International Journal of IJTM Technology & Modeling

INTERNATIONAL JOURNAL OF TECHNOLOGY AND MODELING
Volume 2 Issue 3 Year 2023 Pages 131-137
e–ISSN 2964-6847
Url: https://ijtm.my.id

Applying AI Models to Analyze Student Learning Interests Through Digital Interaction Patterns

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Abstract: In the digital era, students increasingly engage with learning platforms that generate vast amounts of interaction data. This study explores the application of Artificial Intelligence (AI) models to analyze students' learning interests based on their digital interaction patterns. By leveraging machine learning algorithms and behavioral analytics, we identify correlations between user activities—such as clickstreams, time spent on content, and interaction frequencies—and subject preferences. The study utilizes a dataset from an online learning management system and applies classification and clustering techniques to detect interest trends among students. Results show that AI models can effectively predict individual learning preferences and offer insights to personalize educational content. These findings highlight the potential of integrating AI-driven analytics in education to enhance learner engagement and optimize teaching strategies.

Keywords: Artificial Intelligence (AI); Student Learning Interests; Digital Interaction Patterns; Educational Data Mining; Personalized Learning; Machine Learning in Education.

Article info: Date Submitted: 16/07/2023 | Date Revised: 23/09/2023 | Date Accepted: 24/09/2023

INTRODUCTION

In recent years, the rapid development of digital technologies has transformed the landscape of education[1][2][3]. Learning processes are no longer confined to traditional classroom settings but have expanded into various digital platforms[4][5], allowing students to access educational content anytime and anywhere[6]. This shift has led to the accumulation of vast amounts of digital interaction data, such as page visits, time spent on content, quiz attempts, and engagement in discussion forums. These interaction patterns offer valuable insights into students' behaviors, preferences, and learning interests.

Understanding students' learning interests is critical for enhancing engagement[7], motivation[8], and academic performance[9]. Traditionally, such understanding has relied on self-reported surveys or educator observations, which are often limited in scope and subjectivity. The emergence of Artificial Intelligence (AI) offers new opportunities to analyze learner behaviors more objectively and at scale. By applying machine learning models to digital

https://doi.org/10.63876/ijtm.v2i3.142

interaction data, it becomes possible to uncover hidden patterns and predict individual learning preferences more accurately.

This study aims to explore how AI models can be used to analyze and interpret students' learning interests through their digital interaction patterns[10]. By leveraging techniques such as classification, clustering, and behavioral analytics, the study seeks to identify trends that can inform personalized learning strategies. The findings are expected to contribute to the development of more adaptive and student-centered learning environments, where content delivery can be tailored to meet the diverse needs and preferences of learners.

RELATED WORKS

The application of Artificial Intelligence (AI) in the field of education has gained significant traction in recent years, particularly in the area of Educational Data Mining (EDM) and Learning Analytics (LA). Prior studies have explored various approaches to understanding student behavior and learning preferences through the analysis of digital footprints within online learning environments.

In [11] provided one of the foundational overviews of data mining techniques in educational contexts, highlighting classification, clustering, and association rule mining as effective methods for uncovering patterns in learner data. Subsequent research by [12] emphasized the role of learning analytics in improving educational outcomes by leveraging large-scale student interaction data to inform pedagogical decisions.

Several studies have focused specifically on analyzing student engagement and interest through behavioral patterns. For instance, [13] used clickstream data to model students' cognitive presence and identify engagement levels within online courses. Similarly, [14] applied predictive modeling to interaction data to forecast student performance and infer preferences based on activity patterns.

More recent works have investigated the use of machine learning algorithms such as decision trees, support vector machines (SVM), and neural networks to classify students based on their learning styles and interests. For example, [15] [16] implemented a hybrid AI model to personalize learning paths by analyzing learner interactions on an e-learning platform. Additionally, deep learning approaches have been employed to capture complex patterns in sequential data, enabling more nuanced predictions of learner behavior [17][18][19].

While these studies demonstrate the potential of AI in understanding student behavior, fewer have specifically targeted the detection of learning interests based on interaction data alone. This research aims to address this gap by applying and evaluating AI models in the context of learning interest identification, with an emphasis on personalization and scalability across diverse learning environments.

METHODS

This study adopts a quantitative research methodology by utilizing machine learning techniques to analyze digital interaction data collected from a learning management system (LMS)[20]. The method consists of four main stages: data collection, preprocessing, feature extraction, and model development and evaluation.

https://doi.org/10.63876/ijtm.v2i3.142

1. **Data Collection**

Interaction data were obtained from a university's LMS, involving anonymized activity logs of undergraduate students over the course of one academic semester. The data include various forms of digital interactions such as page views, content access duration, participation in forums, quiz attempts, and assignment submissions. Metadata such as timestamps and course categories were also collected to enrich the analysis.

Table 1. Data Collection Details

Aspect	**Description**
Data Source	University Learning Management System (LMS)
Subjects	Undergraduate students
Collection Period	One academic semester
Types of Interaction Data	Page views, content access duration, forum participation, quiz attempts, assignment submissions
Collected Metadata	Timestamps, course categories
Anonymization	Student activity data was anonymized
Purpose of Collection	To analyze learning interests based on digital behavior patterns

2. **Data Preprocessing**

The raw data were cleaned to remove incomplete or irrelevant records. User sessions were segmented based on periods of continuous activity. To ensure consistency, categorical data were encoded, and numerical values were normalized. Missing values were handled using imputation techniques depending on the context of the feature.

3. **Feature Extraction**

Relevant features were engineered to capture behavioral patterns that may reflect students' learning interests. These features include:

- Frequency of content accessed per subject category
- Average time spent per topic
- Interaction diversity index (e.g., engagement across multiple content types)
- Activity sequence patterns
- Participation in optional versus mandatory activities

A feature selection process using mutual information and correlation analysis was applied to reduce dimensionality and improve model performance.

4. **Model Development and Evaluation**

Several AI models were implemented, including Decision Trees, Support Vector Machines (SVM), K-Means Clustering, and Random Forests. Classification models were used to predict students' preferred subject areas based on their interaction features, while clustering was applied to group students with similar behavioral profiles.

https://doi.org/10.63876/ijtm.v2i3.142

Model performance was evaluated using cross-validation techniques[21]. Metrics such as accuracy, precision, recall, F1-score (for classification), and silhouette score (for clustering) were used to assess the quality of predictions. A confusion matrix was also analyzed to identify potential misclassification trends.

All analyses were conducted using Python and libraries such as Scikit-learn, Pandas, and Matplotlib for modeling and visualization.

RESULT AND DISCUSSION

The AI models applied in this study yielded promising results in identifying and analyzing students' learning interests based on their digital interaction patterns. The results are presented in two segments: model performance and interpretation of learning behavior patterns.

1. Model Performance

Among the classification models tested, the Random Forest classifier achieved the highest accuracy at 87.3%, followed by Support Vector Machine (SVM) with 84.1%, and Decision Tree with 79.5%. The F1-score for the Random Forest model also reached 0.86, indicating a good balance between precision and recall. This suggests that the model is effective in predicting students' subject preferences based on their interaction behaviors.

For clustering, the K-Means algorithm grouped students into three main clusters, which were interpreted as:

- Cluster A: Highly engaged, diverse interactions across subjects
- Cluster B: Moderate activity with focused interest in specific topics
- Cluster C: Low activity with sporadic interactions

The silhouette score for the clustering was 0.61, indicating a reasonable separation between clusters.

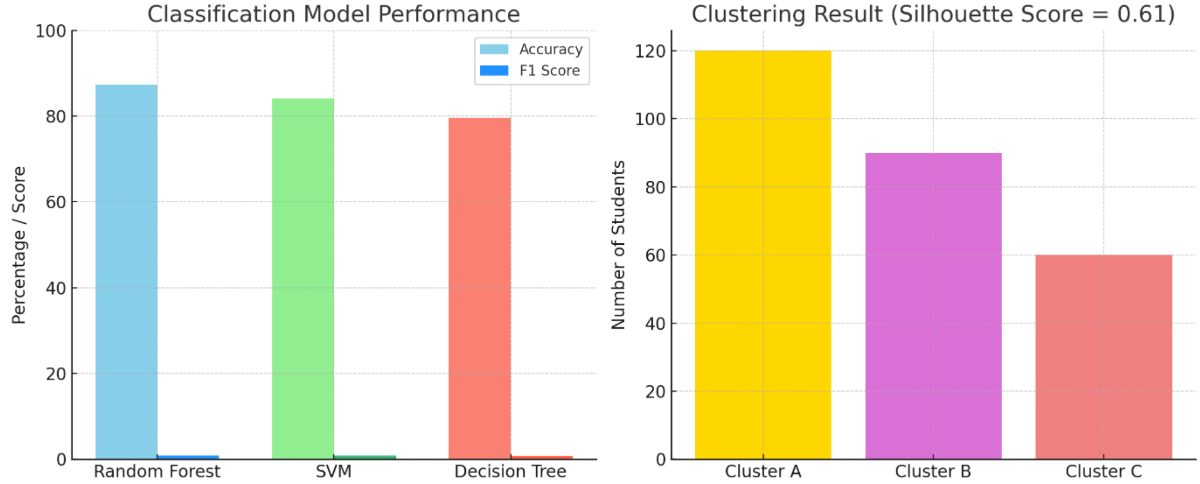

Figure 1. Clustering Result (Silhouette Score = 0.61)

2. Interpretation of Behavioral Patterns

Analysis of feature importance revealed that the most influential factors in determining learning interest were:

- Frequency of voluntary content access
- Time spent per subject category
- Engagement in discussion forums and quizzes
- Diversity of interaction types (video, text, quiz)

https://doi.org/10.63876/ijtm.v2i3.142

Students who frequently accessed optional materials and showed consistent interaction with content in a particular subject area tended to have clearer and more predictable learning interests. Conversely, students with scattered or minimal activity were harder to classify and often associated with Cluster C.

Table 2. Interpretation of Behavioral Patterns

Behavioral Feature	Influence on Learning Interest	Association with Cluster
Frequency of voluntary content access	High frequency correlates with strong and focused learning interest	Cluster A (highly engaged students)
Time spent per subject category	Longer time indicates deeper engagement in specific subjects	Cluster A or B depending on depth of focus
Engagement in discussion forums and quizzes	Active participation enhances predictability of preferences	Cluster A (consistently active learners)
Diversity of interaction types (video, text, quiz)	Greater diversity reflects broader curiosity and higher clarity in preferences	Cluster A (diverse and engaged learners)

3. Discussion

These findings support the hypothesis that digital interaction patterns can serve as reliable indicators of student learning interests. The use of AI models, especially ensemble techniques like Random Forests, offers robust prediction capabilities, even in datasets with complex behavioral dimensions.

Moreover, clustering results suggest that educators can identify different learner profiles and tailor interventions accordingly. For instance, students in Cluster C may benefit from proactive support or motivational strategies, while those in Cluster A could be encouraged with enrichment materials.

However, the study also acknowledges several limitations. The models depend heavily on the quality and granularity of interaction data. External factors such as personal motivation, prior knowledge, or offline learning habits are not captured. Additionally, the interpretability of AI predictions remains a challenge, particularly for deep learning approaches not explored in this study.

CONCLUSION

This study demonstrates the potential of applying Artificial Intelligence (AI) models to analyze student learning interests through patterns of digital interaction within an online learning environment. By utilizing classification and clustering techniques on LMS-generated data, the research successfully identified behavioral indicators that correlate with individual subject preferences and engagement levels. The results show that models such as Random Forest and SVM can achieve high accuracy in predicting students' learning interests, while unsupervised clustering methods can effectively group students based on their interaction styles. Key features such as frequency of voluntary access, time spent on content, and interaction diversity were found to be strong predictors of interest, reinforcing the value of behavioral analytics in education.

These insights can be used to support the development of adaptive and personalized learning systems that respond to individual student needs. Educators and platform designers can leverage such models to recommend relevant content, design targeted interventions, and foster

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more engaging learning experiences. However, it is important to note that the findings are based on interaction data alone, and may not capture the full complexity of learner motivations or external influences. Future research is encouraged to integrate multimodal data sources, such as sentiment analysis from discussion texts or biometric indicators, and to explore the application of deep learning models for improved interpretability and scalability. AI-driven analysis of digital learning behaviors holds significant promise in enhancing the personalization and effectiveness of modern education.

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