Exploring the Potential of Deep Learning for Personalized Learning Environments

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Abstract

This study investigates the current potential for artificial intelligence (AI) to support personalized learning (PL). Personalized learning can provide a customized learning environment to support student learning processes based on individual needs, competencies, and interests. One way to conduct personalized learning is by using a recommender system that employs deep learning, an AI technique. To date, a limited number of researchers have discussed the application of deep learning methods to develop advanced recommenders in personalized learning environments. This study examines the literature that describes deep learning as a recommender system to support personalized learning environments. This initial phase of the project seeks to synthesize the issues and opportunities associated with personalized learning experiences and the potential of using deep learning to support the process. Because the topic intersects the education and information technology (IT) fields, we selected three databases for this literature review project: Scopus, ERIC, and Engineering Village. We used the phrase "deep learning recommender system for personalized learning environments" as our search string. We focused only on papers that experts had evaluated in the field to ensure accuracy. Therefore, terms such as "peer review," "literature review," and "systematic review" were added to the original search string. The initial search results included 409 documents. After applying inclusion/exclusion criteria, 20 papers emerged as the focus of this study. Thematic analysis was used to look for various themes to identify how deep learning methods are used in education and their potential to inform personalized learning environments. The analysis process utilized Mendeley and NVivo to quickly capture themes by focusing on six features to peruse within the articles. The features involved research questions, goals of studies, research methodology, research design, primary outcomes, and limitations. We then generated three themes from the six features in the analysis phase of the 20 papers. The first theme categorized the type of study into primary and secondary studies. These categories identify the types of studies that employed deep learning methods in the development of a recommender system and their integration with personalized learning. The second theme, recommender system (RS) techniques, highlighted the AI methodologies most frequently utilized in previous research. And the third theme was a list of e-learning platforms that applied RS for personalized learning. The main findings revealed that the deep learning method was effective in big data analysis due to its ability to forecast students' achievements, behaviors, and future paths. Therefore, we considered that deep learning could be widely applied as a technique to develop recommender systems to support personalized learning environments. Furthermore, because we found that only a few studies have investigated the implementation of this AI technology, researchers will have a great opportunity to explore deep learning to develop more innovative solutions in educational fields.

Keywords: Deep learning, Recommender systems, Personalized learning environments, Artificial intelligence.

1. Introduction

The presence of many computer applications in the Internet era has transformed the shape of global education. The term 'chalk and talk,' associated with the traditional teaching model, has progressively been supplemented by educational tools that helped teachers elevate student outcomes privately [1]. Moreover, since the booming of massive open online courses (MOOC) and the high use of smartphones, both students and educators can learn as much as they need about topics they are interested in using methods that align with their learning styles [2]. Both phenomena have led to the emergence of a new educational term called personalized learning.

Personalized learning (PL) is an environment that supports learners based on their needs and strengths. It gives learners full privileges in controlling their learning activities and deciding which actions they should take to achieve a particular level of knowledge that will enrich their learning experience [3], [4]. According to Childress and Benson [5], the best way to conduct personalized learning is by utilizing pedagogical and technological innovations. Their studies found that PL has the potency to prepare all students, especially those whose parents have low income in the US, to reach their passions and dreams for a better future career. Breazeal *et al.* [6] and Alliance for Excellent Education [7] also supported this finding. They reported that PL helped rural students in different countries surpass limitations in access to learning sources.

The Center for Curriculum Redesign [3] reported that the peak momentum of PL components is the emergence of artificial intelligence (AI) technologies. The increasing use of smartphones, big data, and machine learning has allowed personalization in every sector of human life, including education. Further, Rad *et al.* [8] reported the portion of AI in the education field would grow exponentially. It was due to its ability to serve personalized learning for each student and interpret complex emotions while studying different learning materials.

Up to now, AI has branched into different subfields, including deep learning (DL). It is a subsidiary of machine learning and has roots in AI [9]. DL learns directly from data around it, like babies learning from the world around them [2]. Zhang *et al.* [10] reported how DL had been applied in computer vision, speech recognition, and recommender systems. DL can effectively capture data sources and detect complex relationships within the data itself. Besides, according to Peters [11], DL can provide cognitive solutions that help teachers understand the learning paths of their students. However, DL's potential as an advanced recommender has not yet been widely applied to education, especially personalized learning. Therefore, this paper aims to serve as a basis for a more comprehensive work in answering the following research question (RQ): How does the literature describe deep learning as a recommender system to support personalized learning environments?

To communicate our work more effectively, we organize the remaining parts of this paper into the following sections: Section 2 highlights related studies on AI applications in the education sector, which revealed a scarcity of research on the application of deep learning (DL) in the context of the personalized learning environment. In section 3, we describe the procedures that we performed in the literature collection and analysis. We then present the findings of this study in section 4. In the subsequent section, we discuss major discoveries that emerged from each finding and its significance to our study. Then, we finally conclude this paper.

2. Related Work

Deep learning for personalized learning environments (PLE) has not been widely exploited, although three recent studies of AI utilization in education demonstrate its potential. Each proposed a framework to identify the major components involved in the learning system.

First, Lan [12] proposed a framework for machine learning algorithms with four basic components of a personalized learning system (PLS) that involved learning analytics, content analytics, grading and feedback, and scheduling. This research integrated learning resources for math composed of textbooks, lecture notes, and homework assignments as data input into a PLS. The results showed that the four algorithms enabled the PLS to produce analytics, feedback, and personalized recommendation. This study needs further research to investigate more theories, algorithms, and applications to understand students' responses and contents better.

Second, Rad *et al.* [8] revealed an "AI thinking framework" to discover advanced cognitive and adaptation in machine learning courses to enhance communication between students and educators. The method used in this work was computational thinking which comprised deep-wide learning and cognitive modules. The result of this study was a Cloud-eLab environment that has five capabilities to deal with 1) open-ended problems, 2) represent ideas in a meaningful computational way, 3) break down large problems, 4) evaluate strengths and weaknesses of problem representation, and 5) generate algorithmic solutions. Further work is needed for this study, including intelligently understanding and recognizing students' effort during the learning process and recommendations to solve the learning challenge.

Another study by Yousuf and Conlan [13] developed a visual narrative (VisEN) framework to facilitate PL in an adaptive online learning environment. This study used visualization within Educational Data Mining (EDM) domain that looks for patterns in sequences so that predictions can be made. The main finding of this study was a personalized explorable narrative that visualizes student engagement with course content. In addition to that, a narrative message was displayed to give a recommendation to students. The future work of this research will focus on human-computer interaction (HCI) to analyze the impact of VisEN on online learning.

These three studies indicated a need for more research focused on deep learning (DL) utilization in a personalized learning environment (PLE) context. Thus, more studies are worth exploring on using deep learning—as a branch of AI—to recommend learning content in PLE.

3. Methods

This study identifies the current state-of-the-art methods for using AI learning environments. As the goal of the work is to inform a larger development project to design PLEs with recommender systems, we used the systematized review method. Grant and Booth [14] defined that systematized literature reviews (SLR) try to incorporate one or more aspects of the systematic review method without claiming that the final product is a systematic review. This type of literature study usually serves as the foundation for a more comprehensive work such as a dissertation or an independent, grant-supported research initiative. Procedures taken in conducting the systematized review for this study started with establishing search procedures to obtain prospective papers, followed by defining a series of restrictions to evaluate the most relevant literature to include in this study and extracting the literature for data analysis.

Search Procedure

The first thing to execute was the criteria established for gathering data. Since the data are in the form of papers, we set up a search query based on our research question. Hence, the key search string was "deep learning recommender system for personalized learning environment." To gain more specific data, we limited the type of papers to peer-reviewed articles. Consequently, the search string was modified by adding peer review, literature review, and systematic review terms.

The query string was then executed to perform the search procedure using scientific databases, including Scopus, ERIC, and Engineering Village. The motive for using such databases was because the topic of this study had an intersection between the education and computer engineering areas. According to Zakharov [15], Scopus offers peer-reviewed research literature that supports research needs in various disciplines. ERIC indexes articles in the education area. In addition, Engineering Village provides access to COMPENDEX and INSPEC, which offer a considerable amount of literature in engineering and information technology (IT) fields.

TABLE I SEARCH STRINGS AND INITIAL RESULTS OF THE DATABASE QUERY

Search String	**Databases**	**Initial Results**
TITLE-ABS-KEY (Deep learning OR algorithm OR artificial intelligence OR technology) AND (recommend* AND system) AND (personal* OR individual* OR flexi* OR (student centeredness)) AND (learning environment OR (online learning) OR (enhanced-learning) OR MOOC) AND (literature OR peer OR systematic AND (review))	Scopus	15
(Deep learning OR algorithm OR artificial intelligence OR technology) AND (recommend* AND system) AND (personal* OR individual* OR flexi* OR (student centeredness)) AND (learning environment OR (online learning) OR (enhanced-learning) OR MOOC) AND (literature OR peer OR systematic AND (review))	ERIC	54
(((Deep learning OR algorithm OR artificial intelligence OR technology) AND (recommend* AND system) AND (personal* OR individual* OR flexi* OR (student centeredness)) AND (learning environment OR (online learning) OR (enhanced-learning) OR MOOC) AND (literature OR peer OR systematic AND (review))) WN ALL)	Engineering Village	340
Total		409

Table I shows the comparison of search queries and the initial results from the three selected databases. There were 15 documents in Scopus, 54 results from ERIC, and 340 records found in Engineering Village for the initial total number of 409 research papers. We grouped each keyword in the search string column by putting the Boolean operator "OR" between each synonym to obtain these initial results. For instance, we chose the keywords algorithm, artificial intelligence, and technology to specify the term deep learning related to the informatics field. Thus, we set "Deep learning OR algorithm OR artificial intelligence OR technology" in the search box. Also, we used the wildcard operator (*) to retrieve articles containing any possible suffix indicated in the prefix words. Therefore, we applied "Recommend*" to point to different words such as recommender, recommendation, or recommended. A similar approach was applied to "personal*" and its synonyms. This wildcard indicated any possible ending forms of the word "personal," such as personalized, personalization, or personality. So did "individual*" and "flexi*" to represent individuals, individualized, individuality, flexible, and flexibility. Further, we used another Boolean operator, "AND," to join each group of words. This operator also informs the databases that the papers must contain a combination of the given strings.

Furthermore, to locate a specific section in the papers, we used "TITLE-ABS-KEYWORD" to notify the Scopus database to look for the given strings in the title, abstract, and keywords. While in ERIC, we did not select any fields to indicate special sections as we applied in Scopus because ERIC automatically searches for the strings in the whole paper section. As for Engineering Village, "WN ALL" was generated automatically at the end of the search strings to inform the database to search within all fields.

Inclusion and Exclusion Criteria

Based on the initial results above, we investigated which papers would be relevant to answer the given research question by applying a series of restrictions, as shown in Table II, consisting of primary criteria to keep and eliminate the retrieved articles. The first criterion of eligibility was the papers must be peer-reviewed type. Although the initial search strings included the terms literature, peer, and systematic review, the results contained documents in the form of books, theses, dissertations, and lecture notes. For this reason, we did a further inspection by reading and evaluating the title, abstract, and content of the finding documents.

TABLE II INCLUSION AND EXCLUSION CRITERIA

Inclusion Criteria	**Exclusion Criteria**
▪ Review paper type ▪ Must be written in English ▪ Explore recommender systems used in the education field ▪ Contained deep learning in computational meaning	▪ Book ▪ Thesis or Dissertation ▪ Lecture notes ▪ Not discuss algorithms

The next inclusion requirement was that any records unwritten in English must be removed from the list. This was because English is widely used in scholarly articles, and many reputable academic publishers and scientific databases required this language to access publications globally. Nevertheless, some articles indexed by the scientific databases were written in other languages. For example, the title and abstract were written in English, but the rest of the sections were in Chinese. Therefore, we need to scrutinize the content of the articles to ensure the language used.

Further crucial criteria were that the retrieved documents must discuss the recommender system application for educational purposes and encompass deep learning in the computational term. Both criteria were used to eliminate articles that explained the utilization of deep learning methods as recommender systems in e-commerce, rating prediction, news recommendations, personalized preferences, web service recommendation, cloud computing, and image processing. Besides, any documents containing deep learning algorithms must be excluded from this study.

Using the criteria above, we screened 409 papers to gain the most relevant documents that would be included for further analysis. Fig. 1 illustrates the procedures taken during the process by adopting the PRISMA flowchart [16]. The selection of the most appropriate literature comprised three main stages. First, we identified potential articles through three selected databases. At this step, we found 409 documents after performing the search query and removed 44 duplicate articles within ERIC and Engineering Village. Second, we screened the title and abstract of 365 remaining documents and discovered 325 papers did not pass the inclusion criteria as listed in Table II. Then in the third stage, we evaluated the whole sections of 40 documents left and eliminated 20 less relevant articles. After reading the full text, we found those 20 articles were unreliable in answering our research question. Thus, 20 articles were yielded, two of which were from Scopus, six obtained from ERIC, and 12 documents retrieved from Engineering Village.

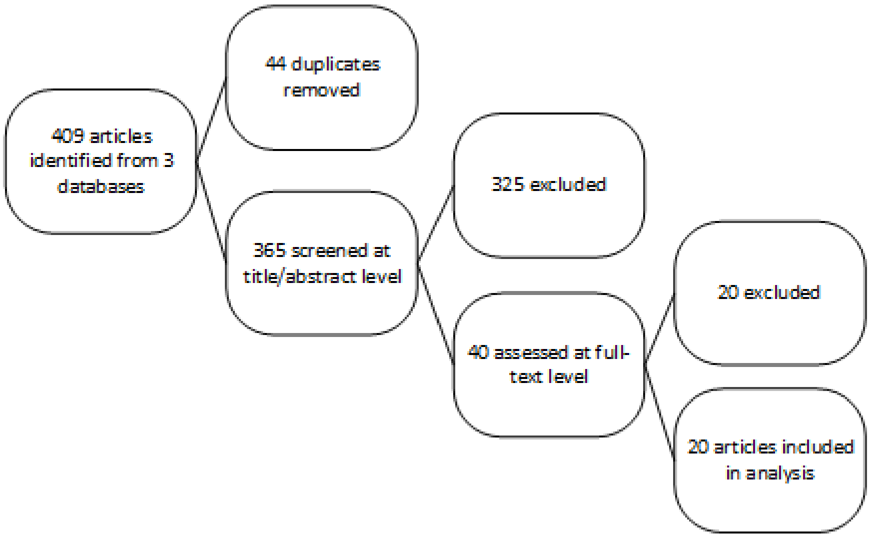

Fig. 1. Adaptation of the PRISMA flowchart for describing the search process [16]

Analysis

An analysis was carried out utilizing the themes across articles by exploring similarities and differences between studies. We conducted the analysis process using the data extraction form elaborated by Petticrew and Roberts [17]. This form listed various characteristics, which should be annotated in the literature analysis, including (1) focus of research questions (RQ) aims to decide whether the selected study has what it takes to answer the RQ; (2) goals of studies used to seek how well the study was carried out; (3) methodology of research is done to see the most frequently used methods; (4) study design is required to examine the effectiveness of interventions; (5) primary outcomes are meant to highlight the most crucial finding among many findings found in the study; and (6) limitations used to list the gap of existing studies to give a hint for the direction of future research. We perused 20 articles to highlight these six features to find themes of this systematized literature review.

We used Mendeley and NVivo to analyze 13 journal articles and 11 papers on conference proceedings. Mendeley was used to export 20 bibliographic data into the "RIS"—abbreviation of Research Information System—file format. NVivo then imported this file to help the coding process to find patterns, themes, theories, and relationships within the articles [18], [19].

In Mendeley, we classified all sources based on the databases. Since we used three scientific databases, thus, we labelled the classification as SCOPUS, ERIC, and EV. Then we selected all articles in each label and exported them to the RIS file. We named each file similar to the label we defined in Mendeley to make it easy to associate with each database source. Following this step, we opened NVivo and created a project name. In the first step of the analysis, we imported the three RIS files created in Mendeley and set the imported files to be sorted by the author and year. In the second step, we ran the Word Frequency Query to gain 100 top words contained in the 20 papers, and we set the minimum length of five characters to be counted as a word. This setting informed NVivo to omit certain words such as "and," "but," and year name. Then, we analyzed these 100 words and removed some irrelevant words that did not correlate to the research question. For example, after reading its context in the referred articles, we removed the "evaluate" word. These frequent words helped us identify potential codes and group them to one of the six characteristics outlined by Petticrew and Roberts [17] above.

Further, we also analyzed word string by modifying the search string that we applied in the searching procedure. We used the Text Search feature in NVivo and put the modified search string as follows: "(Deep learning OR algorithm OR artificial intelligence OR technology) AND (recommend* AND system) AND (personal* OR individual* OR flexi* OR (student centeredness)) AND (learning environment OR (online learning) OR (enhanced-learning) OR MOOC)." This analysis step assisted us in pointing out the relevancy of 20 articles to the research question quickly.

4. Results

The findings presented below show the analysis results of 20 articles found through the systematized search that was conducted at the end of the year 2021. Appendix A delineates a brief description of the papers. Three prominent themes were identified from the analysis that represented the most appropriate answer to the research question. First, there were an equal number of empirical studies and literature reviews. This can reveal a broader insight into the recommender system (RS) application to the personalized learning environment (PLE). Particularly, it can reveal how many studies involved Deep Learning (DL) methods for RS in the PL. Second, the widely applied techniques of RS were used in PLE. This theme will inform what kind of AI approaches were mostly used in the previous studies. Ultimately, a list of learning platforms that applied RS for PLE will show which existing platforms were used by most researchers.

Theme 1: Type of Study

A similar percentage of the 20 papers involved both primary and secondary research. The primary studies described the empirical investigation of what researchers have done in real conditions. In comparison, the secondary studies summarized all kinds of previously conducted research in the field that provided a shortcut to access a broader collection of primary reports.

Ten articles came from the empirical research that was conducted from 2007 until 2020 [20]–[29]. Seven of these ten papers revealed the creation of RS and its integration to PLE [20], [21], [25]–[29], and six of these seven articles employed artificial intelligence (AI) methods that were applied in the development of RS [20], [25]–[29]. There were also two researchers who reported the utilization of AI methods in their investigated learning platform [22], [23], and lastly, three other groups of researchers evaluated the current personalized recommender system [24]–[26].

The remaining ten of 20 papers were in the form of a systematic literature review (SLR). Most of the SLR documents were reported between 2013 and 2021 [30]–[39]. Seven articles summarized various learning platforms that involved AI methods [30], [31], [34], [36]–[39]. Besides, three articles discussed personalized learning technology [32], [33], [36], and another one developed a framework for RS in PLE [35].

Theme 2: AI Techniques for Recommender Systems

The second theme emerged in 15 papers, eight from the empirical study [20], [22], [23], [25]–[29], and seven in the literature review [30], [31], [34], [36]–[39]. Table III classifies AI techniques used by RS that were employed and discussed in the analyzed papers. It is clearly seen that Collaborative Filtering (CF) and Content-based Filtering (CBF) were the most frequently used technique. CF was found in seven articles (i.e., three from empirical studies and four from literature review), while CBF emerged in six papers that come in similar numbers in both types of study. In contrast, the Deep Learning RS method for PLE, which was stated in the research question, appeared only in three papers from the secondary study type [30], [31], [37]. For this type of study, the techniques classified in Table III were based on their application to build RS for PLE.

TABLE III LIST OF AI TECHNIQUES USED IN RECOMMENDER SYSTEMS

Authors, Year	**Type of Study** **ES: Empirical Study** **LR: Literature Review**	**Techniques**
Aslam *et al.*, 2021 [30] Mousavinasab *et al.*, 2021 [37]	LR	Artificial neural network (ANN)
Segal *et al.*, 2014 [28] Aslam *et al.*, 2021 [30] Mousavinasab *et al.*, 2021 [37]	ES LR LR	Bayesian Knowledge Tracing
Uddin *et al.*, 2021 [38]	LR	Bipartite graph processing and context information

TABLE III LIST OF AI TECHNIQUES USED IN RECOMMENDER SYSTEMS, Continued

Authors, Year	**Type of Study** **ES: Empirical Study** **LR: Literature Review**	**Techniques**
Masters *et al.*, 2008 [25] Modritscher *et al.*, 2011 [26] Segal *et al.*, 2014 [28] Khanal *et al.*, 2020 [31] Lu *et al.*, 2015 [34] Wu & Chen, 2013 [39] Uddin *et al.*, 2021 [38]	ES ES ES LR LR LR LR	Collaborative Filtering
Lu *et al.*, 2015 [34]	LR	Computational intelligence-based
Masters *et al.*, 2008 [25] Modritscher *et al.*, 2011 [26] Xie *et al.*, 2019 [29] Khanal *et al.*, 2020 [31] Lu *et al.*, 2015 [34] Wu & Chen, 2013 [39]	ES ES ES LR LR LR	Content-based Filtering
Lu *et al.*, 2015 [34]	LR	Context awareness-based
Aslam *et al.*, 2021 [30]	LR	Decision Tree
Aslam et al., 2021 [30] Khanal et al., 2020 [31] Mousavinasab et al., 2021 [37]	LR LR LR	Deep learning
Falakmasir & Habibi, 2010 [22]	ES	Feature Selection/Attribute Evaluation
Mousavinasab et al., 2021 [37]	LR	Fuzzy based
Lu et al., 2015 [34]	LR	Group recommender systems (GRS)
Masters et al., 2008 [25] Khanal et al., 2020 [31] Lu et al., 2015 [34] Wu & Chen, 2013 [39]	ES LR LR LR	Hybrid filtering
Modritscher et al., 2011 [26] Aslam et al., 2021 [30] Mousavinasab et al., 2021 [37]	ES LR LR	Information retrieval/clustering
Baseera & Srinath, 2014 [20] García & Secades, 2013 [23]	ES ES	Knowledge Discovery from Data (KDD)
Khanal et al., 2020 [31] Lu et al., 2015 [34]	LR LR	Knowledge-Based
García & Secades, 2013 [23] Karaoglan Yilmaz & Yilmaz, 2020 [24] Melesko & Kurilovas, 2016 [36]	ES ES LR	Learning Analytics
Nganji & Brayshaw, 2017 [27]	ES	Logic-based rule induction
Mousavinasab et al., 2021 [37]	LR	Natural language processing

TABLE III LIST OF AI TECHNIQUES USED IN RECOMMENDER SYSTEMS, Continued

Authors, Year	**Type of Study** **ES: Empirical Study** **LR: Literature Review**	**Techniques**
Modritscher et al., 2011 [26]	ES	PageRank-like
Modritscher et al., 2011 [26]	ES	Rule and profile-based
Uddin et al., 2021 [38]	LR	Semantic filtering
Melesko & Kurilovas, 2016 [36] Uddin et al., 2021 [38]	LR LR	Semantic/Ontologies-based
Lu et al., 2015 [34]	LR	Social network-based

Theme 3: Learning Platform

The third theme—learning platform—appeared in nine reports divided into both types of studies. Table IV depicts eight platforms that were used as a means to apply RS for PLE. Moodle is the most used learning technology, which was found in four articles. Following by MOOC in the second place that was discussed in three papers. On the contrary, other platforms, including AHA!, Binocs, CourseAge, Explanet, PLEShare, and Psycho-pedagogical Recommender, each of them was reported in a single study. Table IV also shows that more platforms were employed in the empirical research than in the literature study.

TABLE IV PERSONALIZED LEARNING PLATFORMS

Authors, Year	**Type of Study** **ES: Empirical Study** **LR: Literature Review**	**Platform**
Lu *et al.*, 2015 [34]	LR	AHA!
Modritscher *et al.*, 2011 [26]	ES	Binocs
Lu *et al.*, 2015 [34]	LR	CourseAge
Masters *et al.*, 2008 [25]	ES	ExplaNet
Karaoglan Yilmaz & Yilmaz, 2020 [24] Li & Wong, 2019 [33] Uddin *et al.*, 2021 [38]	ES LR LR	MOOC
Falakmasir & Habibi, 2010 [22] García & Secades, 2013 [23] Karaoglan Yilmaz & Yilmaz, 2020 [24] Melesko & Kurilovas, 2016 [36]	ES ES ES LR	Moodle
Modritscher *et al.*, 2011 [26]	ES	PLEShare
Modritscher *et al.*, 2011 [26]	ES	Psycho-pedagogical Recommender

5. Discussion

Three emergent themes emerged from a systematized review of 20 peer-reviewed academic papers. The findings of this study provided a prospective answer to the given research question on how the literature described deep learning as a recommender system to support personalized learning environments. We elaborated on the significant findings from each theme that led to the most related answer for the research question.

The most exciting finding from the first theme was an equal portion of the articles from the empirical research and the literature studies. The former type of studies revealed that the most eminent research worked on the creation of a recommender system (RS) and its integration into personalized learning environments (PLE). The first research on building RS for PLE was conducted by El-Bishouty *et al.* [21]. They developed an application known as PERKAM, which is an abbreviated word for personalized knowledge awareness map for computer-supported ubiquitous learning. This software was supposed to allow learners to share knowledge, interact, collaborate, and exchange their individual experiences. It uses Radio Frequency Identification (RFID) ubiquities technology to detect the learner's environmental objects and location, and then it suggests the most appropriate learning materials and peer assistants based on the identified objects and current location. PERKAM's RS did not involve the artificial intelligence (AI) approach because it employed RFID.

The first RS application for PLE that implemented AI methods was ExplaNet [25]. It had a similar motivation to PERKAM, which is to exchange educational resources between students. This web-based platform utilized three AI approaches for creating answers and reviewing peer-submitted answers. The three approaches employed in this study were Collaborative Filtering (CF), Content-based Filtering (CBF), and Hybrid Filtering (HF). CF makes suggestions based on the preferences and opinions of a large group of people. CBF generates recommendations by matching object properties to individual preference profiles. And HF combines both CF and CBF by accessing individual preferences as well as group opinions.

The latest RS application in personalized education was developed by Xie *et al.* [29], who integrated the RS into the computer science field to learn English. This PLE involved the content-based (CB) technique, which aimed to identify the most similar items based on the learner's personalized model.

As for the secondary study type, the first investigation on personalized recommendation and e-learning was reported by Wu and Chen [39]. They discovered three frequently used AI approaches in developing RS for education comprised Collaborative Filtering (CF), Content-based Filtering (CB), and Hybrid Filtering (HF). These approaches were similar to the work of Masters *et al.* [25], who created the ExplaNet. Interestingly, the most recent RS application developed by Xie *et al.* [29] was also still using CB, which is one of those three methods. If we compare at a glance, it seems there was a slow progression in applying AI methods for developing RS for learning environments. This statement is supported by Khanal *et al.* [31], who pointed out that CF is still gaining popularity as a recommender system technique used in E-learning personalization. Further, a literature study by Aslam *et al.* [30] demonstrated that the Bayesian approach had been received as the best forecast strategy for e-learning framework boundaries from mid-2000 to now. Although they did not reveal any of the CF, CB, or HF, their finding strongly indicated a slow progression of applying novel AI techniques to create RS in PLE.

This slow progression can also be related to the research question on utilizing deep learning RS in PLE. Based on various techniques listed in Table III, only three articles reviewed the deep learning approach for learning environments. The first literature study by Khanal *et al.* [31] merely explained the potential approaches for e-learning systems and deep learning architectures that researchers suggested. This study did not exemplify previous empirical research that applied deep learning RS in any learning platform. Nevertheless, two latest studies by Aslam *et al.* [30] and Mousavinasab *et al.* [37] disclosed the real application of deep learning in education.

Aslam *et al.* [30] reviewed a series of research from 2009 until 2019, which modeled and implemented deep learning to predict student achievement. The research revealed that deep learning network models are effective in big data analysis, such as the processing of 530 college students' datasets which involved not only traditional academic achievement but also services, behavior, sports, and art. Additionally, this study demonstrated a deep learning model called the Tensor Flow engine that successfully forecasted 2000 students' future pathways with accuracy rates of up to 91%. Another review by Mousavinasab *et al.* [37] showed an example of deep learning utilization in a study that was conducted in 2015. A learning platform, LEONARDO, applied machine learning based on the deep artificial neural network. It was tested by a group of school students in Physic science. The platform predicted student performance, grouped learners based on answers, evaluated learners drawing actions, and inferred learners' conceptual understanding. However, this study was unable to demonstrate further information on the accuracy level.

Another finding of our study also discovered the two most prominent learning platforms researchers used for applying RS techniques. Falakmasir and Habibi [22] applied one of the data mining methods—feature selection—to rank students' activities in Moodle based on their impact on final exam performance. A further study by García and Secades [23] applied a statistical model to examine Moodle in recommending interaction during the teaching/learning process. Another empirical study on learning analytics was also investigated on Moodle to capture personalized recommendations based on log data [24]. Learning analytics and deep learning approach were also implemented in MOOC platforms to increase students' engagement and provide a flexible curriculum, as well as an instructional design [33], [38].

6. Conclusions

This systematized literature review conducted an investigation into the utilization of deep learning recommender systems to support personalized learning environments that were presented in previous research. A search of three databases yielded 409 articles, which were whittled down to 20 articles that were read and annotated to generate significant themes. These themes were related to the type of study used by the papers, recommender system techniques, and the personalized learning platform to answer the given research question. The findings revealed that the recommender system in the personalized education field was first created in 2007 by employing Radio Frequency Identification (RFID) instead of AI technology. A year later, a recommender system software for personalized learning environments that incorporated three artificial intelligence approaches—Collaborative Filtering (CF), Content-based Filtering (CBF), and Hybrid Filtering (HF)—was built. Since then, the recommender system has been developed based on these three techniques. Even though this work did not find any empirical research that reported the application of deep learning recommender systems for learning personalization, three literature studies recently discovered the capability of deep learning methods to generate an accurate prediction. Two attempts made between 2009 and 2019 indicated that the deep learning method was effective in big data analysis due to its ability to forecast students' achievement, behavior, and future pathways. Therefore, deep learning was potentially considered to be widely applied as a recommender system technique in personalized learning environments. However, because this work is a systematized literature review rather than a real systematic review and that involved three scientific databases only, we cannot claim the same level of accuracy in drawing our conclusion. Nevertheless, this work has an added value as a basis for us to conduct more extensive research in the future. Additionally, academics will have a wider opportunity to explore deep learning to produce more novel educational solutions since our study discovered that only a small number of studies had investigated the application of this AI technology.

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Appendix A. Description and Summary of Reviewed Articles

Ref.	Title	Authors (Year)	Brief Overview
[30]	Feature evaluation of emerging e-learning systems using machine learning: An extensive survey	Aslam, S. M., Jilani, A. K., Sultana, J., & Almutairi, L. (2021)	The evaluation of e-learning models using AI methods shows that the Bayesian has been regarded as the best forecast strategy for e-learning from the mid-2000 until the present. The paper also reveals that the emergence of Deep Learning, as an advancement of Machine Learning, has been a prominent research interest in the personalization of e-learning since 2016.
[20]	Design and development of a recommender system for e-learning modules	Baseera, & Srinath. (2014)	An attempt was made to build and develop a recommender system (RS). The result shows that web mining techniques were the most appropriate approach in creating online learning activities and improving course materials' navigation.
[21]	PERKAM: Personalized knowledge awareness map for computer supported ubiquitous learning	El-Bishouty, M. M., Ogata, H., & Yano, Y. (2007)	A knowledge awareness map was tailored to help a student identifies the nearby learning sources. The result of the software prototype implementation shows that the system was able to select the best resources and peers to help students' personal learning interests.
[22]	Using educational data mining methods to study the impact of virtual classroom in e-learning	Falakmasir, M. H., & Habibi, J. (2010)	Data mining methods were used in a web-based virtual learning environment to record students' activities. The results reveal that students obtained a higher final grade because they engaged in the virtual classroom.
[23]	Big data and learning analytics: A potential way to optimize elearning technological tools	García, O. A., & Secades, V. A. (2013)	The combination of data-processing and analytical learning was applied to record the frequently used features in the e-learning system. This analytical practice reveals that students and teachers often use three tools. They used Forum to learn collaboratively, Resource tool to access the learning content storage, and Assignment tool to measure lesson tasks.

[24]	Student opinions about personalized recommendation and feedback based on learning analytics	Karaoglan Yilmaz, F. G., & Yilmaz, R. (2020)	A group of pre-service teachers was interviewed on personalized learning analytics-based recommendations and guidance that was given by students. The primary finding of this interview shows that learning analytics had positive impacts on improving academic performance and developing a positive attitude towards the course. Most teachers opined that learning analytics-based recommender improved students' behavior, such as a sense of responsibility and self-directed regular learning. In contrast, a small number of teachers contended that learning analytics could cause stress, create a feeling of being monitored constantly, and the results may not reflect accurate information.
[31]	A systematic review: machine learning based recommendation systems for e-learning	Khanal, S. S., Prasad, P. W. C., Alsadoon, A., & Maag, A. (2020)	This paper reviews current e-learning recommendation approaches and machine learning algorithms used in recommender systems (RS). This article also explained the emergence of Deep Learning as an advancement of Machine Learning. It was found that clustering was a popular machine learning technique, and content filtering was a popular RS method used in e-learning. It also recommended a future research point to SVN and neural networks to enhance the results of RS.
[33]	How learning has been personalised: A review of literature from 2009 to 2018	Li, K. C., & Wong, B. T. M. (2019)	This article reviews a complete evaluation and description of studies relevant to characteristics and methods of personalized learning (PL). The results show that, from 2009-2013, a few research involved the development of intelligent learning systems (ILS) for experimenting with new technologies (e.g., semantic web) and coping with learners' individual characteristics (e.g., cognitive abilities). However, the research in ILS and PL started its popularity in 2014 until 2018. It was because of the emergence of learning analytics, MOOC, a flexible curriculum and instructional design, individual education plans, flipped classrooms, and augmented/virtual reality.

[32]	Personalised learning in STE(A)M education: A literature review	Li, K. C., & Wong, B. T. M. (2021)	This study gives an overview of personalized learning (PL) characteristics and patterns in Science, Technology, Engineering, Mathematics, and the Arts. The findings demonstrate that PL is widely used in secondary education in the United States. It also shows that PL is mainly applied in learning Mathematics using the blended learning environment.
[34]	Recommender system application developments: a survey	Lu, J., Wu, D., Mao, M., Wang, W., & Zhang, G. (2015)	Recommender system (RS) techniques applied in eight domains—e-government, e-business, e-commerce/e-shopping, e-library, e-learning, e-tourism, e-resource services, and e-group activities—were reviewed. The result reveals that the Knowledge-Based method was the most frequent technique used for developing RS in the e-learning domain.
[35]	An adaptive recommender-system based framework for personalised teaching and learning on e-learning platforms	Maravanyika, M., Dlodlo, N., & Jere, N. (2017)	A framework for recommender system-based adaptive e-learning for personalized teaching was presented. The framework consists of five primary components: (1) Real-time Recommendation System, (2) Context Model, (3) Learner model, (4) Domain/Content Model, and (5) Pedagogical Strategy. This framework helps designers, teachers, and students to identify solutions for poor engagement in e-learning platforms by recognizing the role of individual differences in teaching and learning.
[25]	ExplaNet: A Collaborative Learning Tool and Hybrid Recommender System for Student-Authored Explanations	Masters, J., Madhyastha, T., & Shakouri, A. (2008)	This study evaluated the effectiveness of ExplaNet. It is a virtual learning tool where students can provide educational resources for other students. The result shows that students who looked over recommendations of the peer-authored solutions had a better score. This indicated that ExplaNet correctly predicted which responses students would prefer in a large class, as well as polarizing viewpoints in both large and small courses. The author also claimed that this was the first system to promote student-authored materials based on student characteristics to other students.

[36]	Personalised intelligent multi-agent learning system for engineering courses	Melesko, J., & Kurilovas, E. (2016)	This work proposed a technology for a personalized learning system based on students' learning styles as well as other personal features and demands. By reviewing previously conducted research, the author concluded that the use of intelligent software agents and multi-agent systems in education had an effective means of personalized learning.
[26]	May I suggest? Comparing three PLE recommender strategies	Modritscher, F., Krumay, B., El Helou, S., Gillet, D., Nussbaumer, A., Albert, D., Dahn, I., & Ullrich, C. (2011)	Three recommender tools for a personalized learning environment (PLE) were compared. Binocs widget involved three recommender techniques: Collaborative Filtering (CF), PageRank-like, and Content-Based (CB). PLEShare used CF and clustering methods. Whereas, Psycho-pedagogical recommender employed a Rule and profile-based approach. The comparison revealed that Binocs was being used by end-users, the pattern repository approach relies on integration with current PLE systems to provide suggestions to end users, and the psycho-pedagogical recommender does not yet have all of its functions fully implemented.
[37]	Intelligent tutoring systems: A systematic review of characteristics, applications, and evaluation methods	Mousavinasab, E., Zarifsanaiey, N., Niakan Kalhori, S. R., Rakhshan, M., Keikha, L., & Ghazi Saeedi, M. (2021)	This paper reviewed various intelligent tutoring systems (ITS) across all educational fields to provide detailed information on their characteristics, applications, and evaluation methods. The outcome of this study demonstrated that ITS was mostly used in the computer programming field. The result also shows that the most common AI methods used in ITS were fuzzy-based techniques and condition-action rule-based reasoning. Besides, this study also mentioned deep learning, although it was not as popular as the main findings here.
[27]	Disability-aware adaptive and personalised learning for students with multiple disabilities	Nganji, J. T., & Brayshaw, M. (2017)	The goal of this study is to look at how virtual learning environments (VLEs) can be created to accommodate learners with multiple disabilities. This attempt reveals that employing AI approaches such as the semantic web and basic Machine Learning (ML) could be collaboratively designed to deliver to the learner's real needs.

[28]	EduRank: A collaborative filtering approach to personalization in e-learning	Segal, A., Katzir, Z., Gal, A., Shani, G., & Shapira, B. (2014)	A new algorithm – EduRank - for personalization in e-learning was tested on two enormous real-world data sets with tens of thousands of students and a million records. It was tested against a range of personalization strategies as well as a non-personalized solution that relied on a domain expert. The result indicated that e-learning personalization could be created by involving Collaborative Filtering (CF) method in EduRank. It worked by automatically adapting problem sets or exams to the ability of individual students in the classroom or advising students about issues they need to improve. It could also be used to supplement existing ITS systems by incorporating a customizable order of questions into the student interaction process.
[38]	A systematic mapping review on MOOC recommender systems	Uddin, I., Imran, A. S., Muhammad, K., Fayyaz, N., & Sajjad, M. (2021)	This research aimed to identify possible research routes in the domain in terms of massive open online courses recommender system (MOOCRS) technologies, techniques, and datasets. The review results show that very few studies focused on recommendations for MOOC developers/teachers. Therefore, future researchers have many opportunities in learning paths, learning objectives, prerequisites, content recommendations, and adaptive learning, use of learners' bio-informatic data for recommendations, sub-topic level micro recommendations, cross-platform recommendations of resources between different MOOC platforms.
[39]	Personalized recommendation research in e-learning systems	Wu, B., & Chen, P. P. (2013)	This paper reviewed previously conducted research that explicitly studied AI techniques for personalized recommendation in E-Learning systems. The review indicated that most researchers used three techniques, including Collaborative Filtering, Content Filtering, and the composition of both Hybrid Filtering.

[29]	A personalized task recommendation system for vocabulary learning based on readability and diversity	Xie, H., Wang, M., Zou, D., & Wang, F. L. (2019)	An attempt was made to integrate a recommendation system (RS) in the computer science field into a set of developed learning tasks in the field of vocabulary learning. This attempt employed the content-based method as the most common approach in creating the RS. This study involved ten Chinese learners of English to utilize the integrated RS. The results show that most learners had a very positive attitude regarding this word-learning technique, and they thought it was motivational and effective because the RS provided recommendations based on their previous learning experiences and personal preferences.