Personalized Learning in the Online Learning from 2011 to 2021: A Bibliometric Analysis

Hoa-Huy Nguyen* and Viet Anh Nguyen

***Abstract*—This paper has analyzed research trends on personalized learning by bibliometric analysis method through a study of 928 articles from the Scopus database. The following issues are investigated: (1) Development scale, growth trajectory and geographical distribution of the research; (2) Outstanding authors and works on Personalized Learning; (3) Outstanding magazines and books on the topic; (4) Key themes found in these documents, and (5) Prominent methods/technologies used for personalized learning. Research results show that personalized learning is a fascinating topic in education and has been overgrown in recent years. Many researches on personalized learning comes from countries such as the United States and China. Our bibliometric analysis has revealed the main themes in the research works on Personalized Learning, such as artificial intelligence, learning style, and learning technology. The research has observed cognitive aspects of learners like knowledge level, learning style, preferences, etc. In most cases, the recommended tools and methods combined the content-based filtering, collaborative filtering, ontological approaches, etc. In addition, future research goals, difficulties, and concerns are highlighted in our work by examining the trends in several personalized learning elements.**

***Index Terms*—Personalization, personalized learning, learning technology, bibliometric analysis**

I. Introduction

Personalized learning has been made possible thanks to fast growth of information and communication technology [1]. It has been made feasible by implementing intelligent learning systems, taking learner preferences into account, performing personalized analyses of learning data, and other techniques. Depending on the needs of the students, all learning objectives, instructional strategies, and instruction content (as well as their order) might change. Additionally, learning activities, which are essential to students, are made related to their interests, and frequently self-initiated [2].

A suitable learning environment is necessary for the personalized learning process, which can be created by taking into account the learners' knowledge, goals, motivations, experience and skills. Furthermore, it is critical to offer an experience that corresponds to these characteristics to promote greater engagement with and performance in the learning activities. There is a sizable and diverse research body focusing on personalized learning due to the complexity of its challenge and its attraction to a wide range of fields. A well-known and crucial area of research in educational technology nowadays is personalized learning supported by technology. The educational community, on the other hand, has been concerned with establishing a personalized learning system to adjust the curriculum, and learning content to fit for learners' learning requirements [3].

This article aims to review the research materials on personalized learning by bibliometric analysis to systematically determine who is researching personalized learning, what personalized learning methods have been investigated.

Our research aims to answer the following five questions: (1) What are the number, growth patterns, and geographic distribution of personalized learning publications worldwide? (2) Who and what are outstanding authors and works in the field of personalized learning in the world? (3) What are prominent journals/books on personalized learning worldwide? (4) What key themes are found in the existing literature on personalized learning worldwide? (5) What are prominent methods/technologies used for personalized learning?

The rest of the paper is organized as follows: Section II presents an overview of the related literature and how to get the data set and the analysis approach are described in Section III. The responses to the research questions are presented in Section IV. The study's shortcomings and implications are discussed in Section V, followed by the Section VI of conclusions.

II. Literature Review

Today's personalized learning theories are inspired by the education philosophy from the progressive era of the last century, especially John Dewey's emphasis on experiential, learner-centered learning, learning society, curriculum expansion, and relevance to a changing world [4, 5].

Personalized learning was approached in many aspects by Organization for Economic Co-operation and Development (OECD) [6], such as 1) the development of key skills which are often domain-specific; 2) the levelling of the educational playing field through guidance for improvement of students' learning skills and motivation; 3) the encouragement of learning through "motivational scaffolding"; 4) the collaboration in knowledge-building; 5) the development of new models of assessment; 6) the use of technology as a personal cognitive and social tool; and 7) the new role of teachers in better integration of education in the learning society".

U.S. Office of Educational Technology defined personalized learning as "instruction that is paced to learning needs, tailored to learning preferences, and tailored to the specific interests of different learners. In an environment that is fully personalized, the learning

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Hoa-Huy Nguyen is with Center for Education Accreditation, Viet Nam National University (VNU-CEA), Hanoi, Vietnam.

Viet Anh Nguyen is with University of Engineering and Technology, Vietnam National University (VNU-UET), Hanoi, Vietnam. Email: vietanh@vnu.edu.vn (V.A.N.)

*Correspondence: huynguyen@vnu.edu.vn (H.H.N.)

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objectives and content as well as the method and pace may all vary (so personalization encompasses differentiation and individualization)" [7].

U.S. Office of Educational Technology further explained that personalized learning is "instruction in which the pace of learning and the instructional approach are optimized for the needs of each learner. Learning objectives, instructional approaches, and instructional content (and its sequencing) all may vary based on learner needs. In addition, learning activities are meaningful and relevant to learners, driven by their interests, and often self-initiated" [8].

In the same vein, Klašnja-Milićević and Vesin *et al.* [9] stated that personalized learning occurs when e-learning systems deliberately design educational experiences tailored to the needs, goals, talents, motivations, background and preferences of learners.

Therefore, providing the same content to students with different backgrounds, personal characteristics, interests and needs is no longer considered adequate when learning can now be personalized [10].

However, the results of some studies show that the concepts and definitions of personalized learning are not clear. Schmid and Petko [11] said that a well-defined concept of personalized learning is lacking; instead, it serves as an umbrella term for educational strategies that strive to be fair to the abilities, knowledge, and learning needs of each student.

Xie and Chu *et al.* [12] provided an initial review of learner characteristics and task engagement events that inform adaptability in technology-based learning environments and provide a general summary of the types of results that personalized learning designers target.

Although the personalized learning literature shows a diversity of developments in this area, there is still a lack of an integrated review that summarizes the issues involved. Most available assessments only addressed specific areas of personalized learning [13, 14]. Xie and Chu *et al.* [12] reviewed several research issues in adaptive/personalized learning, such as learning content, learning support, and learning outcomes reported in related studies on the Web of Science database. Li and Wong [15] used Scopus database to study the features/implementation/factors related to personalized learning practices. Despite such efforts, there are still many issues in personalized learning that have not been comprehensively examined, which makes it challenging to present an overview of its current development and trends in research.

III. Materials and Methods

To provide an overview of personalized learning for the period prior to 2021, in this study, we counted the universities/research institutes, and the countries where the works were located, and the authors whose research has a lasting impact on research trends on this issue. In addition, we also suggest trends in personalized learning research and promising research topics. We used bibliometric analysis on the Scopus database—one of the most extensive academic databases in the world, to achieve these objectives.

A. Criteria for Searching and Identifying Data Sources

Web of Science (WoS), Scopus, Google Scholar, Microsoft Academic and Dimensions is the year database directory that may be used to parse [16]. Scopus is unique as it is produced by the reputable Elsevier Ltd. and is indexed in over 14,000 journals for many fields [17]. Scopus is rated as one of the essential scientific databases with consistent criteria in selecting documents for inclusion in its index [18]. This database has a broader range of literature than the WoS for evaluating educational and social science research [19]. Given these advantages, the Scopus index was utilized to find the materials for this review. During the document search, we adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) standards [20]. PRISMA mandates that all search and screening steps be made explicit by the reviewers. PRISMA flow diagram consists of four stages: Identifying the articles, Screening the articles, Deciding on the studies' eligibility, Finalizing the list of studies to include in the systematic review.

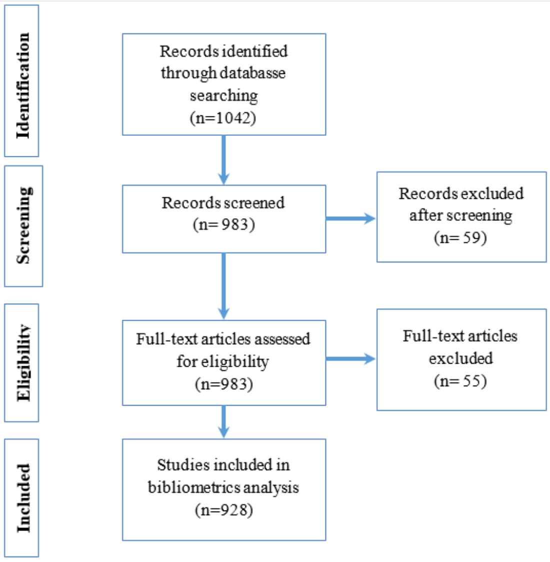

Fig. 1. PRISMA diagram of the scientific list cleaning process for bibliometric analysis.

The document selection process consists of four steps, as illustrated in Fig. 1, specifically as follows:

Step 1: Collect data.

We used the keyword "Personalized Learning" (in both UK and US English) and searched for studies published between 2011 and late 2021, we chose the past ten years since there has been a lot of interest in studies on tailored learning to match learners during this time. Several encouraging outcomes in the area of personalization have been reported in the recent period with the aid of computer science and information technology. In addition, we chose the most recent surveys to investigate the most recent findings in the field using the query:

TITLE-ABS-KEY ("personalised learning" OR "personalized learning") AND PUBYEAR > 2010 AND PUBYEAR < 2022 AND SUBJAREA (soci) AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "re")) AND (LIMIT-TO (LANGUAGE, "English")).

Through the Scopus filter, we collected 1042 publications based on several categories such as document type, language, subject area.

Step 2: Filter data by excluding inappropriate documents.

The eligibility of the documents was assessed based on their titles and abstracts for "thematic relevance". We excluded 54 works because the abstracts and topics are unrelated to the research field (such as Medicine [21, 22]; Environmental science [23, 24]; Health professions [25, 26], Neuroscience [27], and Pharmacology [26, 28]). In addition, five works [29, 30] that did not have a summary are omitted. Finally, we obtained 983 publications.

Step 3: Filter data by reading full text.

We read the full text of articles that were difficult to determine the topic's relevance based on the title and summary. From there, 55 articles with content unrelated to the topic were further excluded, such as Intellectual aptitude [31]; Supporting patients with diabetes [32]; Dropout prevention [33]; Philosophical education and cultural fit [34]; Driving status recognition [35]; Electronic investment for evaluation [36]; Medical education [37]; A guide for students with autism spectrum disorder [38]; Medical field—orthodontic wire bending [39].

We synthesized 928 scientific works, including articles, books/book chapters, and reviews. We also recorded the following fields for each scientific work analyzed: article identifier, article title, journal, number/relationship of citations, author, agency, country, document's link and year of publication.

B. Data Analysis

Besides descriptive statistical analyses, we performed biometric analysis using the VOSviewer tool [40] for scientific mapping, author analysis, co-citation and document citation analysis.

In the subject of knowledge, citation is a factor used to recognize significant authors and their works [41]. Citation analyses performed in VOSviewer calculated how often authors and documents were cited in the database of 928 publications found in additional Scopus records. We refer to these as "Scopus Citations" because they only cite sources that are included in the Scopus index.

To create "co-citation counts" and view the document's intellectual structure as a network map, author co-citation analysis is utilized [41, 42]. Co-citation is the quantity of times two authors are cited together in the overview database's "reference list" [43].

The source of the citation data is a crucial differentiating factor in co-citation analysis. The results are therefore not constrained by the extent of the source index, unlike citation analysis. According to Small, authors who are frequently referenced together (also known as co-cited authors) are likely to have similar intellectual perspectives [43]. VOSviewer generates a co-citation frequency matrix as input for the co-citation mapping and "visualize similarities" [40].

IV. Results

A. Development Scale, Growth Trajectory and Geographical Distribution of Works on Personalized Learning

To answer the first research question, we analyzed 928 scientific works, including 561 articles and 367 conference papers related to personalized learning published from 2011 to 2021. The results are shown in Fig. 2.

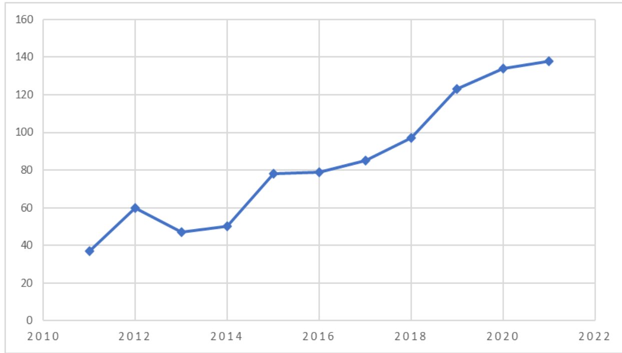

Fig. 2. Growth of Personalized Learning literature, 2011–2021 (n = 928).

Based on the growth trends of Personalized Learning scientific works in the world from 2011 to 2021 shown in Fig. 2, and based on the definition and revisions of the U.S. Office of Educational Technology [7, 8], we divided the development of Personalized Learning into two phases:

- 2011–2016: The beginning of development, in which the topic of Personalized Learning began to attract the attention of scholars, and 351 studies were published (accounting for 37.8% of the total works published from 2011 to 2021);
- 2017–2021: Development phase, in which the topic of Personalized Learning received considerable attention from scholars: a total of 577 works were published (accounting for 62.2% of the total works published from 2011 to 2021);

Fig. 2 shows that in the early period, an average of 58.5 scientific works were published per year. This number in the development phase is 115.4 works per year, nearly doubled that at the beginning of development. Overall, the publishing yield is 84.4 publications per year. Focusing on the development period of the past five years, from 2017 to 2021, publication efficiency is 115.4 publications per year, nearly 1.37 times higher than the overall performance (from 2011 to 2021).

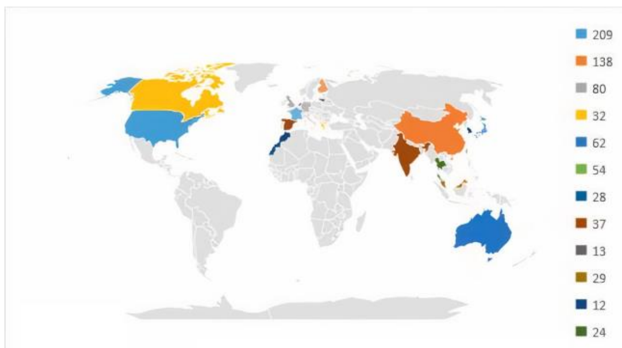

Fig. 3. Geographic distribution of countries with the most publications.

Figs. 3 and 4 show the geographical distribution of countries with research related to personalized learning around the world. At least one paper on the topic has been co-authored by researchers from 88 different nations. Three countries, including the United States (209 works), China (138 works) and the United Kingdom (80 works), are the ones that published the most personalized learning research.

Australia (62 works), Taiwan (54 works) and Spain (37 works) also had a relatively large number of research works on this topic. These six countries contributed 575 of the total 928 relevant published works.

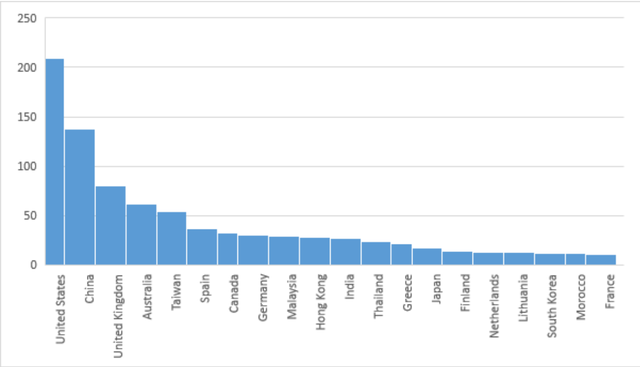

Fig. 4. Top 20 countries with the most research on personalized learning for the period 2011–2021. (Co-authorship—countries; 87 countries; 11 documents of a country; 10 citations of a country; display 20 countries).

Besides, statistics over the years show that the number of studies in countries with the same content was concentrated in the period 2015–2021, new studies were in the period 2018–2021 and were mainly studies of Asian countries such as China (138 works), Hong Kong (28 works), and Thailand (24 works).

Most of the researchers came from developed countries, of which researchers from the United States made up 25%. During this period, researchers from Asia accounted for 45%, specifically from four countries: Thailand, Taiwan, China and Japan. Researchers from Australia also took up a significant proportion, of 20%. Europe had only two representatives (Germany and Lithuania), accounting for 10%.

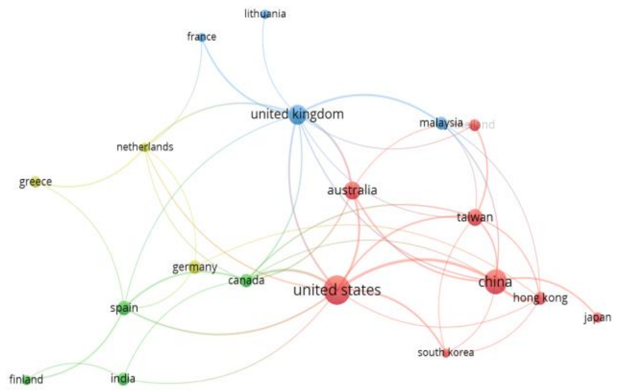

Fig. 5. Map of co-authorship between countries (N=87 countries, 11 documents of a country, 10 citations of a country, 20 meet the thresholds).

Among the countries with 11 studies and 10 or more citations about Personalized Learning, there are 19 countries with strong co-authorship with other countries (Fig. 5). According to the results in Fig. 5, the United States is the most robust total link strength (38), followed by China (30), United Kingdom (27), Canada (19) and Australia, Taiwan (both 19). At the same time, the research cooperation through co-authoring between the United States and China has the strongest link with 8 works, followed by the collaboration between the United States and Canada, and China and Hong Kong have the highest degree of linkage with seven works.

B. Outstanding Researchers and Works on Personalized Learning

Researchers from many countries around the world have studied Personalized Learning. Table I lists top 20 authors with works on Personalized Learning, ranked by the total number of works and citations counted on the Scopus database. Three of the 20 most prominent authors have more than 200 citations and are from the universities in Asia. Among the authors in Table I, G. Hwang from the National Taiwan University of Science and Technology, Taiwan, deserve the most attention when his number of works on the topic of personalized learning (nine works) and the significant number of citations of these works are the highest (502 citations), with an H-index of 66 and a total of 357 works with 15.433 times cited in 8.577 related works. He was followed by Xie Haoran from Lingnan University, China, with seven works and 243 citations. He has an article on the topic of personalized learning with 141 citations in related works [12].

TABLE I: TWENTY AUTHORS WITH THE MOST OUTSTANDING WORKS

N	Author	University	Country	Scopus H-index	All Doc	Doc	Citations
1	G. Hwang	National Taiwan University of Science and Technology	Taiwan	66	357	9	502
2	H. Xie	Lingnan University	China	31	277	7	243
3	H. Ogata	Kyoto University	Japan	29	386	6	37
4	H. Chu	Soochow University	Taiwan	27	84	7	269
5	V. Prain	Deakin University	Australia	27	112	7	100
6	M. A. Chatti	Universität Duisburg-Essen	Germany	22	69	5	31
7	D. Zou	The Education University of Hong Kong	China	20	108	6	87
8	E. Kurilovas	Vilniaus Gedimino Technikos Universitetas	Lithuania	18	68	8	87
9	P. Panjaburee	Mahidol University	Thailand	13	59	11	98
10	N. Srisawasdi	Khon Kaen University	Thailand	13	103	11	81
11	C. G. Deed	College of Arts, Social Sciences and Commerce	Australia	12	47	6	97
12	C. Wongwatkit	Mae Fah Luang University	Thailand	7	39	5	71
13	C. Farrelly	La Trobe University	Australia	7	18	5	86
14	R. A. Carter	University of Wyoming	United States	7	23	5	69
15	V. Lovejoy	La Trobe University	Australia	6	25	6	97
16	S. Yang	University of Kansas	United States	5	13	5	47
17	B. Chen	Ling Tung University	Taiwan	5	15	5	44
18	L. Zhang	University of Kansas Center for Research on Learning	United States	4	13	7	51
19	S. Netcoh	Farmington High School	United States	4	7	5	33

N	Author	University	Country	Scopus H-index	All Doc	Doc	Citations
20	A. J. Bingham	University of Colorado at Colorado Springs	United States	4	10	5	56

Note: N: Order; All Doc: All published articles

TABLE II: THE TEN MOST OUTSTANDING RESEARCH WORKS

No	Documents	Author	Year	Citations
1	E-Learning personalization based on hybrid recommendation strategy and learning style identification	A. Klašnja-Milićević *et al.*	2011	418
2	A research framework of smart education	Z.-T. Zhu *et al.*	2016	236
3	Learning analytics methods, benefits, and challenges in higher education: A systematic literature review	J. T. Avella *et al.*	2016	172
4	Development of a personalized educational computer game based on students' learning styles	G.-J. Hwang *et al.*	2012a	171
5	Conceptualizing the emerging field of smart learning environments	J. M. Spector	2014	169
6	Data mining for providing a personalized learning path in creativity: An application of decision trees	C. F. Lin *et al.*	2013	147
7	Empowering personalized learning with an interactive	Y.-M. Huang *et al.*	2012	142
8	Trends and development in technology-enhanced adaptive/personalized learning: A systematic review of journal publications from 2007 to 2017	H. Xie *et al.*	2019	141
9	A Multimedia Adaptive Tutoring System for Mathematics that Addresses Cognition, Metacognition and Affect	I. Arroyo *et al.*	2014	116
10	Students' perceptions and experiences of mobile learning	D. Kim *et al.*	2013	110

Table II lists 10 articles that have been most cited on the topic of personalized learning [9], with the most cited content is the discussion of a suggested module of the Protus programming tutoring system, which can be automatically tailored to meet the interests and skill levels of students. This technology analyzes learners' learning preferences and mines their server records to identify various learning methods and habit patterns.

The second most cited article was the published smart learning environments [44], which also indicates that the smart pedagogical framework includes classroom-based differentiated instruction, group-based collaborative learning, individual-based personalization and mass-based collective learning.

Notably, G.-J. Hwang has two most cited publications among the publications listed in Table II. This first article (171 citations) argues that research files have been recognized as an important human component that influences researchers learning outcomes. Then, a tailored game-based learning approach is suggested based on Felder and Silverman's sequential/global learning style [45]. The second article (98 citations) presents a context-aware universal learning system with sensor technology to detect, control, and examine students' real-world learning behaviors so that personalized instruction and learning feedback can be provided. As a result, this innovative approach can improve student achievement and enhance learners' motivation [46].

Finally, we analyzed co-authorship among authors to identify cross-country research collaboration.

C. The Most Prominent Journal/Publisher in Current Research on Personalized Learning

Table III lists 10 journals/publishers with the highest number of articles related to the topic of Personalized Learning. The International Journal of Emerging Technologies in Learning of the International Association of Online Engineering (IAOE) is the journal with the most publications (40 articles). Moreover, Computers and Education, a journal of Elsevier Ltd., should be mentioned with 20 articles related to Personalized Learning published during this period, which offer ways to improve teaching and learning in the classroom. Next is the Journal of Educational Technology and Society which published 16 articles related to the works on the topic of Individualized Learning. A variety of qualitative, quantitative, and hybrid research approaches are represented in the articles of this journal. The papers' topics are pertinent to scientific education generally, and they also cover pertinent information technology and design technology education topics.

TABLE III: MOST INFLUENTIAL JOURNALS/PUBLISHERS ON THE TOPIC OF PERSONALIZED LEARNING

N	S	P	ISSN	C	D	S-C	H	SJR	R
1	Computers and Education	Elsevier Ltd.	03601315	Computer Science, Education, E-learning	20	1495	197	3.68	Q1
2	Educational Technology and Society	Taiwan	11763647, 14364522	Engineering, Social Sciences	16	438	95	1.31	Q1
3	Educational Technology Research and Development	Springer Boston	10421629, 15566501	Social Sciences Education	12	579	95	1.72	Q1
4	Smart Learning Environments	Springer Open	21967091	Computer Science, Social Sciences Education	7	515	20	0.9	Q1
5	Interactive Learning Environments	Taylor and Francis Ltd.	10494820	Computer Science, Social Sciences	14	209	49	1.17	Q1
6	British Journal of Educational Technology	Wiley-Blackwell Publishing Ltd	00071013, 14678535	Social Sciences Education E-learning	9	179	102	1.87	Q1

N	S	P	ISSN	C	D	S-C	H	SJR	R
7	International Journal of Mobile Learning and Organization	Inderscience Publishers	1746725X, 17467268	Computer Science, Social Sciences	8	67	26	0.88	Q1
8	Australasian Journal of Educational Technology	Australasian Society for Computers in Learning in Tertiary Education	14495554	Social Sciences Education E-learning	7	180	53	1.25	Q1
9	Education and Information Technology	Kluwer Academic Publishers	13602357	Social Sciences Education E-learning Library and Information Sciences	12	282	48	1.06	Q1
10	IEEE Transactions on Learning Technologies	Institute of Electrical and Electronics Engineers Inc.	19391382	Computer Science, Engineering, Social Sciences Education E-learning	8	154	51	1.29	Q1

Note: N: Order; S: Source; P: Publisher; C: Category; D: number of works; S-C: number of citations according to Scopus database; H: H-index; SJR: data from scimagojr.com as of August-2022; R: Ranking.

D. Main Topics in Current Research on Personalized Learning

In this section, we used co-occurrence analysis to define the structure of personalized learning studies. Co-occurrence keywords play an important role in bibliometric analysis because this method helps quickly detect common research topics and allows tracking of research trends in the scientific field over time [47]. In the resulting map of the co-occurrence in Fig. 6, the size of the node represents the number of occurrences of the keyword in the database and the links between two nodes depict their relationship, nodes of the same color indicate that they can appear in the same research topic. A total of 4342 keywords appeared in all 928 works analyzed. Only keywords that appear at least 30 times are selected to establish a relationship between them. Twenty keywords met our criterion and were shown in the results map. The most popular keywords were the ones we used to search for data for this study and the words close to them are as follows: personalized learning (571), e-learning (254), students (234), learning systems (229) and computer-aided instructions (160). The results presented the graph in Fig. 6 indicate that the problems related to Personalized Learning do not follow concentrated directions but are scattered about different specific issues. The map also shows that there are a number of topics of interest to research associated with Personalized Learning, including teaching (102), education (93), curricula (78), adaptive learning (65), learning analytics (56).), learning style (52), learning environments (41), online learning, higher education (36) and artificial intelligence (31).

The results of the analysis the keywords co-occurrence are presented in Fig. 7, which reveal the most popular research topics and trends in Personalized Learning in recent years. Newly researched topics are often associated with the keywords: “Artificial Intelligence”, “Learning Analytics”, “Learning Style”, “Educational Technology”, “Higher Education”.

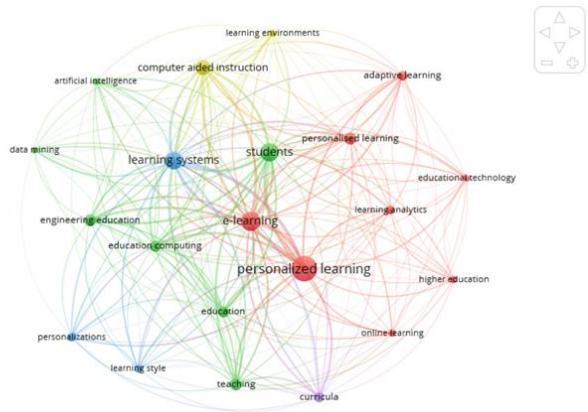

Fig. 6. Key themes in personalized learning research. (Co-occurrence keywords; 4342 keywords; occurrence of 31 keywords; display 20 keywords).

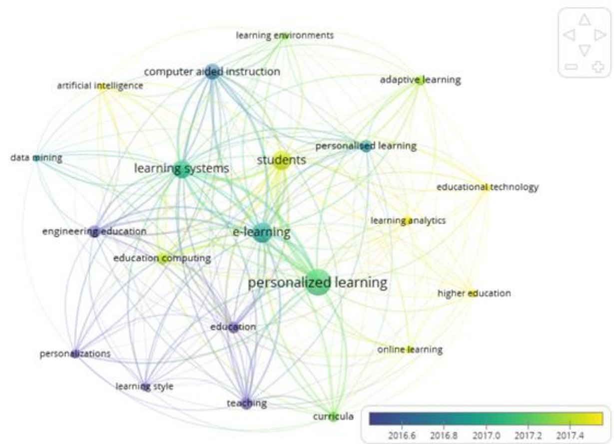

Fig. 7. Map of the temporal distribution of keywords, using co-occurrence analysis. (N=4342 keywords threshold 31 co-occurrence, display 20 keywords).

E. Methods/Technologies Used for Personalized Learning

A number of studies have regularly assessed how the students performed, and recommendations are based on the results (Table IV). Some use learner ratings, both positive and negative, as a learner modeling component. Comparable learners rate the learning objects in similar ways. A few studies have used social tags and trust to categorize learners and provide learning materials to them, driven by the business domain. Recent studies demonstrate interest in exploiting learners' cognitive states by examining how they engage with the system, how engaged they are, and how these states relate to their learning patterns.

TABLE IV: POPULAR PARAMETER VARIABLES USED TO MODEL LEARNERS IN PERSONALIZED LEARNING

Parameters	Citation
Learning style/Learner Preferences	[9, 48–76], …
Knowledge level	[9, 51, 77–83], …
Performance/Score	[39, 84–92], …
Learning need/goal	[11, 82, 93–100], …
Cognitive/Emotional States	[66, 101–108], …
Learning path/patterns	[81, 109–117], …

In order to improve adaptive learning/personalized learning during this period (2011–2020), models built on ontologies place a strong emphasis on the incorporation of fuzzy techniques and hybrid methods that include algorithm genetics. Ontological frameworks and collaborative or content-based models are typically seen in hybrid techniques. Table V, demonstrates that researchers prefer hybrid models to others. Based on various recommendation techniques, the publications are grouped.

TABLE V: PROPOSED METHODS/TECHNIQUES IN PERSONALIZED LEARNING

Method	Citation
Ontology-Based	[33, 50, 62, 72, 77, 116, 118, 119], …
Collaborative Filtering	[86, 95, 108, 120–122], …
Content-Based	[50, 122–124], …
Rule-Based	[125–127], …
Group-based	[44, 128, 129], …
Hybrid	[130–134], …

When paired with the appropriate machine learning algorithms, recommendation systems produce superior outcomes (Table VI). The algorithms put the students into groups, identify learning patterns, and match them to learning materials. It has been noted that most research studies cluster the items using the K-Nearest Neighbor (KNN) and K-Means methods. They are both straightforward and effective grouping algorithms. In supervised learning, KNN is employed, while in unsupervised learning, K-Means.

TABLE VI: SUGGESTED TECHNIQUES GIVE BETTER RESULTS WHEN COMBINED WITH SUITABLE MACHINE LEARNING TECHNIQUES

Machine learning algorithm	Citation
K-Means	[134–136], …
KNN/K-Nearest Neighbor	[78, 137–140], …
Genetic Algorithm	[59, 81, 141–143], …
Association Rule Mining	[144–147], …
LO-based	[148, 149], …
Shortest Path Algorithm	[150, 151], …

V. DISCUSSION

After examining 928 Scopus-indexed documents published between 2011 and 2021 using bibliometrics, we highlight the review's shortcomings, offer some implications and recommendations for future study, and describe the key conclusions in this part.

A. Limitations of the Review

The first limitation is that this analysis does not involve all literature related to the topic of Personalized Learning. Although the Scopus index allows a large volume of documents to be identified, it is impossible to determine how these findings represent the entire document. Sources and indexes define the scope of this review. However, the impact of this limitation has been mitigated by using co-citation analysis.

The second limitation comes from being limited to English literature, which may not reflect all the work of researchers on this issue. In addition to English, this field is also studied in a number of other languages such as Spanish (Gatica and Mart ńez, 2021) and Russian (Rabinovich *et al.*, 2021).

In addition, the names of authors and their organizations normalization is an issue in the Scopus database. An author can have multiple different names printed in articles or spellings and cannot be adjusted manually, which is a major source of analysis errors.

B. Implications

The number of personalized learning studies in recent years has increased rapidly, especially in the period 2017–2021. This is understandable. In this period, along with the development of blended learning, information technology is developing strongly. Educational technology capabilities provide additional insights to determine the best approach when aligning learning objectives in technology-based implementations [152]. From 2019 until now, the COVID-19 pandemic has forced all students at all levels, from primary school to university, to change their learning mechanisms. From the original face-to-face learning approach, the learning system has changed online learning [153].

It is clear that Personalized Learning publications in developed countries outnumbered those in developing countries, probably due to the fact that developed countries are always ahead in technology. There is always a difference between developed and developing countries in personalized learning because this issue is greatly influenced by the educational policies of each country. Every Student Succeeds Act (ESSA), which was passed in December 2015 and is applicable to the United States, offers a historic opportunity for the US to move from K-12 education to customized learning and student-centered learning [154].

Learner modeling in content recommendation involves cognitive and non-cognitive elements of the learners. Examples of cognitive aspects include learning preferences, patterns, and knowledge levels. The probability-based learning style, Felder-Silverman Learning Style Model, has attracted the most significant attention among the others. Most work is done using an initial questionnaire-based learning style or knowledge-level survey to address the cold-start issue. At a high level of recommendation, learners' paths, patterns, or ratings change based on their evolving needs. Investigating and studying the courses and patterns within the system ensures the adaptability and dynamic nature of the designs.

Hybrid systems are the most widely used among the many recommendation strategies. This type of system combines ontology and knowledge-based system approaches. Collaborative filtering has been widely employed as one knowledge-based strategy in most investigations that have followed hybridization. This pattern demonstrates the ongoing efforts of researchers to uncover hidden patterns and the variety of learner behavior.

Collaborative filtering groups the students based on how similar or unlike they are, thus revealing commonalities. This can be achieved by analyzing the preferences and activities of different users and then concluding the preferences of other users.

To promote LOs, collaborative filtering is integrated with content-based, rule-based, and item-based filtering techniques. The two most widely utilized learner grouping algorithms in the articles under study are KNN and K-means.

VI. Conclusions

This paper investigated the academic trends in the literature on Personalized Learning using a bibliometric analysis method with a database from Scopus. The topic of personalized learning is getting more and more attention with increasing research. However, it is still focusing on a few countries, typically the United States and China, with several researches that surpass other countries. This issue has been underresearched in developing countries. Research is popularly published in high-quality, specialized journals on education, such as Elsevier Ltd., and Taylor and Francis Ltd. The analysis results show that the application of computer science to building personalized courses has been a trend, especially, using the Artificial Intelligence, Machine Learning, and Learning Analytics techniques to create an adaptive course for each learner.

Regarding methods and technologies for personalized learning, the analysis results show that the most widely used methodology for recommendation systems is a mix of two or more ways, such as collaborative filtering-based or ontology-based. The designs also make explicit learner qualities a key component. Some studies on recommender systems examine learners' cognitive characteristics as implicit traits. The choice of the input character is frequently made based on learning preferences, knowledge level, and learning style. The learning pattern and path in these studies are computed to suggest material. The latest research in this field focus on ubiquitous and autonomous systems that use recommender system knowledge.

Future research may focus on the components present in various personalized learning-supported adaptive learning systems and the definition of the term to build a unified approach and definition. Future studies focusing on simultaneously what components are being used for each personalized learning approach need to acknowledge it as a term that will evolve over time as we learn more about human psychology (such as learning styles, cognitive styles, interests, learning outcomes, ...) and more technological development.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Hoa-Huy Nguyen conducted the research and mostly drafted papers. Viet Anh Nguyen proposed the main ideas and reviewed the manuscript. Both authors have approved the final version.

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