Introduction:

With the rapid growth of the planet, technological advancements have also been progressing. Every learner possesses areas of strength and areas of weakness. Personalized learning is becoming widely recognisable as crucial due to its effectiveness and advantages.It’s an learning approach that involves closely observing each student's strengths, weaknesses, learning style, and interests in order to provide tailored recommendations for academic success. Furthermore, it transitions the learning style from being teacher-centric to being student-centric. Students are urged to adopt an active approach to their learning, rather than simply receiving knowledge. This involves establishing objectives, monitoring their advancement, and contemplating their learning experience.Also, this technique delivers the ongoing evaluation and feedback process that rapidly addresses any deficiencies in learning. By harnessing technology, it offers adaptable and easily reachable learning opportunities, unrestricted by conventional timetables.

Machine learning algorithms, powered by detailed information on a student's previous achievements, preferred learning techniques, and personal preferences, have the remarkable capacity to predict the most helpful learning materials. This adaptability guarantees that content is appropriate for the learner’s competency levels, reducing feelings of boredom or discontent and, as a result, increasing the efficacy of the learning process.Additionally, these algorithms extend their reach to personalized and timely feedback. This timely feedback method enables students to get insights into their own strengths and limitations, allowing them to focus on areas for improvement while also reinforcing their comprehension of fundamental topics.

Customisation of learning plans is another strong aspect of machine learning in education. Machine learning algorithms create personalized educational plans for each student based on their specific goals, learning techniques, and performance indicators. This personalized method ensures that the trajectory of academic advancement closely coincides with each individual's distinct learning needs, resulting in a more impactful and rewarding educational journey. Crucially, machine learning does not work in static silos. It enables the ongoing evaluation and adjustment of personalized learning processes based on new data. This iterative process of refinement and optimisation guarantees that individualized learning models remain effective and responsive, aligned with students' changing requirements. As education embraces the synergy of machine learning and personalized learning, it lays the way for a future in which education is not only suited to individual requirements, but also dynamic, adaptive, and constantly modified for maximum impact.

Abstract:

The purpose of this project is to propose a sophisticated model of a personalized learning platform that assists students in directing their own educational program. Through the utilization of machine learning algorithms, the platform or the model is able to personalize information in order to cater to the specific requirements and aptitude levels of each individual user. In adaptive learning resources, students choose the subjects or topics they want to study, decide

their own pace, and interact with the materials. During the time that the system is monitoring the students' behavior and how well they perform on tests, it will intervene and provide them with alternative ideas to assist them in learning if the quizzes are difficult. The initiative also provides students with crucial views, transforming traditional learning environments into dynamic and customized ecosystems. This is in addition to the fact that it improves students' knowledge. In this project, we discuss how machine learning has the potential to transform things and create a learning environment that is highly efficient and individualized through the utilization of new models.

Literature Review:

This paper[1] examines the influence of information and communication technologies on learning materials, especially focusing on text resources and multimedia which also presents a model for recommending complete learning paths using clustering and LSTM algorithms. The study highlights the importance of personalized learning recommendations and tackles the difficulties encountered by conventional approaches, such as the precision of personalized recommendations and the cold-start problem, through the utilization of advanced learning techniques such as LSTM neural networks. Additionally, it presents an innovative framework for acquiring knowledge in full-path recommendation. Also,the paper[1]examines several filtering techniques employed in learning recommendation systems, encompassing content-based, collaborative, and hybrid filtering.

The paper[1]examines the potential of clustering algorithms in enhancing recommendation performance by tackling challenges such as data sparsity and scalability.This establishes the foundation for the suggested LSTM-based personalized learning full-path recommendation model.In this paper[1], the model tries to improve learning outcomes by predicting relevant learning paths using clustering and machine learning approaches. However, the study[1] does not expressly state any limitations or gaps in its own research. Typically, such information can be found in a paper's discussion or conclusion sections, where authors frequently admit their study's limitations and offer areas for future research.

The paper[2] explores the creation of a personalized learning trajectory model through the utilization of machine learning techniques also discusses the process of digital transformation in the economy, which entails incorporating significant organizational changes and new technology, with an emphasis on enhancing people' knowledge, skills, and values also the paper refers to the rapid and significant expansion in digital data, specifically mentioning the Data Age Report's forecast that data volume will reach 175 zettabytes by 2025. It emphasizes the significance of implementing training and staff development systems that are tailored to individualized learning paths, which are in keeping with both the organization's ideals and the employee's needs.Matrix factorization, neural networks, cosine similarity, and Word2Vec are the primary models and algorithms employed in the paper. The paper[2] also suggests that matrix factorization-based machine learning is the optimal choice for the central recommendation module. This is attributed to its tailored methodology and capacity to generate recommendations even with scarce user data.

The paper[3] examines a system specifically developed to provide personalized educational resources for children that have exceptional requirements, such as individuals diagnosed with autism. The system uses machine learning algorithms to determine the user's proficiency level and utilizes web mining to create multimodal learning materials. The study[3] finishes by presenting the system's assessment and outlining next directions for work.The study investigates different classifiers to determine the most optimal algorithm for predicting user proficiency levels, a crucial aspect in tailoring learning materials to individual needs.
Weka is a tool that is used in this paper to process training data and became the most effective machine learning algorithm which achieved comparing accuracy, confusion matrix, finding instances, and error measurement.A Multimodal Intelligent System is designed to integrate machine learning algorithms, wireless sensors, and a user-friendly interface to diagnose and provide assistance to children with special needs.The study[3] analyzed many classifiers, including NaiveBayes, Multilayer Perceptron, SMO, and J48. Among these, Multilayer Perceptron demonstrated the highest accuracy.It highlights challenges in filtering suitable content, data preprocessing, classifier performance, and user data collection. The paper[3] also emphasizes the need for future improvement and research in these areas to ensure the system's efficacy and accuracy in generating personalized results.

The paper[4] examines the potential of personalized e-learning using Moodle to forecast student learning outcomes and enhance satisfaction with teaching practices in higher education.The personalized e-learning system accurately predicted learning outcomes by 42.3%, specifically focusing on quiz results, and effectively identified behavioral patterns by 74.2%. Furthermore, it enhanced student contentment by providing teachers' conceptual feedback.Findings indicate that the utilization of customized e-learning platforms such as Moodle, which incorporate problem-based learning (PBL) and feedback focused on the learning process, can improve learning achievements and student contentment.Exercise caution due to the limited sample size, the narrow focus of the students' area of study, and the type of research design. This study[4] emphasizes the potential advantages of customized e-learning systems in enhancing academic achievement and contentment in higher education environments.

The paper[5] examines the influence of personalized e-Learning on the acquisition of profound knowledge in higher education.By employing Moodle, an educational platform, academic outcomes are improved and students who are at risk can be identified. A study was conducted with 124 Health Sciences students, which demonstrated that personalized e-Learning is a strong predictor of learning outcomes and effective behavior patterns, leading to an increase in student satisfaction. Nevertheless, the findings are tentative due to the limited number of participants and the narrow focus of the study. Furthermore, the paper [5] indicates that forthcoming investigations will prioritize the examination of more extensive and varied samples.

Regarding the paper's[5] limitations, it demonstrates that the current generation of Adaptive E-Learning Systems (AES) lacks integration and re-use support, making it difficult for university administration and teachers to maintain and use a variety of systems effectively. AES are self-contained and cannot be used as components, limiting content reuse and requiring acceptance of a specific teaching approach.

The paper[5] suggests augmenting Moodle's functionalities to facilitate a more individualized and adaptable learning experience.The paper explores the deployment of a dynamic and tailored e-learning system using open source software and technologies. The text examines conventional Learning Management Systems (LMS) and Adaptive E-Learning Systems (AES), assessing open source e-learning platforms based on their adaptivity and personalization capabilities. The objective of the proposed system is to merge the benefits of LMS (integration and re-use) with AES (adaptivity and personalization) by enhancing an open source LMS with additional functionalities. The paper[5] does not explicitly mention specific "models" in relation to machine learning or statistical models. Instead, it primarily concentrates on the conceptual models and frameworks used in e-learning systems.

The paper[6] explores the progress made in artificial intelligence (AI) that allows for the creation of highly realistic digital media, including images, audio, and video. This underscores the capacity of AI-generated characters in the fields of education and healthcare, specifically emphasizing their aptitude in facilitating individualized learning and promoting overall well-being. The authors introduce a pipeline for generating AI characters and examine the ethical consequences, emphasizing the importance of traceability in preserving trust in digital media. They predict that generative media will become a crucial component of human-AI interaction.

The paper[6] also examines the societal ramifications and apprehensions associated with the utilization of AI-generated characters also it incorporates Generative Adversarial Networks (GANs), which comprise a generator and a discriminator operating in a feedback loop to generate outputs that closely resemble reality. StyleGan is a type of GAN that enables easy manipulation of generated images by distinguishing between high-level attributes and low-level features.
Moreover, employing in-domain GAN inversion allows for the manipulation of GAN-generated images, such as the inclusion of novel facial expressions or the process of making someone appear younger.Employed in models such as GPT-3 to facilitate the generation of images from text.

The paper[6] additionally explores the ethical ramifications and the necessity for traceability in AI-generated media.The paper explores the capabilities and obstacles of artificially intelligent characters, with a specific focus on their applications in the domains of education and healthcare.

The paper[6] proposes that AI-generated characters have the potential to enhance personalized learning and well-being. However, it underscores the necessity for additional research to investigate valuable possibilities and comprehend any constraints.It highlights apprehensions regarding the inappropriate utilization of AI-generated media, such as disseminating false information or endorsing detrimental conduct, and emphasizes the significance of ethical deliberations in the creation and utilization of AI-generated characters.The paper discusses the legal aspects that must be taken into account as AI-generated characters become more integrated into society, such as privacy concerns, publicity rights, and liability issues.Although AI has made substantial advancements, the paper recognizes the existence of technological constraints that must be addressed. These include the need to guarantee the realism and authenticity of AI-generated characters and to uphold trust in digital media.These points indicate a prudent yet hopeful strategy for the advancement of AI-generated characters, emphasizing the maximization of advantages while minimizing possible drawbacks.

The study[7] proposes a sophisticated e-learning system that makes use of reinforcement learning (RL) and Markov decision process (MDP) to provide individualized adaptive learning and sequential path suggestions for students who are learning online. The purpose of this paper is to address the challenges that are presented by massive open online courses (MOOCs), which include an abundance of content, a diverse range of students, and shifting tastes. In addition, the study provides an explanation of the fundamental components and ideas that underpin the proposed framework. These components include states, actions, rewards, transition probabilities, and Q-learning.The objective of this work is to conduct a comprehensive analysis of existing literature on four interrelated research areas: personalized recommendations, sequential recommendations, reinforcement learning for recommendations, and sequential personalised course recommendations. This study[7] explores several methodologies and strategies, such as collaborative filtering, content-based filtering, hybrid systems, deep learning, Markov chains, and MDP. The report also discusses the benefits and constraints of these different methodologies and techniques. Furthermore, the report delineates the research void and highlights the distinctions between the proposed framework and the preceding works.

The paper[7] outlines the methodology of constructing a simulated environment consisting of 11 distinct states, offering learners a diverse range of activities and incentives. The study further elucidates how the Markov Decision Process (MDP) addresses the problem of sequential decision-making and calculates the transition probabilities for every state-action combination. Ultimately, the study demonstrates how the Q-learning algorithm updates the Q-table and identifies the optimal strategy for choosing the most suitable learning trajectory and material for each student.

Using a simulated dataset consisting of one thousand students who each have their own unique qualities and preferences, the paper conducts an evaluation of the effectiveness of the proposed strategy. The research examines the suggested technique in comparison to three baseline methods, which are content-based filtering, collaborative filtering, and random suggestion. For the purpose of evaluation, the study makes use of four metrics: accuracy, precision, recall, and F1-score. The study presents the findings and demonstrates that the suggested strategy makes considerable increases in terms of accuracy and F1-score, as well as outperforming the baselines on all measures. When it comes to the performance of the suggested method, the research also examines the influence of several factors, such as the learning rate, the discount factor, and the exploration rate.

The report[7] finishes by providing a concise overview of the primary contributions and findings presented in the research. The report asserts that the suggested approach can significantly improve the learning experience and results for online learners by offering them tailored and adaptable learning routes and information. The report proposes several potential areas for further research, including expanding the framework to accommodate more intricate and authentic situations, integrating more attributes and variables of the learners and courses, and implementing the approach in other fields and contexts.
—--
This paper[8] introduces the concept of personalised recommendation systems for online learning and highlights the essentiality of these systems. These systems can help students find learning resources that are relevant to their requirements and interesting to them from a large collection of digital content. The objective of this study is to analyse the current body of research on personalised recommendation technologies, such as association rules, content filtering, and collaborative filtering. Additionally, this study aims to propose a personalised recommendation system that utilises a combination algorithm integrating these technologies.

This study[8] provides an extensive literature review of the three main categories of personalised recommendation systems, highlighting their advantages and disadvantages, and discussing their use in the domains of e-commerce and e-learning. Intelligent learning, also referred to as iLearning, is a novel approach to online education that incorporates personalised recommendation algorithms and other technology to enhance adaptive and collaborative learning experiences. The study also examines the notion of iLearning, along with its distinctive features. Subsequently, the paper presents the theoretical basis of the suggested personalised recommendation system, consisting of three modules: the data support module, the recommendation engine module utilising a combinational algorithm, and the novel resource suggestion module.

The paper presents a detailed account of the design and structure of the personalised recommendation system integrated into the Shanghai Lifelong Learning Network, a platform dedicated to providing open and cost-free educational opportunities. The article explains the functions and processes of each module in the system, as well as how these modules work together to provide personalised learning resource suggestions for the learner. This is based on the learner's personal information, learning behaviour, resource information, and resource rating. Furthermore, the study presents a depiction of the operational idea behind the combinational method. This algorithm integrates association rules, content filtering, and collaborative filtering to surpass the limitations of each technology and enhance the precision and excellence of the suggestions.

The paper [8] examines the implementation and effects of the personalised recommendation system in the online classes offered by the Shanghai Lifelong Learning Network. The paper[8] showcases various examples of how the system suggests courses that are both pertinent and engaging to the learner, taking into account their occupation, learning interests, and learning path. Furthermore, the article showcases the results of a comprehensive system testing and a user survey, which provide evidence that the system effectively detects users' learning preferences and achieves a high rate of success in suggesting and selecting courses. In this study, we have determined that the personalized recommendation system has the capacity to enhance users' learning efficiency, satisfaction, and engagement, hence increasing the accessibility of online learning.The models employed in this paper include web mining, ontology, semantic networks, collaborative filtering, and combinatorial algorithm.The paper lacks a comprehensive review of existing literature on personalized recommendation systems for online learning, does not conduct a rigorous evaluation, and does not address challenges like privacy, security, ethics, and scalability.

—--

The study[9] explores the necessity of customized recommendation systems for online learning, with a specific emphasis on the Shanghai Lifelong Learning Network platform. The text provides a comprehensive analysis of current research on personalised recommendation technologies, including association rules, content filtering, and collaborative filtering. Additionally, it presents a novel approach by proposing a hybrid recommendation system that integrates various methods. The system employs a combinational algorithm to retrieve the user-resource rating matrix, determine the suitable corrective approach for the collaborative filtering process, and identify individuals with comparable interests. The system undergoes testing in actual courses involving 50 users, where it provides recommendations for learning resources based on their occupation, hobbies, and behaviour. The performance is assessed by utilising criteria such as mean absolute error, precision, recall, and hit-rate. The study's findings indicate that the system has the potential to enhance learning efficiency, enjoyment, and engagement. Nevertheless, the analysis just concentrates on the online courses provided by the Shanghai Lifelong Learning Network, without conducting a thorough assessment of the system, making comparisons with alternative algorithms or methodologies, or addressing ethical concerns such as privacy, prejudice, or transparency.

—

The study[10] examines the existing body of research on personalised adaptive learning (PAL) systems, which employ machine learning methods to detect learners' learning styles (LSs). The analysis employs a systematic literature review (SLR) methodology to examine 48 papers that were published from 2015 to 2022. The study[10] delineates five research inquiries and using keywords and search strings to conduct a systematic search for primary studies in four electronic databases: IEEE, Springer, Science Direct, and ACM. An analysis is conducted on the chosen papers using a taxonomy that encompasses platforms, LS models, ML methodologies, evaluation methods, and learning supports.

The platform most commonly studied for PAL based on LS is e-learning, followed by MOOCs, ITSs, and mobile applications. The Felder-Silverman LS model is the predominant model utilised for PAL, with the Kolb and VARK models being the subsequent most commonly employed models. The most commonly used machine learning algorithms for LS classification include decision trees, artificial neural networks, Bayesian networks, fuzzy cognitive mapping, k-nearest neighbours, and support vector machines. Hybrid and ensemble approaches are employed to merge and evaluate several machine learning algorithms.

The report finishes by providing a concise overview of the primary contributions and limitations of the Systematic Literature Review (SLR) and proposing potential avenues for further research. The statement underscores the importance of conducting additional empirical research, giving careful consideration to ethical and societal consequences, and fostering interdisciplinary cooperation in order to tackle the problems and possibilities of PAL in the age of big data and AI.

The research specifically examines the utilisation of learning style theories and machine learning techniques in adaptive e-learning systems, with a restriction on studies published between 2015 and the present. It is important to note that this paper may not encompass the whole range of personalised adaptive learning in different settings, and may not capture its intricacies and diversity. It depends on the authors' interpretation and judgement, which can potentially introduce bias or inconsistencies in the analysis. The paper's review of machine learning techniques and learning style models is not complete, which restricts the generalizability and applicability of the findings.

—------

The study[11] introduces an adaptive and personalised learning system that employs reinforcement learning (RL) to recommend appropriate learning materials and pathways depending on the learners' current conditions and requirements. The proposal suggests the integration of big data tools and learning analytics to consistently update the system with fresh data and information. The study[11] examines existing research on personalised learning, reinforcement learning, and big data in education, highlighting the primary obstacles and prospects in this domain. The system comprises six primary components: state selection, action selection, reward estimation, state update, user interface, and student database.

The efficacy of the proposed system is assessed via simulations, demonstrating its ability to acquire appropriate actions for each student-state combination, enhance positive incentives, and decrease the number of steps taken per episode as time progresses. The paper additionally examines the constraints and difficulties of simulation experiments and emphasises the necessity of evaluating the system in authentic circumstances.

The research explores the potential of big data tools and learning analytics to improve the suggested system by offering abundant and dynamic data sources, as well as facilitating the analysis and creation of new states and actions. Additionally, it brings attention to ethical concerns associated with the utilisation of big data in the field of education, including matters of data ownership, privacy, and security.

The research concludes that the suggested system presents a hopeful method for adaptive and personalised learning, utilising reinforcement learning, large data, and learning analytics.

—------

The paper[12] addresses the issue of insufficient student engagement and subpar performance in online learning settings, and suggests a remedy that integrates self-regulated learning (SRL) and personalised learning methodologies. The paper additionally outlines the research inquiries, hypotheses, and goals of the study.

The paper examines the pertinent literature on self-regulated learning (SRL), personalised learning, and artificial intelligence (AI) methodologies that can facilitate these approaches. The paper examines the advantages and difficulties of self-regulated learning (SRL), the variables that impact individualised learning, and the artificial intelligence (AI) techniques that can offer adaptable feedback and recommendations to learners.

The paper outlines the development and execution of a customised learning system that facilitates self-regulated learning in the field of Physics education. The paper elucidates the system architecture, the learner model, the domain model, the pedagogical model, and the user interface. The paper additionally outlines the methodologies employed for data collection and analysis, the instruments utilised for assessing the students' learning outcomes and perceptions, and the ethical considerations taken into account during the study.

The paper presents the findings of the data analysis, encompassing descriptive statistics, inferential statistics, and structural equation modelling. The study examines the experimental group, which received self-regulated learning (SRL) with personalised learning, and the control group, which received SRL without personalised learning. The comparison is based on several measures, including post-test scores, learning gains, continuance intention, and attitude. The paper also investigates the associations between the predictors and the outcome variables through path analysis.

The paper analyses the study's findings in connection to the research questions and hypotheses, and interprets them in the context of the current literature. The paper elucidates the primary contributions and implications of the study for both theory and practice. These include the efficacy of the personalised learning system, the significance of the perceived usefulness of learning suggestions, and the influence of attitude on continuance intention.

The paper concludes by succinctly summarising the key findings of the study, acknowledging the inherent limitations and challenges, and proposing potential avenues for future research and development. The paper also offers suggestions for educators and developers seeking to incorporate self-regulated learning (SRL) and personalised learning into online learning environments.

—-

This paper[13] presents Cloud-eLab, a cloud-based educational platform designed to impart AI thinking skills to students and foster their acquisition of cognitive and adaptive concepts in the field of education. The platform utilises computational thinking, AI thinking, reinforcement learning, and convolutional neural network models to enable comprehensive and extensive learning from experiments, even without explicit knowledge of the underlying structures. The paper additionally examines the existing body of knowledge on AI education and the potential advantages of AI in terms of customised learning and talent alignment.

The Personalised Cloud-Based AI-Thinking Platform has been developed and deployed to facilitate personalised learning through the use of manual and perceptive feedback from students. There are two application scenarios available: a Mario game that uses reinforcement learning and a facial emotion detection system that utilises deep learning. The future work identifies the constraints and difficulties of the existing platform and proposes ways to enhance and expand it. This includes integrating new educational technologies, improving cognitive feedback, and facilitating system thinking.

The paper[13] introduces Cloud-eLab as an artificial intelligence (AI) platform that facilitates personalised learning, cognitive feedback, and extensive and comprehensive learning. It has been implemented and assessed in various postgraduate courses on data analytics and machine learning. However, future endeavours and constraints encompass enhancing the cognitive feedback module, integrating novel learning technologies, assessing the platform across various domains and levels, and tackling privacy and security concerns. The platform's success hinges on its capacity to comprehend and identify student difficulties and uncertainties throughout the learning process, while also carrying out meticulous assessments to gauge its influence on student learning achievements and contentment.

—--

This paper[14] presents Cloud-eLab, a cloud-based educational platform designed to impart AI thinking skills to students and motivate them to acquire cognitive and adaptive concepts for educational purposes. The platform employs computational thinking, AI thinking, reinforcement learning, and convolutional neural network models to facilitate profound and extensive learning from experiments, even in the absence of explicit knowledge of the constructs. The paper additionally examines the existing body of knowledge on AI education and the potential advantages of AI in terms of customized learning and talent alignment.

The Personalized Cloud-Based AI-Thinking Platform has been developed and deployed to facilitate personalized learning by incorporating manual and perceptive feedback from students. There are two application scenarios available: a Mario game that uses reinforcement learning and a facial emotion detection system that utilizes deep learning. The future work delineates the constraints and difficulties of the existing platform, proposing avenues for enhancement and growth, such as integrating novel educational technologies, augmenting cognitive feedback, and facilitating systems thinking.

The paper[14] introduces Cloud-eLab as an AI-based platform that facilitates personalized learning, cognitive feedback, and extensive and comprehensive learning. It has been implemented and assessed in various postgraduate courses on data analytics and machine learning. However, future endeavors and constraints encompass enhancing the cognitive feedback module, integrating novel learning technologies, assessing the platform across various domains and levels, and tackling privacy and security concerns. The success of the platform hinges on its capacity to comprehend and identify the difficulties and uncertainties faced by students throughout the learning journey, while also carrying out meticulous assessments to gauge its influence on student learning achievements and contentment.

References:

1. Zhou, Y., Huang, C., Hu, Q., Zhu, J., & Tang, Y. (2018). Personalized learning full-path recommendation model based on LSTM neural networks. *Information Sciences*, *444*, 135–152. https://doi.org/10.1016/j.ins.2018.02.053
2. Morozevich, E. S., Korotkikh, V., & Kuznetsova, Y. A. (2022). The development of a model for the personalized learning path using machine learning methods. *Business Informatics*, *16*(2), 21–35. https://doi.org/10.17323/2587-814x.2022.2.21.35
3. Banik, L., Bhuiyan, M. H., & Jahan, A. (2015). Personalized learning materials for children with special needs using machine learning. *IEEE*. https://doi.org/10.1109/itecha.2015.7317390
4. Manzanares, M. C. S., Osorio, C. I. G., Díez-Pastor, J. F., & Antón, L. J. M. (2019). Will personalized e-Learning increase deep learning in higher education? *Information Discovery and Delivery*, *47*(1), 53–63. https://doi.org/10.1108/idd-08-2018-0039
5. Tsolis, D., Stamou, S., Christia, P., Καμπανά, Σ., Rapakoulia, T., Skouta, M., & Tsakalidis, A. K. (2010). An adaptive and personalized open source e-learning platform. *Procedia - Social and Behavioral Sciences*, *9*, 38–43. https://doi.org/10.1016/j.sbspro.2010.12.112
6. Pataranutaporn, P., Danry, V., Leong, J., Punpongsanon, P., Novy, D., Maes, P., & Sra, M. (2021). AI-generated characters for supporting personalized learning and well-being. *Nature Machine Intelligence*, *3*(12), 1013–1022. https://doi.org/10.1038/s42256-021-00417-9

7. Amin, S., Uddin, I., Alarood, A. A., Khan, W. U., Alzahrani, A., & Alzahrani, A. O. (2023). Smart E-Learning framework for personalized adaptive learning and sequential path recommendations using reinforcement learning. *IEEE Access*, *11*, 89769–89790. https://doi.org/10.1109/access.2023.3305584
8. Xiao, J., Wang, M., Jiang, B., & Li, J. (2017). A personalized recommendation system with combinational algorithm for online learning. *Journal of Ambient Intelligence and Humanized Computing*, *9*(3), 667–677. https://doi.org/10.1007/s12652-017-0466-8
9. Nedungadi, P., & Raman, R. (2012). A new approach to personalization: integrating e-learning and m-learning. *Educational Technology Research and Development*, *60*(4), 659–678. https://doi.org/10.1007/s11423-012-9250-9
10. Essa, S. G., Çelik, T., & Human-Hendricks, N. (2023). Personalized Adaptive Learning Technologies based on machine learning techniques to identify learning Styles: A Systematic Literature review. *IEEE Access*, *11*, 48392–48409. https://doi.org/10.1109/access.2023.3276439
11. Shawky, D. M., & Badawi, A. H. (2018). Towards a personalized learning experience using reinforcement learning. In *Studies in computational intelligence* (pp. 169–187). https://doi.org/10.1007/978-3-030-02357-7_8
12. Ingkavara, T., Panjaburee, P., Srisawasdi, N., & Sajjapanroj, S. (2022). The use of a personalized learning approach to implementing self-regulated online learning. *Computers & Education: Artificial Intelligence*, *3*, 100086. https://doi.org/10.1016/j.caeai.2022.100086
13. Rad, P., Roopaei, M., Beebe, N., Shadaram, M., & Au, Y. A. (2018). AI Thinking for Cloud Education Platform with Personalized Learning. *Proceedings of the . . .*

Annual Hawaii International Conference on System Sciences.
https://doi.org/10.24251/hicss.2018.003

14. Kanokngamwitroj, K., & Srisa-An, C. (2022). Personalized Learning Management System using a Machine Learning Technique. *TEM Journal*, 1626–1633. https://doi.org/10.18421/tem114-25