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A Systematic Review of Application of Machine Learning in Curriculum Design Among Higher Education

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***Abstract*— Machine learning has become an increasingly popular area of research in the field of education, with potential applications in various aspects of higher education curriculum design. This study aims to review the current applications of AI in the curriculum design of higher education. We conducted an initial search for articles on the application of machine learning in curriculum design in higher education. This involved searching three core educational databases, including the Educational Research Resources Information Centre (ERIC), the British Education Index (BEI), and Education Research Complete, to identify relevant literature. Subsequently, this study performed network analysis on the included literature to gain a deeper understanding of the common themes and topics within the field. The results showed a growing trend in publishing research on the application of machine learning within the educational domain. Our review pinpointed merely 11 publications specifically targeting the application of machine learning in higher education course design, with only three being peer-reviewed articles. Through the word cloud visualization, we discerned the most prominent keywords to be AI, foreign countries, pedagogy, online courses, e-learning, and course design. Collectively, these keywords underscore the significance of AI in molding the educational landscape, as well as the expanding tendency to incorporate AI technologies into online and technology-enhanced learning experiences. Although there is a significant amount of research on the application of machine learning in education, the literature on its specific use in higher education course design still needs to be expanded. Our review identified only a small number of studies that directly focused on this topic, and among them. The network analysis generated from the included literature highlights important themes related to student learning and performance and the use of models and algorithms. However, there is still a need for further research in this area to fully understand the potential of machine learning in higher education course design. This study would contribute literature in this specific field. The review can update teacher's awareness of using machine learning in teaching practice. Additionally, it implies more and more researchers conduct related research in this area. Future studies should consider the limitations of the existing literature and explore new approaches to incorporate machine learning into curriculum design to improve student learning outcomes.**

Keywords—Machine Learning, Computer System, Curriculum Design, Review

I. INTRODUCTION

Several sources define curriculum design. According to McKimm, curriculum is sometimes misunderstood for the syllabus when it is actually the planned sequence of learning experiences leading to defined outcomes. The International Education Association of Australia defines it broadly as "*anything that shapes the student's learning experience*" [1,2]. Curriculum design entails integrating educational philosophy and theory into practical and coherent learning experiences in a school or educational institution. This involves assessing students' needs, teachers' skills, and the learning environment [3]. Content, teaching and learning methods, assessment, and evaluation must be organized logically and consistently.

Various theories have been proposed regarding curriculum design. As depicted in Figure 1[4], the central circle represents the core goals of curriculum design, which are crucial in determining the purpose of a course and the outcomes students can expect. Surrounding the core are Content and Sequencing, Format and Presentation of Material, and Monitoring and Assessment. The three circles connected to the core represent principles, needs, and environment.

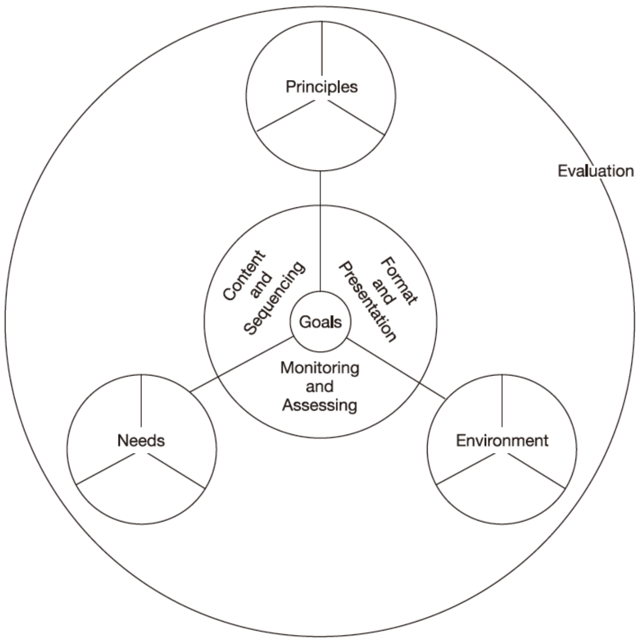

Figure 1. A model of the parts of the curriculum design process [4]

In terms of principles, four examples include learners should obtain an immediate and useful return on their learning, avoid interference, employ thoughtful processing, and engage in fluency practice. Learners' needs analysis primarily focuses on the curriculum goals and its content of a course. It is to examine what learners have already learned and what they still need to learn in the following classes. This analysis ensures that the course contains the relevant and supportive learning materials. The effective learners' needs analysis involves inquiring about the correct questions and finding out the corresponding answers in the most efficient approach.

Environment analysis [4] examines factors that strongly influence decisions about the course goals, content, teaching methods, and assessment. These factors can arise from the learners, teachers, and the overall teaching and learning situation. In the outer circle, evaluation assesses all aspects of curriculum design to determine if the course is optimal (which is why the outer circle encompasses all elements of the curriculum design process). Evaluation entails examining both the course outcomes and the planning and implementation of the course [5]

Chang et al. propose a five-stage analysis method for curriculum design consisting of Extract, Transform, Load (ETL), Analysis, Visualization, Intervention, and Expansion & Refinement [6]. In the first stage, ETL, school data is extracted and transformed for analysis. Student grades are then analysed using descriptive statistics, inferential statistics, and data mining to identify trends, correlations, and patterns. Visualization is used to represent these trends and phenomena in data or analysed results using tools such as 3D graphs, tables, charts, geographical maps, or association networks. Domain knowledge is required to create interventions, which are submitted to the committee for further improvements in curriculum design. Finally, actions are taken from different dimensions, such as data modelling and data collection from social media, to expand and refine the curriculum design.

The process of curriculum design is complex and multifaceted, involving careful planning, implementation, and evaluation to create effective educational programs [6]. This process is particularly nuanced when integrating modern technologies such as Artificial Intelligence (AI) and adopting interdisciplinary approaches. Curriculum design includes several critical stages. It needs assessment, goal setting, content selection, organization, implementation, and evaluation [3,6]. Needs assessment identifies the educational requirements and gaps, while goal setting defines the objectives that the curriculum aims to achieve. Content selection and organization involve choosing relevant materials and structuring them coherently to facilitate learning. Implementation focuses on delivering the curriculum effectively, and evaluation assesses the program's success and areas for improvement. In summary, curriculum design is a purposeful development of educational content, instructional techniques, learning experiences, and assessment procedures. Various frameworks and analysis methods are proposed to guide curriculum designers in creating effective courses for learners.

Machine learning is an artificial intelligence technology that enables computer systems to learn from experience and make predictions [7]. It is a subset of AI in which algorithms and statistical models to analyse are used to evaluate and interpret, allowing the machine to learn and develop on its own [7] Machine learning algorithms are built to operate with enormous volumes of data and may spot patterns and correlations in data that people would find difficult or impossible to discern.

Machine learning began in the 1950s with artificial intelligence [8, 9]. Researchers created algorithms and models that could play chess or solve math issues [10]. However, these early models did not learn from experience, a critical machine learning trait [11]. Researchers created data-learning algorithms and models. Late 1960s–early 1970s [12]. Machine learning was born, and researchers and practitioners immediately adopted it [12]. Throughout the next few decades, academics developed decision trees, neural networks, and supported vector machines to advance machine learning [13]. Big data and the inability of powerful computer system in the 1990s and 2000s boosted machine learning [14]. These advances let researchers develop larger, more complex models for picture and speech recognition [15]. Recommendation systems and fraud detection have helped machine learning grow [16]. Researchers and practitioners are creating deep learning and reinforcement learning algorithms and models to further machine learning [17]. These models are used in a wide range of applications, including computer vision, natural language processing, and robotics.

Machines learning algorithms are classified into numerous types, including supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. Supervised learning algorithms are used for classification and regression tasks and are learned using labelled data. Supervised learning involves training algorithms on labelled datasets to predict outputs for given inputs. Examples of such algorithms include linear regression, logistic regression, decision trees, and random forests [18].

Unsupervised learning includes k-means clustering, principal component analysis (PCA), and deep neural networks [19]. Reinforcement learning is a sort of machine learning in which the algorithm discovers new information through trial and error [20]. Semi-supervised learning is a blend of supervised and unsupervised learning. The algorithm is trained on a mixture of labelled and unlabelled data, using the labelled data to make predictions and the unlabelled data to identify patterns and structures [21].

Each type of machine learning algorithm has its own strengths and weaknesses [22, 23], and the choice of which one to use depends on the specific problem at hand. Some of the most used machine learning algorithms include decision trees, support vector machines, k-nearest neighbours, Naive Bayes, and artificial neural networks. Deep learning algorithms, such as convolutional neural networks and recurrent neural networks, have grown in recent years popular due to their capacity to learn from massive volumes of data [24].

Regardless of the specific type of algorithm used, machine learning has the potential to greatly improve the accuracy and efficiency of decision-making in many applications, including in the field of education and curriculum design [25, 26]. In the age of big data, learning analytic has become increasingly important, as institutional experts use complex formulas to decide admissions and improve student retention and success [27]. This method combines data, statistics, and predictions to provide helpful information [28].

Machine learning algorithms find patterns in student data like exam results, attendance, and feedback [29]. This data can be utilized to create individualized learning programs and give students real-time feedback to track their progress and alter their learning tactics. Machine learning has made education dynamic and data-driven, allowing educators to make informed decisions regarding student performance and tailor courses based on data. Machine learning can automate time-consuming procedures, freeing educators to focus on more important instructional responsibilities [30].

Students who receive one-on-one tutoring demonstrate performance improvements equivalent to two standard deviations compared to those participating in conventional educational methods [31].

Machine learning has emerged as a critical component in personalized learning, altering educational delivery to accommodate individual needs and preferences [32, 33] and creating separate learning pathways for students [34]. Educators may now develop adaptive learning systems that suit to each student's unique learning style, pace, and talents by leveraging the capabilities of machine learning algorithms, resulting in a more focused and efficient educational experience [35].

Machine learning in personalized learning encompasses intelligent teaching systems, autonomous learning material, learning progress organization, and group cooperative learning [36]. It evaluates curricular resources and enables adaptive learning and recommendation engines to advance learning analytics. These platforms analyse vast volumes of student performance, engagement, and learning preferences. Analysing this data reveals patterns and trends, enabling customised learning paths for each learner [37]. Machine learning algorithms can assess student performance, interests, and preferences, recommending relevant and engaging learning materials like articles, videos, and quizzes [38]. This ensures that students receive content that is appropriate for their ability level and matches with their interests, ensuring that students remain motivated and engaged throughout the learning process.

Machine learning can also be employed to evaluate and predict student performance [39]. Analysing historical data allows algorithms to identify patterns and trends in student performance, which can be used to forecast future performance [40]. This information helps identify at-risk students and provide targeted interventions, ensuring necessary support for success.

Numerous machine learning-based systems have been developed for personalized learning, such as Adaptive Learning Systems, E-learning Systems, Intelligent Tutoring Systems (iDRIVE, CSAL, AutoTutor Operation ARA/ARIES), Dyslexia Adaptive E-Learning Management System (DAELMS), and Adaptive Self-regulated Learning Questionnaire (ASRQ), all of which cater to personalized learning experiences [41-45].

Real-time feedback relies on machine learning. Machine learning algorithms examine data, find trends, and provide quick feedback to improve performance. Machine learning can assess student performance, track engagement, and identify misconceptions, enabling tailored guidance and support. Real-time feedback helps students identify problems, improve their comprehension, and improve learning results. This feedback can also help teachers better meet students' needs.

Machine learning-based instructional software provides real-time feedback to pupils. Kaburlasos et al. [46] proposed a prototype software platform named Platform for Adaptive and Reliable Evaluation of Students (PARES) for student testing and evaluation. Ross et al. [47] used consumer RGB-D sensor data to classify students as attentive or inattentive using machine learning methods (K-means and SVM). Nguyen et al. [48] suggest dense solution space sampling in highly organized MOOC homework assignments for large-scale feedback. Hence, the researchers proposed "code words" to classify online assignment submissions. They constructed a searchable index using this terminology to quickly search the enormous dataset of student homework submissions [48]. Sivakumar et al. [49] suggested a new method for assessing Twitter API student feedback by detecting semantic relatedness between aspect terms and student opinion phrases. Uskov et al. [50] reported on a Bradley University (Peoria, IL, USA) research and development effort that set up and benchmarked eight machine learning algorithms for predictive learning analytics to forecast student academic success in a course. Lastly, Wu et al. [51] addressed the "zero-shot" feedback difficulty with a human-in-the-loop "rubric sampling" strategy.

Data-driven teaching, which utilizes machine learning algorithms to analyse student performance data, enables educators to make informed decisions, personalize learning experiences, and optimize instructional strategies. In particular, adaptive dialogue systems and natural language generation, studied by Rieser et al. [52] represent a data-driven methodology for dialogue management.

Through the analysis of vast amounts of data, such as historical grades, attendance records, and engagement metrics, machine learning algorithms can identify patterns and correlations that may impact academic success, as evidenced by Iqbal et al. [53] and Adnan et al. [54]. This information allows educators to identify at-risk students and provide targeted interventions and support to improve performance and reduce dropout rates. By leveraging this data, educators can refine their teaching techniques, adapt curricula, and implement best practices to enhance learning outcomes [55].

Vrakas et al. [56] showcased PASER, an innovative system that automatically synthesizes curricula by employing AI Planning and Machine Learning techniques. This is based on an ontology of educational resources metadata, which has the potential to revolutionize curriculum development. In the realm of game-based learning, Wallace et al. [57] described two projects from the MLeXAI, demonstrating the potential for AI and machine learning to enhance educational gaming experiences. The IBM AutoAI Playground, as described by Wang et al. [58] is a pioneering system that empowers non-technical users to define and customize their business goals, showcasing the increasing accessibility of AI technology. Lastly, Chamunyonga et al. [59] reviewed AI and ML applications in radiation therapy courses and suggested considerations for enhancing radiation therapy curricula.

II. METHOD

We undertook a thorough and extensive review of peer-reviewed literature that focuses on the application of machine learning in higher education course design. As an integrative review, we aimed to include a wide range of research designs to gain a comprehensive understanding of this emerging field. By including studies that employ different research methods and approaches, we were able to synthesize a diverse range of perspectives and insights on the use of machine learning in higher education. This allowed us to explore not only the benefits and challenges of incorporating machine learning into course design, but also the various ways in which it can be applied and the potential implications for teaching and learning.

A. A preliminary search in Web of Science for the use of machine learning in education

To generate an overview of the use of machine learning in education over the past 20 years, we conducted a systematic search of (database) using the preliminary search term (“education”, “machine learning”) up to July 2024. After filtering the results based on inclusion and exclusion criteria, we extracted data on the number of articles published each year that focused on machine learning in education. We then plotted these data points on a line graph to visualize the trends in publication frequency over time.

B. Data Sources and Search Strategy

We searched the Education Research Information centre , British education index, and Education Research Complete and Web of Science (WoS)to identify articles addressing machine learning in higher education course design. We developed the search strategy in collaboration with an academic health sciences librarian. The key search terms were ("machine learning") AND ("curriculum design" OR "higher education").

C. Selection of Articles for Review

We conducted a screening process by reviewing the titles and abstracts of all identified articles using the previously established search criteria and subsequently applying the exclusion criteria. Any articles deemed relevant or inconclusive were then assessed in their entirety by reading the full text.

D. Data Extraction

All eligible publications underwent a meticulous evaluation process, from which relevant data was extracted. The extracted data encompassed various aspects such as authorship, year of publication, study type, study quality, participants, subject matter, participant numbers, study objectives, and main findings.

E. Data analysis

This study utilized VOSviewer that allowed to construct and visualize networks by inputting the full text of all relevant articles identified in our review. This software did network visualization-keywords analysis, density visualization-keywords analysis and overlay visualization-abstract and keywords analysis. It analysed the frequency and network relations of keywords and abstracts used in the selected articles. It generated a visual representation of the most frequently occurring keywords and relationships among keywords groups in the form of a keywords network.

III. RESULT

A. A preliminary search in Web of Science for the use of machine learning in education

Figure 2 showed a year-by-year breakdown of the number of publications related to machine learning in the education field from 2003 to 2024. The numbers show a gradual increase in publications from 1,201 in 2003 to 1,9482 in 2018. A particularly striking aspect of the data is the significant surge in publications from 2018 to 2020, with the numbers almost quadrupling from 29,955 in 2019 to 60,435 in 2021. The trend continues to grow in the following years, with 72,900 publications in 2022 and 44,940 in July 2024.

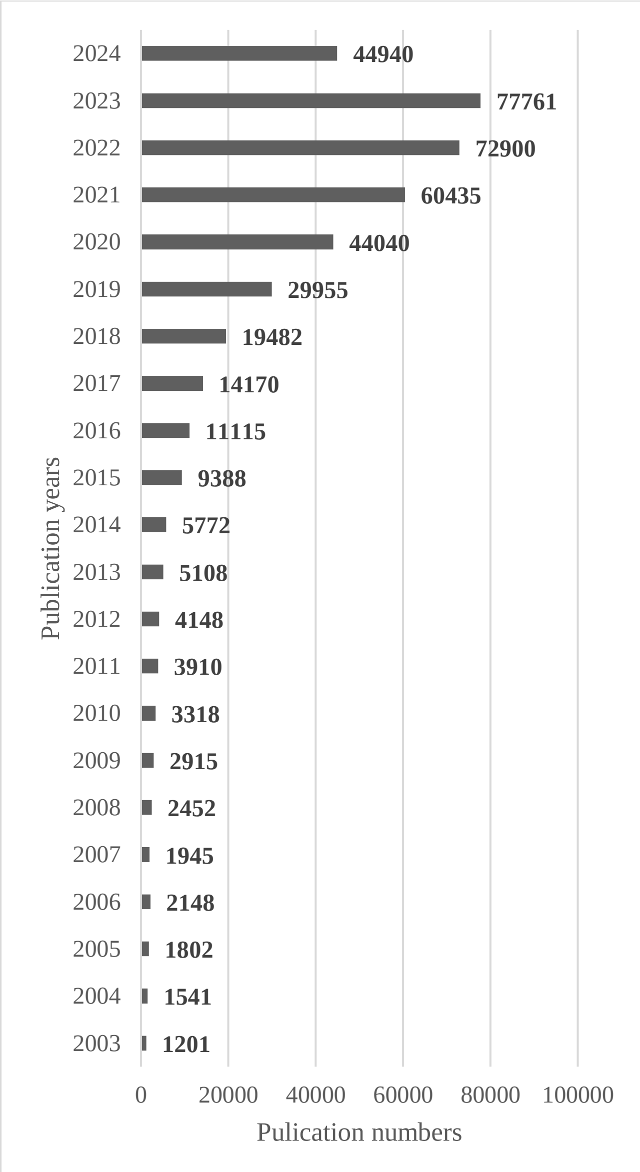

Figure 2. Number of publications on machine learning in education

B. Inclusion and exclusion criteria and searching results

The inclusion and exclusion criteria were shown step by step in Figure 3. The exclusion criteria mainly includes identification, screening, eligibility.

- The inclusion criteria were as follows:
  - The study must focus on the application of machine learning in higher education course design.
  - The study must be published in a peer-reviewed journal or conference proceedings.
  - The study must be published in English.
  - The study must be conducted within the last 20 years to ensure relevance to current practices.
- The exclusion criteria were as follows:

Articles on other aspects of education apart from higher education

- Articles on use of technology (such as online lectures and computer-based education) without incorporation of machine learning (or AI), or articles with only a brief mention of machine learning usage.
- Full texts of articles available in languages other than English

Our search initially yielded 426,261 publications, which were reduced to 21,140 after removing duplicates. We excluded 405,021 duplicates, 18.267 irrelevant articles, 1,942 non-full text ones, 835 articles that did not pertain to machine learning and curriculum design in higher education and 68 papers not mentioned pedagogical application. Out of the remaining 41 articles, we included 28 relevant publications in our review, which provided valuable insights into the application of machine learning in higher education course design (Figure 3).

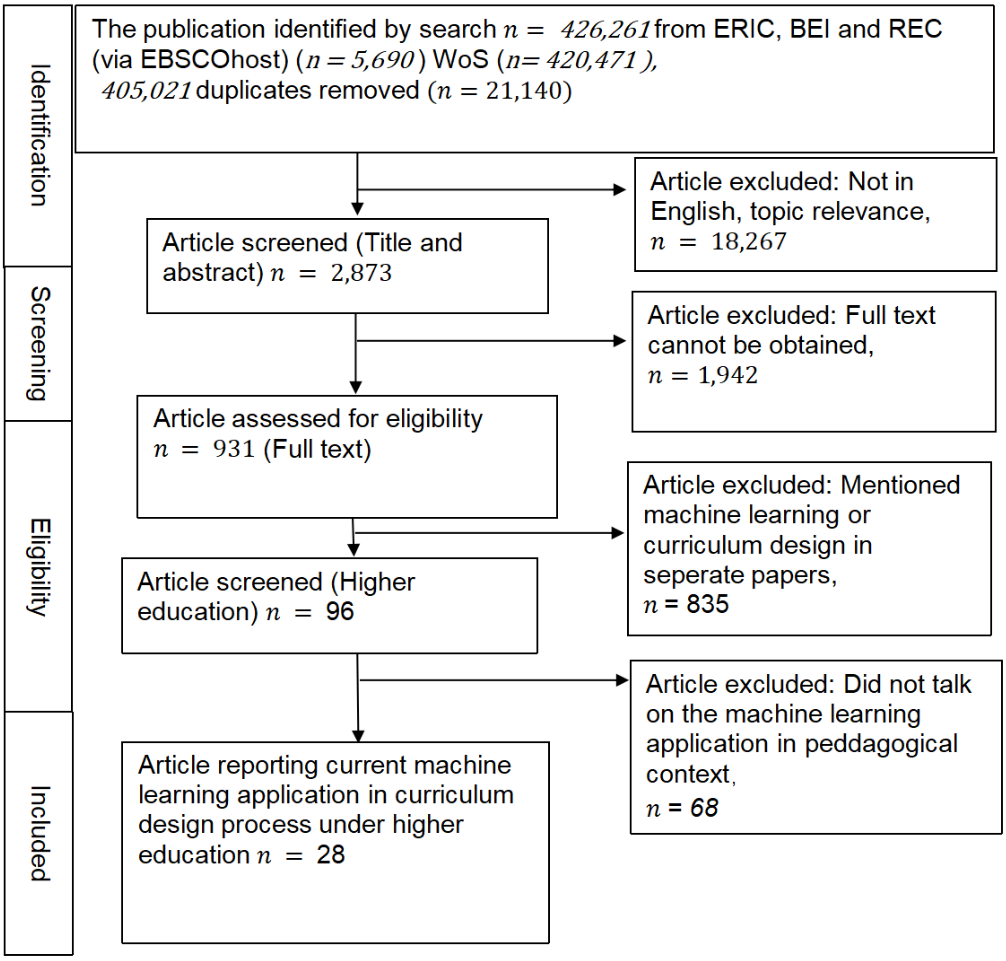

Figure 3. Prisma diagram of included articles in the scoping review.

Based on our review, out of the 11 relevant publications, 3 were peer-reviewed articles, 1 was a review article, and the remaining were conference proceedings. Three of the studies were quantitative research, while one was a qualitative and quantitative research study. The peer-reviewed articles were conducted by Wallace, Maccartney and Russell [57] on game-based AI projects, Musso [60] on predicting student academic performance using ANN. The review article by Kowalska et al., [65] provided a case study of using machine learning-driven classification for analysis of the disparities between categorized learning outcomes. Stadelmann [68] on evaluating the effectiveness of a didactic concept for teaching AI and ML. For a more comprehensive overview of machine learning in higher education curriculum design, the whole selected article in Table 1.

Table 1. The summary of included studies

Studies	Application in curriculum design
Wallace, Meccartney and Russell [57]	Predicting student academic performance compared to traditional methods like discriminant analysis.
Musso and Mariel [60]	The artificial neural networks (ANN) demonstrated higher accuracy in predicting student academic performance compared to traditional methods like discriminant analysis.
Balcioglu and Artar [61]	Predicting academic performance of students with machine learning.
Nawaz et al . [62]	Leveraging machine learning for student survey: actionable insights from textual feedback to enhance quality of teaching and learning.
Dennehy et al. [63]	Adopting learning analytics to inform postgraduate curriculum design: recommendations and research agenda.
Supraja [64]	The research proposes an intelligent model to automatically label practice opportunities (assessment questions) according to the learning outcomes intended by course designers.
(Kowalska et al., [65]	Using machine learning-driven classification for analysis of the disparities between categorized learning outcomes.
Karala rea al. [66]	Predicting students at risk of academic failure using ensemble model during pandemic in a distance learning system.
Chang et al. [67]	The extreme learning machine (ELM) technique evaluates designs integrated into the suitable student monitoring model weighted score (WS) and exam results.
StadelmaN [68]	Providing specific recommendations for adopting technical curricula in various teaching conditions (on-site, hybrid, or online).
Almufarreh et al. [73]	Academic teaching quality framework and performance evaluation using machine learning.
Çağataylı & Çelebi [74]	Estimating academic success in higher education using big five personality traits, a machine learning approach.
Chang et al. [75]	Integration of artificial intelligence and machine learning content in technology and science curriculum.
Villegas-Ch et al. [76]	Machine learning techniques for quality management in teaching learning process in higher education by predicting the student's academic performance.
Ilic et al. [77]	Mchine learning for performance analysis to make changes in higher education.
Go et al. [78]	Machine learning in processing students' e-learning satisfaction.
Elsharkawy e al. [79]	Employability prediction of information technology graduates using machine learning algorithms.
Dipierro and Dewitte [80]	Machine learning approach in analysing effective signals of learning.
Sghir et al. [81]	Predictive learning Go.
Sanchez et al. [82]	Machine learning techniques for quality management in teaching learning process in higher education by predicting the student's academic performance.
Ureel et al. [83]	Active Machine Learning for Chemical Engineers with design learning.
Ibarra-Vazquez et al. [84]	Forecasting gender in open education competencies.
Pelzer & Turner [85]	Generating an interactive machine teacher online to interact with students.
Bruno et al. [86]	Designing a transnational curriculum.
Shang et al. [87]	Interactive teaching using human-machine interaction for higher education systems.
Xiao & Hu. [88]	Using machine learning models to analyse online learning performance.
Kondoyanni et al. [89]	Adding machine-learning functionality to real equipment for water preservation in higher education.
Sheridan and Gigliotti. [90]	Designing online teaching curriculum to optimise learning for all students in higher education.

C. Networks analysis

Figure 4-6 showed a range of keywords, each with their respective attributes, obtained from a word cloud visualization. The keywords are organized into distinct clusters and possess associated weights, average publication years, and total link strengths. These keywords offer insight into various topics and themes connected to machine learning (Artificial intelligence) and education.

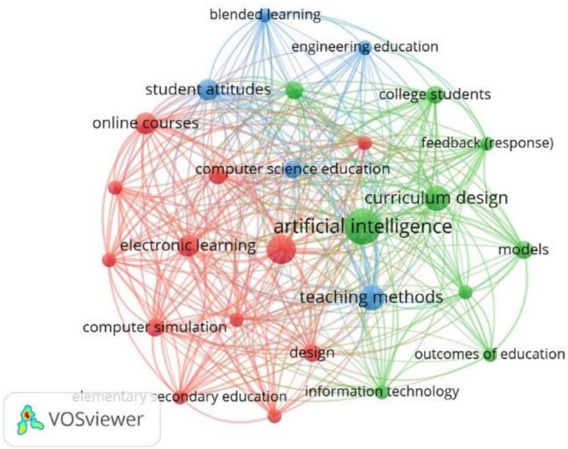

Figure 4. Network visualization-keywords analysis

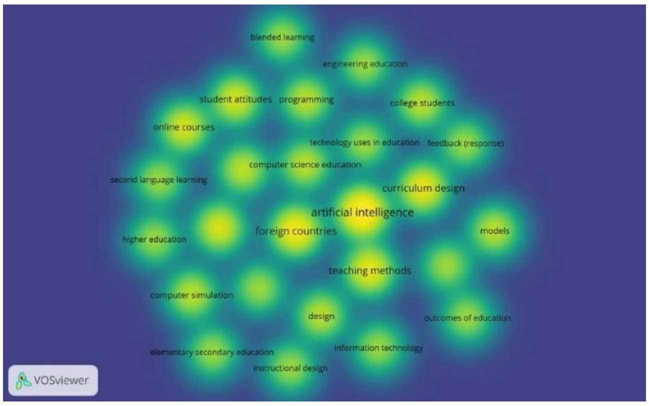

Figure 5. Density visualization-keywords analysis

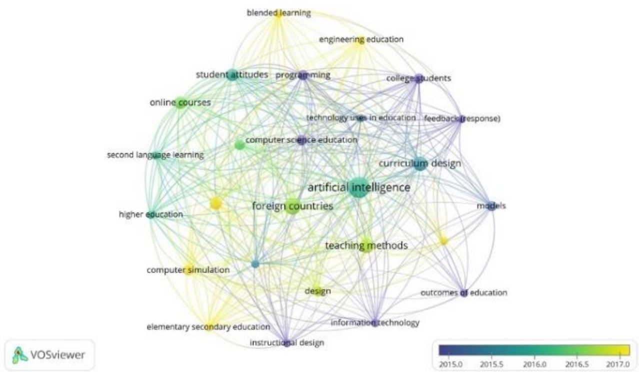

Figure 6. Overlay visualization-abstract and keywords analysis

The word cloud analysis results highlight various key topics in the dataset, including artificial intelligence with an average publication year of 2016 and 10 occurrences, foreign countries with 8 occurrences and an average publication year of 2016.625, and teaching methods with 7 occurrences and an average publication year of 2016.7143. Online courses also feature prominently with 6 occurrences and an average publication year of 2016.5. Other significant topics are electronic learning, curriculum design, student attitudes, educational technology, computer simulation, computer science education, programming, and design. Further areas of interest include faculty development, higher education, second language learning, technology uses in education, college students, elementary secondary education, feedback (response), instructional design, blended learning, information technology, models, engineering education, undergraduate students, and outcomes of education (Table 2).

Artificial intelligence, exhibiting a high total link strength of 117, signifies the importance of AI in the research landscape. Foreign countries as a keyword indicate the desire to examine AI applications and educational practices across different nations. The presence of teaching methods emphasizes the focus on innovative and effective instructional approaches utilizing AI technologies. Online courses suggest a burgeoning trend toward integrating AI technologies into virtual education and e-learning platforms. Similarly, electronic learning underscores the importance of technology-enhanced learning experiences. Curriculum design highlights the strong interest in incorporating AI technologies and principles into educational curriculum development. Lastly, the inclusion of student attitudes implies that researchers are keen on understanding students' viewpoints and experiences with AI technologies in education.

Table 2. Strength of relationships between High-frequency words

label	x	y	cluster	Weight <Links>	Weight <Occurrences>	score<Avg. pub. year>	weight<Total link strength>
artificial intelligence	0.2602	-0.0065	2	25	10	2016	117
foreign countries	-0.1136	-0.1122	1	25	8	2016.625	104
teaching methods	0.3014	-0.3335	3	25	7	2016.7143	94
online courses	-0.7425	0.4685	1	25	6	2016.5	91
electronic learning	-0.5441	-0.0949	1	25	6	2017.3333	88
curriculum design	0.602	0.1265	2	25	7	2015.5714	87
student attitudes	-0.4519	0.6246	3	25	6	2015.8333	83
educational technology	-0.4098	0.2337	1	25	5	2016.4	76
computer simulation	-0.7003	-0.4703	1	25	5	2017	73
computer science education	-0.0629	0.2589	3	25	5	2014.8	72
programming	-0.0561	0.6234	2	25	5	2014.6	71
design	0.0286	-0.5872	1	25	5	2016.8	69
faculty development	-0.3211	-0.4362	1	25	4	2015.5	68
higher education	-0.9092	-0.1608	1	25	4	2016	67
second language learning	-0.8836	0.1721	1	25	4	2016	67
technology uses in education	0.2722	0.3808	1	25	4	2015.25	65
college students	0.5941	0.6052	2	25	5	2013	64
elementary secondary education	-0.5832	-0.7933	1	25	4	2017.25	61
feedback (response)	0.8373	0.3776	2	25	4	2014.75	59
instructional design	-0.1444	-0.881	1	25	4	2014.5	57
blended learning	-0.1893	0.9702	3	24	4	2017	54
information technology	0.3511	-0.7686	2	25	4	2014.25	50
models	1.0047	-0.1112	2	25	5	2015.2	50
engineering education	0.2733	0.8217	3	25	4	2017.25	48
undergraduate students	0.7362	-0.3079	2	25	4	2017	43
outcomes of education	0.8508	-0.5993	2	24	4	2015	38

IV. Discussion

This paper examines the roles and benefits of machine learning in higher education course design, as well as its potential drawbacks. We conducted a narrative review of the literature on the application of machine learning in course design. (1) Recent articles on machine learning in education have increased dramatically. (2) Just 11 relevant publications focused on machine learning in higher education course design, three of which were peer-reviewed. (3) Our review's word cloud includes "Artificial intelligence," "International countries," "teaching methods," "Internet courses," and "Curriculum design."

Recent literature on machine learning in education shows its promise and growing attention. From 2003 to 2023, machine learning education articles increased significantly (Figure 2). Machine learning in education is expanding in popularity and importance. Between 2018 and 2020, publications increased significantly, suggesting that machine learning became a more important topic in education research. In 2021 and 2022, machine learning research in education increased, indicating future advances and applications. As technology advances, machine learning can help educators better understand student learning behaviours [69] diagnose student learning problems [70] and provide personalized learning experiences and support [71], thereby improving learning outcomes and the quality of education [72]. At the same time, machine learning can also help educators better understand students' learning processes by mining data to discover patterns and patterns hidden in the data and provide data-based teaching and learning decisions and predictions [73]. In addition, the growing body of literature on the application of machine learning to education reflects educators' interest and enthusiasm for emerging technologies. They want to apply new technologies such as machine learning to improve the quality of education and learning outcomes, as well as to provide better learning experiences and support for students. This trend is also driving the deepening and growing use of machine learning in education.

V. Conclusion

Although an increasing study indicate more interesting focus on application on machine learning, the studies focus on higher education course design were few. Based on the results of our search, we identified a total of 28 relevant publications that provided valuable insights into the application of machine learning in higher education course design. These publications included peer-reviewed articles and a review article. Possible explanations for the relatively few studies on the application of machine learning in higher education course design may include the relatively recent emergence of machine learning techniques and their complexity, the need for specialized expertise in both machine learning and higher education, and the potential costs associated with implementing machine learning in education.

The 28 relevant publications identified in our review provide valuable insights into the application of machine learning in higher education curriculum design. Based on these included articles, machine learning (ML) is revolutionizing curriculum design in higher education by enhancing each stage of the process, from needs assessment to evaluation, especially for students' learning outcome evaluation including academic performance [57, 60, 61, 73, 76, 77, 82, 88] and learning behaviour perdition [63, 81]. It enables data-driven identification of educational gaps [78], personalized goal setting, and tailored content selection, thereby improving the relevance and effectiveness of educational programs. Additionally, it has significant trend to apply machine learning in generating an interactive machine teacher online to interact with students [85]. ML facilitates the organization of coherent learning pathways and adaptive implementation through intelligent tutoring systems, ensuring continuous support and engagement. It also automates evaluation, providing timely insights for curriculum refinement. Despite challenges such as data privacy, bias, infrastructure needs, and stakeholder acceptance, the benefits of ML in creating personalized, efficient, and data-driven educational experiences are substantial, promising significant improvements in student outcomes and satisfaction [78]. The machine learning can also help Forecasting gender in open education competencies [84]. Overall, it has improved individual massive curriculum design from students' learning needs collection, analysis, conclusion to prediction, which has significant positive impact on learning and teaching effectiveness from this review. However, its accuracy of making analysis and conclusion needs to be improved.

VI. Limitations And Recommendations

However, there are some limitations. Firstly, there is a lack of consistency in the study design and methodology across the studies, making it difficult to compare and generalize findings. Additionally, most studies have a small sample size, which may limit the generalizability of the results. Secondly, the studies are primarily focused on the technical aspects of machine learning and its application in course design, with less attention given to the pedagogical implications and effectiveness of these approaches. More research is needed to understand how machine learning can improve teaching and learning outcomes in higher education. Thirdly, the majority of the studies are focused on undergraduate education, with little attention given to graduate or postgraduate education. This is an important area for future research, as the application of machine learning in advanced education may have different challenges and opportunities. Lastly, many of the studies are focused on specific technical areas, such as AI or neural networks, leaving out other areas where machine learning could be applied in course design, such as natural language processing or computer vision. Therefore, future research could explore the potential applications of machine learning in these areas. Overall, while the studies reviewed provide valuable insights into the application of machine learning in higher education course design, there are limitations and areas for future research that need to be addressed.

Conflict Of Interest

The author declares that there is no conflict of interest.

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