

AN EXPLAINABLE LEARNING PATH RECOMMENDATION SYSTEM FOR RURAL STUDENTS

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Rural students often face difficulty in selecting appropriate learning paths due to limited access to academic guidance and career counseling. The current recommendation systems generally give broad suggestions and do not show how the system works. The present work introduces a personalized learning path recommendation framework based on explainable AI that is specifically designed for rural students. The framework derives personalized learning paths using students' academic performance, interests, and basic aptitude indicators. Explainable AI methodologies are equipped to support each suggestion in an easy and understandable way. Trust, transparency, and practical usability are emphasized over complex predictive models. Experiments conducted on a simulated dataset demonstrate that the proposed framework can effectively support learning decisions in data-limited rural settings.

capturing academic performance, subject interests, and aptitude. Learning paths were classified into three categories—Science-oriented, Humanities-oriented, and Skill-based—facilitating transparent recommendation and effective evaluation.

Table 1. Dataset Feature Description

Feature Name	Description	Type
Academic Score	Average academic performance	Numerical
Subject Interest	Preference across subject domains	Categorical
Mathematics Aptitude	Logical and numerical ability	Numerical
Science Interest Level	Interest in science subjects	Numerical
Learning Style Indicator	Preferred learning approach	Categorical
Aptitude Index	Aggregated aptitude score	Numerical
Learning Path Class	Recommended learning path category	Categorical

The proposed explainable AI-based learning path recommendation framework (LP-RF) is designed as a decision-support system for rural students. It operates through five key stages: student profile input, profiling, learning path recommendation, explainability, and output generation. The framework relies on minimal and interpretable student data to ensure transparency and usability in data-scarce settings. Student profiles are created using academic performance, subject interests, and aptitude indicators. Missing values are handled using simple statistical methods, and features are normalized for consistency. Learning path recommendations are generated using interpretable models such as rule-based logic and simple machine learning classifiers, avoiding complex black-box techniques. An explainability module provides human-readable justifications for each recommendation, supporting trust and informed decision-making by students and educators.

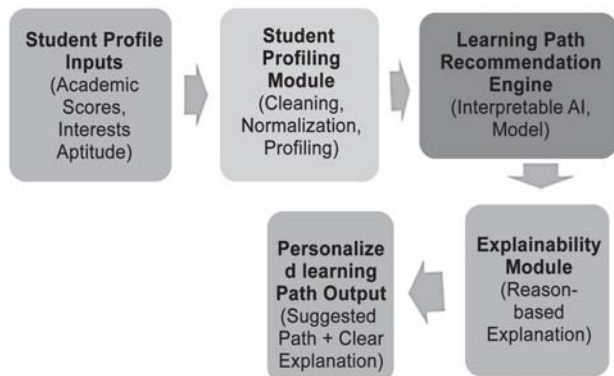


Fig. 1. Explainable AI-based learning path framework for rural students

Results and Discussion

The proposed framework was evaluated using a simulated dataset comprising approximately 200 rural student profiles. Performance was assessed using accuracy and precision metrics. The dataset was split into training and testing sets using an 80:20 ratio, and experiments were repeated five times with average values reported. The interpretable machine learning model achieved higher accuracy and precision compared to the rule-based approach, as shown in Table 2. However, both models produced consistent and transparent recommendations, demonstrating suitability for rural and data-limited educational environments.

Table 2. Performance comparison of interpretable learning path recommendation models

Model Type	Accuracy	Precision
Rule-based Model	0.78	0.76
Interpretable ML Model	0.82	0.80

Explain ability represents a key advantage of the framework. Academic performance and subject interest emerged as the most influential factors in learning path recommendations, while aptitude contributed moderately. These explanations enhance user trust and understanding of system decisions.

Conclusion and Future Work

This paper presents a simple and explainable AI-based learning path recommendation framework for rural students. By using minimal student data and interpretable models, the framework delivers transparent and trustworthy recommendations suitable for data-limited environments. Future work includes validation with real institutional data and the integration of human-in-the-loop feedback to further enhance recommendation quality. □

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