (decreasing) trend with $0.01 <= p < 0.05$, $0.001 <= p < 0.01$, and $p <= 0.001$

The MK test indicates that nine topics received significantly increasing attention from scholars who devoted to smart learning research, including *Blended learning for smart learning*, *MOOCs and course content management*, *IoT and cloud computing*, *Ecosystem and ambient intelligence*, *STEM education*, *Affective and biometric computing*, *Smart learning analytics*, *Software engineering for e-learning systems*, and *Apps for smart learning*. On the contrary, there was one topic named *Smart learning for special needs education* that experienced a significantly decreasing trend in research interest. First, the smart learning strategy has been applied to STEM learning. Brusilovsky et al. (2018) presented a general architecture for the integration of various smart contents into a single system and proposed a grids practice system for Python learning. Second, there is a trend for integrating affective and biometric computing into smart learning systems for emotion detection to facilitate teaching and learning, for example, enhancing the interaction between instructor and students and promoting learning interest and motivation (Ammar et al. 2010; Lin et al. 2016). Third, recently, as a useful tool for improving the educational environment, learning analytics has been increasingly adopted to facilitate learning in smart classrooms (González-Eras et al. 2017). Furthermore, smart learning is related to software engineering, as evidenced from the statement by Uskov et al. (2018) that "smart education, smart classroom, and smart university innovative concepts are heavily based on implementation and active utilization of sophisticated smart software or hardware systems and smart technology on campuses and in the classrooms (p.1)."

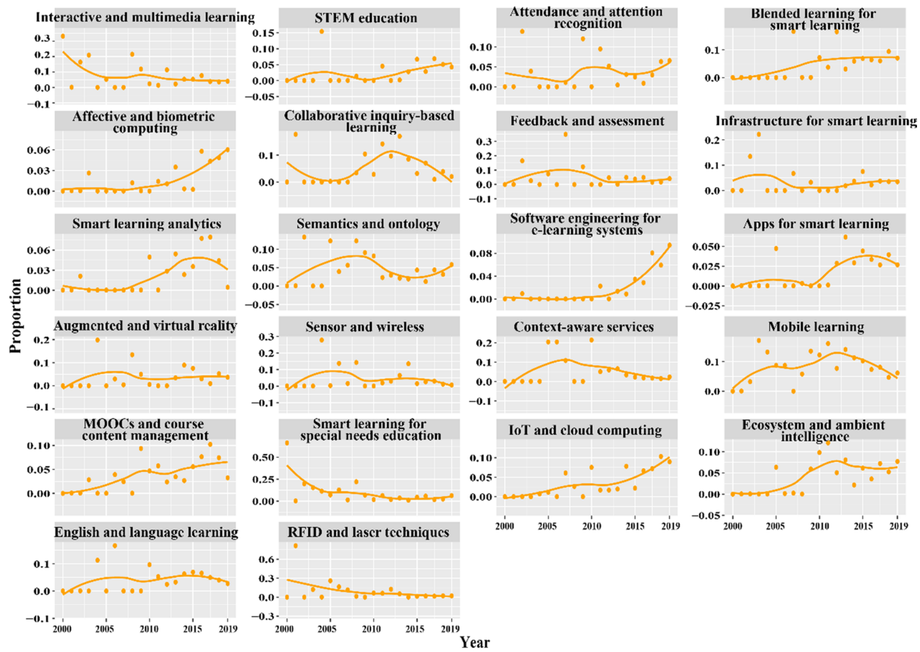

Fig. 7 Visualization of the annual proportion of the 22 research topics

In addition, there is increasing interest in designing various types of apps for smart learning. For instance, Mahesh et al. (2016) developed a mobile app to assist institution authorities in controlling learners' mobile phones, where attendance was taken automatically to save time.

The annual distributions of the topic proportion for the 22 topics are displayed in Fig. 7, from which we are able to intuitively see what each topic experienced during the whole period. For example, *Affective and biometric computing, Software engineering for e-learning systems*, *MOOCs and course content management*, and *IoT and cloud computing* received constantly increasing research interest. Meanwhile, several topics showed decreasing research interest, particularly in recent years, for example, *Collaborative inquiry-based learning, Context-aware services, Mobile learning, Smart learning for special needs education*, as well as *RFID (radio frequency identification device) and laser techniques*.

Topic clustering

Figure 8 visualizes the result of hierarchical clustering. From the figure, several potential inter-topic research directions were identified, for example, *Attendance and attention recognition* and *IoT and cloud computing*, *Semantics and ontology* and *Mobile learning*, *Feedback and assessment* and *MOOCs and course content management*, *Blended learning for smart learning* and *Ecosystem and ambient intelligence*, *Software engineering for e-learning systems* and *English and language learning*, as well as *Interactive and multimedia learning* and *Smart learning for special needs education*. First, there is a potential research direction concerning the development of face recognition systems with the use of IoT and cloud computing techniques. As indicated by Qi et al. (2018), among various IoT application scenarios, video surveillance and video analytics are commonly used

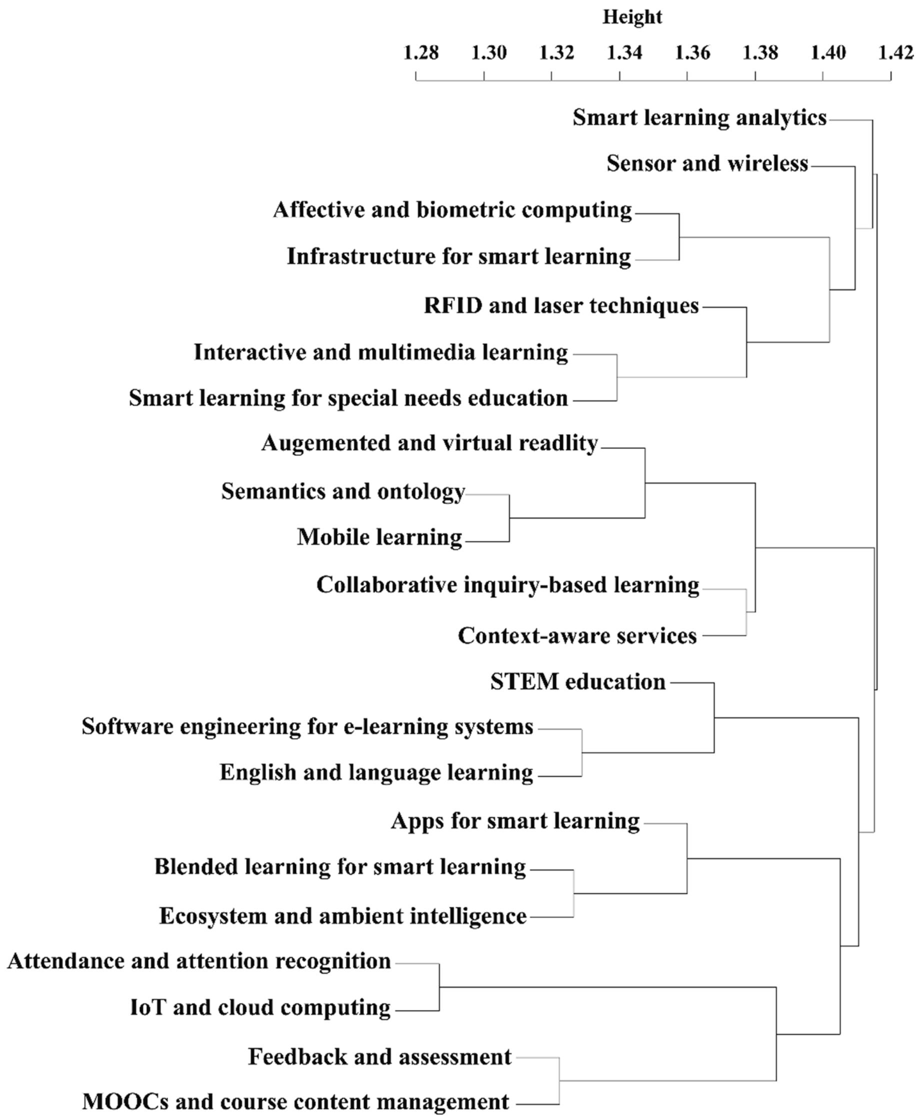

Fig. 8 Visualization of the hierarchical clustering results

for recognizing identities and revealing human-related attributes like gender and age, where face feature play a key role. Second, there is a tendency for the use of semantics and ontology for designing mobile learning systems. For example, Ngwenya et al. (2015) proposed a conceptual ontology-driven framework for mobile learning by taking into account "a knowledge base, ontology, software agents, learning resources and learning/teaching content (p.342)." Third, *Feedback and assessment* and *MOOCs and course content management* form a potential research direction. Recently, there is a trend in research on content-related feedback provision in online learning contexts (D'antoni et al. 2015). The aim of content-related feedback is to "build learners' content knowledge and to reduce the burden of obtaining information from multiple resources (Shatnawi et al. 2014, p.2)." Fourth, there is a tendency for research into *Blended learning for smart learning* and *Ecosystem and ambient intelligence*. Ambient intelligence has become a characteristic of ubiquitous learning as well as an emergent technique for supporting daily activities. Thereby the concept of ubiquitous learning has been blended with ambient intelligence to enhance ubiquitous learning environments with optimized activities (Kanagarajan and Ramakrishnan 2018). Furthermore, there is a potential research direction concerning *Software engineering for e-learning systems* and *English and language learning*. Computer-assisted language learning takes advantage of ICTs in second language teaching and learning. The software designed for teaching a second language can be customized based on learner's needs and requirements, particularly with the use of smart e-learning systems, which gives an impetus to individualized instruction (Tiwari et al. 2011). In addition, there is a tendency for *Interactive and multimedia learning* and *Smart learning for special needs education*. Recently, researchers have shown interest in developing and investigating the effectiveness of innovative, technology-assisted learning environments to support the education of children with special needs (Cagiltay et al. 2014).

Topic distributions of prolific countries/regions and institutions

Figure 9 depicts the topic distributions of the top prolific countries/regions and institutions. From a country perspective, most of the listed countries/regions showed a balanced interest in all research issues concerning smart learning, while several countries/regions showed a particular interest in certain issues. For example, Canada was especially interested in *Collaborative inquiry-based learning*, while South Korea was particularly enthusiastic about issues concerning *Mobile learning*. Additionally, the research enthusiasm for *Smart learning analytics* and *Semantics and ontology* on the part of Venezuela and Ecuador were worth noting.

In comparison to countries/regions, institutions listed in the figure showed more interest in particular issues. For instance, University of Toronto was especially productive in *Collaborative inquiry-based learning* and Central China Normal University was particularly active in *Blended learning for smart learning*. The research enthusiasm for *Smart learning for special needs education* on the part of Bradley University, as well as *Ecosystem and ambient intelligence* on the part of Foundation for Research and Technology-Hellas, were worth noting.

Coupled with the results of scientific collaboration analysis, it was obvious that countries/regions from the same continents and institutions from the same countries/regions with similar research interests tended to collaborate more in research on smart learning. For example, Venezuela and Ecuador were the closest collaborators, and they had similar patterns of topic distributions, with a particular interest in issues concerning *Smart learning analytics* and *Semantics and ontology*. In addition, as closest collaborators, University of Crete and Foundation for Research and Technology-Hellas showed similar research interests, particularly in *Ecosystem and ambient intelligence*.

Discussion

Based on the 555 studies collected from the Scopus database, this study provides an overview of smart learning research by using topic modeling and bibliometrics. The trend analysis of publications indicates a growing interest in smart learning research as a promising area. The analysis of the publication sources indicates that smart learning

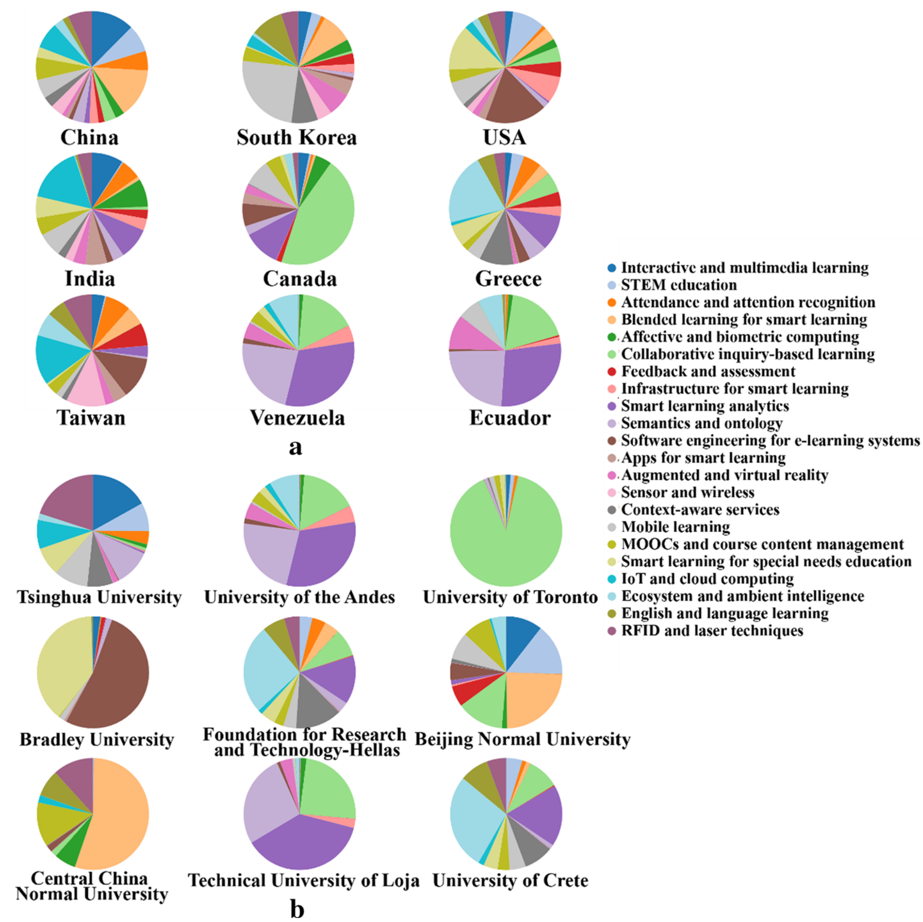

Fig. 9 Topic distributions of prolific countries/regions and institutions

studies are particularly welcomed by interdisciplinary sources focusing on the connection of education and technologies. China has contributed to approximately 20% of the studied literature, with Tsinghua University being the most prolific institution. Scientific collaboration analysis indicates that countries/regions (e.g., the USA, China, Canada, and Korea) showing greater interest in international collaborations are more likely to develop faster. In addition, collaborations between the same regions or institutions are more significant. However, cross-regional/institutional collaborations may consider being further enhanced.

Future directions for smart learning

Our study has identified similar research topics and issues with previous review studies or position papers (i.e., Papamitsiou and Economides 2016; Hwang 2014; Chen et al. 2020f; Ha and Kim 2014) (see Additional file 1: Table S1). These topics include (1) learning analytics as a popular data analysis methodology in smart learning studies, (2) the use of computers, online platforms such as MOOCs, virtual reality, and particularly mobile devices as learning settings to realize smart learning, (3) attention to issues concerning feedback and assessment as well as dropout and attention recognition in SLEs,

(4) the utilization of sensors, wireless, cloud computing, and RFID technologies to construct SLEs, (5) smart learning as a strategy for computer science education, (6) integration of collaborative learning strategy into smart learning, and (7) smart learning in various educational contexts, particularly university or college education.

Additionally, this study also reveals new developments and tendencies in smart learning, which can be divided into four major themes, including technology-related topics, learning strategy-related topics, application domain-related topics, and learning process-related topics. These four themes, combined with the above-mentioned topics, are potential directions for future research on smart learning.

Technology-related topics

Above all, some types of technologies that have not been identified in previous reviews have received great attention recently and are important for the development of SLEs. In addition to commonly mentioned technologies such as MOOCs, virtual reality, mobile devices, sensor, wireless, cloud computing, and RFID technologies, as well as smart learning analytics, various new technologies were identified, including artificial intelligence, deep learning, ambient intelligence, semantics and ontology technologies, as well as affective and biometric computing. The popularity of these technologies is perhaps a result of the technological revolution, with educational applications being increasingly user-friendly. Additionally, governments have paid great attention to renew technological instruments, enabling the increasing prevalence of intelligent systems that incorporate various novel and advanced technologies from different fields and areas for educational use.

Affordances of the above-mentioned newly emerged technologies in smart learning settings have been demonstrated in the literature. The implementation of artificial intelligence technologies or applications for educational purposes (Chen et al. 2020d, e), particularly for smart learning, is probably due to the rapid advancement of computing technologies. Thanks to artificial intelligence technologies aiming at simulating human intelligence to make inferences, judgments, or predictions, computer systems can "provide personalized guidance, supports, or feedback to students as well as assisting teachers or policymakers in making decisions (Hwang et al. 2020b, p.1)." Artificial intelligence technologies are being piloted in smart learning with positive effects obtained, for instance, using machine learning schemes and learning behavior features to forecast computer-mediated communication competence (Ying-You 2020), as well as a chatbot for administrative and learning support based on text classification and named entity recognition (Hien et al. 2018). It is noticeable that in addition to machine learning techniques, there is an increasing trend of applying the latest technologies in the field of artificial intelligence, that is, those based on advanced deep learning algorithms such as deep neural networks (Pacheco et al. 2018), recurrent neural network (Bhat et al. 2018), and convolutional neural network (Zeng et al. 2019) in smart learning and teaching and have demonstrated positive effects, for example, learner affect detection, particularly when combined with affective and biometric computing technologies.

The fact the affective computing has received increasing attention among smart learning scholars is probably due to the fact that affect and cognition can have a significant impact on education/learning (Popescu et al. 2018). Particularly, in the era of smart classroom environments, the detection and understanding of a student's affect during the learning process plays a vital role as it helps to foster the affective states that are beneficial to learning (Gupta et al. 2019). By using affective computing technologies, a student's affective state can be identified and measured in a real-time mode, enabling instructors to understand the association between emotions, motivation, and learning outcomes. Currently, there is a trend of research on real-time detection of learners' behavior and affect during different smart learning activities through the collection of biometric data such as heart rate, eyeball movements, galvanic skin response, facial expression/voice/gesture using low cost, non-intrusive sensors such as chair pressure sensors, heart rate sensor, and eye-trackers, and to further identify behavior and patterns covered within the collected data by using artificial intelligence technologies such as fuzzy inference and fuzzy expert system (Hwang et al. 2020a), and particularly deep learning algorithms such as convolutional neural network (Gupta et al. 2019; Zeng et al. 2019) and deep belief networks (Kim et al. 2018). Deep learning algorithms for multimodal fusion are also effective for emotion classification by automatically generating feature representation through the learning of the high-level dependencies of input dimensions (He et al. 2015). In sum, the future holds the promise of smart learning by combining the power and continuous breakthrough of artificial intelligence with the increasing use of sensor devices and advances in various fields such as ambient intelligence and semantic web technologies.

Recently, increasing research studies on smarter classrooms have revolved around the advances in ambient intelligence and IoT, which contribute to "the enhancement of the traditional classroom equipment and furniture with processing power and interaction capabilities (e.g., intelligent desk and smart whiteboard) and the integration of emerging solutions in teaching and learning methods (e.g., augmented reality and virtual reality) (Korozi et al. 2019, p.200)." In particular, there is a claim that the emergence of SLEs results from the intensive research on ambient intelligence (Mikulecky 2013), enabling personalized and adapted learning to be transformed from paper concepts and prototypes to real-life scenarios through ambient intelligence (Leonidis et al. 2010). The success of the application of ambient intelligence technologies in smart learning has been evidenced in the literature. For example, a novel ambient intelligence algorithm for smart classrooms (Kim 2019) was reported successful in providing information to instructors by measuring learner engagement in real-time. Specifically, the algorithm evaluated learners' psychological states by measuring a thermal infrared image and allowed instructors to offer feedback to learners while monitoring them in real-time. Ambient intelligence-based smart classroom model (Radosavljevic et al. 2019) has been reported effective in detecting a student and determining their level of fatigue based on the data about their previous daily academic activities.

In addition to the above technologies, the increasing prevalence of semantic web and ontology technologies in smart learning should also be highlighted. The semantic web extends the read/write Web 2.0, allowing "meaning to be assigned to content and the links between content, leading to the machine processability and potential benefit to smart teaching and learning (Pilkington and Pretorius 2019, p.449)." Semantic web ontology-based personalization of learning environments plays an important role in building smart e-learning ecosystems (Ouf et al. 2017) with positive effects reported in the literature, for example, semantic wiki for providing a semantically enriched environment to support learning (Pilkington and Pretorius 2019), a semantically enriched hybrid e-TextBook to act as a comprehensive interactive learning environment by providing the tools needed by teachers in smart classrooms (Ghaem Sigarchian et al. 2018), as well as a semantic ontology for supporting dynamic composition and collaboration in SLEs (Jeong et al. 2015).

Learning strategy-related topics

From the perspective of learning strategy, as indicated by Liu et al. (2016), SLEs are "open-ended, intelligent, and integrated learning space based theoretically on constructivist learning theory, blended learning theory, and modern education methods (p.77)." Blended learning is thus in close relation to smart learning, and particularly, since the blended smart-learning strategy has generated a lot of positive consequences, there is an increase in interest in its applications in various fields and contexts of learning. Affordances of blended smart-learning strategy have been evidenced in the literature, for example, increasing numbers of learning times and decreasing feelings about learning as burdensome (Ohkawa et al. 2019), enhancing students' acceptance toward blended learning, increasing perceived ease of use, perceived usefulness, and behavior intention (Songsangyos et al. 2016), as well as providing self-directed and personalized learning experience where learners choose learning content based on their own plans and interests (Zhang et al. 2017). It is thus claimed that the blended learning concept is a promising perspective for adaptive learning strategies inclusion into the increasingly prevalent SLEs (Mikulecky 2019). In addition to blended learning, context-awareness that is able to enhance human-centric, intelligent behavior in SLEs has also attracted increasing attention owing to the increasingly available of effective infrastructure for supporting context-aware applications (Qin et al. 2006; Miraoui 2018). Adaptive and context-aware features of SLEs are constructed to "render support to learners in such a way that learning is possible anywhere, anytime and at the learner's convenience (Agbo and Oyelere 2019, p.1061)." A novel context-aware architecture for a smart classroom (Paudel et al. 2019) with the use of the convolutional three-dimensional network model and long short term memory network is demonstrated effective in saving energy in classroom environments. Context-aware automation of classrooms (Miraoui 2018) improved education quality by "automating tasks that are not directly related to the content of the courses and consume time and effort that would affect the smooth running of the educational process (p.1)." Researchers are suggested to keep up the trend of smart context-aware learning to instruct practice.

Application domain-related topics

In terms of application domains, in addition to commonly known STEM education, the application of smart learning strategy for language education and special education are worth highlighting. The popularity of smart learning in language education may be due to its potential to integrate components of edutainment practice such as games to provide language learners with background knowledge, deep comprehension, and goal achievement, as well as enhancing learners' information processing ability (Novikova and Beskrovnaya 2015). Furthermore, in smart language learning, instructors and instructional elements are factors to positively assist students in completing learning tasks, while students, as well as their learning autonomy and psychological activities, become the focus of instruction (Wang and Liu 2019). In addition, the implementation of smart classrooms is promising for learners with "disabilities in general and more specifically students with learning disabilities, speech and language impairments, visual impairments, and hearing impairments (Bakken et al. 2016, p.21)." Smart classrooms have the potential to help them overcome their weaknesses in learning and self-organization. Thus, smart learning systems are becoming increasingly popular to help learners with disabilities by allowing them to access content and learn more effectively and efficiently (Bakken et al. 2019).

Learning process-related topics

In addition to the above directions, research on the interaction and communication in SLEs is receiving popularity. The deep integration of ICTs into smart classrooms has exerted an increasingly significant impact on teacher-student interactions. SLEs equipped with mobile devices and digital learning resources can support diverse interactions (Wang et al. 2019), particularly in real-time interactive mode. A range of tools and applications have been developed to support interaction and communication between instructors and learners as well as between learners in SLEs, with positive effects demonstrated. For example, an interactive audience response system (ARS) in an integrated smart classroom proposed by Dai (2019) could dramatically enhance learners' autonomous learning, collaborative communication, and innovative thinking.

Limitations

Limitations exist in this study. Firstly, we only used Scopus to collect data, and it does not include all academic publications. Thus, publications from other databases such as WoS might not have been included. Secondly, the latest publications that have been accepted but have not been indexed in Scopus were ignored. Nevertheless, such limitations are unlikely to affect the patterns and trends identified in this study. Furthermore, in data retrieval, we only used "smart* learning*" and "smart* classroom*" as search terms. Although using precise search terms may lead to a narrower dataset, the topic modeling results showed that our dataset is acceptable as all major issues in the field of smart learning are covered. By comparison, we conducted a pilot study and used an extended list of search terms for data retrieval. All potential technologies that can be used for achieving smart learning were considered, including "smart* learning*," "smart* classroom*," "learning analytics," "multimodal technolog*," "education data mining," "augmented reality," "virtual reality," "artificial intelligence," "machine learning," and "ambient intelligence." This resulted in a huge dataset with over forty thousand publications. We did a random examination and noticed that the data included much noise. Many papers mentioned learning analytics, multimodal technologies, education data mining, artificial intelligence, augmented reality, and ambient intelligence but were not related to smart learning. Handling such a huge and noisy dataset is very demanding and time-consuming. Thus, we decided to use more precise search terms (i.e., "smart* learning*" and "smart* classroom*"), focusing on the realization of smart learning rather than the potential techniques that may be involved. Many previous review studies also adopted a similar strategy in data search. For example, in the review by Xie et al. (2019) about personalized/adaptive learning, they used search terms "personalized learning" and "adaptive learning." In the study by Chang et al. (2018) on mobile/ubiquitous learning, only "mobile learning" and "ubiquitous learning" were used to search for data. Particularly, it is worth mentioning that such strategy was also adopted by reviews related to smart learning, i.e., the use of "smart learning environment" in the study by Klimova (2016) as well as "smart learning" and "smart classroom" in the study by Papamitsiou and Economides (2016).

As for the analyzing methodologies that have been proven effective in investigating meaningful topics hidden within smart learning studies as well as their correlations and development trends, this study did not make comparisons about different types of topic models. In future work, it would be interesting and valuable to conduct comparisons of different topic models in the identification of predominant topics and issues in a particular research field.

Conclusion, significance, and implications

The world is now changing the way of higher education from the traditional way to smart learning. To detect the research topics and their dynamics in smart learning, this paper conducts analyses on 555 smart learning publications using topic modeling and bibliometrics. The distribution of the annual number of smart learning publications reflects a dramatically increasing interest that this research field has received. Such active research on smart learning presents an indication of a promising future development trend. Interdisciplinary journals focusing on the connection between education and technology are active in smart learning research. China and Tsinghua University were the most productive country and institution in the publication of smart learning research. International collaborations can contribute to better scientific performance. Phrases such as "smart classroom," "learning process," "smart device," "mobile device," and "learning analytics" are commonly used and mentioned in smart learning publications. Predominant research topics include *Mobile learning*, *Blended learning for smart learning*, *IoT and cloud computing*, *Ecosystem and ambient intelligence*, and *MOOCs and course content management*. Nine topics, including *STEM education*, *Blended learning for smart learning*, *Affective and biometric computing*, *Smart learning analytics*, *Software engineering for e-learning systems*, *Apps for smart learning*, *MOOCs and course content management*, *IoT and cloud computing*, as well as *Ecosystem and ambient intelligence*, have received significantly increasing attention from scholars devoted to smart learning.

The contributions of this study to the smart learning research community can be summarized as follows. Firstly, this study helps scholars, policymakers, and practitioners develop a better understanding of the past, present, and future academic structure of smart learning. Secondly, bibliometrically speaking, as indicated in the literature (e.g., Song et al. 2019), performance analysis concerning top institutions and countries/regions can "help people identify influential actors in the research area from whom they may learn (Hao et al. 2020, p.1336)." Hence, the results of major contributors in smart learning research are helpful for scholars to recognize potential institutions and countries/regions to share smart learning research experience. Furthermore, results of top institutions and countries/regions, combined with findings from scientific collaboration analysis, can help scholars identify potential collaborators to explore scientific collaborations on smart learning research. In addition, as for topic distributions of the top countries/regions and institutions, not only does such analysis reveals their research strength by showing topics that are productive in and devoted to the field, but also by further combining results of scientific collaborations, it reveals that countries or institutions "with similar research interests were more inclined to conduct collaborative research (Chen and Xie 2020, p.21)." Hence, in line with previous bibliometric literature (e.g., Chen et al. 2020b), such results are helpful for facilitating scientific collaborations by incorporating "the strengths of different research units or disciplines to overcome challenges and advance the whole field (Chen et al. 2020a, p.19)" of smart learning.

Findings concerning topic modeling and key phrases analysis bring potentially informative implications, which are helpful for scholars in capturing the core of smart learning research to further enhance decision making about what issues to investigate. Above all, technologies have permeated smart learning, and the development and application of technologies for supporting smart learning will remain an active field of research. Thus, attention should reach beyond computer/web-based technologies to keep up with the application and incorporation of different latest technologies (e.g., virtual reality, mobile devices, RFID technologies, cloud computing, affective and biometric computing technologies, ambient intelligence, learning analytics, artificial intelligence, and particularly deep learning algorithms) to make learning more effective and smart. Attention should also be paid to how technologies can be integrated into smart classrooms to facilitate various aspects of teaching and learning, for example, feedback and assessment, dropout and attention recognition, learning style mining, and critical thinking development. It is necessary to provide support to instructors about how to use new technologies and to help them investigate technology functionality affordances concerning smart teaching and learning, particularly about how to best integrate various strategies such as collaborative learning, blended learning, and context-aware learning in SLEs. Moreover, STEM education is more affordable with technological use in smart classrooms and has received great attention. However, the investigation into the potential of smart learning in other subjects or contexts such as language and special education are also needed. In addition, attention should reach beyond knowledge-transference to how to best transfer knowledge through effective interaction and communication during smart learning with the deep integration of ICTs such as ARS and multimedia. With the continuing technological advances, it may be impossible to promote the in-depth development of smart learning depending solely on educators. Close collaboration between scholars from different fields is essential to allow technological innovations to fully fill the needs and overcome the challenges in smart learning.

Supplementary Information

Supplementary information accompanies this paper at https://doi.org/10.1186/s41239-020-00239-6.

Additional file 1. Additional tables.

Abbreviations
STEM: Science, technology, engineering and, mathematics; MOOCs: Massive open online courses; IoT: Internet of things; WoS: Web of Science; MK: Mann–Kendall; H-index: Hirsch index; LDA: Latent Dirichlet allocation; TF-IDF: Term frequency-inverse document frequencies; ACP: Average citations per article; RFID: Radio frequency identification device; SLEs: Smart learning environments; ARS: Audience response system; ICT: Information and communication technology.

Acknowledgement
Not applicable.

Authors' contributions
XC: Conceptualization, Methodology, Software, Validation, Formal analysis, Resources, Data Curation, Writing—Original Draft, Visualization. DZ: Conceptualization, Writing—Review and Editing, Supervision, Project administration, Funding acquisition. HX: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Writing—Review and Editing, Funding acquisition. FLW: Conceptualization, Methodology, Resources, Writing—Review and Editing, Supervision. All authors read and approved the final manuscript.

Funding
This work was supported by the Research Seed Fund (102367) and Direct Grant (101138) at Lingnan University, Hong Kong, and the Internal Research Fund at The Education University of Hong Kong (RG1/19-20R), Hong Kong.

Availability of data and materials
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Competing interests
The authors declare that they have no competing interests.

Author details
[1] Department of Mathematics and Information Technology, The Education University of Hong Kong, 10 Lo Ping Road, Tai Po, New Territories, Hong Kong, Hong Kong SAR. [2] Department of English Language Education, The Education University of Hong Kong, 10 Lo Ping Road, Tai Po, New Territories, Hong Kong, Hong Kong SAR. [3] Department of Computing and Decision Sciences, Lingnan University, 8 Castle Peak Road, Tuen Mun, New Territories, Hong Kong, Hong Kong SAR. [4] School of Science and Technology, The Open University of Hong Kong, 30 Good Shepherd Street, Ho Man Tin, Kowloon, Hong Kong, Hong Kong SAR.

Received: 3 July 2020 Accepted: 13 December 2020
Published online: 15 January 2021

References

Abrami, P., Bernard, R., Wade, A., Schmid, R., Borokhovski, E., Tamin, R., & Nicolaidou, I. (2006). A review of e-learning in Canada: A rough sketch of the evidence, gaps and promising directions. *Canadian Journal of Learning and Technology/La Revue Canadienne de l'apprentissage et de La Technologie, 32,* 3.

Agapiou, A., & Lysandrou, V. (2015). Remote sensing archaeology: Tracking and mapping evolution in European scientific literature from 1999 to 2015. *Journal of Archaeological Science: Reports, 4,* 192–200.

Agbo, F. J., & Oyelere, S. S. (2019). Smart mobile learning environment for programming education in Nigeria: adaptivity and context-aware features. In *Intelligent Computing-Proceedings of the Computing Conference* (pp. 1061–1077). Springer.

Alajmi, Q., Al-Sharafi, M. A., & Abuali, A. (2020). Smart Learning Gateways for Omani HEIs Towards Educational Technology: Benefits, Challenges and solutions. *International Journal of Information Technology and Language Studies, 4,* 1.

Ammar, M. B., Neji, M., Alimi, A. M., & Gouardères, G. (2010). The affective tutoring system. *Expert Systems with Applications, 37*(4), 3013–3023.

Andres, J. M. L., Baker, R. S., Gašević, D., Siemens, G., Crossley, S. A., & Joksimović, S. (2018). Studying MOOC completion at scale using the MOOC replication framework. In *Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (pp. 71–78).

Augusto, J. C., & McCullagh, P. (2007). Ambient intelligence: Concepts and applications. *Computer Science and Information Systems, 4*(1), 1–27.

Bakken, J. P., Uskov, V. L., Penumatsa, A., & Doddapaneni, A. (2016). Smart universities, smart classrooms and students with disabilities. In *Smart Education and e-Learning 2016* (pp. 15–27). Springer.

Bakken, J. P., Uskov, V. L., & Varidireddy, N. (2019). Text-to-voice and voice-to-text software systems and students with disabilities: a research synthesis. In *Smart Education and e-Learning 2019* (pp. 511–524). Springer.

Behrens, J. T., Piety, P., DiCerbo, K. E., & Mislevy, R. J. (2018). Inferential foundations for learning analytics in the digital ocean. *Learning Analytics in Education*, 1–48.

Bhat, A., Rao, A. C., Bhaskar, A., Adithya, V., & Pratiba, D. (2018). A Cost-Effective Audio-Visual Summarizer for Summarization of Presentations and Seminars. In *2018 3rd International Conference on Computational Systems and Information Technology for Sustainable Solutions (CSITSS)* (pp. 271–276). IEEE.

Blei, D. M., Edu, B. B., Ng, A. Y., Edu, A. S., Jordan, M. I., & Edu, J. B. (2003). Latent Dirichlet Allocation. *Journal of Machine Learning Research, 3,* 993–1022.

Brusilovsky, P., Malmi, L., Hosseini, R., Guerra, J., Sirkiä, T., & Pollari-Malmi, K. (2018). An integrated practice system for learning programming in Python: design and evaluation. *Research and Practice in Technology Enhanced Learning, 13*(1), 18.

Cagiltay, K., Cicek, F., Karasu, N., Cakir, H., & Akilli, G. K. (2014). Innovative educational technology for special education and usability issues. In *International Conference of Design, User Experience, and Usability* (pp. 155–163). Springer.

Chang, C.-Y., Lai, C.-L., & Hwang, G.-J. (2018). Trends and research issues of mobile learning studies in nursing education: A review of academic publications from 1971 to 2016. *Computers & Education, 116,* 28–48.

Chen, X., Xie, H., Wang, F. L., Liu, Z., Xu, J., & Hao, T. (2018a). A bibliometric analysis of natural language processing in medical research. *BMC Medical Informatics and Decision Making, 18,* 1.

Chen, X., Chen, J., Cheng, G., & Gong, T. (2020a). Topics and trends in artificial intelligence assisted human brain research. *PLoS ONE, 15*(4), e0231192.

Chen, X., Hao, J., Chen, J., Hua, S., & Hao, T. (2018b, August). A bibliometric analysis of the research status of the technology enhanced language learning. In *International Symposium on Emerging Technologies for Education* (pp. 169–179). Springer, Cham.

Chen, X., Liu, Z., Wei, L., Yan, J., Hao, T., & Ding, R. (2018c). A comparative quantitative study of utilizing artificial intelligence on electronic health records in the USA and China during 2008–2017. *BMC Medical Informatics and Decision Making, 18*(5), 117.

Chen, X., Lun, Y., Yan, J., Hao, T., & Weng, H. (2019a). Discovering thematic change and evolution of utilizing social media for healthcare research. *BMC Medical Informatics and Decision Making, 19*(2), 50.

Chen, X., Wang, S., Tang, Y., & Hao, T. (2019b). A bibliometric analysis of event detection in social media. *Online Information Review, 43*(1), 29–52.

Chen, X., & Xie, H. (2020). A Structural Topic Modeling-Based Bibliometric Study of Sentiment Analysis Literature. *Cognitive Computation*, 1–33.

Chen, X., Yu, G., Cheng, G., & Hao, T. (2019c). Research topics, author profiles, and collaboration networks in the top-ranked journal on educational technology over the past 40 years: a bibliometric analysis. *Journal of Computers in Education, 1,* 1–23.

Chen, X., Zou, D., Cheng, G., & Xie, H. (2020b). Detecting latent topics and trends in educational technologies over four decades using structural topic modeling: A retrospective of all volumes of computer & education. *Computers & Education*, 103855.

Chen, X., Zou, D., & Xie, H. (2020c). Fifty years of British Journal of Educational Technology: A topic modeling based bibliometric perspective. *British Journal of Educational Technology, 51*(3), 692–708.

Chen, X., Xie, H., & Hwang, G. J. (2020d). A Multi-Perspective Study on Artificial Intelligence in Education: Grants, Conferences, Journals, Software Tools, Institutions, and Researchers. *Computers and Education: Artificial Intelligence*, 100005.

Chen, X., Xie, H., Zou, D., & Hwang, G. J. (2020e). Application and theory gaps during the rise of Artificial Intelligence in Education. *Computers and Education: Artificial Intelligence, 1,* 100002.

Chen, X., Zou, D., Xie, H., & Wang, F. L. (2020f). Smart Learning Environments: A Bibliometric Analysis. In *International Conference on Blended Learning* (pp. 353–364). Springer.

Cook, D. J., Augusto, J. C., & Jakkula, V. R. (2009). Ambient intelligence: Technologies, applications, and opportunities. *Pervasive and Mobile Computing, 5*(4), 277–298.

D'antoni, L., Kini, D., Alur, R., Gulwani, S., Viswanathan, M., & Hartmann, B. . (2015). How can automatic feedback help students construct automata? *ACM Transactions on Computer-Human Interaction (TOCHI), 22*(2), 1–24.

Dai, S. (2019). ARS Interactive Teaching Mode for Financial Accounting Course based on Smart Classroom. *International Journal of Emerging Technologies in Learning (IJET), 14*(03), 38–50.

Dawson, S., Joksimovic, S., Poquet, O., & Siemens, G. (2019). Increasing the impact of learning analytics. In *Proceedings of the 9th International Conference on Learning Analytics & Knowledge* (pp. 446–455).

Ghaem Sigarchian, H., Logghe, S., Verborgh, R., De Neve, W., Salliau, F., Mannens, E., & Schuurman, D. (2018). Hybrid e-TextBooks as comprehensive interactive learning environments. *Interactive Learning Environments, 26*(4), 486–505.

González-Eras, A., Buendia, O., Aguilar, J., Cordero, J., & Rodriguez, T. (2017). Competences as services in the autonomic cycles of learning analytic tasks for a smart classroom. In *International Conference on Technologies and Innovation* (pp. 211–226). Springer.

Gupta, S. K., Ashwin, T. S., & Guddeti, R. M. R. (2019). Students' affective content analysis in smart classroom environment using deep learning techniques. *Multimedia Tools and Applications, 78*(18), 25321–25348.

Ha, I., & Kim, C. (2014). The research trends and the effectiveness of smart learning. *International Journal of Distributed Sensor Networks, 10*(5), 537346.

Hao, T., Chen, X., & Song, Y. (2020). A Topic-Based Bibliometric Analysis of Two Decades of Research on the Application of Technology in Classroom Dialogue. *Journal of Educational Computing Research, 58*(7), 1311–1341.

Hao, T., Chen, X., Li, G., & Yan, J. (2018). A bibliometric analysis of text mining in medical research. *Soft Computing, 22*(23), 7875–7892.

He, L., Jiang, D., Yang, L., Pei, E., Wu, P., & Sahli, H. (2015). Multimodal affective dimension prediction using deep bidirectional long short-term memory recurrent neural networks. In *Proceedings of the 5th International Workshop on Audio/Visual Emotion Challenge* (pp. 73–80).

Hien, H. T., Cuong, P.-N., Nam, L. N. H., Nhung, H. L. T. K., & Thang, L. D. (2018). Intelligent assistants in higher-education environments: the FIT-EBot, a chatbot for administrative and learning support. In *Proceedings of the Ninth International Symposium on Information and Communication Technology* (pp. 69–76).

Hwang, G.-J. (2014). Definition, framework and research issues of smart learning environments-a context-aware ubiquitous learning perspective. *Smart Learning Environments, 1*(1), 4.

Hwang, G.-J., Sung, H.-Y., Chang, S.-C., & Huang, X.-C. (2020a). A fuzzy expert system-based adaptive learning approach to improving students' learning performances by considering affective and cognitive factors. *Computers and Education: Artificial Intelligence, 1,* 100003.

Hwang, G.-J., Xie, H., Wah, B. W., & Gašević, D. (2020b). Vision, challenges, roles and research issues of Artificial Intelligence in Education. Elsevier.

Jeong, K., Kim, H.-S., & Chong, I. (2015). Knowledge driven composition model for WoO based self-directed smart learning environment. In *2015 International Conference on Information Networking (ICOIN)* (pp. 537–540). IEEE.

Kanagarajan, S., & Ramakrishnan, S. (2018). Ubiquitous and ambient intelligence assisted learning environment infrastructures development-a review. *Education and Information Technologies, 23*(1), 569–598.
Kim, P. W. (2019). Ambient intelligence in a smart classroom for assessing students' engagement levels. *Journal of Ambient Intelligence and Humanized Computing, 10*(10), 3847–3852.
Kim, S., Song, S.-M., & Yoon, Y.-I. (2011). Smart learning services based on smart cloud computing. *Sensors, 11*(8), 7835–7850.
Kim, Y., Soyata, T., & Behnagh, R. F. (2018). Towards emotionally aware AI smart classroom: Current issues and directions for engineering and education. *IEEE Access, 6,* 5308–5331.
Klimova, B. (2016). Teacher's role in a smart learning environment—a review study. In *Smart Education and e-Learning 2016* (pp. 51–59). Springer.
Koper, R. (2014). Conditions for effective smart learning environments. *Smart Learning Environments, 1*(1), 5.
Korozi, M., Stefanidi, E., Samaritaki, G., Prinianakis, A., Katzourakis, A., Leonidis, A., & Antona, M. (2019). Shaping the Intelligent Classroom of the Future. In *International Conference on Human-Computer Interaction* (pp. 200–212). Springer.
Kovanović, V., Joksimović, S., Mirriahi, N., Blaine, E., Gašević, D., Siemens, G., & Dawson, S. (2018). Understand students' self-reflections through learning analytics. In *Proceedings of the 8th international conference on learning analytics and knowledge* (pp. 389–398).
Lee, J., Zo, H., & Lee, H. (2014). Smart learning adoption in employees and HRD managers. *British Journal of Educational Technology, 45*(6), 1082–1096.
Leonidis, A., Margetis, G., Antona, M., & Stephanidis, C. (2010). ClassMATE: enabling ambient intelligence in the classroom. *World Academy of Science, Engineering and Technology, 66,* 594–598.
Lester, C. A., Wang, M., & Vydiswaran, V. G. V. (2019). Describing the patient experience from Yelp reviews of community pharmacies. *Journal of the American Pharmacists Association, 59*(3), 349–355.
Lin, H.-C.K., Su, S.-H., Chao, C.-J., Hsieh, C.-Y., & Tsai, S.-C. (2016). Construction of multi-mode affective learning system: taking affective design as an example. *Journal of Educational Technology & Society, 19*(2), 132–147.
Liu, X., Huang, R., & Chang, T.-W. (2016). Design of theoretical model for smart learning. In *State-of-the-Art and Future Directions of Smart Learning* (pp. 77–86). Springer.
Mahesh, G., Jayahari, K. R., & Bijlani, K. (2016). A smart phone integrated smart classroom. In *2016 10th International Conference on Next Generation Mobile Applications, Security and Technologies (NGMAST)* (pp. 88–93). IEEE.
Mann, H. B. (1945). Nonparametric tests against trend. *Econometrica: Journal of the Econometric Society*, *13*, 245–259.
Manning, C. D., Schütze, H., & Raghavan, P. (2008). *Introduction to information retrieval*. Cambridge university press.
Manning, C., & Schutze, H. (1999). *Foundations of statistical natural language processing*.
Mayer-Schönberger, V., & Cukier, K. (2013). *Big data: A revolution that will transform how we live, work, and think*. Houghton Mifflin Harcourt.
Mikulecky, P. (2013). Smart Environments for Learning–Multi-Agent Systems Approach. In *Proceedings for the 12th European Conference on eLearning* (pp. 304–310).
Mikulecky, P. (2019, September). Blended learning in smart learning environments. In EPIA Conference on Artificial Intelligence (pp. 62–67). Springer, Cham.
Miraoui, M. (2018). A Context-aware Smart Classroom for Enhanced Learning Environment. *International Journal On Smart Sensing And Intelligent Systems, 11*(1), 1–8.
Molenaar, I., Horvers, A., Dijkstra, R., & Baker, R. S. (2020). Personalized visualizations to promote young learners' SRL: the learning path app. In *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge* (pp. 330–339).
Ngwenya, S., Mangena, S. B., Trimble, J., Hlatywayo, J. D., & Chilumani, K. R. (2015). An ontology-based framework for mobile learning in rural secondary schools. *African Journal of Science, Technology, Innovation and Development, 7*(5), 342–347.
Novikova, V., & Beskrovnaya, L. (2015). Smart edutainment as a way of enhancing student's motivation (on the example of board games). In *Smart Education and Smart e-Learning* (pp. 69–79). Springer.
Ohkawa, Y., Kodama, M., Konno, Y., Zhao, X., & Mitsuishi, T. (2019). Development and Evaluation of Smartphone Learning Material for Blended Language Learning. In *2019 4th International Conference on Information Technology (InCIT)* (pp. 108–113). IEEE.
Ouf, S., Abd Ellatif, M., Salama, S. E., & Helmy, Y. (2017). A proposed paradigm for smart learning environment based on semantic web. *Computers in Human Behavior, 72,* 796–818.
Pacheco, A., Flores, E., Sánchez, R., & Almanza-García, S. (2018). Smart Classrooms aided by Deep Neural Networks inference on Mobile Devices. In *2018 IEEE International Conference on Electro/Information Technology (EIT)* (pp. 605–609). IEEE.
Papamitsiou, Z., & Economides, A. A. (2016). Learning analytics for smart learning environments: A meta-analysis of empirical research results from 2009 to 2015. *Learning, Design, and Technology: An International Compendium of Theory, Research, Practice, and Policy*, 1–23.
Patakamuri, S. K., Muthiah, K., & Sridhar, V. (2020). Long-term homogeneity, trend, and change-point analysis of rainfall in the arid district of ananthapuramu, Andhra Pradesh State, India. *Water, 12*(1), 211.
Paudel, P., Kim, S., Park, S., & Choi, K.-H. (2019). A Context-aware Architecture for Energy Saving in Smart Classroom Environments. In *2019 IEEE International Conference on Consumer Electronics (ICCE)* (pp. 1–2). IEEE.
Piety, P. (2020). Expanding the Frame: Designing a Learning Analytics System Using a Theory of Learning.
Piety, P. J., & Pea, R. D. (2018). Understanding learning analytics across practices. *Learning Analytics in Education, 215,* 232.
Pilkington, C., & Pretorius, L. (2019). Learning with the Semantic Web: The Case of a Research Methodology Semantic Wiki. In *International Conference on Innovative Technologies and Learning* (pp. 449–458). Springer.
Pirahandeh, M., & Kim, D.-H. (2017). Energy-aware and intelligent storage features for multimedia devices in smart classroom. *Multimedia Tools and Applications, 76*(1), 1139–1157.
Popescu, R., Ponescu, D., Roibu, H., & Popescu, L.-C. (2018). Smart Classroom-Affective Computing in Present-Day Classroom. In *2018 28th EAEEIE Annual Conference (EAEEIE)* (pp. 1–9). IEEE.

Qi, X., Liu, C., & Schuckers, S. (2018). IoT edge device based key frame extraction for face in video recognition. In *2018 18th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing (CCGRID)* (pp. 641–644). IEEE.
Qin, W., Suo, Y., & Shi, Y. (2006). Camps: A middleware for providing context-aware services for smart space. In *International Conference on Grid and Pervasive Computing* (pp. 644–653). Springer.
Radosavljevic, V., Radosavljevic, S., & Jelic, G. (2019). Ambient intelligence-based smart classroom model. *Interactive Learning Environments*, 1–15.
Salton, G. (1991). Developments in automatic text retrieval. *Science, 253*(5023), 974–980.
Shatnawi, S., Gaber, M. M., & Cocea, M. (2014). Automatic content related feedback for MOOCs based on course domain ontology. In *International Conference on Intelligent Data Engineering and Automated Learning* (pp. 27–35). Springer.
Shi, Y., Xie, W., Xu, G., Shi, R., Chen, E., Mao, Y., & Liu, F. (2003). The smart classroom: merging technologies for seamless tele-education. *IEEE Pervasive Computing, 2,* 47–55.
Siemens, G. (2019). Learning analytics and open, flexible, and distance learning. *Distance Education, 40*(3), 414–418.
Siemens, G., & Baker, R. S. J. d. (2012). Learning analytics and educational data mining: towards communication and collaboration. In *Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 252–254).
Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. *American Behavioral Scientist, 57*(10), 1510–1529.
Sneath, P. H. A., & Sokal, R. R. (1973). *Numerical taxonomy. The principles and practice of numerical classification*.
Song, Y., Chen, X., Hao, T., Liu, Z., & Lan, Z. (2019). Exploring two decades of research on classroom dialogue by using bibliometric analysis. *Computers & Education, 137,* 12–31.
Songsangyos, P., Kankaew, S., & Jongsawat, N. (2016). Learners' acceptance toward blended learning. In *2016 SAI Computing Conference (SAI)* (pp. 890–892). IEEE.
Spector, J. M. (2016). Smart learning environments: Concepts and issues. In *Society for Information Technology & Teacher Education International Conference* (pp. 2728–2737). Association for the Advancement of Computing in Education (AACE).
Tatar, D., Roschelle, J., Vahey, P., & Penuel, W. R. (2003). Handhelds go to school: Lessons learned. *Computer, 9,* 30–37.
Tiwari, S., Khandelwal, S., & Roy, S. S. (2011). E-learning tool for Japanese language learning through English, Hindi and Tamil: A computer assisted language learning (CALL) based approach. In *2011 Third International Conference on Advanced Computing* (pp. 52–55). IEEE.
Tober, M. (2011). PubMed, ScienceDirect, Scopus or Google Scholar-Which is the best search engine for an effective literature research in laser medicine? *Medical Laser Application, 26*(3), 139–144.
Traxler, J. (2007). Defining, Discussing and Evaluating Mobile Learning: The moving finger writes and having writ. *The International Review of Research in Open and Distributed Learning, 8,* 2.
Uskov, V., Bakken, J. P., Shah, A., Syamala, J., Rachakonda, R., & Uskova, M. (2018). Software/hardware systems and technology for smart engineering education. In *2018 IEEE World Engineering Education Conference (EDUNINE)* (pp. 1–6). IEEE.
Wang, D., Han, H., & Liu, H. (2019). Analysis of Instructional Interaction Behaviors Based on OOTIAS in Smart Learning Environment. In *2019 Eighth International Conference on Educational Innovation through Technology (EITT)* (pp. 147–152). IEEE.
Wang, X., & Liu, C. (2019). Research on the cultivation of English translation ability of undergraduates in smart learning environment. In *International Conference on Application of Intelligent Systems in Multi-modal Information Analytics* (pp. 1023–1028). Springer.
Xie, H., Chu, H.-C., Hwang, G.-J., & Wang, C.-C. (2019). Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017. *Computers & Education*, 103599.
Ying-You, L. (2020). Developing a Computer-Mediated Communication Competence Forecasting Model Based on Learning Behavior Features. *Computers and Education: Artificial Intelligence*, 100004.
Zeng, W., Meng, Q., & Li, R. (2019). Design of intelligent classroom attendance system based on face recognition. In *2019 IEEE 3rd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC)* (pp. 611–615). IEEE.
Zhang, Z., Cao, T., Shu, J., Zhi, M., Liu, H., & Li, Z. (2017). Exploration of blended teaching pattern based on Hstar and smart classroom. In *2017 International Symposium on Educational Technology (ISET)* (pp. 3–7). IEEE.
Zhu, Z.-T., Yu, M.-H., & Riezebos, P. (2016). A research framework of smart education. *Smart Learning Environments, 3*(1), 4.

Publisher's Note