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The Use of Artificial Intelligence (AI) in Online Learning and Distance Education Processes: A Systematic Review of Empirical Studies

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Abstract: Artificial intelligence (AI) technologies are used in many dimensions of our lives, including education. Motivated by the increasing use of AI technologies and the current state of the art, this study examines research on AI from the perspective of online distance education. Following a systematic review protocol and using data mining and analytics approaches, the study examines a total of 276 publications. Accordingly, time trend analysis increases steadily with a peak in recent years, and China, India, and the United States are the leading countries in research on AI in online learning and distance education. Computer science and engineering are the research areas that make the most of the contribution, followed by social sciences. t-SNE analysis reveals three dominant clusters showing thematic tendencies, which are as follows: (1) how AI technologies are used in online teaching and learning processes, (2) how algorithms are used for the recognition, identification, and prediction of students' behaviors, and (3) adaptive and personalized learning empowered through artificial intelligence technologies. Additionally, the text mining and social network analysis identified three broad research themes, which are (1) educational data mining, learning analytics, and artificial intelligence for adaptive and personalized learning; (2) algorithmic online educational spaces, ethics, and human agency; and (3) online learning through detection, identification, recognition, and prediction.

Keywords: artificial intelligence; deep learning; machine learning; distance education; online learning

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1. Introduction

We live in a technology-intensive digital knowledge age, and artificial intelligence technologies (i.e., machine learning, deep learning) have penetrated every dimension of our lives, including education. Accordingly, artificial intelligence can be used to overcome many challenges faced in online distance education and can be further helpful in optimizing teaching and learning processes [1]. The availability of big data, artificial intelligence technologies' ability to generate their own models, and widespread adoption of learning analytics approaches force us to consider how to effectively use artificial intelligence in education in general and online distance education in particular [2]. Motivated by the current state of the art in artificial intelligence technologies, the main purpose of this paper is to examine the research on artificial intelligence in online distance education.

2. Literature Review

Existing studies on AI and online education have different approaches in terms of methodologies and scope. There are similar studies proposed to examine the literature onAI and higher education. For instance, in their study, Zawacki-Richter et al. [3] investigated 2565 articles published between 2007 and 2008 and, as a result, they analyzed 146 papers after exclusion of irrelevant content. The results of their study showed that the vast majority of academic papers on AI and higher education were from computer science and STEM. The number of relevant papers on the topic peaked in 2018, and 50% of the identified papers come from four major countries: the USA, China, Taiwan, and Turkey. The conclusion of the study mentioned that AI-driven educational technology lacks related psychological and pedagogical learning theories. Similarly, Ouyang et al. [4] conducted a study on a systematic review of empirical research on AI in online higher education on the WoS, Scopus, IEEE, and EBSCO databases. The study examined a total of 434 initially identified articles published between 2011 and 2020. They reported that only 32 research papers out of 434 were empirical research, and 72 of the papers were published after 2016. Their paper reported that educational theories were usually not applied in research on AI in online higher education.

Tang et al. [5], adopting systematic review strategies and co-citation network analysis, examined publication patterns on AI-supported e-learning in the WoS database between 1998 and 2019. The results showed that there were no AI-supported e-learning or related papers from 1998 to 2004. The number of papers on AI-supported e-learning began to increase in 2007, and most of the papers were about intelligent learning systems that give feedback about students' learning status. Their review also showed that there were only a limited number of papers published in the scope of educational and psychological theories integrating AI applications in online higher education. Bozkurt et al. [6] conducted a study to review AI studies from pedagogical and technological perspectives. Their study investigated a total of 276 papers published in the Scopus database. The results of the study showed that there was a dramatic increase in the number of published papers on AI and education by 2018 and 2019. The main fields of the publications were computer science, engineering, mathematics, and social sciences. The paper asserted that there is a lack of literature on AI applications in education and that there is a need to focus more on ethics, as also suggested by Tang et al. [5] and Zawacki-Richter et al. [3]. To lessen the gap in the related literature on AI and ethics, Casas-Roma and Conesa [7] conducted a literature review focusing on AI and ethics in online learning. As a result, their paper suggested that the integration of AI into online learning in higher education institutes should provide a fair, accessible, and quality education for all of society. Nassoura [8] investigated faculty members' opinions about AI as a teaching and learning tool. The results of the study revealed that 40% of the papers published by the top three educational technology journals were hypothetical.

The review of previous studies revealed that research on AI in online learning in higher education had a noticeable increase after 2007, and most of the papers published in the databases show that research on AI in higher education lacks educational and psychological theories. The vast majority of the papers published about AI and higher education or online education are from the computer science or engineering field, focusing on technological implementations of AI in higher education. Based upon the above arguments and gaps identified in the related literature, the purpose of this study is to systematically review empirical papers on AI in online distance education. In this context, the paper seeks answers to the following research questions. What are:

1. the general bibliometric outlook and;
2. the research trends and patterns in the sampled publications?

3. Methods

3.1. Research Design

In order to systematically review [9] and investigate the use of artificial intelligence technologies in online distance education, this study benefited from traditional bibliometric analysis [10] and data mining and analytic approaches [11], such as social network analysis [12], text mining [13], and t-distributed stochastic neighbor embedding (t-SNE) [14]. The rationale for using different approaches was to triangulate the research data [15] and, thus, increase the validity and reliability of the study.

3.2. Inclusion Criteria and Sample

The peer-reviewed publications that were included in the research corpus met the following criteria: (1) they had the search queries in their titles (Table 1), (2) were indexed by Scopus, and (3) were written in English. The rationale for including publications that have the search queries in their titles was to identify peer-reviewed publications with a strong focus on the research in question and whose primary objectives align with the overall purpose of this study. The justification to use Scopus was its being the largest database [16], covering most of the publications already indexed by other databases such as Web of Science (WoS) and the Education Resources Information Center (ERIC). Lastly, sampling publications written in English enables conducting of valid and reliable visual analysis because text-mining analysis can be better performed to identify lexical relations in the textual data when the research corpus consists of papers written only in one language.

Table 1. Information on the research corpus and search queries adopted for the inclusion criteria.

Research Corpus	
Database	Scopus
Period	1999–2022
Search Queries	
Subject-specific queries	TITLE ("artificial intelligence" OR "machine learning" OR "deep learning")
Boolean search parameter	AND
Field-specific queries	TITLE ("distance education" OR "distance teaching" OR "distance learning" OR "remote education" OR "remote learning" OR "remote teaching" OR "online education" OR "online learning" OR "online teaching" OR "online course" OR "elearning" OR "e-learning" OR "m-learning" OR "edtech" OR "educational technology")

During the processes of sampling and generation of the research corpus, the study adopted the PRISMA protocol (Table 2) [17], and the final phase included a total of 276 publications.

Table 2. The PRISMA Protocol.

Identification	The total number of identified documents on Scopus (n = 301)
Screening	Documents in other languages excluded (n = 2)
	Non-empirical documents excluded (total n = 18; book chapter [n = 16], editorial [n = 5], book [n = 1], erratum [n = 1])
Included	A total of 276 papers (142 articles; 134 conference publications) included in the final research corpus.

3.3. Data Analysis and Research Procedures

With an assumption that the title, abstract, and keywords represent the very essence of academic publications, this paper examines articles through four lines of data analysis procedures. First, traditional bibliometric analysis techniques are used to provide a general outlook for the research corpus. Second, t-SNE analysis [14] is used to examine the titles of the sampled publications and identify the broad tendencies of AI in online distance education studies. Third, the abstracts of the sampled studies are examined through text mining [18] to visualize a thematic map. Finally, social network analysis [12] is used to identify the significant keywords. Both text mining and social network analysis outputs were used to identify broad research themes in the sampled publications.

3.4. Strengths and Limitations

The strengths of this study lie in it using innovative analytical approaches, which were helpful to analyze the large volume of textual data and then visualize them. However, the current study also acknowledges some limitations. First, although Scopus is the largest database, it does not index and include all publications on the research in question. Therefore, the researchers of this study acknowledge that the findings of this study still present a partial overview. Second, due to technical reasons, only publications written in English were included in the final research corpus; however, publications in other languages can still provide a complementary overview.

4. Findings and Discussions

4.1. A General Bibliometric Outlook

In order to capture a holistic perspective within the scope of this study, the authors did not set a specific time framework. Accordingly, from 1999 to 2022, the research corpus includes publications spread over more than two decades. Over 276 publications, a total of 769 authors contributed to the literature on AI in online distance education studies. Of these, 42 of the publications are single-authored.

As shown in Figure 1, though studies on artificial intelligence in online distance education date back to the late 1990s and early 2000s, interest started increasing in the second decade of the 2000s, with a notable focus by 2015 and a peak by 2021.

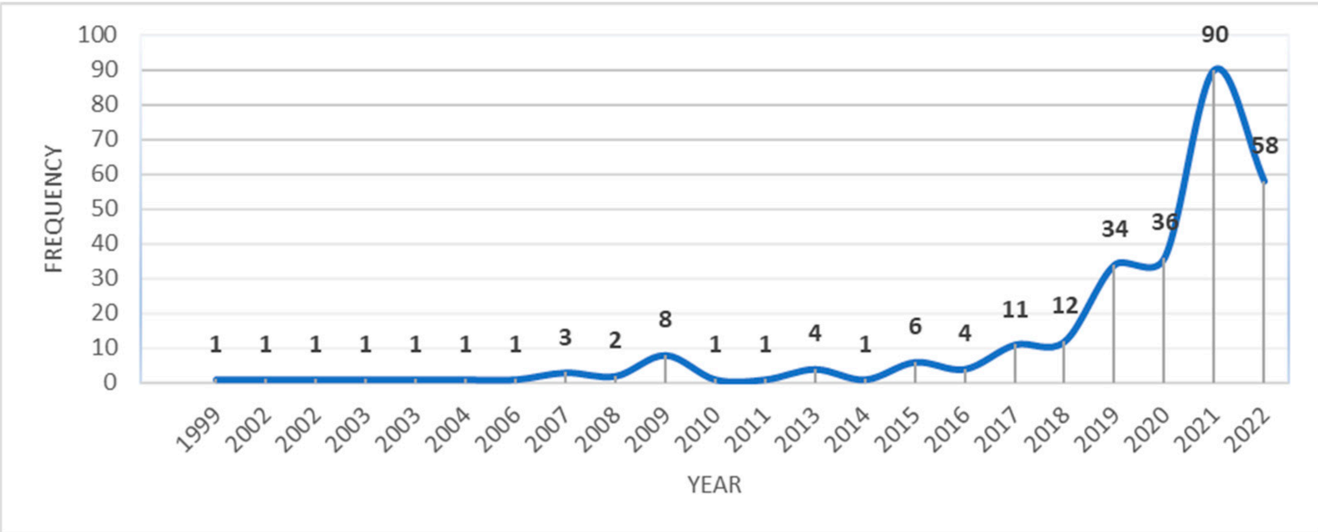

Figure 1. Time trend of AI in online distance education publications.

The most-cited publications are usually on predicting behaviors and designing interventions, respectively (see, for example, [19–21]). The most productive countries are China (n = 88), India (n = 46), and the United States (n = 17) (see Figure 2).

In terms of disciplinary outlook, the top five subject areas constituted most of the research corpus (see Figure 3). Expectedly, technical subject areas such as computer science, engineering, and mathematics outweigh other research areas. Surprisingly, only around 13.3% of studies are in social sciences. This finding implies that most of the publications have a specific interest in the technical dimensions and less interest in pedagogical aspects.

4.2. Research Trends and Patterns

4.2.1. Analysis of the Titles

t-SNE is an unsupervised “nonlinear dimensionality reduction technique that aims to preserve the local structure of data” [14] (p. 2580), used for exploring and visualizing high-dimensional data. To reveal the foci of the publications, t-SNE analysis was conducted using textual data extracted from the titles of the publications included in the research corpus (Figure 4). Accordingly, there are three dominant clusters. The green cluster highlights that AI technologies are used in online teaching and learning processes. The patterns in the green cluster are in line with the Horizon Report [1], which highlights the widespread use of AI technologies, especially in higher education, and further reports that "AI is appearing throughout higher education teaching and learning, in domains such as learning management systems, proctoring, grading/assessment, student information systems, office productivity, library services, admissions, disability support, and mobile apps to name a few" (p. 13). The blue cluster indicates how algorithms are used for the recognition, identification, and prediction of students' behaviors. For instance, Wang [22] studied emotion recognition in college students' online learning engagement and reported that deep learning techniques can be effective. Ganidisastra and Bandung [23] argue that deep learning techniques through face recognition can be used for m-learning online exam proctoring. Feng et al. [24] found that academic emotion recognition can be performed in online learning environments as a psychological indicator of the learners. Wang et al.'s [25] study argued that learning performance can be predicted by using machine learning techniques. Likewise, Luo et al. [26] also reported that machine learning techniques can be used effectively to predict learning outcomes in a blended learning environment. Finally, Park and Yoo [27] found that machine learning can be used for early dropout prediction among learners in online learning environments. The final, pink cluster is about adaptive and personalized learning empowered through artificial intelligence technologies. Srisa-An and Yongsiriwit [28] noted that machine learning can be effectively used for enabling personalized learning. Chetyrbok et al. [29] argue that artificial intelligence technologies promise a lot for adaptive learning and, confirming this view, Adnan et al. [30] found that deep learning techniques demonstrate a significant effect on adaptive learning. In brief, all these clusters indicate that artificial intelligence can be used for online distance education and further imply that there is an algorithmic future that requires approach with caution and conducting of more multidimensional research before fully integrating these technologies into online distance education processes.

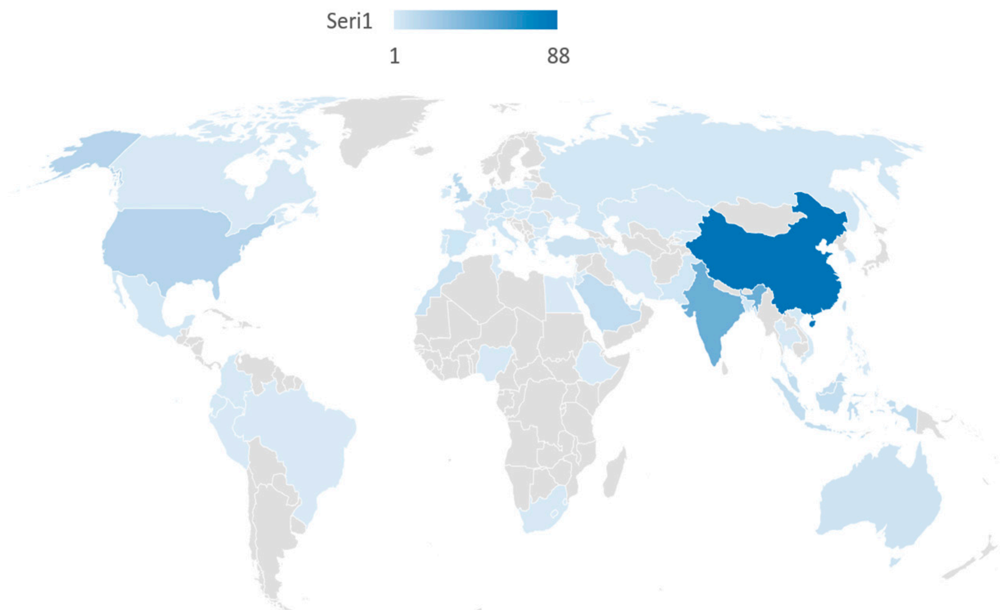

Figure 2. Geographical distribution of AI in online distance education publications.

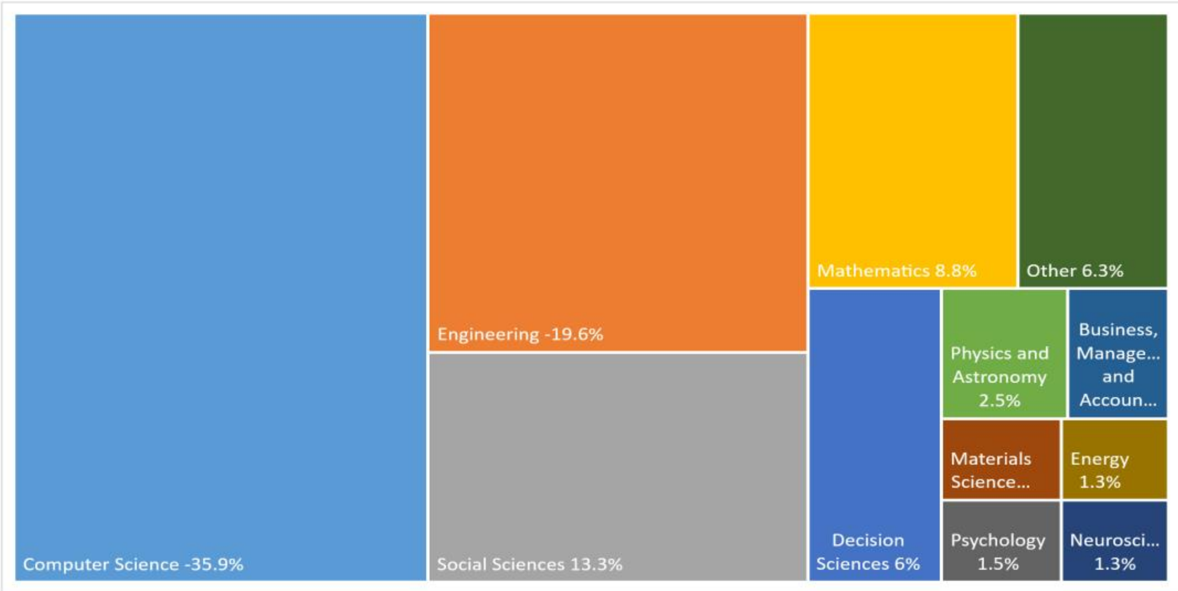

Figure 3. Subject areas of the publications on AI in online distance education (one publication can be coded for more than one subject area).

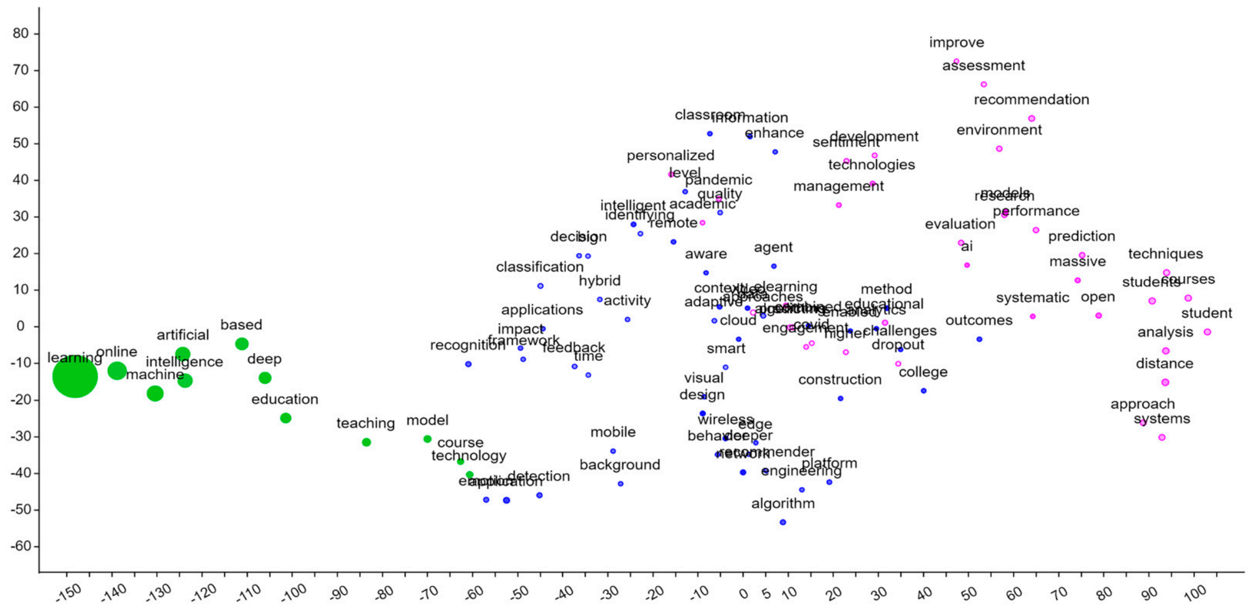

Figure 4. t-SNE analysis of the titles of the sampled publications.

4.2.2. Analysis of the Abstract and Keywords

This section proposes broad emerging research themes identified using the text-mining outputs of the abstracts (see Figure 5) and social network outputs of the keywords (see Figure 6). For text mining of the abstracts, the researchers performed a lexical analysis that employs "two stages of co-occurrence information extraction—semantic and relational—using a different algorithm for each stage" [18] (p. 262). Thus, text-mining analysis enabled the researchers to identify hidden patterns and visualize them on a thematic concept map. Keywords are the granular representatives, and, for the analysis of the keywords, SNA was used. SNA "provides powerful ways to summarize networks and identify key people, [entities], or other objects that occupy strategic locations and positions within a matrix of links" [12] (p. 6). In this study, the keywords were analyzed based on their co-occurrences and visualized on a network graph. By doing this, the authors were able to identify strategic keywords and analyze them accordingly. The emerging themes are reported by providing traces from Figures 5 and 6 and then discussed, benefiting from the related literature.

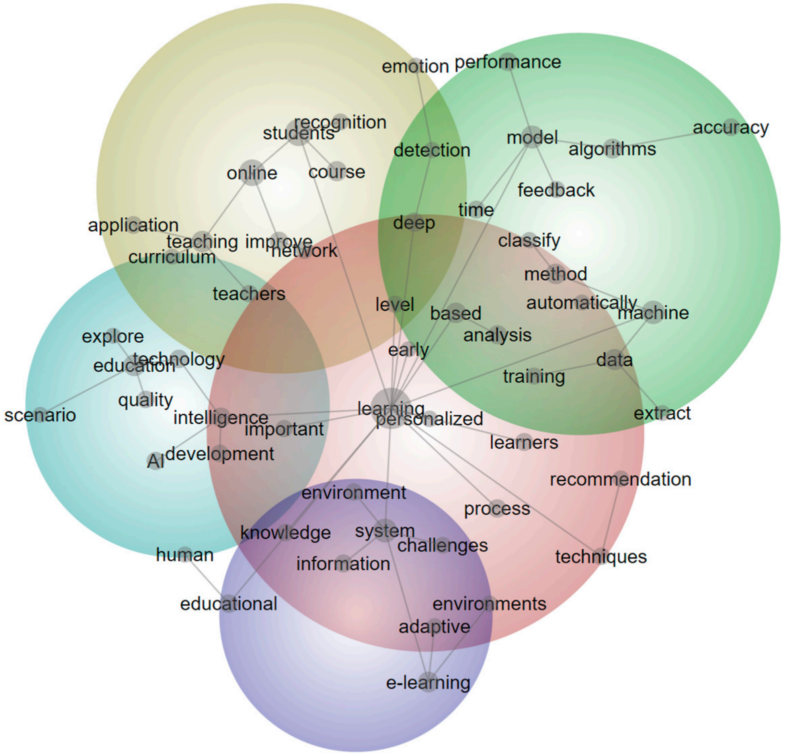

Figure 5. Concept map of abstracts visualized through text mining.

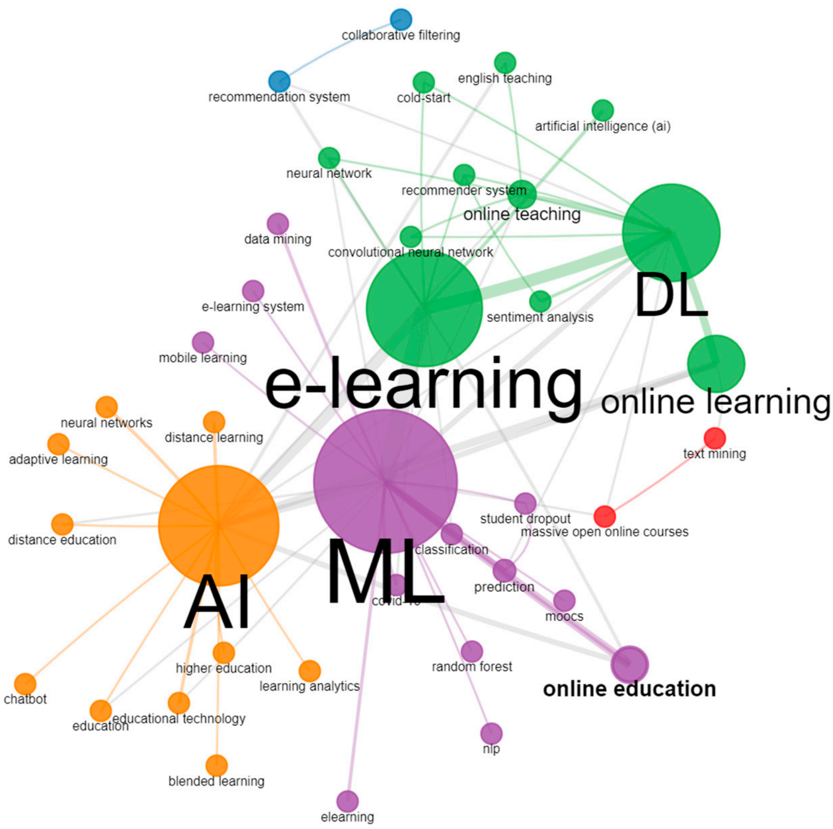

Figure 6. Social network analysis of the keywords.

Educational data mining, learning analytics, and artificial intelligence for adaptive and personalized learning (see the connected paths in Figure 5: *AI, intelligence, learning, personalized, system, e-learning, adaptive, environments;* see the connected nodes in Figure 5: *adaptive learning, AI, learning analytics, educational technology, higher education* and *data mining, machine learning, classification, prediction, online education* and *online learning, deep learning, e-learning, recommendation system*).

The first theme identified by the analysis was educational data mining, learning analytics, and artificial intelligence for adaptive and personalized learning. Educational data mining (EDM) is an emerging interdisciplinary research field dealing with the development of methods for examining educational data [31]. Data mining in education is an alternative for exploring data with the goal of extracting knowledge and useful information to make teaching and learning more efficient [32]. The rapid growth and availability of large volumes of data in education show that the distillation of vast amounts of data requires increasingly sophisticated technologies, such AI and AI-powered algorithms. The field of EDM, which emerged from the aforementioned needs [33,34] demonstrated a capacity increase with the use of AI technologies. Conventional algorithms for data mining cannot be applied to educational problems directly, because they often have a peculiar function and goal [35] (p. 15991). EDM is concerned with all kinds of data coming from educational environments, which create a base and further promote another concept, dealing with collection, measurement, analysis, and reporting of data about learners and their contexts for the purpose of understanding and optimizing learning and learning environments, known as learning analytics (LA) [36] (p. 2).

LA focuses on analysis of data on educational environments to improve teaching and learning activities [37–39]. Salas-Pilco et al. [40] categorize LA into two analytic approaches: (1) descriptive analysis, which focuses on the data-based actions learners leave behind when they use digital tools or interact on online platforms, and (2) predictive analysis, which uses learner behavioral data, historical data (e.g., previous course grades), and sociodemographic data to predict educational outcomes such as dropout rates. However, the use of AI raises many critical questions about the role and competencies of teachers and the role of students as autonomous, self-directed learners. In current adaptive learning environments, learning activities occur as individualized, personalized learning experiences [41].

The related literature also supports the above-mentioned arguments. For instance, in their study, Lin et al. [42] used data mining algorithms for customizing learning environments to create personalized learning for a creativity course, and participants in their study achieved a 90% chance of having higher-than-average scores in the personalized learning environment designed with the help of AI. Similarly, Garrido and Onaindia [43] utilized AI for the planning and construction of personalized e-learning routes for learners by creating learning objects, and their findings showed that using AI for planning the study of learners makes it easier to have a personalized learning route for learners. Likewise, many other studies show that utilizing AI and machine learning through EDM and LA brings success to the planning and construction of personalized learning environments, especially in e-learning. In sum, AI has empowered EDM and LA approaches and paved the way for adaptive and personalized learning.

Algorithmic online educational spaces, ethics, and human agency (see the connected paths in Figure 5: *AI, intelligence, learning, model, algorithms* and *learning, machine, automatically, method, classify, training, data, extract* and *human, educational, knowledge, environment*; see the connected nodes in Figure 5: *neural networks, AI, machine learning, online learning, deep learning, sentiment analysis, recommender system, e-learning*).

The second theme identified was algorithmic online educational spaces, ethics, and human agency. Algorithmic online educational spaces refer to learning environments that utilize AI and machine learning techniques for implementation and design of the learning environment. Using AI has advantages in creating a success path for learners. AI can provide the learner an enhanced learning experience with personalized features leading to better learning outcomes [44]. AI-driven learning experiences in online learning environments, such as massive online open courses (MOOCs), utilize machine learning algorithms (ML) to track learner actions for enhancing learners' performance. Processing large amounts of learning data with ML algorithms can clarify the relationship between learning behavior and effectiveness and create efficient paths with a recommender system making decisions for learners in online learning [45].

However, there are serious constraints on the way these algorithms function when using educational data to make decisions [46]. Algorithmic decision-making should be considered within the social structure which algorithms are designed for and function in [47]. Studies in this context show that the data used to train models for prediction of educational data in AI-driven systems may have strong bias and create inequalities in online education [47–49]. In AI-driven systems, the quality of data used by the algorithms can be poor or biased, or unjustified decisions can be made. The decisions may also lack equality and fairness for social groups [7,50]. The unequal or unfair decisions made by algorithms are not easy to track. In short, AI-driven learning designs utilizing ML algorithms to provide better learning experiences can also have ethical problems when functioning due to the algorithms' way of working and create inequalities for learners in online learning environments. Finally, it is perhaps more important to ask, if we design a learning environment based on AI-powered decision-making processes, what is the value of human agency, and how should we position learners in an algorithmically woven learning space?

Online learning through detection, identification, recognition, and prediction (see the connected paths in Figure 5: *teaching, online, students, recognition* and *recommendation, techniques, learning, based, analysis* and *learning, deep, detection, emotion*; see the connected nodes in Figure 5: *machine learning, classification, prediction*).

The third theme revealed was online learning through detection, identification, recognition, and prediction. Using machine learning and deep learning in online education provides teachers with the ability to create personalized recommendation systems (RS) by analyzing vast amounts of data about the learners. Intelligent personalized recommender systems use various recommendation technologies to direct resources to users based on their characteristics or preferences, such as interests, hobbies, occupations, and professional attributes [51].

In online learning environments, RS may suggest onboarding activities prior to attempting learning modules. Through detection and recognition of individuals' learning interests, RS provides personalized recommendations of learning paths and materials [52]. However, some RS provide highly accurate recommendations, and they can also be useless in some real-life scenarios for online learning. Therefore, to overcome the ineffectiveness of such recommendations in an e-learning environment, a good RS should be socially situated. A good RS should also be able to track, understand and model the different stages of the learner's acquisition of knowledge [53]. In brief, ML algorithms and DL are used to recognize and analyze individuals' learning behaviors to provide personalized recommendations for a better online learning experience. RS are crucial for providing personalized learning paths and materials that can increase the effectiveness of learning in e-learning environments.

5. Conclusions and Implications

This study examined artificial intelligence in online distance education through a systematic review approach. Accordingly, the research found that there is increasing research interest and a wide range of use of artificial intelligence technologies which further necessitates examining the use of artificial intelligence from different perspectives. The findings indicate that there is a high reliance on artificial intelligence technologies and algorithmic future scenarios await us. The research proposed three broad research themes, which were (1) educational data mining, learning analytics, and artificial intelligence for adaptive and personalized learning, (2) algorithmic online educational spaces, ethics, and human agency, and (3) online learning through detection, identification, recognition, and prediction.

Based on the findings of the study and impressions gained through the reviewed publications, the following implications can be considered for future research directions. First, most of the artificial intelligence applications in online distance education are purely technical studies that ignore issues such as pedagogy, curriculum, and instructional/learning design. However, these applications should center on human agency and merge the technical processes through theory and practice. Second, although artificial intelligence technologies use human-generated data, there is a lack of regulation on how to use these data and how to apply artificial intelligence ethics. In this regard, it is suggested that future research can focus on this issue, and it is believed that developing policies and strategies is a high priority for educational institutions to better benefit from artificial intelligence technologies and design human-centered online learning processes.

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