ISSN 2706-6827 Vol. 3, Issue 19: 91-97, DOI: 10.25236/IJFS.2021.031918

A System Literature Review of Personalized e-Learning

Zhen Li *

Liberal Arts and Science Experimental School (Group) Science and Technology Innovation School, Shenzhen 518000, Guangdong, China
jeanlee6143@163.com
**Corresponding author*

Abstract: *This paper investigates earlier research publications on personalized learning, exceptionally personalized e-learning, appearing in the World of Science Education and Educational Research categories. The researcher initially consults HistCite to identify the range of relevant articles and their citation links. The HistCite technique finds and isolates personalized e- learning studies. In addition, several articles are selected based on criteria and the EPPI guide for in-depth analysis to discover trends, design principles, and future research prospects.*

Keywords: *System literature review, Personalized e-learning, Histcite*

1. Procedures for HistCite Analysis

The researcher used WoS's database for most of the journal research. Researchers found a study on "personalized learning" and "personalized e-learning." The HistCite builds chronological historiography (i.e., a network map of time) from the relationship between the cited works (i.e., the locally cited score), the number of citations within one of the collections. The chronological historiographies of the broad pool of studies were then selected and highlighted to identify the subset of research studies that dealt with personalized e-learning. The HistCite tool analyzed personalized e-learning studies using the subject of personalized e-learning or personalized online learning to determine the citation pattern for each research and select the most relevant studies for further in-depth analysis.

Researchers then used the HistCite program to analyze the structure of the studies and the relationships between the 830 publications identified in the WoS. (See Fig.1). In the broader pool of customized learning research studies, the WoS database yielded 75 personalized e-learning studies (see Figure 2).

Researchers present the first page of the HistCite customized learning file in the first line (see Figure 3), which provides broad information about the findings. WoS covers the period from 1992 to 2021 based on the subscription history of the accessible library. According to a display of the ranked citation index of 830 research articles published in 380 journals by 1,985 authors and 19,086 cited references, personalized learning in education emerged cyclically. Research. The following are the definitions of the acronyms used in Fig. 3 and throughout the text:

GCS: The number of citations to work is given as the global citation score (GCS).

LCR: local cited references track the number of citations in a paper's reference list that points to other documents within the collection.

- LCS: local citation score shows the total number of citations to an article in the collection.

-CR: cited references display the number of citations in the paper's bibliography.

Date: Oct 20, 2021
Results: 830
(*From All Databases*)
You searched for:
TOPIC: ("personalized learning")
Refined by: RESEARCH AREAS= (EDUCATION EDUCATIONAL RESEARCH)
Time span=All years.
Search language=Auto

Fig. 1: WoS topic search result for personalized learning

Date: Oct 2021
Results: 75
(*From All Databases*)
You searched for:
TOPIC: ("personalized e-learning" or "personalized online learning")
Refined by: RESEARCH AREAS= (EDUCATION EDUCATIONAL RESEARCH)
Timespan=All years.
Search language=Auto

Fig. 2: WoS topic search result for personalized e-learning

File Analyses View Tools Help HistCite™

Untitled Collection
List of All Records

Grand Totals: LCS 252, GCS 5846, CR 22327
Collection span: - 2021

Records: 830, Authors: 1988, Journals: 381, Cited References: 19114, Words: 1730
Yearly output | Document Type | Language | Institution | Institution with Subdivision | Country

|< << < > >> >|

#	Date / Author / Journal	LCS	GCS	LCR	CR
1	99 Chen CM **Intelligent web-based learning system with personalized learning path guidance** COMPUTERS & EDUCATION. 2008 SEP; 51 (2): 787-814	25	198	1	24
2	41 Chen CM, Lee HM, Chen YH **Personalized e-learning system using item response theory** COMPUTERS & EDUCATION. 2005 APR; 44 (3): 237-255	15	268	0	37
3	154 Hwang GJ, Kuo FR, Yin PY, Chuang KH **A Heuristic Algorithm for planning personalized learning paths for context-aware ubiquitous learning** COMPUTERS & EDUCATION. 2010 FEB; 54 (2): 404-415	13	119	1	33
4	98 Chen CM, Chung CJ **Personalized mobile English vocabulary learning system based on item response theory and learning memory cycle** COMPUTERS & EDUCATION. 2008 SEP; 51 (2): 624-645	10	202	0	40
5	244 Lin CF, Yeh YC, Hung YH, Chang RI **Data mining for providing a personalized learning path in creativity: An application of decision trees** COMPUTERS & EDUCATION. 2013 OCT; 68: 199-210	10	92	2	75
6	203 Hwang GJ, Sung HY, Hung CM, Huang I, Tsai CC **Development of a personalized educational computer game based on students' learning styles** ETR&D-EDUCATIONAL TECHNOLOGY RESEARCH AND DEVELOPMENT. 2012 AUG; 60 (4): 623-638	8	120	2	63
7	614 Bingham AJ, Pane JF, Steiner ED, Hamilton LS **Ahead of the Curve: Implementation Challenges in Personalized Learning School Models** EDUCATIONAL POLICY. 2018 MAY; 32 (3): 454-489	8	18	0	49
8	134 Looi CK, Wong LH, So HJ, Seow P, Toh Y, et al. **Anatomy of a mobilized lesson: Learning my way** COMPUTERS & EDUCATION. 2009 DEC; 53 (4): 1120-1132	7	95	0	50
9	205 Nedungadi P, Raman R **A new approach to personalization: integrating e-learning and m-learning** ETR&D-EDUCATIONAL TECHNOLOGY RESEARCH AND DEVELOPMENT. 2012 AUG; 60 (4): 659-678	6	54	0	20
10	206 Song YJ, Wong LH, Looi CK **Fostering personalized learning in science inquiry supported by mobile technologies** ETR&D-EDUCATIONAL TECHNOLOGY RESEARCH AND DEVELOPMENT. 2012 AUG; 60 (4): 679-701	6	53	4	52

Fig. 3: Articles about personalized learning are available in the HistCite database.

GCS (inside a WOS) and LCS (within a collection) are two types of historiographies generated by Hiscite. Researchers created this historiography through LCS because researchers analyzed the number of times other publications on the same subject referenced an article within the local collection. In Figure 4, the LCS is partly used to illustrate and depict the evolution of the personalized e-learning studies over time by identifying the related papers by using circles to denote the critical nodes of the network of citations over time. However, due to the location and number combination, several

ISSN 2706-6827 Vol. 3, Issue 19: 91-97, DOI: 10.25236/IJFS.2021.031918

publications were not detectable and highlighted, where some of these numbers caused uncertain significance in the historiography. In Fig.4, the circle represents the development of personalized learning through the year 2021, as indicated by the history of personalized e-learning. Therefore, this approach is unique to individualized learning, especially in computer science education; it has received extensive research attention over the last two decades.

Another HistCite analysis also reveals 75 articles found in 51 journals by 207 authors with 2,103 cited references, providing a timeframe for the emergence of personalized e-learning research.

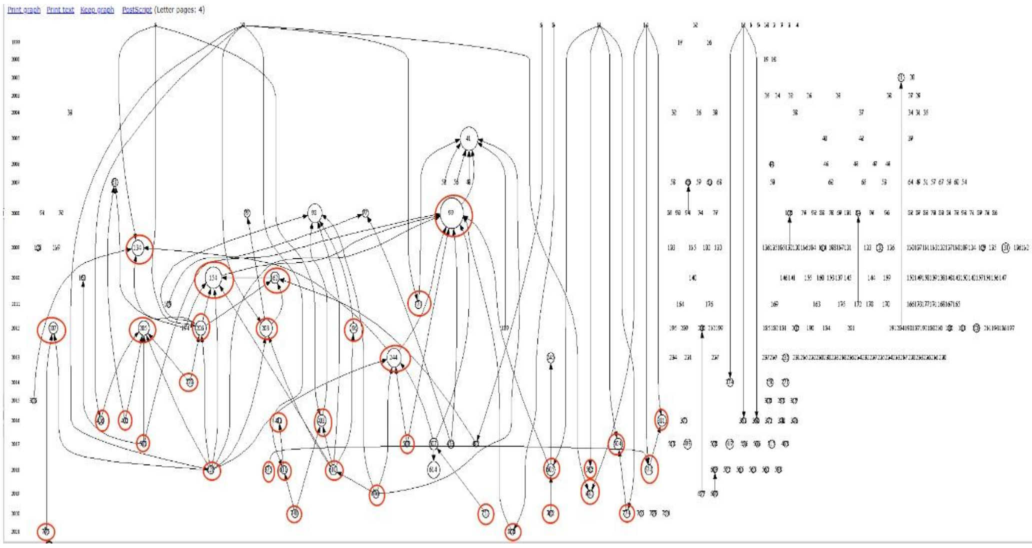

Fig. 4: The chronological historiographies of personalized learning were published from 1992 until early 2021 (Circle denotes the growth of personalized e-learning)

Figure 5 presents the HistCite graph maker presentation of the e-learning historiography built using the LCS and the connection of cited works, with circle sizes representing the LCS and arrows indicating the direction of citations. Despite the fewer articles on personalized learning than traditional personalized learning, they are still substantial enough to be tracked chronologically.

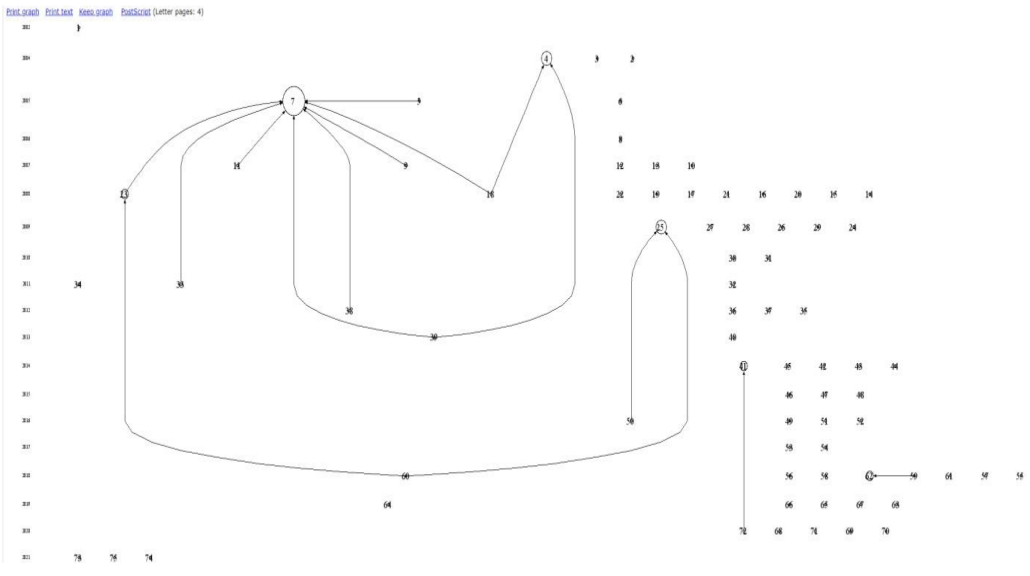

Figure 5: The HistCite graph maker presentation of personalized e-learning historiography from 1993 to 2021.

2. In-Depth Examination of Selected Articles

As part of this study section, the EPPI guide was used to analyze the 75 customized e-learning research papers for a comprehensive evaluation, using two of its components: reporting and study quality. In addition to the double screening of each article, researchers were also required to make

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categorization decisions based on the fundamental questions of each study. In this way, this procedure can be seen as legitimate, consistent, and impartial, and it can be copied and increased in the future.

Research and development systematic reviews on personalized e-learning are intended to determine if there is evidence that personalized teaching and learning approaches emphasizing growth and evaluation can improve English reading understanding and attitudes toward this new model. The studies included in the review satisfied the following criteria: Their primary focus is on the effects of personalized e-learning approaches on design, understanding, attitudes, gender, and practices. These papers present evaluations of personalized e-learning materials published in English-language journals or presented at conferences between 1992 and 2021.

Additionally, 52 articles summarized the literature review for personalized e-learning (50) and reported the personalized e- learning design (52). Data extracts from those selected articles (Table 1) offer a complete assessment of the 25 studies (for alist of references, see Appendix). Results indicated that 25 papers were devoted to online e-learning design, one to comprehension, five to attitudes, and six to gender. Nine factors were deemed to be of very low relevance by prior researchers, while seven studies reported combining these three features. The gender issue arose in six studies. As a result, the following sections explore an overview of these papers and the evidence.

3. Findings

3.1 An Overview of Related Research

Four geographic areas supplied most of the research projects, and a large number of these were on a modest scale. Articles are arranged by the nation of origin, with four subgroups (the number in brackets refers to the number of articles): Europe (7), the United States (2), Australia (5), and Asia (1). Most of the research and development money went toward personalized e-learning, which is crucial to its development. A significant number of studies conducted on personalized e- learning involved small samples, with roughly 85 percent involving fewer than 200 participants. More considerable analysis of the data could not be performed due to the small sample size. Due to the lack of effect sizes in most studies, a meta-analysis could not be completed. The problem could result from limitations of the investigated e-learning systems, which cannot be used, controlled, and monitored simultaneously by several participants.

Most of the studies were completed at the university level and involved computer science, based on an evaluation of their education level and topic. Twenty studies involved undergraduate or postgraduate students as participants; undergraduate students and postgraduate students conducted nearly all the studies. Researchers discovered three examinations at the elementary school level (C.-M. Chen, 2008a); three at the high school level (Huang et al., 2016); and three for adults (Chen, 2009). A few were related to arithmetic at elementary schools (Chen, 2008; Chen, 2009; Wang, 2014), one for English at junior high (Huang et al., 2016), and one for teachers (Sergis & Sampson, 2015). (See Appendix A.)

These investigations were conducted using different methodologies. Nine studies used experimental designs, while twelve employed non-experimental designs. It was not explicitly stated in seven of the ten experimental research studies how many participants were in the experimental and control groups. Mixed techniques, two quantitative methods, and six qualitative methods were employed during data collection and analysis. No study covered the magnitude of the impact, nor did they explain how the study was ethically approved.

3.2 Design Evidence for Personalized E-learning Systems

Questionnaire items, open-ended questions, and interviews were used to collect data for the personalized e-learning design. Based on the reviews of twenty articles (Table 1) that discussed the creationr of personalized e-learning (e.g., format, content, quality, and manual guide), sense of reality, acceptance, usability, usefulness, and technical problems encountered, information was provided to support it. In terms of design, realism, acceptability, usability, and effectivenesscreation, the personalized e-learning system proved to have educational benefits. Participants struggled to complete tasks because personalized e-learning was a novel concept. Another access restriction was that assistance was challenging to provide. One study relied on a mobile phone, while the majority used PCs.

3.3 Attitude Evidence Using Personalized E-Learning Systems

Data on opinions were obtained primarily by questionnaires and open-ended questions. A review of ten papers shows that personalized e-learning systems are associated with attitudes towards learning (see Table 1). In several studies, descriptive statistics (e.g., mean, standard deviation, percentage) summarize findings from open-ended questions concerning attitude and narrative remarks (e.g., average, standard deviation, percent). The results of the subjects were not, however, thoroughly compared. The statistical hypothesis should be evaluated further through inferential statistical analyses.

3.4 Gender and Practice Evidence from Personalized E-Learning Systems

Gender and practices were seldom considered in research. In addition, only two studies (Wongwatkit et al., 2020) reported a statistically significant gender difference, and one study (Pardo et al., 2019) claimed that no statistical analysis could be conducted due to a lack of female participants. Seven research articles commented on students' practices in Table 1 (see below); this was another crucial feature that received little attention. Our research groups gathered e-learning practices from tasks/assignments, questionnaire items, and standardized test items.

3.5 Research Gaps and Prospective Research Directions

Using this two-step technique, the study found research gaps and integrated ideas from several research subjects, making the analysis more straightforward. In addition, this method decreased research bias (e.g., not having the results of study abstracts significantly influence the review procedure). Researchers can use this analysis style to summarize various assessment components in a review that involves a detailed or extensive examination of the methodology and results. It should prove helpful in finding conclusions, making recommendations, and presenting the findings. Accordingly, the aim of this study was to determine the significance and novelty of sophisticated processes for document analysis and systematic reviews.

A HistCite analysis provided insight into the links of referenced works in the historiography of customized learning and personalized e-learning research investigations. Additionally, the further analysis gave rise to identifying and removing certain studies that passed the automated screenings but did not meet the EPPI requirements. A closer look at the remaining studies revealed two results. Computer science and personalized mathematics e-learning are well established (in Table 1, most of this study aimed at the computer science and mathematics areas). Still, other regions should receive more attention, such as language. This technology has attracted attention in high school and primary school education (Wongwatkit et al., 2020; Wang, 2014b; Hariyanto et al., 2014). Additionally, while developing and evaluating personalized e-learning in education, pilot testing, ethical approval, informed consent, and gender considerations should be considered. In education, literature on individualized e-learning sheds light on the hype surrounding personalized learning. Many educational disciplines may also be affected by it.

Research on personalized learning, of which e-learning is a subset, will be expanded and applied to topics like language and K–12 education reforms in the future. To closely match contemporary education reforms and curricula and to maximize the essential features of personalized e-learning, further development of personalized e-learning at the K–12 school level will need to consider the underlying personalized learning concepts and practices, as well as cross-cutting principles (i.e., long-time observation, real-time interactivity, anytime and anywhere access, and engagement). The personalized education system can be used in conjunction with conventional e-learning approaches (for example, massive open online courses and mobile learning), both of which are important in remote education. As well as studying realistic personalized e-learning across different disciplines (e.g., language), future studies should focus on the development of realistic e-learning. As a result of this future orientation, this study will evaluate the efficacy of personalized recommendations based on the teaching of English e- reading to secondary students in Shenzhen, China.

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Appendix A: Reporting Details on Evaluation of the 23 Studies

Author(s)	Sample(n)	Participan ts	Discipline	Methods			Author(s)	Sample(n)
					Design	Attitude	Gender	Practice
(Yousuf & Conlan, 2018)	233	U		NE M	√	√		
(Juan Yanget al., 2014)	155	U/G	Computer Science	E	√			
(Wongwatkitet al., 2020)	115	H		E	√	√	√	√
(T.-H. Wang, 2014b)	107	P	Mathematics	E	√			√
(H.-C. Wang & Huang, 2013)	30	G	Bioinformatics	NE Quan	√	√		√
(Sergis & Sampson, 2016)		A			√			
(Santosoet al., 2021)	31	U	Computer Science	NE Quan	√	√		
(Pardoet al., 2017)	145	U	Engineering	NE	√			
(Pardo, Gasevic, et al., 2019)	290	U	Engineering	NE	√			
(Melia & Pahl, 2009)	139			E	√			
(Karagiannis & Satratzemi, 2018)					√	√		
(Hariyantoet al., 2020)	62	H	Computer Science	NE Qua		√		
(Firat & Bozkurt, 2020)	6507	A		NE Qua				
(Fellmanet al., 2020)	98	U	medical	NE Qua				√
(Elliset al., 2019)	335	U	Computer Science	NE Qua	√			√
(Dwivediet al., 2018)	200	U		E	√			√
(Drissi & Amirat, 2016)	60	U	chemistry	E Qua	√	√		
(Chen, 2008b)	220	P	Mathematics	E Qua	√	√		
(Capuanoet al., 2014)	24	U/G		E	√			
(Baranyi & Molontay, 2021)	20,000	U	Mathematics	NE	√			
(Thanyaphongphat & Panjaburee, 2019)	190	U		E	√	√		√
(Pardo, Jovanovic, et al., 2019)	120	U	Business	NE	√	√	√	
(Logueet al., 2019)		U	Mathematics	NE	√			
(Chenet al., 2005)				NE	√			

Notes. Sample: Participants: A=adults G=postgraduate, U=undergraduate, H=high school S=secondary, P=primary; Methods: E=experimental, NE=nonexperimental, M=mixed, Qua=qualitative, Quan=quantitative; Outcomes: D=design, U=understanding, A=attitude, G=gender, P=practices