IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 3, June 2026
Impact Factor: 8.2

Personalized Lifelong Learning Pathways Using Machine Learning: A Multi-Age Group Analysis

Dr.Sameer Pundalik Patil
Asst. Professor, Dept. of Computer Science
Shree Damodar College of Commerce and Economics, Margao, Goa, India
patilfriends@gmail.com

Abstract: *This study is about making learning better for people of all ages. It uses machine learning to create personalized learning paths for students. The goal is to understand how students learn, what they need, and what problems they face in learning.*
The study uses basic information about learners like age, gender, education level, digital skills, learning choices, and online learning activity. It also studies how learners feel about AI-based learning systems and how personalized learning affects their interest and course completion.
Three machine learning models are used in this study: Naïve Bayes, Decision Tree, and Random Forest. These models help predict student learning results. The results show that Decision Tree and Random Forest work best with 92% accuracy. Naïve Bayes gives 84% accuracy. This means tree-based models are better at understanding complex learning patterns.
Overall, the study shows that machine learning and simple statistics can help build better personalized learning systems. These systems can help students stay more engaged, participate more, and perform better in their studies.
In the future, this study can be improved by using more data from different places. Better models can also be used. More evaluation methods like precision, recall, and F1-score can also make the results more accurate and reliable.

Keywords: Personalized Learning; Lifelong Learning; Machine Learning; Multi-Age Group Analysis; Student Performance Prediction; Educational Data Mining; Naïve Bayes; Decision Tree; Random Forest; Chi-Square Test; Learning Analytics; AI-Based Recommendation Systems; Online Learning Platforms.

I. INTRODUCTION

Today, technology is changing the way people learn. Many students and working people now use online learning platforms to study new subjects and improve their skills. However, every learner is different. Some learn fast, while others need more time. Some like videos, while others prefer reading or practical activities. Because of these differences, one teaching method may not work well for everyone.

Artificial Intelligence (AI) and Machine Learning (ML) help make learning more personal and useful. Machine Learning systems can study learners' interests, past learning activities, skills, and performance. Based on this information, the system can suggest the right courses and learning materials for each learner. This is called personalized learning.

Personalized learning pathways help learners study at their own speed and according to their own needs. These systems can improve learner interest, motivation, participation, and course completion. They also help learners choose better learning paths for their future goals.

Lifelong learning is important in today's world because technology and job requirements change very quickly. People of different age groups continue learning throughout their lives for education, career growth, and personal development. However, learners from different age groups may have different learning styles, digital skills, and challenges while using online learning systems.

DOI: 10.48175/IJARSCT-36455

This study focuses on personalized lifelong learning pathways using Machine Learning for learners from different age groups. The study aims to understand learners' preferences, digital literacy, engagement, and interest in AI-based learning systems. It also studies how personalized learning affects motivation and course completion. The results of this study may help researchers, teachers, and developers create better and smarter online learning systems for all types of learners.

II OBJECTIVE OF STUDY

A.General Objective:-

- To study how Machine Learning helps create personalized lifelong learning pathways for learners of different age groups.

B. Specific Objectives:-

- To study the basic details of learners such as age, gender, and educational qualification.
- To understand learners' digital skills and their participation in online learning platforms.
- To identify the learning goals and preferred learning content of learners from different age groups.
- To understand whether learners accept and like AI and Machine Learning–based learning recommendation systems.
- To study how customized learning content affects learner interest, participation, and satisfaction.
- To examine how personalized learning pathways influence course completion.
- To study whether age groups affect learning preferences and learning content needs.
- To identify the main problems faced by learners in personalized online learning systems.
- To give suggestions for improving Machine Learning–based lifelong learning systems for learners of different age groups.

III. HYPOTHESIS OF STUDY

1. Null Hypothesis :-There is no connection between age group and the type of learning content learners prefer.
Alternative Hypothesis :-There is a connection between age group and the type of learning content learners prefer.
2.Null Hypothesis:-Digital skills do not affect participation in online learning platforms.
Alternative Hypothesis :-Digital skills affect participation in online learning platforms
3.Null Hypothesis:-Personalized learning recommendations do not affect learner engagement.
Alternative Hypothesis:-Personalized learning recommendations affect learner engagement.
4. Null Hypothesis:-Age group does not affect personalized learning content preferences.
Alternative Hypothesis:-Age group affects personalized learning content preferences.
5.Null Hypothesis:-Customized learning pathways do not improve course completion.
Alternative Hypothesis:-Customized learning pathways improve course completion.
6. Null Hypothesis:-Educational qualification does not affect acceptance of AI-based personalized learning systems.
Alternative Hypothesis:-Educational qualification affects acceptance of AI-based personalized learning systems.
7.Null Hypothesis:-The challenges faced in personalized online learning are the same for all age groups.
Alternative Hypothesis:-The challenges faced in personalized online learning are different across age groups.

IV. LITERATURE REVIEW

In recent years, online learning has grown very fast. Many researchers are trying to make learning better using computers and data.

Studies show that not all students learn in the same way. Some learn fast, and some learn slowly. Some like videos, while others like reading or practice. Because of this, one single teaching method does not work for everyone.

To solve this problem, researchers use personalized learning. This means giving different learning content to different students based on their needs.

Machine learning is very helpful in this area. It uses data to understand student behavior. It can predict how students will perform in their studies. Models like Naïve Bayes, Decision Tree, and Random Forest are often used for this.

These models help find patterns in student data. Decision Tree and Random Forest usually work better because they can understand complex patterns more easily.

Research also shows that many things affect learning. These include age, digital skills, motivation, and interest. These factors change how students use online learning platforms.

Some studies also use simple statistical tests like the Chi-Square Test. These tests help find if two things are related. For example, age and learning preference can be related.

New AI systems can also suggest learning materials to students. These systems help students learn better by showing the right content at the right time.

However, some studies have problems. Many use small data. Some only check accuracy and ignore other important measures.

Because of this, more research is needed. It should include more data, more age groups, and better testing methods. This will help make learning systems more accurate and useful for everyone.

Farhood et al.[1] reviewed 125 research studies published between 2015 and 2025 on the use of Artificial Intelligence (AI) in personalized learning. The study showed that AI and machine learning help create learning systems that can adjust to the needs of each learner. These systems can recommend suitable learning materials, provide personalized support, and give feedback based on a learner's performance.

The researchers found that AI-based personalized learning is being used in schools, colleges, and online learning platforms. These systems help learners stay engaged, improve their performance, and achieve better learning outcomes. The study also highlighted that learners have different goals, interests, and learning speeds. Therefore, learning systems should be flexible and adapt to these changing needs over time.

The findings of this study support the idea of lifelong learning, where people continue learning throughout different stages of their lives. This is important for the present study, which focuses on using machine learning to create personalized lifelong learning pathways for learners from different age groups. The goal is to provide learning recommendations that match the needs and interests of individuals as they grow and develop.

Bayly-Castaneda, Ramirez-Montoya, and Morita-Alexander[2] studied how Artificial Intelligence (AI) can be used to create personalized learning pathways for lifelong learning. They reviewed 78 research articles published between 2019 and 2024. The study found that AI helps create learning experiences that match the needs, interests, and goals of individual learners.

The researchers explained that lifelong learning happens throughout a person's life. Therefore, learning systems should be flexible and able to change as learners grow and develop. AI-based learning systems use machine learning, learning analytics, and adaptive technologies to recommend suitable learning materials, adjust the speed of learning, and support independent learning.

The study also found that effective personalized learning pathways should consider a learner's background, previous knowledge, learning behavior, and changing goals. By doing this, AI-powered systems can improve learner engagement, help develop new skills, and support continuous learning. These findings are important for the present study, which focuses on using machine learning to create personalized lifelong learning pathways for learners from different age groups. The aim is to provide learning experiences that adapt to the needs of individuals throughout their lives.

Davuluri [3] studied how Artificial Intelligence (AI) and Machine Learning (ML) can help create personalized learning pathways for students. The study found that machine learning can analyze learner data to understand their strengths, weaknesses, interests, and learning styles. Based on this information, learning systems can provide suitable learning materials and learning activities for each learner.

The study explained that different machine learning techniques can be used to predict learner performance, recommend useful resources, and adjust learning content when needed. It also highlighted the importance of adaptive learning systems, intelligent tutoring systems, and learning analytics in improving the learning experience.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 3, June 2026
Impact Factor: 8.2

The findings showed that AI-based learning systems can move away from the traditional one-size-fits-all approach and provide learning experiences that match the needs of individual learners. Such systems can improve learner engagement, learning outcomes, and academic performance. These findings support the present study, which focuses on developing personalized lifelong learning pathways using machine learning for different age groups. The goal is to provide learning experiences that adapt to the changing needs, abilities, and goals of learners throughout their lives.

Naliaka[4] studied how Artificial Intelligence (AI) can help create personalized learning pathways for lifelong learning. The study found that AI can provide learning experiences based on a learner's needs, interests, and career goals. AI systems can study learner information and recommend suitable learning materials, learning activities, and skill development opportunities.

The research explained that lifelong learning is a continuous process that takes place throughout a person's life. Therefore, learning systems should be flexible and able to adapt to changing learner needs. The study also showed that AI can provide real-time feedback, personalized recommendations, and adaptive learning content to support continuous learning.

These findings are important for the present study because they show how AI can be used to create personalized lifelong learning pathways for people of different age groups. The goal is to provide learning experiences that change according to learners' interests, abilities, and goals throughout their lives.

Hardaker and Glenn [5] studied how Artificial Intelligence (AI) can support personalized learning. The study found that AI can create learning experiences that match the needs, interests, and learning styles of individual learners. AI systems can recommend suitable learning materials, adjust learning activities, and provide support based on each learner's progress.

The researchers explained that personalized learning allows learners to learn at their own pace and receive resources that fit their needs. The study also showed that technologies such as machine learning, intelligent tutoring systems, and adaptive learning platforms help improve learner engagement and learning outcomes.

In addition, the study highlighted the need for flexible learning environments that can adapt to changing learner needs over time. These findings are important for the present study because they show how machine learning can be used to create personalized lifelong learning pathways. Such pathways can support learners from different age groups by providing learning experiences that match their changing skills, interests, and goals throughout life.

V. RESEARCH METHODOLOGY

A.Research Design:**-** This study uses both quantitative and qualitative research methods. In the quantitative method, numerical data is collected through structured questionnaires and analyzed. The qualitative method is used to understand learners' thoughts, experiences, and suggestions about personalized lifelong learning systems. Using both methods helps the study collect detailed and meaningful information.

B.Research Approach :- This study uses a descriptive and analytical research approach. The study describes and examines how Machine Learning helps create personalized lifelong learning pathways for learners of different age groups. It helps understand learning needs, preferences, and learning patterns among different learners.

C.Data Collection Methods:-Primary data for this study was collected using an online questionnaire created with Google Forms. The questionnaire was prepared to gather information about:

- Demographic details
- Digital literacy
- Learning preferences
- Personalized learning experiences
- Learner engagement
- AI-based recommendation systems
- Challenges faced during online learning

The questionnaire included different types of questions such as:

- Multiple-choice questions
- Likert-scale questions
- Open-ended questions for detailed opinions and suggestions

D.Target Population :- The target population of this study includes learners from different age groups who use online learning platforms for education, professional growth, or personal learning. These learners use digital platforms to improve their knowledge, skills, and learning experiences.

E.Sampling Technique **:-**The study used a convenience sampling method to collect responses from participants who were easy to reach through online platforms, educational groups, and social media networks. This method helped collect data quickly and easily from learners who were willing to participate in the study.

F.Sample Size:- A total of 200 respondents participated in this study. The responses collected from these participants were used for data analysis and interpretation. The collected data helped the researcher understand the learning experiences and opinions of the participants.

G.Research Instrument :- A structured questionnaire was used as the main tool for collecting data in this study. The questionnaire was divided into different sections.

Section A – Demographic Information
This section collected basic information about the participants, such as:

- Age
- Gender
- Educational qualification

Section B – Quantitative Questions
This section included Likert-scale questions related to:

- Personalized learning
- Learner engagement
- AI-based recommendation systems
- Customized learning pathways
- Course completion behavior

Section C – Qualitative Questions
This section included open-ended questions to collect:

- Learners' opinions
- Challenges faced during online learning
- Suggestions for improving personalized learning systems

H. Reliability Test :- Reliability testing was done using Cronbach's Alpha. This test was used to check whether the Likert-scale questions in the questionnaire measured the same idea in a consistent and reliable way. The Cronbach's Alpha value obtained was 0.907, which shows that the questionnaire has excellent reliability and strong consistency.

VI. STATISTICAL ANALYSIS AND HYPOTHESIS TESTING

*A.Data Analysis Techniques :-*The collected data was analyzed using statistical techniques and Machine Learning methods. Different methods were used to understand the data and identify important patterns and relationships.

B. Quantitative Analysis:

The following statistical methods were used:

- Descriptive Statistics to summarize the data
- Frequency Analysis to count responses
- Percentage Analysis to show data in percentage form
- Chi-Square Test to find relationships between variables
- Correlation Analysis to measure the connection between variables
- Reliability Testing using Cronbach's Alpha to check the consistency of the questionnaire

C.Result and Interpretation of Age Group Distribution

The age group of the respondents was studied using frequency and percentage analysis. The results showed that 8 respondents belonged to Age Group 1, 105 respondents belonged to Age Group 2, 63 respondents belonged to Age Group 3, and 24 respondents belonged to Age Group 4.

The findings show that most respondents belonged to Age Group 2, followed by Age Group 3. This means that the majority of participants were from the middle age groups included in the study. The age distribution helped provide variety in the collected data and supported further statistical and Machine Learning analysis.

Table 1: Demographic Profile of Respondents by Age Group

Age Group	Frequency	
1	8	10-18
2	105	19-25
3	63	26-45
4	24	46+
Total	200	

The gender distribution of the respondents was studied using frequency and percentage analysis. The results showed that 97 respondents were female and 103 respondents were male.

The findings show that both male and female respondents participated almost equally in the study. The number of male respondents was slightly higher than female respondents. This balanced participation helped collect different opinions and improved the quality of the data for further statistical and Machine Learning analysis.

The educational status of the respondents was studied using frequency and percentage analysis. The results showed that 105 respondents were college students, 89 respondents were working professionals, and 6 respondents were retired people.

The findings show that most respondents were college students, followed by working professionals. Only a few respondents were retired people. This means that the study included people from different educational and professional backgrounds. These different responses helped improve the quality of the data and supported further statistical and Machine Learning analysis.

VII. HYPOTHESIS TESTING

Hypothesis testing was done to study the relationship between different factors such as personalized learning pathways, learner engagement, digital literacy, and adaptive learning preferences. Statistical tests were used to check whether the relationships between these variables were meaningful and significant.

A. Chi-Square Test for Hypothesis Testing

The Chi-Square Test was used to study the relationship between age group and the type of learning content preferred by learners. This test helped check whether the two variables were related in a meaningful way.

***Hypotheses1*:-(H0)There is no connection between age group and the type of learning content learners prefer.**
(H1)There is a connection between age group and the type of learning content learners prefer.

Interpretation of Chi-Square Test:-

The Chi-Square Test was used to study the relationship between age group and the type of learning content preferred by learners.

The test result showed a Chi-Square value of 107.26 and a p-value of 0.0004292.
Since the p-value is less than 0.05, the null hypothesis (H0) was rejected and the alternative hypothesis (H1) was accepted.
This means that age group and learning content preference are related to each other. Learners from different age groups prefer different types of learning content.

Chi-Square Test for Hypothesis Testing
Hypotheses2
Null Hypothesis (H0) :-Digital skills do not affect participation in online learning platforms.
Alternative Hypothesis (H1) :-Digital skills affect participation in online learning platforms.
Statistical Test Used **:-**The Chi-Square Test was used to study the relationship between digital skills and participation in online learning platforms. This test helped check whether the two variables were related in a meaningful way.
Interpretation of Chi-Square Test:-The Chi-Square Test was used to study the relationship between digital skills and participation in online learning platforms.The test result showed a Chi-Square value of 22.825, with 4 degrees of freedom and a p-value of 0.0001372.Since the p-value is smaller than 0.05, the null hypothesis (H0) was rejected and the alternative hypothesis (H1) was accepted.This means that digital skills have an effect on participation in online learning platforms. Learners with different levels of digital skills participated differently in online learning activities and courses.

Hypothesis 3: Personalized Learning Recommendations and Learner Engagement
Hypotheses
Null Hypothesis (H0):-Personalized learning recommendations do not affect learner engagement.
Alternative Hypothesis (H1):-Personalized learning recommendations affect learner engagement.
Statistical Test Used:-A Chi-Square Test was used. This test helps us check if two things are related.Here, it checks whether personalized learning recommendations are connected to learner engagement. It helps us understand if personalized content makes learners more active and involved in learning.
Decision Rule
If the p-value is less than 0.05, we reject the null hypothesis.
If the p-value is greater than 0.05, we accept the null hypothesis.
Interpretation of Hypothesis 3
A Chi-Square Test was used to check if personalized learning recommendations are linked with learner engagement.
The results are:
Chi-square value = 58.107
Degrees of freedom = 12
p-value = 4.985×10^{-8}
The p-value is very small. It is much smaller than 0.05. This means the result is important and not due to chance. It shows that there is a connection between personalized learning recommendations and learner engagement.
Decision on Hypotheses:-Since the p-value is less than 0.05:
We reject the null hypothesis (H0)
We accept the alternative hypothesis (H1)
Personalized learning recommendations do affect learner engagement. When learners get content that matches their needs and learning style, they feel more interested and more involved in learning.

Hypothesis 4: Age Group and Personalized Learning Content Preferences
Null Hypothesis (H0):-Age group does not affect personalized learning content preferences.
Alternative Hypothesis (H1):-Age group affects personalized learning content preferences.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 3, June 2026
Impact Factor: 8.2

Statistical Test Used

A Chi-Square Test is used to check the relationship between age group and learning content preferences.This test helps us understand if the two things are connected or not. It shows whether people of different ages prefer different types of learning content.

Interpretation of Result (Hypothesis 4)

A Chi-Square Test was used to check if age group is linked to personalized learning content preferences.

Chi-square value = 107.26

Degrees of freedom = 63

p-value = 0.0004292

The p-value is very small. It is less than 0.05.This means the result is important. It did not happen by chance.It shows that age group and learning content preference are connected.

Age group does affect the type of learning content people prefer. Different age groups like different types of learning content.

Hypothesis 5 **: Customized Learning Pathways and Course Completion**

Null Hypothesis (H0):-Customized learning pathways do not improve course completion.

Alternative Hypothesis (H1) :-Customized learning pathways improve course completion.

The Chi-Square Test was used to study the relationship between customized learning pathways and course completion. This test helped check whether personalized learning pathways helped learners complete more courses successfully.

The Chi-Square Test was used to study the relationship between customized learning pathways and course completion.The test result showed a Chi-Square value of 85.469, with 8 degrees of freedom and a p-value of 3.852e-15.Since the p-value is smaller than 0.05, the null hypothesis (H0) was rejected and the alternative hypothesis (H1) was accepted.This means that customized learning pathways help improve course completion. Learners who receive personalized learning content are more likely to complete courses successfully. The result also shows that learning content designed according to learners' needs, level, and pace can improve participation and course completion.

Hypothesis 6 : Educational Qualification and Acceptance of AI-Based Personalized Learning Systems

Null Hypothesis (H0):-Educational qualification does not affect acceptance of AI-based personalized learning systems.

Alternative Hypothesis (H1):-Educational qualification affects acceptance of AI-based personalized learning systems.

The Chi-Square Test was used to study the relationship between educational qualification and acceptance of AI-based personalized learning systems. This test helped check whether learners with different educational backgrounds had different levels of interest in AI-based personalized learning systems.

The Chi-Square Test was used to study the relationship between educational qualification and acceptance of AI-based personalized learning systems.The test result showed a Chi-Square value of 1.3537, with 4 degrees of freedom and a p-value of 0.8522.Since the p-value is greater than 0.05, the null hypothesis (H0) was accepted and the alternative hypothesis (H1) was rejected.This means that educational qualification does not strongly affect acceptance of AI-based personalized learning systems. Learners from different educational backgrounds showed almost the same level of interest in AI-based personalized learning technologies.

Hypothesis 7 : Challenges in Personalized Online Learning Across Age Groups

Null Hypothesis (H0):-The challenges faced in personalized online learning are the same for all age groups.

Alternative Hypothesis (H1)The challenges faced in personalized online learning are different across age groups.

The Chi-Square Test was used to study the relationship between age groups and the challenges faced in personalized online learning. This test helped check whether learners from different age groups faced different types of challenges while using personalized online learning systems.

The Chi-Square Test was used to study the relationship between age groups and the challenges faced in personalized online learning.The test result showed a Chi-Square value of 14.03, with 9 degrees of freedom and a p-value of 0.1213.Since the p-value is greater than 0.05, the null hypothesis (H0) was accepted and the alternative hypothesis (H1) was rejected.This means that learners from different age groups faced similar challenges in personalized online learning. The study showed that age group did not strongly affect the types of challenges faced by learners while using personalized online learning systems.

VIII. MACHINE LEARNING USING PYTHON

Python programming language was used in the study for Machine Learning analysis and prediction of learner behavior. Python helped analyze learner data and build prediction models for personalized lifelong learning systems.Different Python libraries such as Pandas, NumPy, Scikit-learn, Matplotlib, and Seaborn were used for:

- Data cleaning
- Data preprocessing
- Data visualization
- Classification
- Pattern identification
- Predictive analysis
- Model evaluation

The study used three Machine Learning algorithms:

- Decision Tree
- Random Forest
- Naive Bayes
- Logistic Regression
- Support Vector Machine (SVM)
- K-Nearest Neighbor (KNN)

These algorithms helped study learner behavior, learning patterns, and learner interest in personalized learning systems.

Naive Bayes Model:-The Naive Bayes Machine Learning model was used to study learner data and predict learner interest in personalized learning systems. In this model, the input variable (X) was “What is your age?” and the output variable (Y) was “Would you be interested in personalized learning systems?”

The model achieved an accuracy of 84%. This means the model correctly predicted 84% of the testing data.

The confusion matrix showed that:

- 21 records in Class 1 were correctly predicted.
- 2 records in Class 1 were predicted incorrectly.
- 1 record in Class 0 and 1 record in Class 2 were also predicted incorrectly.

The classification report showed that the model performed very well for Class 1. The precision, recall, and F1-score values for Class 1 were 0.91.The model showed weak performance for Class 0 and Class 2 because there were very few records available in those classes. Due to the small number of records, the model could not correctly predict those classes.The macro average value of 0.30 showed moderate overall class performance, while the weighted average value of 0.84 showed strong overall prediction accuracy for the full dataset.The findings suggest that learner age can help predict learner interest in personalized learning systems. The Naive Bayes model helped identify learner behavior patterns and supported predictive analysis in AI-based personalized lifelong learning systems.

B. Decision Tree Model

The Decision Tree Machine Learning model was used to study learner data and predict learner interest in personalized learning systems. In this model, the input variable (X) was “Gender” and the output variable (Y) was “Would you be interested in a system that suggests learning paths based on your learning history and goals?”The model achieved an accuracy of 92%. This means the model correctly predicted 92% of the testing data. This shows very good prediction performance.The confusion matrix showed that 23 records in Class 1 were correctly predicted. One record from Class 0 and one record from Class 2 were predicted incorrectly as Class 1.

The classification report showed strong performance for Class 1. The precision value was 0.92, recall value was 1.00, and F1-score value was 0.96. These values show that the model performed very well for predicting learner interest in personalized learning systems.The model showed weak performance for Class 0 and Class 2 because very few records were available in those classes. Due to the small amount of data, the model could not correctly predict those classes.The macro average values showed moderate overall class performance, while the weighted average values showed strong overall prediction accuracy for the full dataset.The findings suggest that gender can help predict learner interest in AI-based personalized learning systems. The Decision Tree model helped identify learner behavior patterns and supported predictive analysis in lifelong learning environments.

C.Random Forest

The Random Forest Machine Learning model was used to study the connection between digital literacy and learner interest in personalized learning systems.The model achieved an accuracy of 92% (0.92). This means the model correctly predicted most learner responses in the testing data.The confusion matrix showed that 23 records from Class 1 were correctly predicted. However, 1 record from Class 0 and 1 record from Class 2 were wrongly predicted as Class 1.The classification report showed very good performance for Class 1. The model achieved a precision value of 0.92, recall value of 1.00, and F1-score value of 0.96. This means the model was very successful in identifying learners who were interested in personalized learning systems.

The model did not perform well for Class 0 and Class 2 because these classes had very few records. Due to the small amount of data, the precision, recall, and F1-score values for these classes were low.The findings suggest that digital literacy may affect learner interest in personalized learning systems. The Random Forest algorithm also showed good performance in predicting learner behavior and supporting smart educational recommendation systems.

IX. QUALITATIVE DATA ANALYSIS

The qualitative responses collected from open-ended questions were analyzed using thematic analysis and content analysis methods. These methods helped identify common learner experiences, challenges faced during online learning, and suggestions for improving personalized learning systems.

A.Tools and Technologies Used

The study used different tools and technologies for data collection, analysis, and visualization. The main tools used in the study were:

- R and Python
- Google Forms
- Microsoft Excel
- Jupyter Notebook

B.Ethical Considerations

Participants were informed about the purpose of the study before collecting the data. Participation in the survey was completely voluntary. The personal information and responses of the participants were kept confidential throughout the research process.

C.Scope of the Study

This study focuses on analyzing personalized lifelong learning pathways using Machine Learning among learners from different age groups. The study examines learner preferences, digital literacy, learner engagement, and the acceptance of AI-based personalized learning systems.

X. LIMITATIONS OF THE STUDY

The study is limited to 200 respondents.

The collected data depends on the honesty and understanding of the participants.The study is based only on responses collected through an online survey.The results of the study may change with a larger sample size or different groups of learners.

Interpretation and Implications (Including Hypothesis Results)

The results show that student learning depends on many connected factors. These include age, digital skills, learning preferences, and behavior.The Chi-Square Test was used to check different relationships in the study.

Age Group and Learning Content Preference:-The Chi-Square value was 107.26 and the p-value was 0.0004292.Since the p-value is less than 0.05, we reject the null hypothesis (H0) and accept the alternative hypothesis (H1).This means age group and learning content preference are related. Different age groups prefer different types of learning content.

Digital Skills and Online Learning Participation:-The Chi-Square value was **22.825** with 4 degrees of freedom and a p-value of **0.0001372**.Since the p-value is less than 0.05, we reject H0 and accept H1.This means digital skills affect participation in online learning. Students with different skill levels take part differently in online learning activities.

Personalized Learning and Engagement:-The results show that personalized learning increases student interest and engagement.When students get learning content that matches their needs, they feel more involved and focused in learning.

Customized Learning Pathways and Course Completion:- The Chi-Square value was **85.469** with 8 degrees of freedom and a p-value of **3.852e-15**.Since the p-value is less than 0.05, we reject H0 and accept H1.This means customized learning pathways help students complete courses. Personalized learning improves completion rates.

Education Level and AI System Acceptance:-The Chi-Square value was **1.3537** with 4 degrees of freedom and a p-value of **0.8522**.Since the p-value is greater than 0.05, we accept H0 and reject H1.This means education level does not strongly affect acceptance of AI-based learning systems. Students from different education backgrounds show similar interest.

***Age Group and Learning Challenges*:-** The Chi-Square value was **14.03** with 9 degrees of freedom and a p-value of **0.1213**.Since the p-value is greater than 0.05, we accept H0 and reject H1.This means age group does not strongly affect learning challenges. Students of all ages face similar problems in online learning.

***Overall Interpretation* :-**Some factors like age, digital skills, and learning pathways are related to learning behavior. But some factors like education level and age do not show a strong effect in all cases.Machine learning and statistical tests together help us understand student learning better.

XI. CONCLUSION OF ANALYSIS

In this study, Decision Tree and Random Forest performed the best, with an accuracy of **92%**. These are the most reliable models for this dataset.Naive Bayes performed lower with **84% accuracy**.We also tested different hypotheses using the Chi-Square Test. Some relationships were found to be important, such as age group with learning preference, and digital skills with participation. Some relationships were not significant, such as education level with AI system acceptance.However, accuracy alone is not enough. More evaluation is needed using precision, recall, F1-score, and cross-validation. This will make the results more strong and trustworthy.

XII. FUTURE ENHANCEMENT

This study can be improved in the future in many ways.

More data can be collected from different colleges and universities. This will make the results more strong and accurate.

Second, better machine learning models like Support Vector Machine, XGBoost, and Gradient Boosting can be used. These models may give better results.

Third, deep learning methods can also be tried. They can help when there is a large amount of data.

Fourth, more performance checks like precision, recall, and F1-score can be added. These will give a clearer picture of how well the models work.

Fifth, a real-time system or website can be created. This can help teachers find students who need help quickly.

Finally, more factors like behavior, motivation, and psychology can be added. This will help make predictions more accurate.

REFERENCES

[1] H. Farhood, M. Nyden, A. Beheshti, S. Muller, Artificial intelligence-based personalised learning in education: A systematic literature review, Discover Artificial Intelligence, 5 (2025) 331. https://doi.org/10.1007/s44163-025-00598-x.

[2] K. Bayly-Castaneda, M.-S. Ramirez-Montoya, and A. Morita-Alexander, "Crafting personalized learning paths with AI for lifelong learning: A systematic literature review," Frontiers in Education, vol. 9, 2024, Art. no. 1424386, doi: 10.3389/feduc.2024.1424386.

[3] M. Davuluri, "AI in Education: Personalized Learning Pathways Using Machine Learning Algorithms," 2021.

[4] E. Naliaka, "Leveraging Artificial Intelligence for Personalized Lifelong Learning Pathways," International Journal of Research Publication and Reviews, vol. 6, no. 6, pp. 11643–11645, 2025. doi: 10.55248/gengpi.6.0625.2368.

[5] G. Hardaker and L. E. Glenn, "Artificial intelligence for personalized learning: A systematic literature review," International Journal of Information and Learning Technology, vol. 42, no. 1, pp. 1–14, 2025. doi: 10.1108/IJILT-07-2024-0160.