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TECH-DRIVEN LEARNING: INVESTIGATING THE EFFICACY OF MACHINE LEARNING IN E-LEARNING

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Abstract

The way individuals learn, teach, and engage with educational content determines the extent of learning and assimilation that have been going on. Without tech-driven teaching and learning, there exists serious gap in knowledge. Utilizing, technology to create personalized, interactive, and accessible learning experiences that cater to the diverse needs of all learners—including those with disabilities, different learning styles, and varying proficiency levels—is an effective way to integrate technology for inclusive learning. This study is motivated by series of problems being encountered by educators such as lack of Personalization, inefficient assessment and feed back, teacher overload, little or no interactive learning and dull learners being left behind. Integration of Machine Learning (ML) techniques into teaching and learning marks a new and transformative era for e-learning systems. Teachers may design inclusive, productive, and engaging learning experiences that equip students to thrive in the digital age by utilizing technology. A variety of technological instruments are available for use in education. One data science tool that has demonstrated improved learning is machine learning. It is endowed with personalization of learning potentials. We hinged our study on reinforcement theory of technology adoption as machine learning reinforces the aim of e-learning administrators. Our goal is to investigate the methods for implementing it for adaptive and personalized learning applications. We investigated the challenges of its adoption and found adaptability to individual learner, lack of interoperability, bias among others. We recommend personalized learning models, bias mitigation strategies and interoperability standards as solutions to its effective adoption and utilization.

Key words: Machine learning, e-learning, adaptive learning, Personalized Learning

Introduction

Before the advent of machine learning (ML), teaching and learning were fundamentally shaped by human cognition, traditional pedagogical methods, and limited technological interventions. Education relied heavily on direct instruction, rote memorization, and structured curricula, with knowledge transmission occurring primarily through verbal and written communication [1] (Bransford, Brown, & Cocking, 2000). Before ML, educational technology (EdTech) consisted of basic computer-assisted learning (CAL) programs, which followed predefined rules rather than adaptive algorithms (Suppes, 1966) [2]. These systems lacked the ability to learn from student interactions or improve over time.

The learning content was chosen in traditional learning systems (also known as "all to all" systems) without taking into account the unique requirements and traits of the learners. Because of this, every student was studying the same material, which compromised the activity's efficacy. Various techniques to teaching and learning have emerged in the last ten years as a result of technological advancements; e-learning, in particular, has increased during the covid19 epidemic. To achieve learning objectives, it is intriguing to consider the right learning path and content for each individual learner, particularly in light of current teaching and educational practices. An intelligent, adaptable e-learning system is essential to achieving learner-centered education.

Before machine learning, education was predominantly teacher-centered, with instructors serving as the primary source of knowledge. The "sage on the stage" model dominated classrooms, where teachers delivered lectures while students passively absorbed information (Freire, 1970). This approach often lacked personalization, as educators had limited means to adapt lessons to individual learning styles or paces.

Without machine learning, personalized learning was labor-intensive. Teachers manually assessed students through exams, quizzes, and observations, making it difficult to tailor instruction dynamically (Vygotsky, 1978). While some educators employed differentiated instruction, scaling such methods for large classrooms was challenging.

Textbooks, printed worksheets, and physical resources were the backbone of education. Unlike today's adaptive digital platforms, these materials could not update in real time or respond to learner needs (Cuban, 1986)[5]. Students who struggled with certain concepts had fewer opportunities for immediate feedback or remediation. Evaluating student performance was time-consuming. Teachers graded assignments manually, leading to delays in feedback, which hindered the learning process[6] (Black & Wiliam, 1998). Formative assessments were less efficient, making it harder to identify and address knowledge gaps promptly. Educational systems often followed rigid, standardized curricula that did not account for cognitive diversity. Students with learning disabilities or exceptional abilities frequently struggled within inflexible frameworks (Gardner, 1983)[7]. Special education interventions required extensive human effort and were not always data-driven.

Adaptive learning refers to a technology driven approach that delivers personalized learning that is patterned after the individual's needs, preferences and capacity. Adaptive learning platforms leverage technologies such as AI, and ML analytics to personalize learning experiences based on learner interaction. Incorporating elements such as gamification, adaptive content delivery, and mobile optimization, makes learning more engaging and accessible.To help students find educational materials that address their needs and problems, inte lligent tutoring systems are created in this context. [8]

Compared to traditional learning, adaptive learning offers a different method of instructio n and learning.Taking into consideration the needs and characteristics of learners who are often u nable toattain a given skill within a certain time, this innovative approach enables learners to lear n at any time and anywhere [9], [10].

As a result, learners have distinct learning paths [11, 12,13]. In actuality, learners have diverse learning profiles in terms of learning speed, knowledge, preferen ces, intellectual ability, learning styles, etc.

In this perspective, many studies have been realized during the last decade on the personalization of learning with the help of e-learning systems. However, most of these systems do not have methods to perfectly represent the learner's profile (deep profile), on which the system can propose and intelligently adapt the learning path that corresponds to this learner at the time of the execution of a learning activity.

In this paper, we investigate an intelligent adaptive e-learning system, based on machine learning. Machine learning is artificial intelligence that allows computers to learn from data and enhance their performance without being explicitly programmed (Himanshu Singhal 2024). ML focuses on developing algorithms that enable systems to recognize patterns, make predictions, and automatically adapt to new data. In the field of e-learning, machine learning is being used to create a more customized, personalized and adaptive learning experience for students.

One of the primary advantages of integrating machine learning into e-learning is the capacity to offer students customized recommendations. Machine learning has the ability to pinpoint the areas in which students struggle and recommend specialized activities or resources to help overcome these obstacles. It can assist in instantly adjusting the content, tempo, and degree of difficulty of learning materials, hence maximizing comprehension and engagement.

Regression analysis using machine learning predictive analytics is used to project future Regression analysis using machine learning predictive analytics is used to project future learning requirements. Because it can more accurately predict the demands of each individual learner, predictive analytics is essential for personalizing and optimizing learning experiences. Based on an analysis of a student's performance, interests, and learning style, the system can suggest courses, resources, and learning materials that are specifically matched to their needs. Students can concentrate on the items that are most pertinent to their learning objectives, which makes for a more interesting and useful learning experience. For instance, machine learning algorithms can be used by an online learning platform to monitor a student's development, pinpoint their areas of weakness, and offer customized resources to help them get better.

The system can adjust its recommendations by continuously monitoring their performance, ensuring that students are constantly challenged and motivated to keep learning. Adaptive learning experiences are being created in e-learning through the application of machine learning. With the use of algorithms, adaptive learning technology modifies the material's pace and difficulty in real time in response to a student's performance. Given that users with varying skill levels interact with the system, an e-learning platform that can be tailored to the user's profile is appropriate. Some people pick things up quickly, while others take their time. Some people still need to practice solving additional problems, while others just require examples. These choices are sometimes referred to as a person's learning styles, speed, knowledge, preferences, and intellectual capacity. [8] (2022) Boussakssou et al. Some of the ways in which ML has changed personalized learning include:

- **Adaptive learning platforms –** ML-driven adaptive learning platforms help analyze a learner's performance and behavior in real time. This allows for adjustment to the difficulty and type of content according to the learner's pace of learning, strengths, and weaknesses.
- **Content generation –** ML can assist in generating personalized content, such as customized quizzes, exercises, or simulations on specific learning needs.
- **Personalized recommendations –** ML algorithms analyze an individual's past learning history and preferences to recommend relevant content and individualized learning plans.
- **Instant feedback and assessment –** ML can provide instant feedback on assignments and quizzes, evaluate answers, and provide explanations or additional resources to enhance the learning process.
- **Natural Language Processing (NLP) –** NLP technology enables chatbots and virtual tutors to engage in conversations with learners, answer questions, and provide guidance.

- **Time flexibility –** AI allows for learning at any time and place by enabling learners to access resources 24/7.
- **Data analytics and predictive analytics –** By analyzing datasets to identify trends and patterns in learners' performance, AI can make data-backed recommendations about instructional methods, training content, and interventions.

Literature Review

The most appropriate learning items for each learner's profile have been found by the frequent development of adaptive e-learning systems in recent times. [7-9]. Although the large number of these learning resources offers a variety of opportunities, it also places limitations on learners' ability to find the best learning resources for their individual profiles [2]. To create a tailored learning context, most of these systems rely only on the learner's learning style and degree of knowledge [17].

The Felder-Silverman model [18] serves as the broad foundation for these methods, which identify the learner's learning style and degree of knowledge. Similar hybrid adaptation systems have been developed in the same context by P. Dwivedi et al. [21] and Alshammari et al. [22], which group learners according to their similarities and suggest the best learning items for them.To construct learner profiles, this system takes into account the past activities, learning preferences, and knowledge levels of the users.Next, it uses the Nearest Neighbor algorithm (KNN) to group learners.As a result, it offers adjustments based on the char acteristics of the acquired learner group rather than on an individual basis.

Boussakssou et al. [23] presented an adaptation model based on reinforcement learning. This system takes merely the learning style to adapt and suggest the learning path to the learners' needs. Similarly, Fazazi et al. [24] proposed an adaptive e-learning system design based on the multi-agent system approach and reinforcement learning to recommend an adaptive learning path for a learner with the following profile: intermediate knowledge level, verbal learning style, and hearing impairment. This system tries to recommend a list of learning objects appropriate for this learner profile. Moreover, W. Intayoad et al. [25] proposed a method based on reinforcement learning, more precisely the State-Action- Reward-State-Action algorithm (SARSA). This method is able to explore the environment to obtain information and exploit it to recommend appropriate learning objects to learners in an e-learning system.

Based on previous studies, it was observed that the proposed learning systems do not have powerful techniques in terms of the quality of learner classification (deep profile creation), which allow to significantly represent the learner and provide the learning system with pertinent information to adapt the learning to the learner's profile. Generally, these systems just consider the learning style and knowledge level of the learner to generate the adaptation.

Therefore, the researchers proposed this system to create a personalized learning experience. That is, it can analyze the learner's learning style, preferences, and abilities, etc. to establish a customized learning path for them. As a result, it can adjust the difficulty level of the content, provide feedback, and offer additional resources based on the learner's performance.

In this study, this system takes into account not only learning style and knowledge level but also other types of profiles (preference profile, knowledge profile, feature profile, etc.), as well as the learner's learning objectives, via the application of machine learning algorithms. This deep profile created will be used to adapt the learning to the specific needs and characteristics of the learner in question, using reinforcement-learning approach. This system will be able to search and select the most appropriate learning objects for this depth profile, thus providing each learner with a learning path that is the most advantageous and adequate.

The method suggested in this work uses reinforcement learning and machine learning to intelligently tailor the learning activity's content to each learner's unique needs while accounting for the deep learner's profile. Then the Q-learning algorithm was applied to generate the learning path of each learner according to his or her deep profile. Our system is composed of three principal modules; data pre-processing module, learner deep profile creation module, and learning path recommendation module. These three modules interact with each other to provide a personalized adaptation according to the learner's deep profile.

Theoretical Perspective

Reinforcement Theory

In 1957, B. F. Skinner, an American psychologist at Harvard University, proposed the reinforcement theory of motivation. It was later adapted to explain technology adoption in government. Proponents of this theory argue that administrators adopt IT if it supports their view of the organization change (Sherrod, 1971). Technology is adopted if it agrees with the view of the public manager on the future direction of the organization. For instance, if the chief executive of a public organization does not believe that a new information technology will work in the organization, he/she most likely will not adopt the technology. In the university system, if the dean of student affairs is convinced about electronic voting for students' union election, he/she will adopt it, but if he/she does not share the view it will not be adopted. In the same manner E-learning administrators will adopt the machine learning algorithms that will create adaptive and personalized learning for learners. The concern of e-Learning administrators is how best to make their students learn.

The Efficacy of Machine Learning

Many studies have been carried out on the personalization of learning with the help of e-learning systems. However, from our literature most of these systems do not have methods to perfectly represent the learner's profile (deep profile), on which the system can propose and intelligently adapt the learning path that corresponds to the learner at the time of the execution of a learning activity. We therefore explored the efficacy of machine learning considering it characteristics and potentials.

The efficacy of machine learning was investigated focusing on the creation of the deep learner profile from raw datasets on this learner, by combining two machine-learning algorithms: K-means classification and linear regression after executing the data preprocessing technique. On the other hand, the researchers focused on the adaptation and recommendation of learning paths to the learner according to their created deep profile. Next step is the implementation of the developed algorithm Q-learning of the reinforcement learning approach at the time of the execution of a learning activity, and this via an intelligent and automatic choice of the most appropriate learning objects.

ML-driven intelligent tutoring systems simulate one-on-one tutoring by analyzing student responses and providing customized feedback (VanLehn, 2011) [26]. Unlike static computer-assisted learning (CAL), ITS use reinforcement learning and natural language processing (NLP) to refine their teaching strategies over time (Woolf, 2009)[27].

ML automates grading for structured assignments (e.g., multiple-choice, coding exercises) and even essays using NLP (Shermis & Burstein, 2016)[28]. This reduces teacher workload while providing instant feedback, helping students correct mistakes faster (Hattie & Timperley, 2007) [28]. Educational institutions use predictive analytics to identify at-risk students by analyzing engagement patterns, assignment submissions, and quiz scores (Siemens & Long, 2011). Early warning systems allow instructors to intervene before students fall behind (Baker & Inventado, 2014)[30]. ML improves accessibility through speech-to-text, text-to-speech, and real-time translation tools, aiding students with disabilities and non-native speakers. AI-powered captioning and sign language recognition further democratize education. Generative AI (e.g., GPT-4) assists in creating customized learning materials, such as practice questions, summaries, and interactive simulations (Mollick & Mollick, 2023)[32. This reduces teacher prep time while ensuring content relevance.

Creating the Deep Learner Profile

ML algorithms enable adaptive learning platforms (e.g., Khan Academy, Duolingo) that adjust content difficulty based on student performance (Koedinger et al., 2012). These systems identify knowledge gaps and recommend tailored exercises, allowing students to learn at their own pace. Research shows that personalized learning improves retention and engagement (Pane et al., 2017).

An adaptive e-learning system that offers a personalized learning route while carrying out a pedagogical activity is made possible by machine learning. This adjustment, though, needs to be based on the student's deep profile, which is established as soon as the learner connects to the system and is updated over time based on the feedback the learner provides to the system. One of the most crucial methods for tailoring instruction to the unique needs of students is the use of deep profiles in Computer Environments for Human Learning (CEHL), particularly in platforms for remote learning. It has a fascinating part to play in how learning paths are personalized. Actually, it emphasizes student preferences, such a learner's choice of video over text. However, there are other learner characteristics that are also significant and can be used to characterize the learner in detail. These characteristics include preferred learning time, language, culture, country, hobbies, preferred media type, prerequisites, learning objectives, and more. The learner's characteristics can also be characterized from the perspective of his potential disabilities (e.g., hearing 85%; sight 30%, etc.).

Two sub-machine learning models for building the learner's deep profile in the system:
1. The K-means classification algorithm;
2. The Linear regression algorithm.

K-means classification algorithm

In the literature, there are many classification algorithms including K-means, KNN, SVM, etc. In this paper, the K-means Algorithm, which is one of the most popular algorithms due to its simplicity and intuitive interpretation [21] was adopted. It can be defined as the process of organizing objects in a dataset into clusters, such that objects in the same cluster have a high degree of similarity, while those belonging to different groups have a high degree of dissimilarity. The key step for any unsupervised algorithm is to identify the optimal number of clusters (optimal K) into which the data can be grouped. The Elbow method [22], is one of the most popular methods for identifying this optimal value of K. i.e. the optimal k is the point after which the distortion/inertia starts to decrease linearly, where distortion is computed as the average of the squared distances of the cluster centers of the sample and inertia is the sum of the squared distances of the elements to their nearest center of gravity. It consists in calculating the variance of the different cluster volumes considered, and then placing the variances obtained on a graph.

Linear Regression Algorithm*:*

In the literature, linear regression is classified among the multivariate analysis methods that deal with quantitative data, with the objective to find a linear relationship between a quantitative variable Y and one or more also quantitative variables X, i.e. to find the line that passes "as close as possible" to all the points of the cloud. It is used to predict the behavior or outcome of the variable Y, when each variable of X is manipulated.

The objectives of this system are the creation of a deep profile of a given learner, via the implementation of K-means and linear regression, and the recommendation of adaptive learning paths according to this deep profile, by implementing the Q-learning algorithm. The proposed system is decomposed into three principal modules, data preprocessing module, learner deep profile creation module, and learning path recommendation module. These three modules interact with each other to provide a personalized adaptation according to the learner's deep profile. The results obtained indicate that taking into account the learner's deep profile improves the quality of learning for learners.

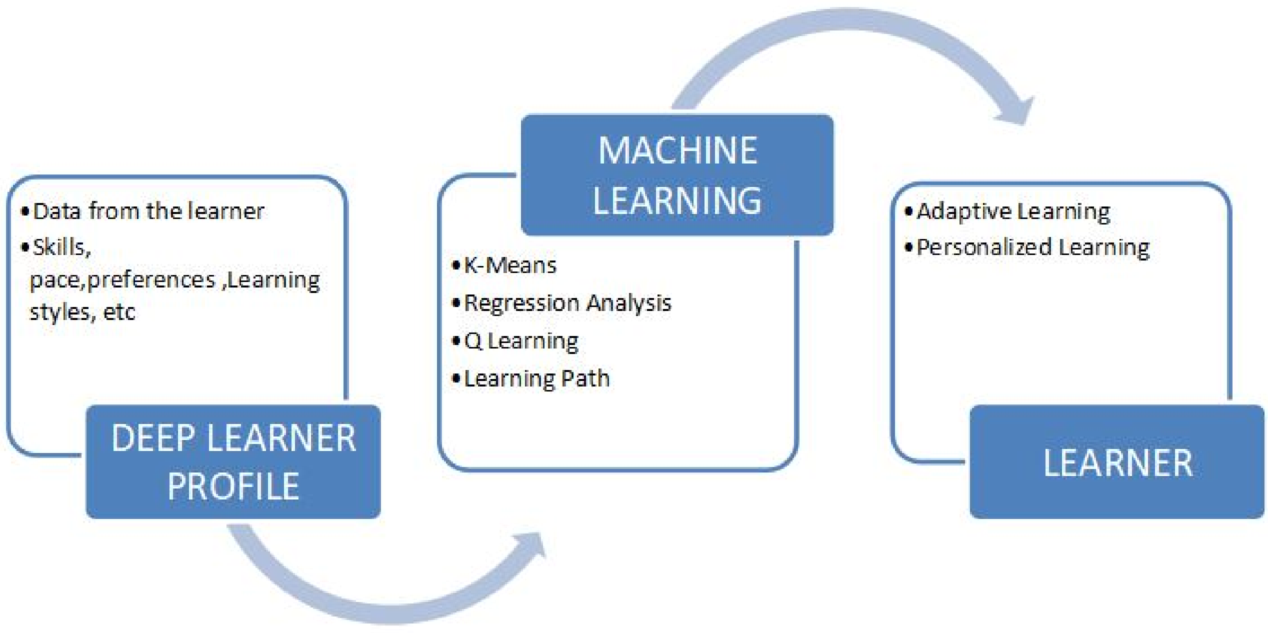

Fig 1: The general process of the study

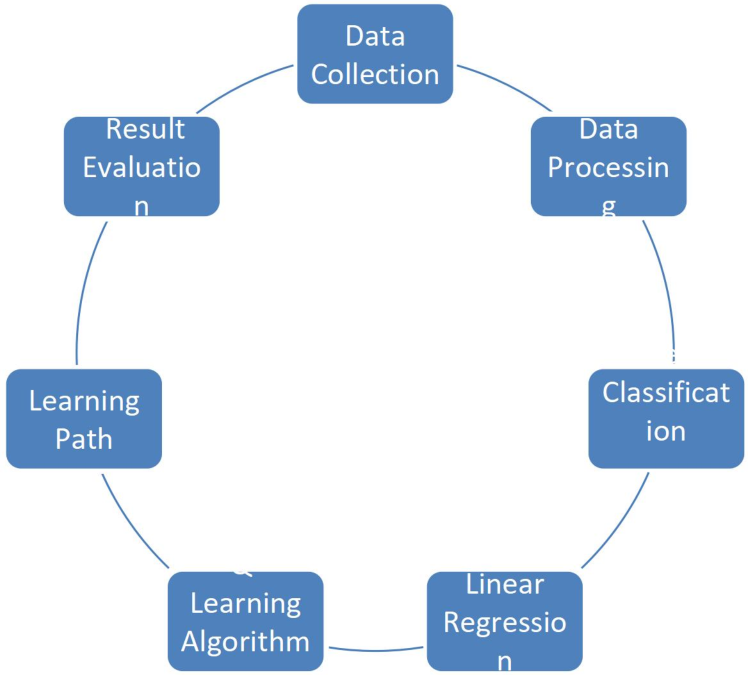

Fig. 2: The overall process for learning path recommendation.

In this section, the general process of the study was presented in Fig. 1. The important step at the beginning of the pipeline is to initiate the data preprocessing process.

- Data collection: A collection of learner information and characteristics to build a raw dataset containing a volume of pertinent learner information of learners.
- Data preprocessing: This technique consists of removing all redundant, non-pertinent, or less important attributes, extracting the information, and transforming the raw datasets into a useful and efficient format, which allows us to proceed to the next step. The extracted information is relevant and truly represents the learner's deep profile in terms of personal data . Among these techniques, the best known according to the literature is Linear Discriminant Analysis (LDA), as a supervised algorithm.
- K-means classification: Once the datasets are well defined, K-means is used for the classification and generation of homogeneous (similar) learner clusters.
- Linear regression: Once the clusters are generated by K-means, the linear regression algorithm is used to distinguish the different data that generate the same cluster i.e. help K-means to represent the data correctly in each cluster.
- Q-learning algorithm: Once the classification of the learners is completed by using K-means and linear regression, the Q-learning algorithm is used to search and determine the optimal learning path taken by the learner according to his or her deepened profile. Specifically the Q-Learning algorithm is used to create an adaptive system that meets the needs of each student Q- Learning algorithms [4] are one of the most widely used Reinforcement Learning algorithms, with the main advantage of their simplicity. They

require a minimum of calculations and, in their basic formulation; they can be expressed by simple equations, and easily implemented in programs. e). Q-Learning is a form of reinforcement learning without a model.

- Learning path recommendation: This step consists of recommending the most appropriate learning objects in real time to the learner based on their deepened profile.
- Result evaluation: The proposed system provides excellent results in terms of precision and quality obtained.

Common Issues and Mitigations in Machine Learning In E-Learning

Machine Learning (ML) has undoubtedly transformed education and learning in particular. However, it grapples with challenges such as inadequate training data, data quality issues, and algorithmic biases. These practical hurdles require a pragmatic approach, emphasizing the importance of high-quality, representative data, and ongoing model monitoring.

1. Inadequate Training Data: The backbone of any ML algorithm is the data it is trained on. The challenge arises when there is a shortage of both quality and quantity in the training dataset. Noisy, incorrect, or unclean data can significantly impact the effectiveness of ML algorithms. Addressing issues such as noisy data, inaccuracies, and difficulties in generalizing output data becomes paramount for accurate predictions.

2. Poor Quality of Data: Data quality is a recurring issue, with noisy, incomplete, and inaccurate data undermining the accuracy of classification and overall results. Achieving high-quality data is essential for the success of ML models, necessitating a meticulous approach to data preparation.

3. Non-representative Training Data: The representativeness of training data directly influences the generalization capability of ML models. If training data fails to cover all relevant cases, the model may produce less accurate predictions, leading to bias against specific classes or groups. Using representative data in training mitigates biases and enhances prediction accuracy.

4. Overfitting and Underfitting: Overfitting occurs when a model captures noise and inaccuracies from a large dataset, adversely affecting its performance. This can be mitigated by employing linear and parametric algorithms, increasing training data, or reducing model complexity. Conversely, underfitting arises from a model being too simple for the data, resulting in incomplete and inaccurate predictions. Methods to address underfitting include increasing model complexity, using better features, and adjusting constraints.

5. Monitoring and Maintenance: Regular monitoring and maintenance are essential to ensure the continued effectiveness of ML models. Changes in data or user expectations may necessitate code adjustments and resource updates, emphasizing the need for ongoing vigilance.

6. Getting Bad Recommendations: ML models operating in a specific context may provide outdated or irrelevant recommendations, known as data drift. Regularly updating and monitoring data helps mitigate this issue, ensuring recommendations align with current user expectations.

7. Learner Segmentation: Accurate learner segmentation is crucial for effective ML algorithms. Developing algorithms that recognize learner behavior and trigger relevant recommendations based on past experiences is essential for personalized user interactions.

8. Data Bias: Data bias introduces errors when certain elements in the dataset are given disproportionate weight. Detecting and mitigating bias requires careful examination of the dataset, regular analysis, and implementing strategies to ensure data diversity.

Conclusion

Machine learning has revolutionized e-learning, especially by creating adaptive and personalized learning. This it was able to do through tools – K means and Linear regression analysis-to create deep learner profile from which path recommendation comes..However, it grapples with challenges such as inadequate training data, data quality issues, and algorithmic biases. These practical hurdles require a pragmatic approach, emphasizing the importance of high-quality, representative data, and ongoing model monitoring. Addressing these issues fosters the responsible development and deployment of machine learning applications, ensuring they contribute positively to education and e-learning.

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