

Smart Learning Management Systems for Inclusive Education Using Cloud Computing Technologies

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ABSTRACT:

The rapid advancement of smart educational technologies has significantly transformed digital learning environments through the integration of cloud computing, intelligent learning management systems (LMS), and educational analytics. The present study investigated students' adaptability toward smart learning management systems within cloud-enabled inclusive educational environments using machine learning-based predictive analysis. A publicly available educational dataset containing 1,205 student records and 14 categorical variables related to demographic characteristics, educational background, technological accessibility, and online learning behavior was utilized for analysis. Data preprocessing and label encoding were performed before statistical and machine learning analysis. Exploratory data analysis, correlation analysis, and Random Forest classification modeling were conducted to evaluate factors influencing adaptability toward smart LMS systems. The findings demonstrated that educational accessibility, technological infrastructure, and socioeconomic conditions significantly influence adaptability levels in online learning environments. Correlation analysis revealed that class duration, institution type, and location positively influenced adaptability, whereas financial condition demonstrated a substantial relationship with adaptability disparities. The Random Forest classifier achieved an overall prediction accuracy of 90.87%, indicating strong predictive capability for adaptability classification. Feature importance analysis identified class duration, age, financial condition, network quality, and device accessibility as major predictors affecting

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adaptability toward smart educational systems. The results further highlighted the importance of cloud-enabled educational accessibility, LMS participation, and digital infrastructure in supporting inclusive and adaptive learning environments. The study demonstrates that machine learning and educational analytics can effectively support adaptive digital learning research and inclusive educational management. Overall, the integration of smart learning management systems and cloud computing technologies provides substantial opportunities for improving accessibility, learner engagement, and adaptive educational delivery within future intelligent learning ecosystems.

Keywords: smart learning management systems, inclusive education, cloud computing, educational analytics, adaptive learning.

1. Introduction

With the speedy development of the digital technologies, the current education systems are greatly affected, particularly the smart learning environment (SLE), cloud technology and intelligent learning management system (LMS) have an influence on the education systems. Cloud-based digital solutions are becoming more instrumental in educational institutions, providing a way to increase accessibility, scalability, flexibility and personalized learning experiences for various learners. Smart LMS frameworks have become key educational technologies that enable adaptive learning, real-time communication, decision-making based on data, and participative education (Machado & Santos, 2023). Increasingly there are smart educational systems deployed, which broaden the learning opportunities for children with diverse education and accessibility needs, and make the digital learning environment more relevant and inclusive.

Cloud computing technologies have significantly transformed the learning process in the education sector, playing a crucial role in the teaching and learning process and providing online education provision (Thavi et al., 2024; Gupta et al., 2023). The recent research shows that cloud-based educational systems are great to enhance the educational flexibility and digital accessibility and to foster collaborative and personalized learning environment (Papadakis et al., 2023). Likewise,

data-driven management systems and cloud-based learning platforms have demonstrated their ability to improve educational outcomes through effective resource management, adaptive learning support, and fostering student engagement (Sharma et al., 2025). The embedding of artificial intelligence, data science, and cloud computing in the educational process has also assisted in the construction of intelligent educational environments that support accessibility and learning by learners (Ojika et al., 2023).

Smart learning management systems have also seen rapid growth with the inclusion of the Internet of Things (IoT) technology, intelligent automation, and artificial intelligence for education analytics. In the context of Cloud Enabled Learning Environments (CELEs), IoT-based smart LMS platforms have enhanced real-time communication, adaptive monitoring, and personalized educational management (Chandak et al., 2024). Smart education systems with IoT technologies also enable interactive and technology-based learning experiences, enhancing students' engagement and educational accessibility (Badshah et al., 2023). Furthermore, intelligent e-learning systems help in the adaptive delivery of education by recommending personalized learning content, analyzing each learner's learning status, and monitoring their learning performance (Liu & Yu, 2023).

Inclusive education is one of the current focuses of educational policy and digital learning research.

Increasingly, it is hoped that educational technologies can support equitable participation for learners with diverse educational, socioeconomic and accessibility needs. For inclusive education, the ability of intelligent systems and AI-based educational systems has shown great promise in the management of inclusive education and in the field of adaptive learning support (Akbarova et al., 2023). Likewise, cloud-based LMS has been demonstrated to be highly effective in enhancing digital transformation capabilities and accessibility for students with visual impairments and other special educational needs (El Koshiry et al., 2024). Inclusive learning design frameworks with the support of AI also highlight the need for adaptive learning systems that can cater to diverse learner traits and personalized learning needs (Aguilar & Baek, 2023).

AI in education has significantly aided in the use of personalized learning, adaptive learning systems, and intelligent support systems for learners. However, AI-powered LMS has been shown to enhance learning interaction, learner engagement and learning accessibility in various educational contexts (Oluwafemi Ayotunde et al., 2023). There are also personalized learning technologies that can be supported by artificial intelligence and learning analytics that can further enhance adaptive learning experiences and individualized educational support (Hashim et al., 2022). Furthermore, the scalability and optimization features of cloud computing and AI-powered educational platforms play a crucial role in the creation of sustainable and intelligent digital learning ecosystems (Martín-Rodilla & González-Pérez, 2023).

Even as more and more of the LMS technologies are being adopted to facilitate learning through the cloud, there are significant issues associated with access to technology, adaptation to technology, and equitable access to technology-based learning opportunities. The understanding of adaptability to smart educational systems could vary substantially due to differences in the socio-economic situation, digital infrastructure, internet access and technological literacy. Moreover,

while some studies examined cloud computing, intelligent educational systems and LMS adoption separately, there is a lack of empirical studies that address predictive analysis of student adaptability toward smart LMS environments in the context of inclusive education. Moreover, several behavioral, technological, and institutional factors also affect the acceptance and adoption of learning management systems, which should also be explored analytically (AL-Nuaimi et al., 2024). Moreover, the incorporation of artificial intelligence and smart education technologies brings in other opportunities and challenges in adaptive learning, accessibility, and education equality (Saputra et al., 2023).

Hence, the present study is conducted to assess the adaptability of students towards smart learning management systems (SLMS) with the help of the cloud-based education variables and machine learning based predictive analysis. The work also explores how the accessibility of education, technological infrastructure, and economic and social factors are associated with adaptability in inclusive digital learning environments.

Research Objectives

1. To evaluate the influence of educational, technological, and socioeconomic factors on students' adaptability toward smart learning management systems.
2. To analyze the role of cloud-enabled educational accessibility variables, including internet connectivity, device usage, and LMS participation, in inclusive digital learning environments.
3. To develop a machine learning-based predictive model for classifying students' adaptability levels in smart cloud-supported educational systems.

2. Materials and Methods

2.1 Data Preprocessing

In the current research, the dataset "Students' Adaptability Level in Online Education" has been collected to analyze the factors affecting

adaptability in the smart learning environment with the use of a cloud education system (Suzan, 2022). There were 1,205 observations and 14 categorical variables related to demographic data, educational background, technological accessibility and online learning behavior. The variables were gender, age, education level, type of institution, experience with IT, location, experience with load shedding, financial situation, type of internet, type of network, class duration, use of self-learning management system, type of device and adaptability level. The three classes of the target variable, Adaptivity Level, were: High, Moderate, and Low adaptivity.

2.2 Exploratory Data Analysis

An Exploratory Data Analysis (EDA) was done to examine the relationship and frequency distribution of educational and technology factors that relate to online learning adaptability. The frequency distribution and visualization through bar charts were made for the specific adaptability classes. Cross-tabulation tests were also done to find any relationships between adaptability class and the variables pertaining to inclusion factors, such as the use of LMS, the kind of internet used, the type of device used, and financial status.

2.3 Correlation Analysis

The correlation matrix was created using the coded data set in order to look at how some educational, demographic, and technological factors relate to each other. These were quantified by calculating the Pearson correlation coefficients, which were then represented in a heatmap. The correlation analysis helped in identifying the accessibility and engagement-related factors affecting the adaptability towards smart learning management systems.

2.4 Machine Learning Classification Modeling

The machine learning classification analysis was done to determine the adaptability level of the students on the cloud-based smart learning environment. The coded data was split into the training and testing data sets through the use of

stratified sampling with an 80:20 proportion. The predictor variables included all the attributes in the database apart from the Adaptability Level, whose predictions were made based on other factors. Random Forest Classifier was applied to solve the problem since it performs well with multiclass categorization in educational data. The classifier was made up of 100 decision trees with a constant random state for consistency of results.

2.5 Model Evaluation

The effectiveness of the prediction made by the Random Forest model was analyzed on the basis of the following metrics: accuracy, precision, recall, F1-score, and confusion matrix. Performance measures were calculated separately for each class: High, Moderate, and Low adaptability. The confusion matrix plot was used to analyze the correct and incorrect classifications.

2.6 Feature Importance Analysis

To determine the importance of educational and technological factors in adaptability prediction, the importance feature analysis was carried out based on the Random Forest approach. The fitted classifier was used for obtaining the feature importance values, which were then sorted based on their importance for predictability. LMS factors, internet connection, digital infrastructure and socio-economic factors associated with inclusive education were highlighted.

2.7 Software and Computational Environment

All computations were done using the Python programming language. Some of the major libraries used include Pandas and NumPy for data manipulation, Matplotlib and Seaborn for visualizing data, and Scikit-Learn for model training and statistical analysis. All computations were done using the Python programming language. Some of the larger libraries that are commonly used include Pandas, NumPy, matplotlib, seaborn and scikit-learn for data manipulation, visualization, and model training and analysis.

3. Results

3.1 Dataset Characteristics and Adaptability Distribution

The database contained 1,205 cases of student profiles, and 14 categorical features related to demographics, education, availability of technologies and online learning habits. We have divided the dependent feature – Adaptivity Level

into three namely Moderate Level of Adaptivity, Low Level of Adaptivity, and High Level of Adaptivity. From the distribution analysis, it can be observed that the highest number of students lie in the Moderate category (625 students), followed by the Low category (480 students) and the relatively small number of students are in the High category (100 students).

Table 1. Distribution of Adaptability Levels

Adaptability Level	Frequency
Moderate	625
Low	480
High	100

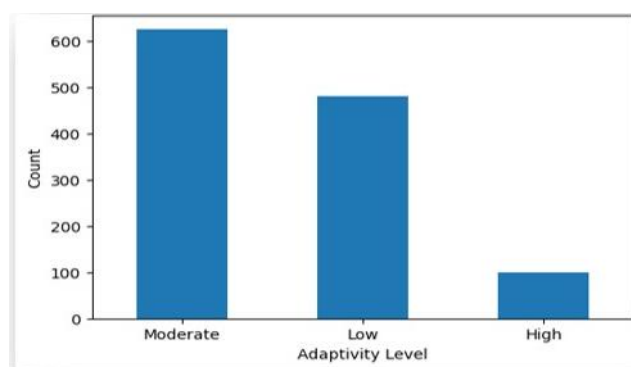


Figure 1. Distribution of Adaptivity Levels

3.2 LMS Usage and Accessibility Analysis

Cross tabulation results showed strong relationships between access to education variables and adaptability levels. The use of self-management systems by students resulted in high proportions of Moderate and High levels of adaptability. Also, students who had internet access through WiFi performed better than those using mobile data to access the internet, signifying the role of internet stability in cloud-

based learning platforms. On the other hand, device utilization also pointed out that mobile phones were the leading device used to participate in the learning environment; however, users of computers showed relatively higher adaptability levels. In terms of financial status, it was shown that students from financially privileged backgrounds performed better regarding adaptability compared to their economically challenged counterparts.

Table 2. Relationship Between Educational Variables and Adaptability Level

Variable	Major Observation
Self LMS Usage	LMS users demonstrated higher adaptability levels
Internet Type	WiFi users showed stronger adaptability patterns
Device Type	Computer users exhibited relatively higher adaptability
Financial Condition	Richer students demonstrated higher adaptability

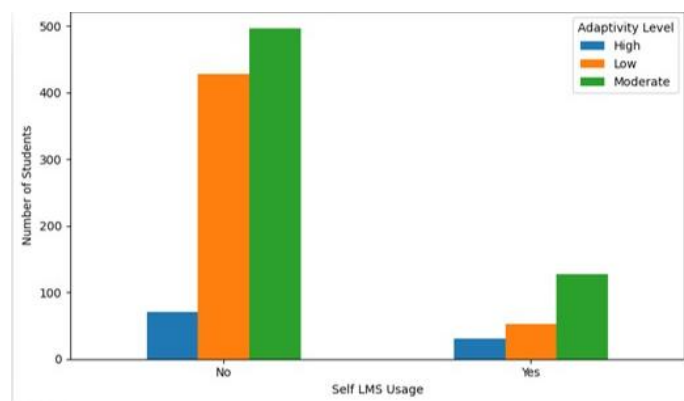


Figure 2. LMS Usage and Adaptability Distribution

3.3 Correlation Analysis of Educational Variables

Various correlations were found between the educational, demographic, and technological variables and the ability to adapt to online learning. Class duration was positively correlated with adaptivity level with the highest value of $r = 0.22$. In other words, those students who spent more time in virtual classrooms were better adapted to online studying than others. Other factors positively correlated with adaptivity level

include institution type ($r = 0.16$) and location ($r = 0.11$). Some socio-economic factors negatively correlate with adaptability levels. Financial condition appears to be the socio-economic variable most strongly correlated with adaptability level ($r = -0.27$). This means that income level has a serious impact on the adaptive behaviors towards learning technologies. Also, there was a negative correlation with age ($r = -0.23$).

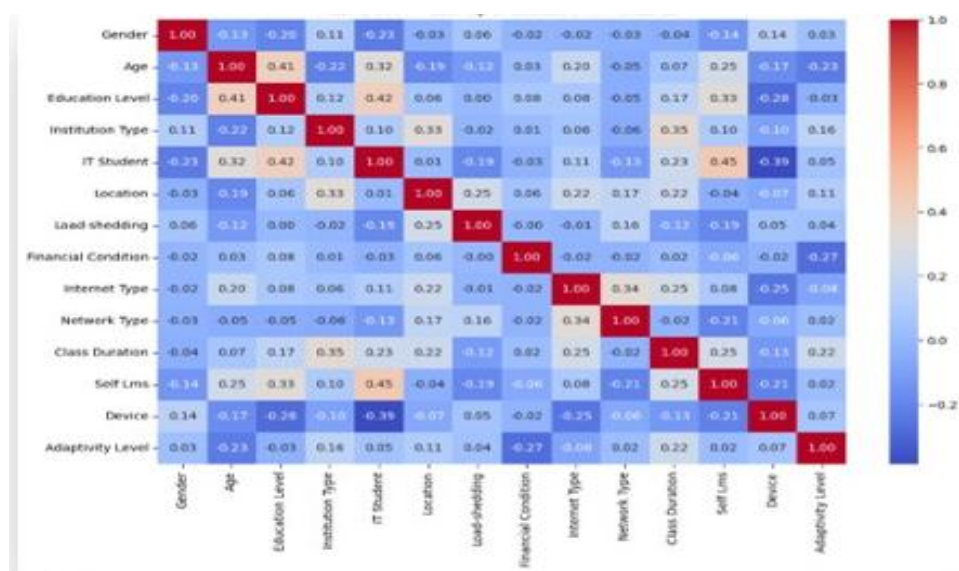


Figure 3. Correlation Heatmap of Educational Variables

3.4 Random Forest Classification Performance

A random forest classifier was employed to identify students' adaptability levels based on education-related, demographic and

technological variables. The random forest classifier obtained a very good classification accuracy score of 90.87% in predicting students' adaptability. The classification results revealed very good prediction accuracy as well as good

prediction precision and recall scores in all adaptability groups. Students belonging to the Moderate adaptability group showed outstanding prediction scores with an F1 score of 0.92, whereas those in the Low adaptability group received an F1 score of 0.91. Students belonging to the High adaptability group revealed relatively low recall scores because of class imbalance, although precision scores remained impressive.

The weighted F1 score of 0.91 indicated once again the excellent predictive power of the classifier. In general, confusion matrix analysis suggested that students were correctly classified in each adaptability group. The only exception involved students in the Moderate and Low adaptability groups since misclassification mainly took place in these groups.

Table 3. Performance Metrics of the Random Forest Classifier

Metric	Value
Accuracy	90.87%
Weighted Precision	0.91
Weighted Recall	0.91
Weighted F1-Score	0.91

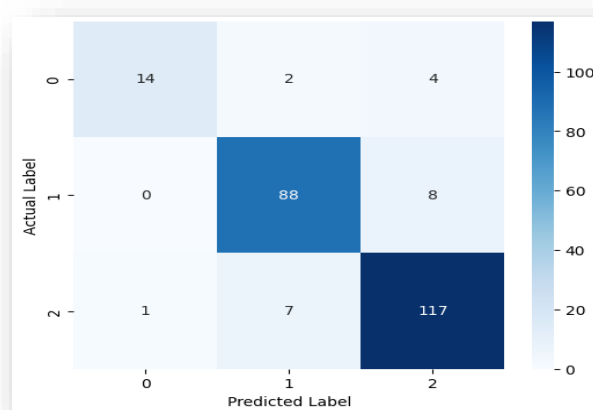


Figure 4. Confusion Matrix of the Random Forest Classifier

3.5 Feature Importance Analysis

The feature importance analysis gave the information about the most important predictors that contribute to adaptability towards smart learning management systems. The importance value of 0.171 was found for Learning Engagement Time, 0.118 for Age and 0.111 for Financial Condition. This result indicated that the

learning engagement time, learning predictor, and economic status are significant factors influencing the adaptability to smart learning environments. Technological access related predictors were also found to be important for predicting adaptability. Network Type, Device Type, Internet Type, and Self LMS were all important predictors for adaptability.

Table 4. Feature Importance Scores for Adaptability Prediction

Feature	Importance Score
Class Duration	0.171
Age	0.118
Financial Condition	0.111
Gender	0.082

Network Type	0.068
Education Level	0.066
Institution Type	0.061
Location	0.061
Device	0.057
Internet Type	0.055
Self LMS	0.054
IT Student	0.051
Load-shedding	0.045

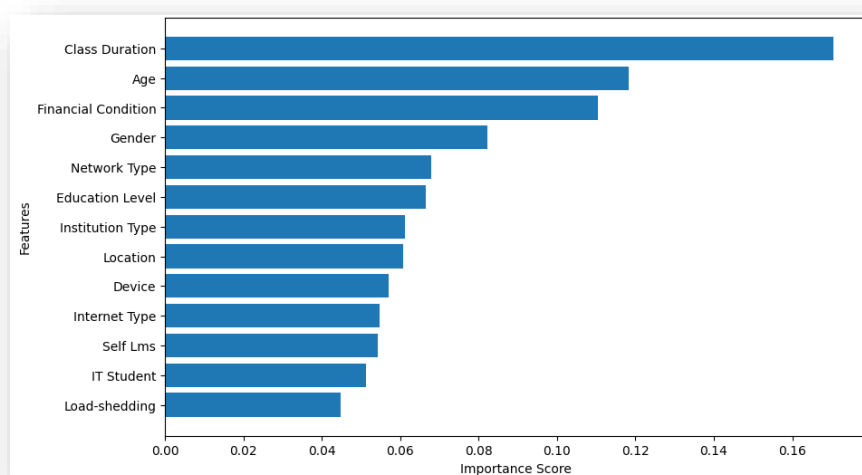


Figure 5. Feature Importance for Predicting Adaptability Level

3.6 Implications for Inclusive Digital Education

Results based on the study, adaptability towards smart learning management system environments was found to be highly correlated with factors related to educational access, socioeconomic factors, and technology. Factors related to education access, such as internet access, computer access, and LMS engagement, were found to make significant contributions to predicting adaptability. The significance of inclusive learning technologies in promoting adaptability towards digital learning systems was also established through this study. The predictive ability of the Random Forest model proved the feasibility of applying machine learning algorithms for educational adaptability analysis. All in all, the findings suggest that smart learning management systems using cloud computing technologies could greatly contribute

to adaptability and inclusivity in the field of education.

4. Discussion

The findings in the current study highlighted how important using smart learning management systems and cloud-based educational technologies are in shaping students' adaptability to the online learning environment. The results showed that educational accessibility, technological infrastructure, and socioeconomic conditions have significant impacts on the level of adaptability of inclusive digital education systems. The high predictive ability of the Random Forest machine learning algorithm further showed that machine learning and educational analytics can be applied in educational settings that involve cloud-based learning.

The results showed that students who used a self-learning management system had comparatively more adaptability patterns as compared to the students who did not use a self-learning management system. This result agrees with previous studies that underscore the vital role of intelligent LMS frameworks in the enhancement of educational accessibility, adaptive learning, and learner engagement (Machado & Santos, 2023). Likewise, in cloud-based learning, IoT-supported smart LMS has been demonstrated to enhance communication efficiency, learner monitoring, and personalized learning management (Chandak et al., 2024). The positive impact of LMS participation reported in the current research also corroborates the significance of intelligent e-learning systems in educational environments with adaptation (Liu & Yu, 2023).

The connection to the internet and technological infrastructure also proved to be significant factors for adaptability. Learners with WiFi connectivity and computer-based devices showed more favorable adaptability patterns, emphasizing the need for a stable online capability to enable successful engagement in cloud-based learning contexts. Cloud computing technologies have also been found to have a significant effect on educational accessibility, scalability, collaboration and flexibility in remote learning in previous studies (Gupta et al., 2023; Thavi et al., 2024). The findings on the role of internet connectivity and the quality of the network further reinforce the importance of cloud-based learning through educational services to create inclusive digital learning environments (Papadakis et al., 2023). Furthermore, widespread cloud computing applications and related accessibility issues are also key factors to consider when implementing educational technology (Pallathadka et al., 2022).

There was evident socioeconomic factors that significantly affected adaptability towards smart LMS systems. Economically related factors appeared as one of the most significant features in the feature importance analysis where economically better-off students tended to demonstrate a comparatively better adaptability

pattern than those from less economically better-off households. The result confirms the unequal access to digital education and the increasing focus on learning equality in inclusive learning environments. As smart schools and technology-enriched learning environments become the norm, there is a growing need for equitable access to digital resources, support and help for learners, and intelligent learning resources through the use of technology. The results also highlight the fact that without tackling the accessibility gap, technology cannot ensure inclusive education.

AI and intelligent educational systems also play a crucial role in adaptive and personalized learning environments. Prior research has shown that AI-powered education technologies provide benefits in terms of personalized learning, learner interaction, and adaptive education delivery in various learning scenarios (Hashim et al., 2022). AI-based educational systems also facilitate access and cooperation in educational settings that use cloud services (Ojika et al., 2023). Likewise, systematic reviews on the integration of AI in education have pointed out the opportunities and challenges of intelligent educational technologies, especially in the field of adaptive learning, learner support and educational ethics (Saputra et al., 2023). Thus, Educational Analytics with the assistance of AI offer valuable opportunities to enhance the prediction of learner adaptability and the process of Adaptive Educational Management.

The present findings are also in line with studies that highlight inclusive educational settings for learners with diversity. AI-enabled inclusive learning design models have shown great potential to increase accessibility and to provide adaptive learning support to students with diverse learning needs (Aguilar & Baek, 2023). Cloud-based LMS platforms have also proved beneficial in enhancing the digital transformation competencies and accessibility for learners with visual impairment and special educational needs (El Koshiry et al., 2024). Therefore, intelligent systems and adaptive educational technologies can play a significant role in providing equitable participation and learning-oriented educational

delivery in the inclusive environment of education (Akbarova et al., 2023).

The results of the adaptability analysis also highlighted the significance of LMS adoption and acceptance by learners. Technological familiarity, institutional support, accessibility, and behavioral factors impact the acceptance and effective use of learning management systems (AL-Nuaimi et al., 2024). Based on the results of the present study, the duration of class and the variables related to LMS make substantial impacts on the adaptive learning behavior in online learning. The use of artificial intelligence, augmented reality, and smart educational technologies also contributes to the engagement and interactive educational experiences in modern digital learning ecosystems (Al-Ansi et al., 2023; Zawacki-Richter et al., 2022).

Even though the results were encouraging, there were some limitations to the present study. Most of the variables used were categorical educational and technological variables and there were no direct measurements of academic performance, disability variables, or psychological indicators of learning. Therefore, technological accessibility and participation related issues were used to assess adaptability more dominantly. Also, the data was of general online learning environments and not LMS implementations in particular institutions. Future research can also use longitudinal information on learners' education, accessibility-specific indicators, AI-based learner analytics, and smart LMS environments on the institution level to enhance the level of prediction and reinforce the research on inclusive education.

In general, the results show that smart learning management systems with the help of cloud computing technologies play a significant role in establishing adaptive and inclusive digital learning environments. In the future smart educational ecosystems, educational analytics, intelligent educational systems, and access frameworks via a cloud may therefore positively affect educational equity, learner participation and adaptive online learning outcome.

5. Conclusion

In the present study, the students' adaptability in the context of smart learning management systems in cloud-based inclusive learning environments was assessed using machine learning and educational analytics approaches. The results showed that educational accessibility, technological infrastructure, LMS participation, and socio-economic conditions have a significant impact on the adaptability towards digital learning systems. The students with better internet connectivity, longer engagement, better technological accessibility, and more participation in LMS had comparatively higher levels of adaptability in an online learning environment. Overall, machine learning methods for educational analytics and adaptive learning research were found to be effective as the Random Forest classification model showed strong predictive performance for adaptability classification. The results of feature importance analysis also showed that class duration, age, financial condition, network quality, and device accessibility are key predictors that affect adaptability toward smart LMS environments. These findings demonstrate the impact the cloud-based learning platform and inclusive digital access have on adaptive online learning. The study also highlighted the need for the use of intelligent Educational Technologies, Artificial Intelligence and Cloud Computing approaches in the current inclusive education. A smart learning management system (LMS) can have a huge impact on engagement, accessibility, personalisation and adaptive learning delivery for learners, all from the cloud. Socioeconomic inequalities and technological accessibility still play a role in equitable participation in digital education environments, however. The general debate over integration of smart learning management system (SLMS), cloud computing (CC) technologies, and predictive educational analytics (PEA) can envision that there are great opportunities to develop adaptive and inclusive learning ecosystem. The results contribute to a growing field of research (intelligent educational systems) and will help achieve data-driven

solutions to increase the access and adaptability of the learners. Future research on disability-specific indicators and institutional learning analytics, combined with the AI-based adaptive

learning models, could prove to be exciting topics, with the potential to further improve inclusive digital education and smart learning environments.

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