International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

A Study on Personalized Learning Experience through AI-driven User Profiling in E-learning Platforms

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Submitted: 29/01/2024 **Revised:** 07/03/2024 **Accepted:** 15/03/2024

Abstract: This research delves how e-learning systems may use artificial intelligence (AI) methods to provide students with more tailored lessons. Less engagement and effectiveness are common outcomes of using traditional e-learning systems because of their inability to adapt to the demands of various learners. This project seeks to improve e-learning systems through the use of AI-driven user profile in order to provide personalised content, resources, and learning pathways to each user. The creation and deployment of an advanced AI system that can study user habits, tastes, and patterns of learning. The algorithm generates unique user profiles by collecting and analysing vast amounts of data; this allows the system to provide tailored suggestions and adaptive learning opportunities. Using measures for user engagement, learning results, and satisfaction surveys, the study assesses the efficacy of the AI-driven personalised learning strategy. When compared to more conventional, cookie-cutter methods, the results show that this one works far better in terms of student engagement, information retention, and happiness. The development of better e-learning tools by proving that user profile powered by AI can lead to more tailored and efficient education. Educators, instructional designers, and developers may use the findings to make online education more effective and accessible.

Keywords: *Personalized Learning, Experience, AI-Driven, User Profiling, E-learning, Platforms*

1. Introduction

Education has changed dramatically due to technology, particularly online learning platforms. These platforms have revolutionised education due to their ease, accessibility, and personalisation. Personalisation adapts instruction to each student's abilities, interests, and learning style, a cornerstone of modern education. This boosts classroom motivation, engagement, and performance. Personalised learning involves tailoring course content, methodologies, and evaluations to each student. Online learning platforms leverage AI to provide mass-produced, customised lectures that traditional classrooms can't handle. Data analytics and machine learning algorithms may be used in AI-driven user profiling to understand and adapt to each learner's unique qualities.

Despite growing interest and investment in AI-driven user profiles for customised learning, notably in E-learning platforms, more empirical research is needed.

Online education "personalisation" implies adapting classes to each student's interests, abilities, and shortcomings. Constructivist teaching emphasises student engagement in knowledge development. Adaptive learning routes, content recommendations, and evaluations are all forms of personalisation. It attempts to boost student engagement, motivation, and learning outcomes by making learning more relevant and engaging.Recent AI advances allow e-learning platforms to incorporate extensive user profiling. AI-driven user profiling gathers, analyses, and interprets student interactions, preferences, and performance data. Clustering, classification, and reinforcement learning are used to extract usable information from enormous datasets and adjust the learning process. Through automation and predictive analytics, these AI-powered solutions may create tailored learning experiences to improve learning results.

2. Purpose of the Study

The main objective of this research is to find out how well E-learning systems that leverage AI-driven user profile actually work for personalised learning. Contributing to the current body of knowledge on educational technology and informing best practices for creating and deploying personalised E-learning environments, this research intends to examine the implementation and effect of personalised learning techniques.

3. Objectives

- To explore the theoretical foundations and conceptual frameworks underlying personalized learning in E-learning environments.

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- To analyze the current state-of-the-art in AI-driven user profiling techniques and their applicability to personalized learning in E-learning platforms.
- To investigate the effectiveness of personalized learning experiences in improving learner engagement, satisfaction, and academic performance.
- To identify key challenges and considerations in the implementation of AI-driven user profiling for personalized learning in E-learning platforms.
- To provide recommendations for educators, instructional designers, and E-learning platform developers based on the findings of the study.

4. Research Questions

1. How does personalized learning through AI-driven user profiling influence learner engagement and satisfaction?
2. What are the perceived benefits and challenges associated with personalized learning experiences in E-learning platforms?
3. To what extent does personalized learning impact academic performance and knowledge retention?

5. Research Methodology

This study uses a mixed-method approach, integrating quantitative and qualitative methods, to investigate the efficacy of e-learning platforms' AI-driven user profile in creating tailored learning experiences. While the quantitative component is concerned with analysing data on e-learning platform user interactions, the qualitative half is with conducting surveys and interviews to get participants' opinions and ideas.

5.1 Data Collection Methods

The e-learning platform passively gathers data on user interactions when users engage with it. Part of this process is keeping tabs on how much time users spend on various courses, how well they do on quizzes, and what kind of information they enjoy.

Surveys and interviews are also used to get participant input. Respondents are asked to rate their degree of satisfaction with personalised learning as well as provide feedback on how it may be improved upon. Participants' opinions and preferences on personalised learning can be better understood through in-depth interviews.

5.2 AI Algorithms Employed

To power the personalisation and user profiling process, we deploy many high-accuracy AI algorithms:

1. Collaborative Filtering: For making tailored content recommendations, this algorithm studies user actions and tastes in order to identify commonalities across users. The following is the image of the collaborative filtering equation:

$$\hat{r}_{u,i} = \frac{\sum_{v\subset N_u(i)} \mathrm{sim}\,(u,v)\cdot r_{v,i}}{\sum_{v\subset N_u(i)} \mathrm{sim}\,(u,v)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where:

r^u,i :represents the predicted rating of user u for item i.

Nu(i) :denotes the set of users who have rated item i.

sim(u,v) :represents the similarity between users u and v.

rv,i :represents the rating of user v for item i.

Collaborative Filtering Algorithm
Import numpy as np
classCollaborativeFiltering:
def __init__(self, num_users, num_items):
self.num_users = num_users
self.num_items = num_items
self.user_item_matrix = np.zeros((num_users, num_items))
def fit(self, ratings):
ratings is a list of tuples (user_id, item_id, rating)
foruser_id, item_id, rating in ratings:
self.user_item_matrix[user_id, item_id] = rating
def predict(self, user_id, item_id, k=5):
Find k most similar users to the target user
similarities = []
forother_user_id in range(self.num_users):
ifother_user_id != user_id:
similarity = self.compute_similarity(user_id, other_user_id)
similarities.append((other_user_id, similarity))
similarities.sort(key=lambda x: x[1], reverse=True)
top_similarities = similarities[:k]
Predict the rating for the target item based on similar users' ratings
numerator = 0
denominator = 0
forother_user_id, similarity in top_similarities:
ifself.user_item_matrix[other_user_id, item_id] != 0:
numerator += similarity *

self.user_item_matrix[other_user_id, item_id]
denominator += similarity
if denominator == 0:
return 0
else:
return numerator / denominator
defcompute_similarity(self, user_id1, user_id2):
ratings1 = self.user_item_matrix[user_id1]
ratings2 = self.user_item_matrix[user_id2]
common_ratings_mask = np.logical_and(ratings1 != 0, ratings2 != 0)
ifnp.sum(common_ratings_mask) == 0:
return 0
else:
returnnp.dot(ratings1, ratings2) / (np.linalg.norm(ratings1) * np.linalg.norm(ratings2))
Initialize CollaborativeFiltering instance
cf = CollaborativeFiltering(num_users=100, num_items=100)
Fit the model to your dataset

cf.fit(ratings)
Predict a rating for a specific user and item
predicted_rating = cf.predict(user_id=0, item_id=10)
print("Predicted rating:", predicted_rating)

2. Deep Learning Neural Networks: Complex patterns in user data are analysed by neural networks to anticipate personalised learning routes. Here is one way to express the neural network training equation:

$$\text{Loss} = \frac{1}{N}\sum_{i=1}^{N} \text{Loss}\,(y_i, \hat{y}_i) \ldots\ldots\ldots\ldots\ldots\ldots.. (2)$$

Where:

N :is the number of training samples.

yi :represents the actual output.

y^i :represents the predicted output.

Loss: is the loss function, such as mean squared error or categorical cross-entropy.

Deep Learning Neural Networks Algorithm
importnumpy as np
importtensorflow as tf
features = np.random.rand(100, 10) # Assuming 100 samples with 10 features each
labels = np.random.randint(2, size=(100, 1)) # Binary classification labels
Splitting data into training and testing sets
split_ratio = 0.8
split_index = int(split_ratio * len(features))
train_features, test_features = features[:split_index], features[split_index:]
train_labels, test_labels = labels[:split_index], labels[split_index:]
Defining the neural network architecture
model = tf.keras.Sequential([
tf.keras.layers.Dense(64, activation='relu', input_shape=(10,)),
tf.keras.layers.Dense(64, activation='relu'),
tf.keras.layers.Dense(1, activation='sigmoid')
])
Compiling the model
model.compile(optimizer='adam',
loss='binary_crossentropy',
metrics=['accuracy'])
Training the model
model.fit(train_features, train_labels, epochs=10, batch_size=32)
Evaluating the model
test_loss, test_accuracy = model.evaluate(test_features, test_labels)
print(f'Test accuracy: {test_accuracy}')
Predicting personalized learning experience for a new user profile
new_user_profile = np.random.rand(1, 10) # Assuming a new user with 10 features
prediction = model.predict(new_user_profile)

print(f'Predicted personalized learning experience: {prediction}')

3. Natural Language Processing (NLP) Models: In order to create a profile for each user, natural language processing models are used to sift through textual data like forum posts and feedback comments for insights and sentiment analysis.

Natural Language Processing (NLP) Algorithm
importnltk
fromnltk.sentiment import SentimentIntensityAnalyzer
text_data = [
"The course material was very helpful and informative.",
"I struggled to understand the concepts in this module.",
"The quizzes were too easy and didn't challenge me enough.",
"I found the interactive exercises engaging and fun.",
"The instructor's explanations were clear and easy to follow."
]
Initialize sentiment analyzer
sid = SentimentIntensityAnalyzer()
Perform sentiment analysis on each text sample
sentiment_scores = []
for text in sample_text_data:
sentiment_score = sid.polarity_scores(text)
sentiment_scores.append(sentiment_score)
Display sentiment scores
fori, score in enumerate(sentiment_scores):
print(f"Text {i+1}: {sample_text_data[i]}")
print(f"Sentiment Score: {score}")
print()
Analyze overall sentiment for the sample data
total_sentiment_score = sum(score['compound'] for score in sentiment_scores) / len(sentiment_scores)
print("Overall Sentiment Score:", total_sentiment_score)

5.3 User Profiling Techniques

User profiling is the process of building in-depth profiles of users according to their behaviours, interests, and preferred methods of learning. Methods encompass:

- **Cluster Analysis:** User behaviour and preferences are used to group users.
  - **Sequential Pattern Mining:** Determining the sequence of events in user interactions in order to foretell their next moves.
  - **Sentiment Analysis:** Determining user attitude and preferences through analysis of feedback.

5.4 Implementation in E-learning Platforms

Built within the preexisting framework of the e-learning platform is the AI-powered user profiling system. This necessitates the smooth incorporation of data gathering methods, AI algorithms, and customisation capabilities into the design of the platform. In order to deliver real-time personalised learning experiences, the system is constantly learning from user interactions and updating user profiles.

6. Results and Discussion

There were one hundred people included in the study, and they came from all walks of life and educational levels. Age, gender, education level, and familiarity with online learning platforms are some of the important demographic details shown in Table 1, which provides a breakdown of the participants.

Table 1: Demographic Profile of Study Participants

Demographic	Frequency	Percentage
Age (years)		
18-25	30	30%
26-35	40	40%
36-45	20	20%
46 and above	10	10%
Gender		
Male	50	50%
Female	45	45%
Other	5	5%
Educational Level		

High School	15	15%
Bachelor's	40	40%
Master's	30	30%
Doctorate	15	15%
Prior E-learning Experience		
Yes	70	70%
No	30	30%

Table 1 shows that the study group is diverse, with most individuals aged 26–35. A slight male predominance, but basically a good gender distribution. A high number of participants have bachelor's degrees, and educational levels are evenly distributed. Several participants had worked with e-learning systems, thus they were likely familiar with virtual classrooms. Table 2 illustrates the distribution of participants across e-learning platforms and how often they utilised them.

Table 2: E-learning Platform Usage

E-learning Platform	Frequency of Usage (%)
Coursera	35
Udemy	25
Khan Academy	20
edX	15
Other	5

Table 2 shows that participants choose Coursera, Udemy, and Khan Academy for e-learning. This distribution reflects the study population's popularity and accessibility to these platforms. Table 2 shows participant usage across e-learning systems. Participants used online learning systems at the following rates: 35% Coursera, 25% Udemy, 20% Khan Academy, 15% edX. The remaining 5%'s e-learning platforms were not listed. These figures show that Coursera is the most popular platform, followed by Udemy, Khan Academy, and edX. The poll found that these are the most popular platforms for accessing online educational content. The distribution of usage can reveal participants' e-learning platform preferences and habits, which are needed to understand how AI-driven user profiling creates tailored learning experiences.

The research population includes individuals of various demographics and e-learning platform familiarity to evaluate AI-driven user profiling-tailored learning experiences.

6.1 Analysis of User Profiling Data

Information gathered from e-learning systems' user profiles powered by artificial intelligence with the purpose of providing a tailored learning experience. User preferences, learning behaviour, and performance indicators are among the characteristics that are the focus of the investigation.

Table 3: User Demographics

Demographic	Frequency	Percentage
Age Group		
18-25	30	30%
26-35	40	40%
36-45	20	20%
46+	10	10%
Gender		
Male	55	55%
Female	45	45%

The age bracket of 26–35 accounts for 40% of the sample, with 30% of the individuals falling into the 18–25 age bracket. With 55% men and 45% women taking part, the gender ratio is almost even.

Table 4: User Preferences

Learning Style	Frequency	Percentage
Visual	35	35%
Auditory	25	25%

Kinesthetic	20	20%
Read/Write	20	20%

According to the results, 35% of participants choose a visual learning approach, making it the most popular choice. Second and third, with 25% and 20% of the sample, respectively, are kinesthetic and auditory types. Twenty percent of people also prefer a read/write learning technique.

Table 5: User Engagement Metrics

Metric	Average Score
Time Spent per Session	45 minutes
Number of Logins/Week	5
Completion Rate	80%
Interactions/Module	15

Users check in an average of five times weekly, and each session lasts about 45 minutes on the e-learning platform. Eighty percent of users have finished all of the modules. This is known as the completion rate. Users are actively participating with an average of fifteen interactions each module.

Table 6: Performance Metrics

Metric	Average Score
Quiz Scores	85%
Assignment Grades	B+
Course Completion Time	8 weeks

The average quiz score of 85% shows that users know and remember course material. B+ grades indicate that pupils understand and can apply the information. Users demonstrate devotion and development by completing the course in 8 weeks. User profile data may help explain e-learning platform users' demographics, preferences, engagement, and performance. These insights can help design and implement AI-driven customised learning systems to increase user satisfaction and learning results.

6.2 Personalization Effectiveness Metrics

Here we highlight how successful e-learning platforms have been in creating personalised learning experiences via AI-driven user profiling. We evaluate a number of indicators to determine how personalisation affects user engagement, happiness, and the results of their learning.

Table 7: User Engagement Metrics

Metric	Control Group (Non-Personalized)	Experimental Group (Personalized)
Average Time Spent	25 minutes	35 minutes
Number of Interactions	50	70
Completion Rate	70%	85%

The table 7 illustrates user engagement data for two groups: one that receives customised learning and one that does not. Experimental users averaged 35 minutes on the site, whereas control users averaged 25. Personalised learning increased site duration, indicating user interest. Additionally, content exchanges differed greatly between groups. Experimental group had 70 interactions, control group 50. This discrepancy shows that audiences were more engaged with customised learning content, maybe due to relevance and suggestions. The experimental group also completed 85%, compared to 70% for the control group. This shows that tailored learning experiences pushed users to keep studying, resulting in a higher percentage of completed tasks or modules. Personalisation enhanced user engagement, time spent, interactions, and completion rates compared to non-personalization.

Table 8: User Satisfaction Metrics

Metric	Control Group (Non-Personalized)	Experimental Group (Personalized)
Satisfaction Rating (1-5)	3.5	4.5
Likelihood to Recommend	60%	85%

The User Satisfaction Metrics table shows substantial differences between the non-personalized control and personalised experimental groups. The customised group was much happier (4.5 on average) than the control group (3.5). This shows that customers prefer tailored learning experiences that fit their needs. Compared to 60% of non-personalized users, 85% of personalised learners were keen to recommend the product. These studies show that customised methods improve user satisfaction and engagement in e-learning systems.

Table 9: Learning Outcome Metrics

Metric	Control Group (Non-Personalized)	Experimental Group (Personalized)
Average Quiz Score	75%	85%
Knowledge Retention	70%	80%
Skill Application Proficiency	Intermediate	Advanced

Test performance improved significantly in the personalised learning experimental group, which averaged 85% quiz scores compared to 75% in the control group. Customised users recalled 80% of the content, compared to 70% for the non-personalized group. The control group showed intermediate competency in skill application, whereas the personalised group showed advanced proficiency, suggesting a better understanding and implementation of the learned ideas. These studies show that tailored learning improves test scores, information retention, and advanced skill development and application. Personalised learning experiences enabled by AI-driven user profile improve user engagement, enjoyment, and learning outcomes compared to non-personalised techniques.

6.3 User Satisfaction and Engagement

The research focused on how e-learning systems' AI-driven user profile contributed to a more engaging and satisfying learning experience for users. A post-interaction survey measured user happiness, while platform analytics gathered engagement indicators. Questions in the post-interaction survey probed users' feelings about their customised learning journey. With 1 being "Very Dissatisfied" and 5 being "Very Satisfied," participants were given a satisfaction rating scale to use.

Table 10: User Satisfaction Ratings for Different Aspects of Personalization

Aspect of Personalization	Mean Satisfaction Score (out of 5)	Standard Deviation
Content Relevance	4.6	0.3
Learning Pace	4.4	0.4
Recommended Resources	4.5	0.2
Feedback and Support	4.3	0.4
Overall Learning Experience	4.5	0.3

Users' satisfaction with e-learning platform modification is shown in the table below. Content relevance had the greatest mean satisfaction score of 4.6, indicating that customers valued the material. Mean learning speed and suggested resource ratings of 4.4 and 4.5 were good. Since feedback and help scored 4.3, it may be improved. However, the mean score of 4.5 suggests that buyers liked the e-learning experience. Results suggest that customised elements make e-learning more fun and engaging.

Time on platform, interaction frequency, and module completion rates measured user engagement. Table 11 shows engagement numbers from platform analytics:

Table 11: User Engagement Metrics

Metric	Average Value
Time Spent on Platform	3.5 hours/day
Number of Interactions/Week	25
Module Completion Rate	85%

With users devoting almost 3.5 hours daily to their learning activities, the average time spent on the site shows a considerable degree of user engagement. On top of that, the average of 25 interactions each week highlights how actively users participate. Users' dedication to finishing the suggested learning materials is further evidenced by the 85% module completion rate.

6.4 Comparison with Traditional Learning Methods

The efficiency of e-learning platforms' personalised learning experiences using AI-driven user profile in comparison to more conventional modes of education. To make the distinctions between the two methods clear, we use tables to provide numerical figures and explanations.

Table 12: Comparison of Learning Outcomes

Learning Outcome	Personalized E-learning	Traditional Learning
Test Scores	Mean: 85%	Mean: 72%
Knowledge Retention	High	Moderate
Skill Acquisition	Rapid	Gradual
Engagement Levels	High	Variable

Table 12 reveals a substantial difference between individualised e-learning and conventional teaching methods. Personalised e-learning helps students achieve mean test scores of 85%, compared to 72% with conventional methods. Compared to conventional learning, tailored e-learning improves knowledge retention and skill development faster. Importantly, personalised e-learning systems sustain high learner engagement. These figures show that AI-driven user profiling can increase learning results and student engagement in educational contexts.

Table 13: Time Efficiency Comparison

Activity	Personalized E-learning	Traditional Learning
Learning	Faster	Slower
Feedback Provision	Immediate	Delayed
Progress Monitoring	Real-time	Periodic

Table 13 illustrates that tailored e-learning saves time compared to traditional methods. Personalised e-learning saves time by speeding up learning, providing immediate feedback, and tracking progress. Traditional learning methods are slower due to static information delivery, delayed feedback, and periodic progress reports. Looking at the data, tailored e-learning may dramatically reduce students' study time, which bodes well for its classroom efficiency.

Table 14: Adaptability and Customization

Aspect	Personalized E-learning	Traditional Learning
Content Adaptation	Dynamic	Static
Learning Pace	Self-paced	Instructor-paced
Individualization	High	Limited

Table 14 indicates that traditional and customised e-learning differ in adaptability and personalisation. Personalised e-learning ensures that course materials meet individual needs and preferences due to dynamic content adaptation. Allowing learners to progress at their own pace promotes a more individualised learning experience. Conventional learning methods, which use instructor-paced, static information, limit customisation and personalisation. The data in the table illustrate that personalised e-learning may alter education due to its adaptability and flexibility.

AI-driven user profile makes e-learning systems more personalised, as seen by the comparison. Compared to traditional schooling, its time savings, flexibility, and customisation are merely frosting on the cake. These findings demonstrate the revolutionary potential of tailored online education to transform schooling.

7. Conclusion

This study aimed to determine how well e-learning platforms that leverage AI-driven user profile to provide personalised learning experiences actually work. Our research shows that tailored methods greatly improve user involvement, happiness, and knowledge retention. We found that using 100 participants and high accuracy algorithms significantly improved personalised material delivery, adaptive assessment methodologies, and personalised suggestions, which led to a better learning experience for users.

Recommendations for Practice:

- E-learning systems can improve their personalisation capabilities through the integration of user profile techniques driven by artificial intelligence.
- Ongoing tracking and evaluation of user information with the purpose of enhancing customised educational experiences as time goes on.
- Teachers, artificial intelligence experts, and instructional designers working together to create personalised lessons and interventions that meet students where they are in their learning journey.
- Prioritising ethical issues in the application of AI-driven user profiling will provide transparency, fairness, and privacy protection.

Personalised learning experiences powered by AI-driven user profiling have the ability to completely transform education by providing customised solutions that meet the unique requirements and preferences of modern learners. With the help of these innovations and highly accurate algorithms, e-learning systems can encourage more participation, provide more relevant lessons, and help students reach their maximum potential.

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