International Review of Research in Open and Distributed Learning

The Use of Deep Learning in Open Learning: A Systematic Review (2019 to 2023)

Odiel Estrada-Molina, Juanjo Mena and Alexander López-Padrón

Volume 25, Number 3, August 2024

Special Issue: Artificial Intelligence in Open and Distributed Learning: Does It Facilitate or Hinder Teaching and Learning?

URI: https://id.erudit.org/iderudit/1113505ar
DOI: https://doi.org/10.19173/irrodl.v25i3.7756

See table of contents

Publisher(s)

Athabasca University Press (AU Press)

ISSN

1492-3831 (digital)

Explore this journal

Cite this article

Estrada-Molina, O., Mena, J. & López-Padrón, A. (2024). The Use of Deep Learning in Open Learning: A Systematic Review (2019 to 2023). *International Review of Research in Open and Distributed Learning*, *25*(3), 370–393. https://doi.org/10.19173/irrodl.v25i3.7756

Article abstract

No records of systematic reviews focused on deep learning in open learning have been found, although there has been some focus on other areas of machine learning. Through a systematic review, this study aimed to determine the trends, applied computational techniques, and areas of educational use of deep learning in open learning. The PRISMA protocol was used, and the Web of Science Core Collection (2019–2023) was searched. VOSviewer was used for networking and clustering, and in-depth analysis was employed to answer the research questions. Among the main results, it is worth noting that the scientific literature has focused on the following areas: (a) predicting student dropout, (b) automatic grading of short answers, and (c) recommending MOOC courses. It was concluded that pedagogical challenges have included the effective personalization of content for different learning styles and the need to address possible inherent biases in the datasets (e.g., socio-demographics, traces, competencies, learning objectives) used for training. Regarding deep learning, we observed an increase in the use of pre-trained models, the development of more efficient architectures, and the growing use of interpretability techniques. Technological challenges related to the use of large datasets, intensive computation, interpretability, knowledge transfer, ethics and bias, security, and cost of implementation were also evident.

International **R**eview of **R**esearch in **O**pen and **D**istributed **L**earning
Volume 25, Number 3

August – 2024

The Use of Deep Learning in Open Learning: A Systematic Review (2019 to 2023)

Odiel Estrada-Molina[1], Juanjo Mena[2], and Alexander López-Padrón[3]
[1]University of Valladolid, [2]University of Salamanca, [3]Technical University of Manabí

Abstract

No records of systematic reviews focused on deep learning in open learning have been found, although there has been some focus on other areas of machine learning. Through a systematic review, this study aimed to determine the trends, applied computational techniques, and areas of educational use of deep learning in open learning. The PRISMA protocol was used, and the Web of Science Core Collection (2019–2023) was searched. VOSviewer was used for networking and clustering, and in-depth analysis was employed to answer the research questions. Among the main results, it is worth noting that the scientific literature has focused on the following areas: (a) predicting student dropout, (b) automatic grading of short answers, and (c) recommending MOOC courses. It was concluded that pedagogical challenges have included the effective personalization of content for different learning styles and the need to address possible inherent biases in the datasets (e.g., socio-demographics, traces, competencies, learning objectives) used for training. Regarding deep learning, we observed an increase in the use of pre-trained models, the development of more efficient architectures, and the growing use of interpretability techniques. Technological challenges related to the use of large datasets, intensive computation, interpretability, knowledge transfer, ethics and bias, security, and cost of implementation were also evident.

Keywords: open learning, deep learning, MOOC, systematic review

The Use of Deep Learning in Open Learning: A Systematic Review (2019 to 2023)

Conceptions about open learning are vast and wide. In a general sense, it refers to educational modalities to broaden education and training by breaking the barriers of time and space. Open learning has provided both students and teachers with greater flexibility, professional development, productivity, culture and socialisation in learning communities (Tzeng et al., 2022; Uddin et al., 2021). This pedagogical conception has been complemented by distributed learning in which teachers, students, and the content to be taught and learned are not centralised but can occur at any time and place (Zakaria et al., 2022; Zheng et al., 2022). In both open and distributed learning, the teacher is a facilitator of learning, the learner assumes an increasingly active and interactive role, and teaching and learning are reinforced and mediated by the use of digital technologies promoting open, online, and ubiquitous distributed learning environments (Mardini et al., 2023; Zheng et al., 2022).

Distance education has gained momentum with the expansion of open educational offerings and online vocational training. This has led to the enrolment of large numbers of students and has reinforced and integrated the use of information and communication technology (ICT). Therefore, the generation of new models and patterns of teaching and learning has been closely linked to new ICT trends creating the inter-, multi-, and trans-disciplinary space of emerging technologies (Mrhar et al., 2021).

Over the last 10 years, common open learning tools have included open educational resources (OER), collaborative teaching platforms, virtual learning environments, and educational social networks. With the evolution of open and distributed learning, distributed learning ecosystems (DLE) have emerged. These ecosystems utilize distributed learning infrastructures that bring together various tools and technologies related to OER, services, resources, and open learning environments (Otto et al., 2023). From an educational and open learning point of view, DLEs have focused on the diversity and interactions of actors and (re)use activities, allowing the creation of solutions such as resource aggregation mechanisms and open learning repositories. In this context, open pedagogy, as well as software advances based on artificial intelligence (AI) and the standardisation of OER metadata have all developed.

DLEs have promoted the effectiveness of open and online learning, although highly dependent on platforms, the Internet, interaction and interactivity, as well as teacher and learner empowerment. Significant progress has been made in the design and development of DLEs; however, there is still a latent lack of theoretical and empirical analysis of how emerging technologies such as AI, virtual reality, and augmented reality have influenced open learning (Otto et al., 2023).

AI has been grounded in various disciplines, such as natural language processing (NLP), artificial neural networks, computer vision, robotics, knowledge engineering, and machine learning (ML), among others (Hassan et al., 2019). The development of DLE has enabled the use of artificial intelligence in education (AIEd), notably, as expressed by Chen, Feng, et al. (2020), in adapting content, designing virtual tutors, automated assessment, data analysis, the use of virtual and augmented reality, creating recommender systems, and developing specific skills. These have all sought to improve the accessibility, personalisation, and efficiency of learning (Alruwais, 2023; Goel & Goyal, 2020).

AIEd can be learner-centred (e.g., adaptive or personalised learning management systems), teacher-centred (e.g., automating tasks such as administration, assessment, learning progress, and detecting plagiarism) or system-centred, providing administrators with decision-making information related to monitoring dropout patterns Chen, Feng, et al. (2020).

ML is one of the most widely used disciplines of AI. It enables, among other applications, the design of intelligent tutoring systems and performance prediction. However, in education, unstructured data such as images, text, and voice have often been handled (An et al., 2019). Conventional ML models may not be as effective in extracting useful features from these types of data, and therefore, it has been necessary to use more powerful models such as deep learning (DL). DL, a subset of ML, refers to the use of deep neural networks, configured with multiple successive layers of neurons (LeCun et al., 2015). It has represented the most advanced machine learning technique for solving problems with large sets of structured training data (Chassagnon et al., 2019) such as the analysis of traces and data from massive open online courses (MOOCs) for predicting school performance. While DL can address some of the limitations of ML, it is not a universal solution and also has its considerations, such as the need for large amounts of training data and computational resources. The choice between ML and DL depends on the specific nature of the problem and the data available in the educational context (El-Rashidy et al., 2023).

Recent studies on AI in open learning have focused on providing a learning experience for each learner by influencing motivation and online participation (Salas-Rueda, 2023). In a general sense, these systems must ensure the ability to provide feedback and structure adaptive learning content according to the individual capabilities of each learner. The usefulness of these tools depend on the design and development of more efficient intelligent tutoring systems, as shown in the teaching of mathematics, languages, and programming (Liang et al., 2023; Su et al., 2023).

In AI, DL as a subset of ML is based on the use of artificial neural networks (ANN), whose typology can be convolutional, recurrent, generative adversarial, deep, or modular neural networks. This area of AI has made inroads in education, mainly in analysing learning interactions in MOOCs, determining the chronological sequence of each student's interactions, predicting academic dropouts, and designing new and more efficient learning courses based on user experience, learning habits, and interactions (Verma et al., 2023). The most widely used technological models have been long short-term memory (LSTM) algorithms, sequential interaction rule mining process, and temporal interaction analysis (Yu et al., 2021).

Another recent application of DL has been automated online discussion message categorization based on convolutional neural network (CNN) and random forest classifiers. This advancement allowed for the analysis of interactions in online and open learning contexts. Utilizing the community of inquiry (CoI) framework, this application of DL has delineated the dimensions of cognitive presence (e.g., knowledge (re)construction, problem-solving), social presence (e.g., social interactions), and teaching presence (e.g., course design, interaction, interactivity) (Hu et al., 2021).

To enhance learning outcomes, DL has facilitated the creation of adaptive e-learning systems that analyze the behavior of individual learners in their interactions with learning objectives. Additionally, deep autoencoders have been utilized to learn and predict learner behaviors. DL has also supported the development of video analysis classification systems aimed at generating engaging video learning reports (Verma et al., 2023).

While there have been numerous studies on DL applications in education, few have focused on open learning. Consequently, there has been a lack of systematic reviews analyzing these applications. This research addresses this gap by examining the scientific literature.

Gaps in the Analysis of Studies on DL in Open Learning

Table 1 shows that some reviews, mappings, and bibliometric studies on AIEd have been published in Scopus and the Web of Science (WoS). Only three of these explicitly included DL studies, (Chen, Xie, et al. (2020); Pan et al., 2023; Vanitha & Jayashree, 2023). The remainder focused on other branches of AI.

Pan et al. (2023) performed a generic mapping of the use of DL in education, Chen, Feng, et al. (2020) analysed common errors in terminologies and the semantic forest of AIEd, and Vanitha and Jayashree (2023) focused on educational time series. However, none of these discussed the use of DL in open learning per se.

Table 1

Systematic Reviews

Research study	Period	Database	Number of studies
Pan et al. (2023)	1992 to 2002	WoS (SSCI)	2,827
Crompton and Burke (2023)	2016 to 2022	EBSCO, Wiley Online Library, JSTOR, Science Direct, and WoS	138
Su et al. (2023)	2016 to 2022	WoS, BSCO, IEEE, ACM, Scopus, and Google Scholar	16
Koong Lin et al. (2023)	2018 to 2023	Scopus	217
Vanitha and Jayashree (2023)	2018 to 2022	Google Scholar and IEEE Xplore	22
Liang et al. (2023)	1990 to 2020	WoS	16
Alhothali et al. (2022)	2017 to 2021	Scopus, Web of Science, Springer, IEEE, Elsevier, and Sage	67
Shafiq et al. (2022)	2017 to 2021	Google Scholar, IEEE Xplorer, ScienceDirect, Springer, ResearchGate, MDPI, Taylor & Francis, ACM Library, Emerald Insight, IOPscience, and Wiley	75
Hwang et al. (2021)	1996 to 2020	WoS (SSCI)	43
Uddin et al. (2021)	2013 to 2021	IEEE Xplore, ACM Digital Library, Science Direct, and Google Scholar	116

Talan (2021)	2001 to 2021	WoS	2,686
Chen, Xie, et al. (2020)	1970 to 2019	WoS (SSCI)	45
Chen, Xie, and Hwang (2020)	1999 to 2019	WoS	9,560

Several points are worth highlighting regarding these studies. Crompton and Burke (2023) discussed how, in higher education, AIEd contributed to learning assessment and prediction from AI assistants, intelligent tutoring systems, and learning management. Along these lines, others have focused on (a) algorithms and systems for learning prediction and student retention (Alhothali et al., 2022; Shafiq et al., 2022); (b) MOOC recommender systems (Uddin et al., 2021); and (c) analysing the impact of deep learning on educational time series datasets (Vanitha & Jayashree, 2023).

Su et al. (2023) focused on artificial intelligence digital literacy and AIEd challenges in the context of K–12 to higher education, while Koong Lin et al. (2023) focused on the unique use of ChatGPT in education.

In their systematic review, Liang et al. (2023) analysed research methods, and the role of AI in language teaching and its learning outcomes. Similarly, other mapping studies and reviews have explained the applications of engineering and computational techniques at certain levels of education, such as higher education (Hwang et al., 2021) and early childhood education (Su et al., 2023).

Although several authors (Chen, Xie, et al., 2020; Pan et al., 2023; Talan, 2021) conducted comprehensive analyses of more than 900 articles, they focused on scholarly output and its bibliometric analysis only, without delving into the advantages of AI in open learning.

In their extensive systematic review of influential AIEd studies, Chen, Xie, et al. (2020) stated that only two studies explicitly identified the use of DL, referring to the study of advanced neural network architecture and the achievements of optimising study strategies from parallel robot instruction. In their study, they concluded that this was understandable, as DL was a newer area of research compared to general AI and machine learning.

In general, the reviews argued that these AIEd studies focused on profiling and dropout prediction, content evaluation, adaptive system design, and intelligent tutoring systems; there is still a lack of studies that systematised the use of DL. This theoretical research reaffirmed the importance of analysing empirical studies on the unique use of DL and its relationship with open learning, as MOOC dropout prediction and course recommendation require the use of powerful computational models (Wang et al., 2024).

To fill this gap, this study analysed AIEd-related scientific articles focusing on DL and open learning published between 2019 and 2023 to explore the important questions that remain to be investigated.

Objectives and Research Questions

This study aimed to identify, through a systematic review, the trends, applied computational techniques, and areas of educational use of deep learning in open learning. For this purpose, we examined the scientific literature from 2019 to 2023, present in one of the main bibliographic reference database collections, namely the Web of Science (WoS).

Aligned with this objective and addressing theoretical gaps, we sought to answer the following questions:

> How does scientific collaboration relate to the study of DL in open learning, highlighting its application areas? (This question was addressed through the bibliometric dimension, specifically co-authorship networks, keyword networks, and main clusters.)
>
> What are the dependent variables studied and their main findings? (This was answered through the pedagogical dimension by analyzing the content of each study.)
>
> What are the DL techniques or algorithms used in open learning (independent variable), and what is their level of accuracy? (This was addressed through the technological dimension, identifying, for each study, DL techniques or algorithms, data sources used, and levels of accuracy.)

Method

We utilized the updated PRISMA statement guidelines to search for and select scientific information (Page et al., 2021). A quantitative procedure was employed for coding to ensure the validity of the study (Zawacki-Ritcher et al., 2020).

Search Strategy and Criteria

Only articles from peer-reviewed journals were selected to ensure a high level of quality. The search parameters were narrowed to the period from 2019 to 2023 to ensure the currency of the literature, which is essential in the AIEd area. Mendeley was used to extract articles and eliminate duplicates.

The electronic search protocol included the WoS databases, namely the Social Sciences Citation Index (SSCI) and the Science Citation Index Expanded (SCIE), housing more than 12,000 journals. A full-text search was conducted in line with the research objectives and questions. The Boolean search included terms related to DL, open learning, and distributed learning.

Since open education, distance education, online education, and distributed learning are related but distinct, they were included as keywords to verify later whether each result was related to open education. Similarly, DL and ML are different, but as some authors mention them interchangeably (Chen, Xie, et al. (2020) they were used as keywords, and subsequently, only works referring to DL were included in the analysis. The techniques used were checked to identify whether they referred to ML (e.g., supervised learning, unsupervised learning, and reinforcement learning) or DL (e.g., convolutional, recurrent, generative adversarial, deep, or modular artificial neural networks).

The initial Boolean search string focused on "deep learning OR DL OR machine learning OR ML," which yielded generic AIEd results. Subsequently, these were filtered according to the search string "open learning OR OL OR distributed learning OR DL" to obtain documents related to the research topic. In summary, the final search string focused on "(deep learning OR machine learning) AND (open education OR distance education OR online education OR distributed learning) AND (educational technologies OR artificial intelligence in education)."

The inclusion and exclusion criteria are detailed in Table 2.

Table 2

Inclusion and Exclusion Criteria

Inclusion criteria	Exclusion criteria
Published in the period 2019 to 2023	Published before 2019
English language	Languages other than English
Original articles	Purely theoretical studies, systematic reviews, conference proceedings, and editorial letters, among others of equal magnitude
Empirical studies on DL use in open learning	

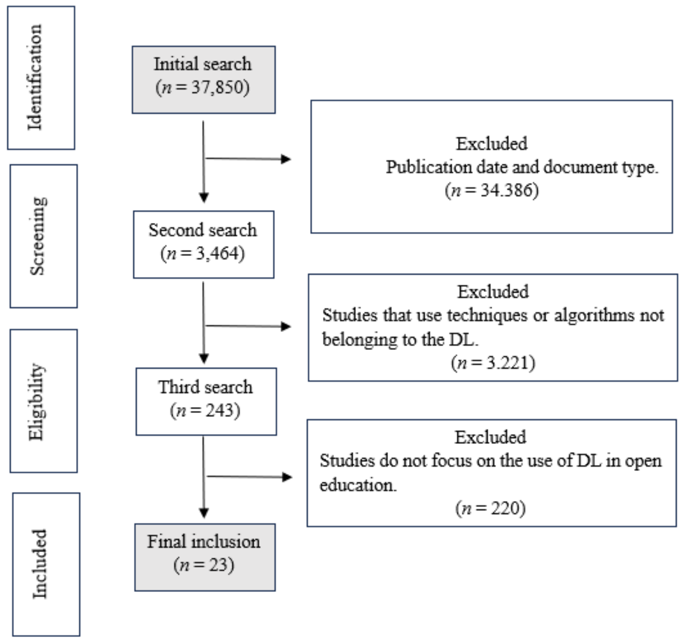
Screening and Validation Strategy

After carrying out the search of papers, two independent researchers used a standard checklist form to exclude irrelevant articles and determine their eligibility. In the process, any discrepancies between reviewers were resolved.

Subsequently, bibliographic data were extracted, and key findings and results were synthesised and recorded. The PRISMA diagram and its checklist for determining study quality were used to assess and carry out the selection process (Page et al., 2021). Finally, the two independent researchers read the selected articles to extract relevant information and answer the research questions. Any inconsistencies between the two researchers' results were resolved by a third reviewer. The process revealed a few articles on the use of DL in open learning (Figure 1

Figure 1

Selecting Studies (PRISMA Protocol)



Coding and Visualisation Tools

The selected studies were coded for deductive aspects and internal validity with a set of three criteria: keywords, authors, and first authors' countries. Concerning inductive coding for conclusion validity, the focus was on the influence of DL on open learning to identify trends. Finally, grounded coding for external validity focused the findings on how DL was used rather than how it could be used. VOSviewer version 1.6.19 was used for bibliometric data visualisation and analysis.

Results

Bibliometric Output Information

In the literature analysis, 23 articles were finally selected (Figure 2) of which two were highly cited (Onan, 2021; Xing & Du, 2019). The analysis showed a trend of three to six manuscripts published annually. The low scientific output regarding the use of DL in open learning was highlighted.

Figure 2

Scientific Production

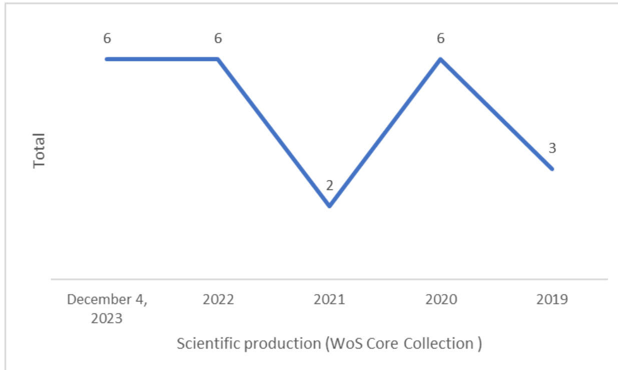
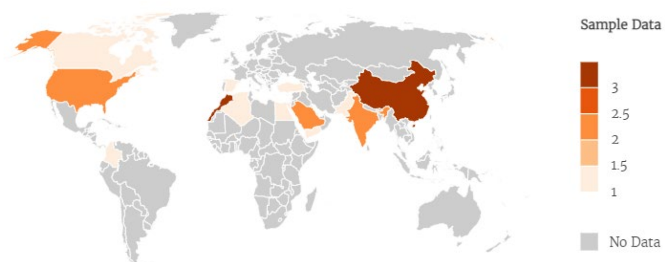


Figure 3 was created with mapsinseconds.com to illustrate the first authors' countries in our sample. The two countries with the highest scientific production were China (n = 10) and Morocco (n = 2).

Figure 3

Origin of the Works Analysed (N = 23)



Bibliometric Dimension (Question 1)

A co-authorship network of the 147 authors was created. Of these, collaboration was shown in 83 (Figure 4). The most cited names were those with the highest presence, represented by 23 clusters.

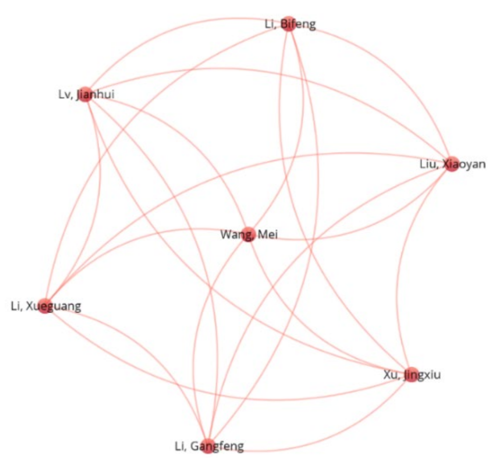
Figure 4

Co-Authorship Network

Of the 83 authors, only seven showed strong collaboration (Figure 5).

Figure 5

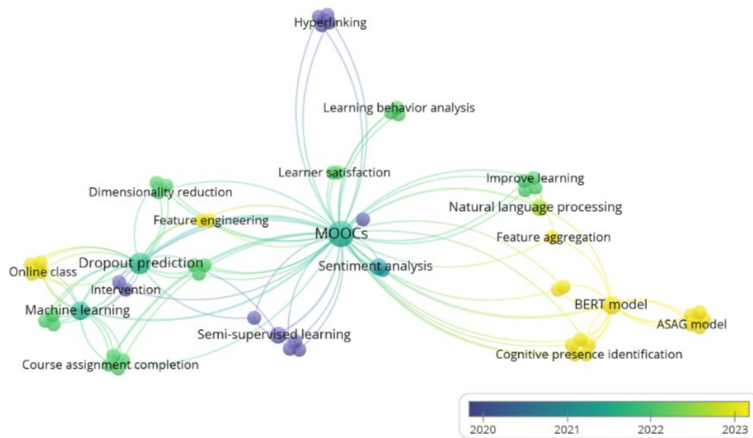
Co-Authorship Network with Consistent Connections



A total of 81 author keywords were identified. After debugging and standardising common keywords and abbreviations, these were reduced to 68 (Figure 6).

Figure 6

Author Keyword Network



In total, 14 clusters were identified, highlighting the following: In the period of 2022–2023, research focused on the utilization of feature aggregation and BERT and ASAG models to analyze students' cognitive presence in Massive Open Online Courses (MOOC) courses.

During the period of 2021–2022, studies emphasized predicting dropout through sentiment analysis, the integrated use of machine learning (ML) and deep learning (DL) techniques, and the analysis of learner traces of interaction and interactivity. Similarly, in the period of 2019–2021, work also concentrated on the prediction of MOOC courses, mainly based on models that integrated DL and semi-supervised learning. The results indicated that the primary areas of application of DL in open learning were MOOC course recommendation, student dropout prediction, cognitive presence analysis, and sentiment analysis. These aspects are further explored in the discussion of the pedagogical dimension.

Pedagogical Dimension (Question 2)

Each study was analyzed in-depth, and the results are presented in Table 3.

Table 3

Dependent Variables and Main Findings (N = 23)

ID	Citation	Dependent variable	Findings
ID 1	Li et al. (2023)	Recommending MOOCs	Automatic detection of user needs
ID 2	Liu et al. (2023a)	Cognitive presence	Cognitive presence assessment
ID 3	El-Rashidy et al. (2023)	Performance of MOOC posts classification	Automatic quality assessment of forums in MOOC courses
ID 4	Alruwais (2023)	Predicting MOOC dropout	Dropout determinants in MOOCs (e.g., video clickstream, forum interaction)

ID 5	Liu et al. (2023b)	Predicting MOOC dropout	Analysed video interactions based on learner and course characteristics
ID 6	Mardini et al. (2023)	Reading comprehension assessment	Automatic grading of short answers
ID 7	Nithya and Umarani (2022)	Predicting MOOC dropout	Relationship between learner behaviour (i.e., interaction and interactivity) and MOOC course dropout
ID 8	Zheng et al. (2022)	Predicting MOOC dropout	Determinants of dropout in MOOCs (i.e., videos, task completion, and interactivity in forums)
ID 9	Lemay and Doleck (2022)	Predicting MOOC dropout	Determinants of video features in MOOCs
ID 10	Zakaria et al. (2022)	Predicting MOOC dropout	Relationship between interactivity and interaction time, and MOOC course dropout
ID 11	Jiang (2022)	Teaching modern and contemporary literature in Chinese	Identifying possible causes of dropout in relation to language and literature learning
ID 12	Tzeng et al. (2022)	MOOC student experiences	Predicting student satisfaction
ID 13	Fan et al. (2022)	Learning behaviours and MOOC recommendation	Relationship between didactic description of the MOOC and personal learning goals
ID 14	Hamal and El Faddouli (2022)	Answering learner questions in a MOOC	Answering learner questions related to French language learning
ID 15	Mubarak et al. (2021)	Predicting learners' performance	Determinants of dropout in MOOCs (analysis of video interactions)
ID 16	Mrhar et al. (2021)	Sentiment analysis on forum interactivity in MOOCs	Correlation between sentiment (forum interactions) and MOOC dropout rate
ID 17	Onan (2021)	Sentiment analysis on assessments in MOOCs	Correlation between sentiment and MOOC dropout rate
ID 19	Goel and Goyal (2020)	Predicting MOOC dropout	Correlations among possible friends, their closeness levels, and the probability of dropout
ID 20	Yin et al. (2020)	Predicting weekly MOOC dropout	Probability of weekly dropout, based on interaction and interactivity
ID 21	Xing and Du (2019)	Predicting weekly MOOC dropout	Probability of weekly dropout, based on analysis of forum-type activities and quizzes

ID 22	Hassan et al. (2019)	Predicting weekly MOOC dropout	Relationship between video click-through rate and likelihood of dropout
ID 23	An et al. (2019)	Predicting MOOC dropout	Probability of dropout, based on analysis of forum-type activities

The main findings focused on the analysis and prediction of learner behaviour, interaction, and interactivity in MOOCs, although some specific cases evaluated other open learning systems (Hamal & El Faddouli, 2022; Mardini et al., 2023).

Technological Dimension (Question 3)

The DL techniques and algorithms used, and their level of accuracy, are shown in Table 4.

Table 4

Techniques, Level of Accuracy, and Data Sources

ID	DL technique or algorithm	Data source	Accuracy
ID 1	Bidirectional encoder representations from transformers (BERT)	Open datasets (MoocCube)	2.150 F1-score@10 0.2854 recall@10 0.172 precision@10
ID 2	MOOC-BERT (BERT model variant)	Datasets from two Chinese university MOOCs	85.8 % precision 86.1% recall 85.9% F1-score 88.1% accuracy
ID 3	BERT New model based on CNNs	Datasets present in the Stanford post-MOOC corpus	83.6 % precision 83% recall 83.3% F1 of urgent 92.7% F1-weighted
ID 4	Factorisation machine with DNN (deep neural network) models	Two datasets (HarvardX person-course academic year 2013 de-identified and MOOC)	99 % accuracy
ID 5	Learning network model (LBDL) and Bi-LSTM	Open datasets (MoocCube)	74.89% F1-score 82.39% ROC curve
ID 6	Deep-learning-based grading system	Universidad del Norte datasets	BERT-1-ES [Pearson correlation (0.78) Root mean squared error (0.66)]
	BERT		BERT-2-ES [Pearson correlation (0.78) Root mean squared error (0.66)]
ID 7	FIAR-ANN Model	KDD Cup 2015 dataset	3.16 F1-score 92.42% accuracy.
ID 8	CNNs and bidirectional long short-term memory network (Bi-LSTM)	KDD Cup 2015 dataset	87.1% area under the receiver operating characteristic curve

			87.3 % area under the precision-recall curve (AUC) 86.8% F1-value 86.4% accuracy
ID 9	Logistic regression, SMO (Sequential minimal optimisation), Naïve Bayes, J48, JRip, IBK and WekaDeeplearning4J	Dataset analysis of MOOCs offered at the University of Pennsylvania	High accuracy (~80%) Variance (26.9%) Kappa > 0 and AUC > 0.5
ID 10	Deep neural network (DNN)	KDD Cup 2015 dataset	0.943 accuracy 0.876 AUC
ID 11	Basic teaching and learning optimisation algorithm	Questionnaires to students enrolled in MOOC courses	No validation of the algorithm presented, only students' opinions
ID 12	Deep neural network (DNN)	Eight MOOC courses from National Tsing Hua University (NTHU) Video analysis. Questionnaire analysis	Cronbach's alpha (0.842) Mean absolute error (0.41 to 0.55)
ID 13	Multi-attention deep learning model	Records of 6,628 students from 1,789 MOOCs	0.90 Hit ratio-20. 0.58 Normalised discounted cumulative gain-20
ID 14	DL in NLP	Proposal validated by two datasets (FQuAD, SQuAD-FR)	FCuAD: 79.81 F1-score SquaD-FR: 80.61 F1-score
ID 15	LSTM	Stanford University MOOCs	89%–95% accuracy 89% automata theory accuracy 90.30% in the "Mining of Massive Datasets"
ID 16	Bayesian CNN-LSTM Model	100,000 Coursera course reviews	90% precision 85% recall 88% F1-score 91.27% accuracy
ID 17	Three word embedding schemes (word2vec, fastText and GloVe) Long short-term memory networks (LSTM)	66,000 course reviews on coursetalk.com	95.80% accuracy
ID 18	Semi-supervised deep learning (SSDL) framework	Stanford MOOC posts dataset	89.73% accuracy 93.55% F1-score
ID 19	Self-training model	XuetangX (Datasets from China)	94.29% average F1-score
ID 20	Deep neural network model	KDD Cup 2015 dataset	Weekly average accuracy: Week 1 (0.84%) Week 2 (0.73%) Week 3 (0.87%) Week 4. (0.91%)

			Week 5 (0.84%)
ID 21	Temporal prediction mechanism	MOOC course dataset	Accuracy range 0.928 to 0.981 Dropout precision 93%
ID 22	Long short-term memory (LSTM deep)	Open University learning analytics	97.25% learning accuracy, 92.79% precision 85.92% recall
ID 23	New incremental model of LSTM–CRF	Real-world forum posts from Coursera	Dropout precision 65.6% 3.16 F1-score

As can be seen, the most commonly used DL techniques or algorithms were related to the classical use or modern variants of BERT, LSTM, DNN, and NLP. Their levels of accuracy are adequate to measure the dependent variables (refer to Table 3).

Discussion and Conclusions

This study aimed to identify, through a systematic review, the trends, applied computational techniques, and areas of educational use of deep learning in open learning. To this end, the WoS Core Collection, including both SCIE and SSCI, was searched. The PRISMA protocol guided the selection of 23 articles, reflecting a low academic production related to the research objective, which indicates that deep learning (DL) in education is relatively recent.

Concerning the first research question, the application of DL has mainly focused on predicting student dropout, automatic grading of short answers, and recommending MOOC courses. Technological underpinnings were based on (a) the flow of student clicks on videos, (b) student interaction and interactivity, (c) the quality of responses in interactive activities such as forums, and (d) the length of time spent on activities. The low academic research output reflects that there is still insufficient scientific collaboration in this research area, which may be a consequence of how recent the use of DL is in open learning (Pan et al., 2023; Vanitha & Jayashree, 2023).

For the second and third research questions, dealing with pedagogical and technological dimensions, respectively, we identified trends in the use of DL in open learning in several key directions.

Pedagogical Dimension

Predicting Dropout or Attrition From MOOCs

There is agreement that the quality and length of videos in MOOCs influence dropout (Alruwais, 2023; Goel & Goyal, 2020; Hassan et al., 2019; Lemay & Doleck, 2022; Liu et al., 2023a; Mubarak et al., 2021; Nithya & Umarani, 2022; Tzeng et al., 2022; Zakaria et al., 2022; Zheng et al., 2022). In this regard, several researchers (Nithya & Umarani, 2022; Zheng et al., 2022) found that browsing and closing pages had no effect on dropout; completing tasks, watching videos, and discussing problems in forums did. On the other hand, Zakaria et al. (2022) successfully elucidated the relationships among access, video engagement, homework completion, and discussion participation in predicting dropout. Others (Alruwais, 2023; Goel & Goyal, 2020; Hassan et al., 2019; Liu et al., 2023b; Mubarak et al., 2021; Zheng et al., 2022) agreed that the lower the clickstream on videos, the higher the probability of dropping out of a MOOC course.

As an interesting note, we agreed with Goel and Goyal (2020) that AI studies in general have identified that there is a possible relationship between personal or friendship relationships and the likelihood of dropout— in other words, virtually all likely friends among all enrolled students showed the same behaviour in both video interaction and dropout likelihood.

A relationship has been established between the course content, the characteristics of open educational resources, their complexity, and student cognitive fatigue (Jiang, 2022; Zakaria et al., 2022). In addition, analysing these factors as well as student interactivity and interaction, through logs and traces, has established the probability of weekly dropout (Yin et al., 2020). Similarly, analysis of interaction in forums (An et al., 2019; El-Rashidy et al., 2023) and quizzes (Xing & Du, 2019) in a MOOC course can help predict the probability of weekly dropout.

Analysis of students' cognitive presence in sustained discourse in a virtual community (e.g., integration, problem-solving, and intuition) is a high predictor of academic performance in MOOCs (Liu et al., 2023a).

Sentiment analysis or opinion mining of individual student responses allows for some assessment and prediction of retention or dropout in a MOOC course. In this regard, research has been conducted on mass assessments (Onan, 2021) and forum interactions (Chen, Feng, et al., 2020; Mrhar et al., 2021). There has been some hesitation from students regarding mass assessments related to quality and veracity, although the computational results provided good reliability rates (Onan, 2021). A hybrid procedure between automated and teacher-led assessments was suggested in several reviews (Mrhar et al., 2021). Furthermore, the analysis of interaction and interactivity in activities posted in forums within MOOCs showed that there was a correlation between learner sentiment and engagement, and the likelihood of dropping out. As the number of students dropping out of the MOOC course decreased, the feelings and motivation towards the course increased (Chen, Feng, et al., 2020; Mrhar et al., 2021).

In this area (MOOC dropout), the results can be grouped into the following clusters:

- Cluster 1: Dropout prediction using artificial neural networks, association rules mining, data analytics, ML, and personalisation.
- Cluster 2: Sentiment classification using asymmetric data, co-training, self-training, and semi-supervised learning.
- Cluster 3: The identification of cognitive presence through the community of inquiry model, online discussions, pre-trained language model, and text analysis.
- Cluster 4: Students' dropout through deep-neural networks and the deepfm model.

Automatic Grading of Short Answers

Scoring short answer reading comprehension questions is effective if a comparison is made between the student's answer and the target answer, yet it is a complex process that has not yet been fully resolved (Hamal & El Faddouli, 2022; Mardini et al., 2023). Research related to this topic has been based on the use of feature aggregation, intelligent systems, and the use of DL in NLP.

Recommending MOOCs Personalized recommendations of Massive Open Online Courses (MOOCs) have been based on two trends: (a) the use of big data and deep learning (DL) through the analysis of content features (Li et al., 2023); or (b) through learning logs, content, and course descriptions (Fan et al., 2022). These authors agreed that the accurate wording of learning objectives and didactic description of a course influenced the effectiveness of the recommendations.

Related research has been focused on automated grading, big data, reading comprehension assessment, sentence embedding, the ASAG model, and the skip-thoughts model. Although significant results have been achieved, three techno-pedagogical challenges associated with these systems have remained: (a) ensuring pedagogical usability, (b) the design of quality computational models, and (c) confidence in communicating and grading learning outcomes.

Synthesis The literature review allowed us to identify some pedagogical challenges of using DL in open learning, including (a) effective personalization of content for different learning styles; (b) transparent interpretation and explanation of model decisions; and (c) the need to address possible inherent biases in the datasets (e.g., socio-demographics, traces, competencies, learning objectives) used for training. In addition, continuous adaptation as technologies evolve and ethical integration of artificial intelligence are key aspects to consider in educational settings (Tzeng et al., 2022).

Technological Dimension The following technological challenges were apparent in the literature we analyzed (N = 23):

- Large datasets: DL models often require massive datasets for optimal performance, which can be difficult to obtain in open learning environments where data availability may be limited.

- Intensive computing: DL algorithms are computationally intensive, which implies the need for powerful hardware resources. This can be a challenge in environments where access to high-end computational resources is limited.

- Interpretability: DL models are often perceived as black boxes due to their complexity. Understanding how they make decisions can be crucial, especially in contexts where transparency is essential.

- Knowledge transfer: Adapting pre-trained models to new tasks can be challenging, as knowledge transfer is not always straightforward and may require sensitive fine-tuning.

- Ethics and bias: The presence of biases in datasets can lead to biased and discriminatory results. Addressing these ethical issues is essential for inclusive and fair open learning.

- Safety: DL models can be vulnerable to adversarial attacks, where carefully designed inputs can mislead the model. Ensuring the robustness of the model is a constant challenge.

- Cost of implementation: Developing and implementing DL solutions can be costly in terms of human resources, hardware, and time. This can limit its adoption in resource-constrained contexts.

Despite these challenges, research advances have continued to address these concerns and improve the applicability of DL in open learning environments. In this educational domain, various DL algorithms have been employed, such as convolutional neural networks (CNNs) for processing visual data, recurrent neural networks (RNNs) for temporal sequences, and transformers for natural language processing (NLP) tasks (Hamal & El Faddouli, 2022). Techniques have included transfer learning, data augmentation, and personalized optimization. In terms of trends, there has been an increase in the application of pre-trained models, the development of more efficient architectures, and the growing use of interpretability techniques. In this sense, the integration of Artificial Intelligence (AI) in the personalization of the learning experience is an emerging trend reiterated in the Horizon Reports (EDUCAUSE, 2023).

Conclusion

This study aimed to contribute to the educational community by identifying the pedagogical potential of Deep Learning (DL) in open learning, such as:

- Content recommendation and automatic grading of short answers with feedback as key tools for meaningful personalized learning, achieved through constructive alignment between objectives, activities, and learning assessment.

- Predicting student dropout based on levels of student interactivity and interaction with digital educational resources, and the quality of responses to self-assessment as well as formative and summative assessment activities. This would be linked to an adequate multidirectional synchronous and asynchronous pedagogical communication and interaction process, providing support and tutoring services to motivate the student to learn in an autonomous, personalized, and collaborative way.

The results obtained in the application of DL in open learning have influenced the efficiency of higher education administrations, early counseling, and mentoring, as well as the design and implementation of educational interventions. However, there is agreement on the need to delve deeper into the ethical and moral issues of artificial intelligence (AI) concerning cultural differences, inclusion, and student emotions, as well as the pedagogical use of AI by teachers (Mouta et al., 2023).

At the algorithmic level, the most commonly employed DL algorithms were variants of artificial neural networks such as DNN (Alruwais, 2023; Tzeng et al., 2022; Yin et al., 2020; Zakaria et al., 2022), LSTM (An et al., 2019; Hassan et al., 2019; Liu et al., 2023b; Mrhar et al., 2021; Mubarak et al., 2021; Onan, 2021; Zheng et al., 2022), and BERT (El-Rashidy et al., 2023; Li et al., 2023; Liu et al., 2023a; Mardini et al., 2023; Zheng et al., 2022).

The studies reviewed demonstrated their contribution to education; however, there was a lack of research to follow up on these results by answering questions such as: Have Massive Open Online Courses (MOOCs) been redesigned based on the results of DL application in open learning? (See Table 3); and Is the dropout rate maintained?

Learning as an educational, cultural, and psychosocial process depends on a variety of cognitive, motivational, affective, communicative, sociological, pedagogical, didactic, and technological factors. In terms of technology, DL and AI in education have brought us closer to identifying some criteria for approaching success in open learning. The algorithms and methods used have offered a high cognitivist weight of pedagogical value but could be enriched with other pedagogical foundations. It is interesting that the description of the DL methods used has hardly described the pedagogical basis, which to some extent obscures educational assessment.

Limitations of the Study

This study was limited to consulting only the Web of Science (WoS) Core Collection, specifically SCIE and SSCI. Therefore, it is possible that interesting results published in journals indexed in Scopus or other databases were omitted. Additionally, only articles in English were analyzed, overlooking articles published in other languages that could have enriched the results obtained in this research.

Future Lines of Research

There has been a lack of studies that have analyzed and compared the results obtained in the use of DL and machine learning (ML) in open learning, which would help to make decisions and consequently define the most efficient techniques and algorithms. In this sense, a systematic review and meta-analysis are recommended.

References

Alhothali, A., Albsisi, M., Assalahi, H., & Aldosemani, T. (2022). Predicting student outcomes in online courses using machine learning techniques: A review. *Sustainability, 14*(10), 6199. https://doi.org/10.3390/su14106199

Alruwais, N. M. (2023). Deep FM-based predictive model for student dropout in online classes. *IEEE Access, 11*, 96954–96970. https://doi.org/10.1109/ACCESS.2023.3312150

An, Y. H., Pan, L., Kan, M. Y., Dong, Q., & Fu, Y. (2019). Resource mention extraction for MOOC discussion forums. *IEEE Access, 7*, 87887–87900. https://doi.org/10.1109/ACCESS.2019.2924250

Chassagnon, G., Vakalopolou, M., Paragios, N., & Revel, M. (2019). Deep learning: Definition and perspectives for thoracic imaging. *European Radiology*, *30*(4), 2021–2030. https://doi.org/10.1007/s00330-019-06564-3

Chen, J., Feng, J., Sun, X., & Liu, Y. (2020). Co-Training semi-supervised deep learning for sentiment classification of MOOC forum posts. *Symmetry, 12*(1). https://doi.org/10.3390/sym12010008

Chen, X., Xie, H., & Hwang, G. J. (2020). A multi-perspective study on artificial intelligence in education: Grants, conferences, journals, software tools, institutions, and researchers. *Computers and Education: Artificial Intelligence, 1*, 100005. https://doi.org/10.1016/J.CAEAI.2020.100005

Chen, X., Xie, H., Zou, D., & Hwang, G. J. (2020). Application and theory gaps during the rise of artificial intelligence in education. C*omputers and Education: Artificial Intelligence, 1*. https://doi.org/10.1016/J.CAEAI.2020.100002

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education, 20*(1), 1–22. https://doi.org/10.1186/S41239-023-00392-8/FIGURES/11

EDUCAUSE. (2023). *2023 EDUCAUSE Horizon Report® Teaching and learning edition*. *https://library.educause.edu/-/media/files/library/2023/4/2023hrteachinglearning.pdf*

El-Rashidy, M. A., Farouk, A., El-Fishawy, N. A., Aslan, H. K., & Khodeir, N. A. (2023). New weighted BERT features and multi-CNN models to enhance the performance of MOOC posts classification. *Neural Computing & Applications, 35*(24), 18019–18033. https://doi.org/10.1007/s00521-023-08673-z

Fan, J., Jiang, Y., Liu, Y., & Zhou, Y. (2022). Interpretable MOOC recommendation: A multi-attention network for personalized learning behavior analysis. *Internet Research, 32*(2), 588–605. https://doi.org/10.1108/INTR-08-2020-0477

Goel, Y., & Goyal, R. (2020). On the effectiveness of self-training in MOOC dropout prediction. *Open Computer Science, 10*(1), 246–258. https://doi.org/10.1515/comp-2020-0153

Hamal, O., & El Faddouli, N. E. (2022). Intelligent system using deep learning for answering learner questions in a MOOC. *International Journal of Emerging Technologies in Learning, 17*(2), 32–42. https://doi.org/10.3991/ijet.v17i02.26605

Hassan, S., Waheed, H., Aljohani, N. R., Ali, M., Ventura, S., & Herrera, F. (2019). Virtual learning environment to predict withdrawal by leveraging deep learning. *International Journal of Intelligent Systems, 34*(8), 1935–1952. https://doi.org/10.1002/int.22129

Hu, Y., Ferreira Mello, R., & Gašević, D. (2021). Automatic analysis of cognitive presence in online discussions: An approach using deep learning and explainable artificial intelligence. *Computers and Education: Artificial Intelligence, 2*, 100037. https://doi.org/10.1016/J.CAEAI.2021.100037

Hwang, G.-J., Tu, Y.-F., Hwang, G.-J. , & Tu, Y.-F. (2021). Roles and research trends of artificial intelligence in mathematics education: A bibliometric mapping analysis and systematic review. *Mathematics, 9*(6). https://doi.org/10.3390/MATH9060584

Jiang, H. (2022). Modern and contemporary literature courses in colleges and universities using the teaching mode of deep learning. *Mobile Information Systems, 2022*, 1–13. https://doi.org/10.1155/2022/3517022

Koong Lin, H.-C., Ye, J.-H., Hao, Y.-W., Wu, Y.-F., Bahroun, Z., Anane, C., Ahmed, V., & Zacca, A. (2023). Transforming education: A comprehensive review of generative artificial intelligence in educational settings through bibliometric and content analysis. *Sustainability, 15*(17). https://doi.org/10.3390/SU151712983

LeCun, Y., Bengio, Y., & Hinton, G. E. (2015). Deep learning. *Nature*, *521*(7553), 436–444. https://doi.org/10.1038/nature14539

Lemay, D. J., & Doleck, T. (2022). Predicting completion of massive open online course (MOOC) assignments from video viewing behavior. *Interactive Learning Environments, 30*(10), 1782–1793. https://doi.org/10.1080/10494820.2020.1746673

Li, B., Li, G., Xu, J., Li, X., Liu, X., Wang, M., & Lv, J. (2023). A personalized recommendation framework based on MOOC system integrating deep learning and big data. *Computers and Electrical Engineering, 106*, 108571. https://doi.org/10.1016/j.compeleceng.2022.108571

Liang, J. C., Hwang, G. J., Chen, M. R. A., & Darmawansah, D. (2023). Roles and research foci of artificial intelligence in language education: An integrated bibliographic analysis and systematic review approach. *Interactive Learning Environments, 31*(7), 4270–4296. https://doi.org/10.1080/10494820.2021.1958348

Liu, Z., Kong, X., Chen, H., Liu, S., & Yang, Z. (2023a). MOOC-BERT: Automatically identifying learner cognitive presence from MOOC discussion data. *IEEE Transactions on Learning Technologies, 16*(4), 528–542. https://doi.org/10.1109/TLT.2023.3240715

Liu, H., Chen, X., & Zhao, F. (2023b). Learning behavior feature fused deep learning network model for MOOC dropout prediction. *Education and Information Technologies, 29*, 3257–3278. https://doi.org/10.1007/s10639-023-11960-w

Mardini, G., Quintero, C., Viloria, C., Percybrooks, W., Robles, H., & Villalba, K. (2023). A deep-learning-based grading system (ASAG) for reading comprehension assessment by using aphorisms as open-answer-questions. *Education and Information Technologies, 29*, 4565–4590. https://doi.org/10.1007/s10639-023-11890-7

Mouta, A., Pinto-Llorente, A. M., & Torrecilla-Sánchez, E. M. (2023). Uncovering blind spots in education ethics: Insights from a systematic literature review on artificial intelligence in education. *International Journal of Artificial Intelligence in Education, 2023*. https://doi.org/10.1007/s40593-023-00384-9

Mrhar, K., Benhiba, L., Bourekkache, S., & Abik, M. (2021). A Bayesian CNN-LSTM model for sentiment analysis in massive open online courses MOOCs. *International Journal of Emerging Technologies in Learning, 16*(23), 216–232. https://doi.org/10.3991/ijet.v16i23.24457

Mubarak, A. A., Cao, H., Zhang, W., & Zhang, W. (2021). Visual analytics of video-clickstream data and prediction of learners' performance using deep learning models in MOOCs' courses. *Computer Applications in Engineering Education, 29*(4), 710–732. https://doi.org/10.1002/cae.22328

Nithya, S., & Umarani, S. (2022). MOOC dropout prediction using FIAR-ANN model based on learner behavioral features. *International Journal of Advanced Computer Science and Applications, 13*(9), 607–617. https://dx.doi.org/10.14569/IJACSA.2022.0130972

Onan, A. (2021). Sentiment analysis on massive open online course evaluations: A text mining and deep learning approach. *Computer Applications in Engineering Education, 29*(3), 572–589. https://doi.org/10.1002/cae.22253

Otto, D., Scharnberg, G., Kerres, M., & Zawacki-Richter, O. (2023). Distributed learning ecosystems: Concepts, resources, and repositories. In D. Otto, G. Scharnberg, M. Kerres, & O. Zawacki-Richter (Eds.), *Distributed learning ecosystems* (pp. 1–10). Springer VS. https://doi.org/10.1007/978-3-658-38703-7_1

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., . . . Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*(71). https://doi.org/10.1136/bmj.n71

Pan, Q., Zhou, J., Yang, D., Shi, D., Wang, D., Chen, X., & Liu, J. (2023). Mapping knowledge domain analysis in deep learning research of global education. *Sustainability, 15*(4), 3097. https://doi.org/10.3390/su15043097

Salas-Rueda, R. A. (2023). Use of deep learning to analyze Facebook and Google Classroom in the educational field. *Pixel-Bit. Revista De Medios y Educación, 67*, 87–122. https://doi.org/10.12795/pixelbit.96994

Shafiq, D. A., Marjani, M., Habeeb, R. A. A., & Asirvatham, D. (2022). Student retention using educational data mining and predictive analytics: A systematic literature review. *IEEE Access, 10*, 72480–72503. https://doi.org/10.1109/ACCESS.2022.3188767

Su, J., Ng, D. T. K., & Chu, S. K. W. (2023). Artificial intelligence (AI) literacy in early childhood education: The challenges and opportunities. *Computers and Education: Artificial Intelligence, 4*, 100124. https://doi.org/10.1016/J.CAEAI.2023.100124

Talan, T. (2021). Artificial intelligence in education: A bibliometric study. *International Journal of Research in Education and Science, 7*(3), 822–837. https://doi.org/10.46328/IJRES.2409

Tzeng, J.-W., Lee, C.-A., Huang, N.-F., Huang, H.-H., & Lai, C.-F. (2022). MOOC evaluation system based on deep learning. *The International Review of Research in Open and Distributed Learning, 23*(1), 21–40. https://doi.org/10.19173/irrodl.v22i4.5417

Uddin, I., Imran, A. S., Muhammad, K., Fayyaz, N., & Sajjad, M. (2021). A systematic mapping review on MOOC recommender systems. *IEEE Access, 9*, 118379–118405. https://doi.org/10.1109/ACCESS.2021.3101039

Vanitha, S., & Jayashree, R. (2023). Towards finding the impact of deep learning in educational time series datasets: A systematic literature review. *International Journal of Advanced Computer Science and Applications, 14*(3), 804–815. http://dx.doi.org/10.14569/IJACSA.2023.0140392

Verma, N., Getenet, D. S., Dann, D. C., & Shaik, T. (2023). Designing an artificial intelligence tool to understand student engagement based on teacher's behaviours and movements in video conferencing. *Computers and Education: Artificial Intelligence, 5*, 100187. https://doi.org/10.1016/J.CAEAI.2023.100187

Wang, D., Tao, Y., & Chen, G. (2024). Artificial intelligence in classroom discourse: A systematic review of the past decade. *International Journal of Educational Research, 123*, 102275. https://doi.org/10.1016/J.IJER.2023.102275

Xing, W., & Du, D. (2019). Dropout prediction in MOOCs: Using deep learning for personalized intervention. *Journal of Educational Computing Research, 57*(3), 547–570. https://doi.org/10.1177/0735633118757015

Yin, S., Lei, L., Wang, H., & Chen, W. (2020). Power of attention in MOOC dropout prediction. *IEEE Access, 8*, 202993–203002. https://doi.org/10.1109/ACCESS.2020.3035687

Yu, J., Alrajhi, L., Harit, A., Sun, Z., Cristea, A. I., & Shi, L. (2021). Exploring Bayesian deep learning for urgent instructor intervention need in MOOC forums. In A. I. Cristea & C. Troussas (Eds.), *Intelligent tutoring systems, ITS 2021: Lecture notes in computer science* (pp. 78–90). Springer. https://doi.org/10.1007/978-3-030-80421-3_10

Zakaria, A., Anas, B., & Oucamah, C. M. M. (2022). Intelligent system for personalised interventions and early drop-out prediction in MOOCs. *International Journal of Advanced Computer Science and Applications, 13*(9). https://doi.org/10.14569/IJACSA.2022.0130983

Zawacki-Richter, O., Kerres, M., Bedenlier, S., Bond, M., & Buntins, K. (2020). *Systematic reviews in educational research*. Springer VS. https://doi.org/10.1007/978-3-658-27602-7

Zheng, Y., Shao, Z., Deng, M., Gao, Z., & Fu, Q. (2022). MOOC dropout prediction using a fusion deep model based on behaviour features. *Computers and Electrical Engineering, 104*, 108409. https://doi.org/10.1016/j.compeleceng.2022.108409