Machine Learning for Higher Education: Current State and Future Prospects

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Abstract Machine learning (ML) algorithms are transforming our society from an expert based approach to a data-based approach in which the knowledge is elicited from the vast amount of information that as a society we generate. Education is already evolving from a traditional expert-based framework to a digital and data-based approach that includes a variety of ML-based technologies and tools. This paper explores and classifies the current landscape of ML applications within higher education, focusing on the technical approaches used, and highlighting its problems and limitations. Through an examination of both current solutions and the discussion of future horizons, this study highlights the pivotal role machine learning plays in shaping the future of higher education.

1 Introduction

The use of artificial intelligence (AI) in education has dramatically increased in recent years, in general due to the rapid development of AI techniques and tools and in particular due to the impact that COVID-19 had in education[1]. Although the definition of AI has evolved since its inception in the 1950s, it can be broadly defined as the ability of computers to perform tasks associated with humans, such as reasoning, perception, processing language or learning and is comprised of related fields, such as Reasoning, Planning, Knowledge Representation, Robotics and Machine Learning, among others.

Machine Learning (ML) is generally defined as the ability to identify patterns (i.e. extract knowledge) from data, and has also had an exponential growth due to the wide availability of data and the development of new hardware platforms, like

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Graphic Processing Units (GPU) or Tensor Processing Units (TPUs)). ML is broadly divided in supervised and unsupervised learning (although a third type is also usually considered, Reinforcement Learning). Supervised learning deals with datasets that have been labelled, for example, a grade (label) is assigned to an exam or the level of satisfaction of a student with a professor. As such supervised techniques build models that assign a label to a new instance. Unsupervised learning deals with non-labelled and/or non-structured data, and as a results unsupervised techniques find common elements between instances for data grouping (clusters).

There are a wide variety of techniques for both supervised and unsupervised learning. It is not the goal of this paper to present a review of ML techniques, which can be found in a variety of papers [2][3]. One of the first techniques proposed was Artificial Neural Networks (ANN), going back to the 1950s with the implementation of the perceptron. ANNs have evolved into deep learning (DL) architectures which have revolutionized ML and its applications[3]. Machine Leaning and Deep Learning have been used in a variety of applications, including medical applications, business and marketing or automotive.

In this context, the proliferation of digital educational platforms is allowing for the gathering of a wide variety of educational data from different stakeholders (students, instructors, learning platform logs, etc.), which has opened the door for the development of ML tools for education. As the field of ML in education is rapidly growing, it is very relevant to understand how ML is being used. This paper presents a review of state of the art of recent (2018-2023) ML applications in higher education. Although we can find in the literature a range of papers already presenting a review of AI in (Higher) Education[4][6][5], these focus on classifying the applications from a users perspective, while in our case we focus on a ML perspective to classify the tools being developed. The focus of the paper is to identify ML trends for education and present which techniques are typically used in each context

2 Taxonomy of ML Applications in Higher Education

Machine Learning (ML) applications in education can be classified according to the type of task, which from a ML perspective is typically classified as: (i) Prediction, (ii) Recommendation, and (iii) Classification. Prediction is the capability of anticipating student behavior using historical data. A basic assumption is made with this approach is that a student immediate future is very similar to his/her immediate past. Recommendation is the capability of suggesting interesting elements to a student based on some extra information; for example, from the items to be recommended or from the behavior of other students. Classification builds a model that maps or classifies data items into one of several predefined classes. Considering the latest advancements in deep learning architectures, in particular in transformers, we are going to add a fourth type of task, (iv) generative text, which uses vast amounts of (educational) texts to derive new information.

Table 1 Prediction Applications for Education, including reference, application (churn, satisfaction or success), ML technique implemented that produced the best result and data used

Reference	Application	ML Technique	Data Used
[7](2022)	Churn & Satisfaction	KNN and SVM	Real-time Survey
[8](2018)	Churn	PCA+SVM	Demographics+Aptitudes
[9](2020)	Churn	LDA+SVM, RF	Demographics+Grades+Credits
[10](2019)	Churn	ANN+AdaBoost	Demographics+Academic Performance
[11](2019)	Churn	Deep Learning	MOOC logs + friends network
[12](2019)	Churn	Deep Learning	MOOC logs
[13](2021)	Churn	Deep Learning	MOOC logs
[14](2021)	Success	Random Forest	Grades + Demographics
[15](2019)	Success	Random Forest	Gender + Grades + Proficiency
[16](2022)	Success	ANN	Grades + Proficiency
[17](2021)	Success	Deep Learning	Demographic + Enrollment + Race
[18](2021)	Satisfaction	Deep Learning	Questionnaire + Demographics
[19](2020)	Satisfaction	GBT	Content + Assesment + Schedule
[20] (2023)	Satisfaction	Deep Learning	Opinions + Activities
[41] (2020)	Attendance	Random Forest	Attedance data

KNN= k-nearest neighbors, SVM= Support Vector Machines, ANN= Artificial Neural Network, PCA= Principal Component Analysis, GBT=Gradient Boosting Trees, RF= Random Forest

2.1 Prediction Applications

Student prediction applications use historical data to predict future behaviors/decisions. As such, these applications are key to implement policies to reinforce o correct such behavior. For example, a system that predicts student dropping out of college can be used to preemptively contact that student to understand an correct the situation. The main prediction applications for higher education found in the literature are: (1) student dropout (churning), (2) student satisfaction, (3) student success (grades) and (3) student attendance. Typically these applications are solved using supervised ML approaches because there are labels that can be used to train the model, for example, we can use the grades of previous students to train a predictive system for student success and predict the outcome for new students. Nevertheless, unsupervised approaches are also possible. Table 1 presents recent examples of prediction applications, presenting the ML technique and the input data used. In general the majority of papers tend to use a battery of ML techniques to identify the best solution, but in 1 we only indicate the technique used that provided the optimum solution. Note that the three applications are not necessarily unconnected, for example the outputs of a satisfaction model and success model can be the inputs of a churn model.

If traditional ML techniques are considered, SVM or Classification Trees in its different approaches (random forest or GBT) tend to provide the best solutions. In this context, as with any machine learning application, preprocessing the data, including feature selection and dimensionality reduction is key to improve the results. We can see some examples of that in [8][9]. One particular characteristic of the data being used in these applications is its imbalanced nature. For example, churn is a

Table 2 Recommendation Applications for Education, including reference, application, ML technique implemented that produced the best result and data used

Reference	Application	ML Technique	Data Used
[21](2022)	Course Rec.	Random Forest	
[22](2020)	Advisor Rec.	TF-IDF	Publication Data
[23](2019)	Thesis Topic Rec.	Linear Regression	Course Grades + Thesis Topics
[24](2019)	Major Rec.	K-NN	GPA+Interests+Electives
[25](2020)	Major Rec.	SVM + KNN	Scores University Access
[26](2020)	Major Rec.	Decission Trees	High School Grades + Major Data
[27](2019)	Educational Content Rec.	Decission Trees	Demographics + Logs
[28](2023)	Educational Content Rec	ANN	Learning Styles
[29](2019)	Educational Content Rec	Genetic	Courses Data + Objectives
[30](2021)	Course Rec.	Deep Learning	MOOC logs
[31](2023)	Educational Content Rec	Deep Learning	Student Traits + MOOC info

Rec= Recomendation, TF-IDF= Term frequency–Inverse document frequency, K-NN=K-Nearest Neighbor, SVM=Support Vector Machines, ANN=Artificial Neural network

typical problem where only a small number of students will be labelled as churners, while the majority will be non churners. This imbalance affects the ability of the ML techniques to predict both classes, as there is one that is overrepresented. Te preprocessing of the data also benefits from implementing techniques to eliminate the original imbalance of the labels, as done in [9].

Table 1 also highlights the tendency to use deep learning approaches in recent years. These outperform SVM and classification tress [17][18], although, again, the preprocessing and feature selection of the data is key. In any case, although the use of DL techniques outperforms traditional ML approaches, there are still in the literature a considerable number of solutions that use traditional approaches. This is caused mainly by the fact that DL solutions need huge amounts of data to be implemented, that in the case of education is only possible if MOOCs are being considered, as traditional classroom environments have a reduced number of students that limits the applicability of DL.

2.2 Recommendation Applications

Student recommendation applications use student data (demographics, preferences, learning styles, etc.) and content data from other sources, such as courses, other students, majors, research resources, etc. to suggest (or recommend) new elements. For example the selection and grades of previous school subjects can be used to recommend future school subjects using the information provided by other students that have a similar set of preferences.

The main recommendation applications are: (1) recommendation of educational content (for adaptive learning platforms) and (2) recommendation of Courses, Topics or Advisors to students. Recommendation of educational content is at the core

Table 3 Classification Applications for Education, including reference, application, ML technique implemented and data used

Reference	Application	ML Technique	Data Used
[32](2021)	Engagement	Deep Learning	Image Dataset (FER-2013)
[33](2022)	Engagement	Deep Learning	Video
[34](2018)	Engagement	SVM	Video
[35] (2018)	Learning Style	Decision Tree	Demographics + Survey
[36] (2019)	Attendance	K-NN	Facial metrics with DL (CNN)
[37] (2020)	Engagement	Deep Learning	Image Dataset (FER-2013)
[38] (2021)	Learning Style	Deep Learning	MOOC Behavioral Data
[39] (2019)	Learning Style	NB Classification	MOOC logs
[40] (2020)	Attendance	SVM	Student Images
[42](2022)	Sentiment	Deep Learning	MOOC text feedback
[43](2021)	Sentiment	Deep Learning	MOOC feedback

SVM=Support Vector Machines, ANN=Artificial Neural network, DL = Deep Learning, CNN = Convolutional Neural Network, NB= Naive Bayes, SVM = Support Vector Machines

of adaptive learning, and allows Intelligent Tutoring Systems (ITS) to build an individualized learning plan by choosing the most appropriate content using the learner's characteristics such as learning style, past preferences, or learning progress.

There are two main approaches to implement recommendation systems: content-based filtering and collaborative filtering. Content-based filtering uses the description of an element (such a school subject) and the student preferences to make recommendations based on some concept of similarity. ML is used in this context to find similarities between content and students for the recommendation. It is typically the approach used for recommending educational content for adaptive learning . Collaborative filtering is typically used for the recommendation of courses, topics or advisors and is based in the fact that individuals (students) that have had a common behavior in the past, will have a common behavior in the future. ML is used in this context to identify students with similar behavior and use that information for a recommendation.

Table 2 presents recent examples of recommendation applications, focusing on the ML technique used and the input data. There is a recent tendency towards Deep Learning solutions, specially in the context of MOOCS[31][30]. For a context where less data is generated and/or available, traditional and simple ML approaches still provide effective solutions [23](2019). Recommendation applications do not suffer from the problem of imbalance dataset as prediction, but they have their own, such the cold start problem, i.e. how to recommend something for a student for which no information is available. In the case of adaptive learning environments if the student information does not provide enough context that can produce low quality recommendations (personalization of content), so developing solutions for those situations, such as [27] is very relevant.

2.3 Classification Applications

Student Classification uses data from an academic institution to build a model that classifies students into a set of predefined classes. For example, in the context of adaptive e-learning systems it is very relevant to classify each student according to learning styles, which refer to students' preferred ways to learn, in order to personalize the learning materials. The main classification applications present in the literature are: (1) engagement classification, (2) learning style/cognitive style classification, (3) attendance classification and (4) sentiment classification. Engagement classification identifies the level of engagement of students in a classroom (high - neutral - low) and can be used to alert about the situation if the global level of engagement is low. Learning style classification is used by adaptive learning system to personalize the materials for each individual student. Attendance classifies students using a binary classifier that automatically identifies if a student is or is not attending a class. Last, sentiment classifies each student according to their opinion of the class/instructor.

Considering the nature of the classification applications, supervised machine learning is typically applied. Nevertheless, in some circumstances, supervised techniques can be used in combination with unsupervised techniques [39]. Note that Prediction and Classification applications have many elements in common, specially the set of techniques used, but while prediction reflects on a future behavior, classification presents a current attribute. In some cases both applications can be valid, for example attendance can be predicted, and also is a classification application -i.e. the system classify if a student is present or not. Table 3 presents recent examples of classification applications, focusing on the ML used and the input data.

In the case of classification applications, due to the nature of the data (images, video, text) deep learning has been the standard in recent years, as it outperform the rest of techniques historically used. In this context, CNN (Convolutional Neural Networks) is typically used for engagement and attendance applications, as it has become the standard for processing images and video. LSTM architecture (Long Short-Term Memory) is typically used for sentiment identification, and in general for text processing. While to a large extent classification applications (engagement, attendance) focus on on-line environments, the same concepts and techniques have the potential of being applied to physical classrooms.

2.4 Generative Applications

Recent advances within deep learning have led to new techniques of automatic content generation, called generative modelling, that have the potential for a huge impact in the education context. Generative modelling (or generative AI) is an unsupervised machine learning approach that uses existing content (text, video, images) to learn patterns and generate new content based on those patterns. Focusing in generative text applications, transformers and in particular generative pre-trained transformers (GPT) are the defacto standard to implement text generative models.

Table 4 Generative Applications for Education, including reference, application, ML technique implemented and data used

Reference	Application	ML Technique	Data Used
[44](2023)	Grading/Test Generation	OpenAI GPT-3	CS Exams
[45](2023)	Grading	OpenAI GPT-4	Questionnaires
[46] (2023)	Exam Solution	OpenAI GPT-4	Law Exams
[47](2023)	Cheat Detection	OpenAI GPT-3	HUman essais
[48](2023)	Tutoring/Test Generation	OpenAI GPT-3	Math Exercises
[49] (2023)	Tutoring	OpenAI GPT-3	Word Vocabulary
[50] (2023)	Tutoring	GPT Teach - LLM	Course Information
[51] (2023)	Test Generation	OpenAI GPT-4	
[52] (2023)	Exam Solution	OpenAI GPT-3.5&4	High School Exams
[54] (2023)	Cheat Detection	OpenAI GPT-3.5	Human and GPT Texts

CS= Computer Science

GPT uses large amounts of text data to create a generative model that captures no only the structure of a phrase, but also connection between ideas. As a result GPT models (called LLM, Large Language Models) are able to produce human-like text outputs and open the door to a variety of educational applications. Some of the applications of Generative text in Education found in the literature include: (1) Automatic Grading/Assessment; (2) Exam Solution; (2) Automatic Test Generation; (4) Cheat Detection; and (5) Tutoring.

Table 4 presents recent examples of generative AI applied to Education, focusing on the LLM used and the input data. Although there is a variety of LLMs available (OpenAI ChatGPT; Bing, Gopher; BLOOM; etc.) the different versions of ChatGPT have become the standard to implement research studies, and the use of other commercial LLM is residual. From the examples presented in Table 4 only [**?**] builds its own LLM. While using a commercial LLM allows to focus on research questions directly, this approach has its drawbacks as there is no control or knowledge over the data used to train the LLM. Potentially these applications can be implemented for any area of knowledge, but this initial studies tend to focus in specific areas like math or programming - where there is a reduced language and it is easier to evaluate the quality of the responses. There are also some limitations to the use of LLMs, mainly, again the bias, which if a commercial solution is used there is no clear indication about the bias beign introduce to generate the model. For educational purposes it will be interesting to build focused LLMs in specific topics, to control the data fed to the LLM and guarantee the quality of the answers.

3 Challenges

While ML has the potential of transforming higher education, it suffers from a variety of challenges. The majority of these challenges are common to any area that uses data[53], like: (1) data privacy, (2) data security and (3) data Ethics. In all the previous cases, the use of ML in education involves storing and handling students and professors sensitive data, and as such data privacy, security and ethics will have to be considered. While also present in other application areas, there are some challenges specially relevant for higher education: (1) bias and fairness; (2) integration with traditional teaching, and and (4) data imbalance.

Bias and fairness refers to the tendency of ML algorithms to perpetuate biases present in the original data[56], potentially leading to different treatment for certain groups of students. Any prediction, classification and recommendation application, will use student data to build a model. If a subgroup of students is underrepresented in the input data the model will potentially generate less accurate prediction for them and as a result will probably treat them unfairly. This has the potential of reducing opportunities for the underrepresented students, for example, if a Major Recommendation o Educational Content recommendation system is used, the model has the potential of perpetuating current tendencies and inequalities. As a result in the context of higher education is essential to consider data bias and fairness when generating models in order to limit, or at the very least be aware, of the shortcomings of the system when applying it. These challenges can be tackled both at an algorithmic level and at a data preprocessing level[56].

Effective integration of ML tools in and with traditional teaching methods is not straightforward. Any new technology that is introduced and interfaces with humans requires an introduction plan in the institution, which implies especial training for faculty and/or students. Also, as presented in the different sections, there have been a lot of applications developed for education, but it is not clear if and to which extent those applications improve the learning process and what are their pedagogical benefits. If the benefits are clearly demonstrated introducing AI tools will be much straightforward, but in general the studies presented do not evaluate its pedagogical.

Data imbalance is a common problem in ML, and has special implications for education applications. It refers to the characteristics of some datasets where some of the classes are underrepresented. For example, student dropout affects to a reduced number of students in traditional learning settings, and such imbalance will be reflected in the dataset. Note that in online learning settings the situation is the opposite, a reduced number of students enrolled finish the course while the majority drops. In any case, in both scenarios, we have an unbalanced dataset in which one of the classes is overepresented. ML techniques do not work well with data imbalance as they are not able to characterize correctly the class that is underrepresented and as such techniques such as oversampling, unsersampling or boosting are used to limit the implications[55].

4 Emerging Trends

Considering the current state of the art, some of the main research trends for machine learning that are emerging are:

• Tutoring with LLMs. LLMs have already demonstrated its capabilities to maintain human-like conversations. There is a potential to use LLMs for automatic tutoring of students[48][50]. The literature already shows its potential and limitations, but much more studies need to me done regarding how it affects the quality of education, its pedagogical implications and the satisfaction of students.

• Augmented reality / Virtual Reality with LLMs. Virtual reality and augmented reality have the potential to enhance and improve the learning process, ad to build immersive environments for students to learn. The combination of this environments with LLMs will open the possibility for real-time interaction and immersive educational games.

• Processing images and voices from an (online) classroom. Processing images (and/or voice) of a classroom, thanks to the latest DL advancements, opens the door to a new set of applications such as evaluating student engagement[33], control of class assistance[40] or evaluate class sentiment on real-time. These applications imply processing student images, specially their face and voice, in order to identify their state and recommend actions to modify it if necessary. Also, it will be very important to evaluate to which extent those applications improve the learning process in order to justify the processing of student images. While from a technological perspective the use of deep learning architectures solves to a large extent the processing of student images, the ethical and privacy implications need to be clarified and evaluated against the possible benefits.

• Adaptive Learning to improve engagement. Adaptive learning is already present in the state of the art by using preferences and/or learning styles to personalize content. As for future research trends, adaptive learning will be improved implementing the ability to provide constructive feedback to the student, and also to improve engagement with the learning process, i.e. the content provided to each student will be evaluated against the engagement it has produced. In this context adaptive learning can also benefit from image processing to adapt the content based on engagement.

• Ethical and Transparent ML: As in other fields, ethical and transparent ML is going to be key to implement ML solutions into the learning process. Ethical ML implies eliminating bias in data and in algorithms used to guarantee the fairness of the model. Transparency, or interpretability, implies implementing decision processes that can be explained and validated by the algorithm and understood by a human. In education, ethic and transparency will be key to generate trust between students, instructors and institutions and facilitate the introduction of ML tools.

5 Conclusion

ML in (higher) education is already having a relevant impact and is redefining the process of education. The current state of the art highlights its potential for adaptive learning, support students and instructors and improve student and institution's performance. Nevertheless it suffers from a main drawback: the majority of the studies here presented do not evaluate the actual impact in the learning process of the tools and/or its pedagogical advantages. Future studies will have to focus on this areas to better justify its implementation in a learning setting.

Although all educational institutions at all levels have the potential of benefiting from this advances, it is the online, open and distance learning institutions where the potential benefits (and risks) are higher due to their need to provide education platforms to a large number of students. This implies more data available and as result the capability of generating better, more inclusive and fairer student models. In any case, in order to benefit from all the potential of ML tools, specially the opportunities offered by generative LLMs, the collaboration between institutions, EdTech industry and regulators will be key to create an environment where AI can be deployed following guidelines for fairness, controlling bias and explaining decisions that facilitate the implementation of ML solutions.

References

1. Chen, X., Zou, D., Xie, H., Cheng, G., Liu, C. (2022). Two decades of artificial intelligence in education. Educational Technology & Society, 25(1), 28-47.
2. Ray, S. (2019). A quick review of machine learning algorithms. In 2019 Int. conf. on machine learning, big data, cloud and parallel computing (COMITCon) (pp. 35-39). IEEE.
3. Shrestha, A., Mahmood, A. (2019). Review of deep learning algorithms and architectures. IEEE access, 7, 53040-53065.
4. Kucak, D., Juricic, V., Dambic, G. (2018). Machine Learning in Educatuion- A survey of current research trends. Annals of DAAAM Proceedings, 29.
5. Zhai, X., Chu, X., Chai, C. S., Jong, M. S. Y., Istenic, A., Spector, Li, Y. (2021). A Review of Artificial Intelligence (AI) in Education from 2010 to 2020. Complexity, 2021, 1-18.
6. Rastrollo-Guerrero, J. L., Gómez-Pulido, J. A., Durán, A. (2020). Analyzing and predicting students' performance by means of machine learning: A review. Applied sciences, 10(3), 1042.
7. Paul, R., Rashmi, M. R. (2022, October). Student Satisfaction and Churn Predicting using Machine Learning Algorithms for EdTech course. In 2022 10th Int. Conf. Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO) (pp. 1-6). IEEE.
8. Whitlock, J. L. (2018). Using data science and predictive analytics to understand 4-year university student churn (Doctoral dissertation, East Tennessee State University).
9. Del Bonifro, F., Gabbrielli, M., Lisanti, G., Zingaro, S. P. (2020). Student dropout prediction. In Artificial Intelligence in Education: 21st International Conference, AIED 2020, Ifrane, Morocco, July 6–10, 2020, Proceedings, Part I 21 (pp. 129-140). Springer.
10. Berens, J., Schneider, k., GÖrtz, S., Simon Oster, and Julian Burghoff. 2019. Early detection of students at risk - Predicting student dropouts using administrative student data from German Universities and machine learning methods. Journal of Educational Data Mining 11, 3 (2019)
11. Feng, Wenzheng, Jie Tang, and Tracy Xiao Liu. "Understanding dropouts in MOOCs." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 33. No. 01. 2019.
12. Qiu, L., Liu, Y., Hu, Q., Liu, Y. (2019). Student dropout prediction in massive open online courses by convolutional neural networks. Soft Computing, 23, 10287-10301.
13. Mubarak, A. A., Cao, H., Hezam, I. M. (2021). Deep analytic model for student dropout prediction in massive open online courses. Computers Electrical Engineering, 93, 107271.
14. Bujang, S. D. A., Selamat, A., Ibrahim, R., Krejcar, O., Herrera-Viedma, E., Fujita, H., Ghani, N. A. M. (2021). Multiclass prediction model for student grade prediction using machine learning. IEEE Access, 9, 95608-95621.
15. Abana, E. C. (2019). A decision tree approach for predicting student grades in Research Project using Weka. International Journal of Advanced Computer Science and Applications, 10(7).

16. Sreenivasulu, M. D., Devi, J. S., Arulprakash, P., Kazi, K. S. (2022). Implementation of latest machine learning approaches for students grade prediction. Int. J. Early Child, 14(3).
17. Jiang, W., Pardos, Z. A. (2021, July). Towards equity and algorithmic fairness in student grade prediction. In Proc. of the 2021 AAAI/ACM Conf. on AI, Ethics, and Society (pp. 608-617).
18. Ho, I. M. K., Cheong, K. Y., Weldon, A. (2021). Predicting student satisfaction of emergency remote learning in higher education during COVID-19 using machine learning techniques. Plos one, 16(4), e0249423.
19. Hew, K. F., Hu, X., Qiao, C., Tang, Y. (2020). What predicts student satisfaction with MOOCs: A gradient boosting trees supervised machine learning and sentiment analysis approach. Computers Education, 145, 103724.
20. Sandiwarno, S., Niu, Z., Nyamawe, A. S. (2023). A Novel Hybrid Machine Learning Model for Analyzing E-Learning Users' Satisfaction. Int. J. of Human–Computer Interaction, 1-22.
21. Anupama, V., Elayidom, M. S. (2022, March). Course Recommendation System: Collaborative Filtering, Machine Learning and Topic Modelling. In 2022 8th Int. Conf. on Advanced Computing and Communication Systems (ICACCS) (Vol. 1, pp. 1459-1462). IEEE.
22. Rismanto, R., Syulistyo, A. R., Agusta, B. P. C. (2020). Research supervisor recommendation system based on topic conformity. Int. J. Modern Education and Computer Science, 12(1), 26.
23. Slamet, C., Maliki, F. M., Syaripudin, U., Amin, A. S., Ramdhani, M. A. (2019, December). Thesis topic recommendation using simple multi attribute rating technique. In Journal of Physics: Conference Series (Vol. 1402, No. 6, p. 066105). IOP Publishing.
24. Taufik, I., Gerhana, Y. A., Ramdani, A. I., Irfan, M. (2019, December). Implementation K-nearest neighbour for student expertise recommendation system. In Journal of Physics: Conference Series (Vol. 1402, No. 7, p. 077004). IOP Publishing.
25. Ezz, M., Elshenawy, A. (2020). Adaptive recommendation system using machine learning algorithms for predictin
26. Dhar, J., Jodder, A. K. (2020). An Effective Recommendation System to Forecast the Best Educational Program Using Machine Learning Classification Algorithms. Ingénierie des Systèmes d Inf., 25(5), 559-568.
27. Pliakos, K., Joo, S. H., Park, J. Y., Cornillie, F., Vens, C., Van den Noortgate, W. (2019). Integrating machine learning into item response theory for addressing the cold start problem in adaptive learning systems. Computers & Education, 137, 91-103.
28. Troussas, C., Giannakas, F., Sgouropoulou, C., Voyiatzis, I. (2023). Collaborative activities recommendation based on students' collaborative learning styles using ANN and WSM. Interactive Learning Environments, 31(1), 54-67.
29. Hssina, B., Erritali, M. (2019). A personalized pedagogical objectives based on a genetic algorithm in an adaptive learning system. Procedia Computer Science, 151, 1152-1157.
30. Wu, L. (2021). Collaborative filtering recommendation algorithm for MOOC resources based on deep learning. Complexity, 2021, 1-11.
31. Li, X., Xu, H., Zhang, J., Chang, H. H. (2023). Deep reinforcement learning for adaptive learning systems. Journal of Educational and Behavioral Statistics, 48(2), 220-243.
32. Bhardwaj, P., Gupta, P. K., Panwar, H., Siddiqui, M. K., Morales-Menendez, R., Bhaik, A. (2021). Application of deep learning on student engagement in e-learning environments. Computers Electrical Engineering, 93, 107277.
33. Sharma, P., Joshi, S., Gautam, S., Maharjan, S., Khanal, S. R., Reis, M. C., ... de Jesus Filipe, V. M. (2022, August). Student engagement detection using emotion analysis, eye tracking and head movement with machine learning. In Int. Conf. on Technology and Innovation in Learning, Teaching and Education (pp. 52-68). Cham: Springer Nature Switzerland.
34. Thomas, C., Jayagopi, D. B. (2017, November). Predicting student engagement in classrooms using facial behavioral cues. In Proceedings of the 1st ACM SIGCHI international workshop on multimodal interaction for education (pp. 33-40).
35. Topîrceanu, A., Grosseck, G. (2017). Decision tree learning used for the classification of student archetypes in online courses. Procedia Computer Science, 112, 51-60.
36. Tata Sutabri, T. S., Pamungkur, P., Ade Kurniawan, A. K., Raymond Erz Saragih, R. E. S. (2019). Automatic attendance system for university student using face recognition based on deep learning. International Journal of Machine Learning and Computing, 9(5), 668-674.

37. Mohamad Nezami, O., Dras, M., Hamey, L., Richards, D., Wan, S., Paris, C. (2020). Automatic recognition of student engagement using deep learning and facial expression. In Joint european conf. on machine learning and knowledge discovery in databases (pp. 273-289). Springer.
38. Zhang, H., Huang, T., Liu, S., Yin, H., Li, J., Yang, H., Xia, Y. (2020). A learning style classification approach based on deep belief network for large-scale online education. Journal of cloud computing, 9, 1-17.
39. El Aissaoui, O., El Madani, Y. E. A., Oughdir, L., El Allioui, Y. (2019). Combining supervised and unsupervised machine learning algorithms to predict the learners' learning styles. Procedia computer science, 148, 87-96.
40. Patil, V., Narayan, A., Ausekar, V., Dinesh, A. (2020, September). Automatic students attendance marking system using image processing and machine learning. In 2020 International Conference on Smart Electronics and Communication (ICOSEC) (pp. 542-546). IEEE.
41. Rashid, E., Ansari, M. D., Gunjan, V. K., Khan, M. (2020). Enhancement in teaching quality methodology by predicting attendance using machine learning technique. Modern Approaches in Machine Learning and Cognitive Science: A Walkthrough: Latest Trends in AI, 227-235.
42. Edalati, M., Imran, A. S., Kastrati, Z., Daudpota, S. M. (2022). The potential of machine learning algorithms for sentiment classification of students' feedback on MOOC. In Proc. 2021 Intelligent Systems Conf. (IntelliSys) Vol.3 (pp. 11-22). Springer.
43. Yu, H., Ji, Y., Li, Q. (2021). Student sentiment classification model based on GRU neural network and TF-IDF algorithm. Journal of Intelligent Fuzzy Systems, 40(2), 2301-2311.
44. Drori, I., Zhang, S. J., Shuttleworth, R., Zhang, S., Tyser, K., Chin, Z., ... Udell, M. (2023, August). From Human Days to Machine Seconds: Automatically Answering and Generating Machine Learning Final Exams. In Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (pp. 3947-3955).
45. Moore, S., Nguyen, H. A., Chen, T., Stamper, J. (2023, August). Assessing the Quality of Multiple-Choice Questions Using GPT-4 and Rule-Based Methods. In European Conference on Technology Enhanced Learning (pp. 229-245). Cham: Springer Nature Switzerland.
46. Blair-Stanek, A., Carstens, A. M., Goldberg, D. S., Graber, M., Gray, D. C., Stearns, M. L. (2023). GPT-4's Law School Grades: Con Law C, Crim C-, Law, Econ C, Partnership Tax B, Property B-, Tax B. Crim C-, Law & Econ C, Partnership Tax B, Property B-, Tax B.
47. Yan, D., Fauss, M., Hao, J., Cui, W. (2023). Detection of AI-generated essays in writing assessment. Psychological Testing and Assessment Modeling, 65(2), 125-144.
48. Liang, Z., Yu, W., Rajpurohit, T., Clark, P., Zhang, X., Kaylan, A. (2023). Let GPT be a Math Tutor: Teaching Math Word Problem Solvers with Customized Exercise Generation. arXiv preprint arXiv:2305.14386.
49. Zografos, G., Moussiades, L. (2023, May). A GPT-Based Vocabulary Tutor. In International Conference on Intelligent Tutoring Systems (pp. 270-280). Cham: Springer Nature.
50. Markel, J. M., Opferman, S. G., Landay, J. A., Piech, C. (2023). GPTeach: Interactive TA Training with GPT Based Students.
51. Fleming, S. L., Morse, K., Kumar, A. M., Brunskill, E. P., Shah, N. (2023). Assessing the Potential of USMLE-Like Exam Questions Generated by GPT-4. medRxiv, 2023-04.
52. de Winter, J. C. (2023). Can ChatGPT pass high school exams on English language comprehension. Researchgate. Preprint.
53. Holzinger, A., Kieseberg, P., Weippl, E., Tjoa, A. M. (2018). Current advances, trends and challenges of machine learning and knowledge extraction: from machine learning to explainable AI. In Machine Learning and Knowledge Extraction: Second IFIP ,2018 (pp. 1-8).
54. Orenstrakh, M. S., Karnalim, O. (2023). Detecting LLM-Generated Text in Computing Education: A Comparative Study for ChatGPT Cases. arXiv preprint arXiv:2307.07411.
55. Thabtah, F., Hammoud, S., Kamalov, F., Gonsalves, A. (2020). Data imbalance in classification: Experimental evaluation. Information Sciences, 513, 429-441.
56. Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., Galstyan, A. (2021). A survey on bias and fairness in machine learning. ACM computing surveys (CSUR), 54(6), 1-35.