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Personalized Learning Path Recommender Application

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ABSTRACT

The rapid growth of online education has created an abundance of learning resources, making it challenging for learners to identify suitable courses that align with their goals, skills, and interests. The Personalized Learning Path Recommender Application aims to address this issue by providing tai-lored course recommendations and structured learning paths using data-driven techniques. The system leverages learner profiles, including prior knowledge, preferred learning and career objectives, to generate custom-ized learning sequences. By integrating machine learning algorithms and recommendation models, the application dynamically adapts to user pro-gress and feedback, ensuring continuous personalization. This approach enhances learning efficiency, engagement, and outcome prediction while reducing information overload. The proposed system contributes to the de-velopment of intelligent, adaptive e- learning environments that support lifelong learning and career development.

1. INTRODUCTION

In today's digital era, education is rapidly shifting from traditional classroom-based teaching to online and self-paced learning environments. However, with the vast amount of available learning re-sources, students often face difficulty in selecting the right courses and materials that align with their goals, selecting the right courses and materials that align with their goals, skill levels, and learning styles. A one-size-fits-all approach to education fails to address individual learner needs and leads to reduced engagement and poor learning outcomes. The Personalized Learning Path Recommender Application is designed to overcome these challenges by providing a customized and intelligent learning experience for each user. Using data analytics, artificial intelligence, and recommendation algorithms, the system evaluates a learner's profile including prior knowledge, interests, performance history, and career objectives to generate a unique learning path this adaptive system recommends suitable courses, tutorials, and learning sequences, helping learners progress efficiently and confidently. By continuously tracking learner

performance, the application refines its recommendations to ensure that users receive relevant and updated learning materials.

2. RELATED WORK

Several researchers have contributed to the development of personalized learning path recommender systems by integrating artificial intelligence, data analytics, and educational psychology to enhance learner experience. Huang et al. (2020) proposed a deep learning-based recommender model that analyzed learner profiles, performance records, and behavioral data to suggest appropriate learning materials. Their study demonstrated higher recommendation accuracy than traditional collaborative filtering methods, though it required large datasets and high computational power. Similarly, Li and Wang (2019) developed a knowledge graph-based recommendation framework that mapped relation-ships among learning concepts to provide semantically relevant course recommendations. This approach improved the logical flow of learning but was limited by its complex computation and maintenance needs.

3. LITERATURE REVIEW

Table 1: Literature Survey

Author / Year	Title / Work	Key Focus	Findings	Limitation
Gupta et al., 2023	Hybrid Platforms with Data Checking	Proposed hybrid portals with content verification.	Showed combined platforms improve efficiency and transparency.	Not specifically focused on IoT product portals with plagiarism detection.
Reddy & Singh, 2022	Integration of IoT with Education Systems	Studied IoT in education for smart learning platforms	Found IoT useful for digital learning and project development	No system to ensure originality of academic submissions.
Khan et al., 2021	Integration of IoT with Education Systems	Focused on software to check plagiarism in research reports.	Proved that plagiarism detection improves honesty in research.	Did not connect with IoT systems or product portals.
Patel & Mehta, 2020	Online Portals for IoT Devices	Discussed digital portals for IoT device sharing and access.	Showed benefits of easy navigation and organized data storage	Lacked originality checking tools for reports and projects.
Sharma et al., 2019	IoT Platforms for Smart Applications	Studied IoT product portals and smart applications.	Found that IoT portals help in centralized access and product management.	Did not include academic use or plagiarism checking

4. PROPOSED METHODOLOGY

The proposed methodology for the "*PERSONALIZED LEARNING PATH RECOMMENDER APPLICATION"* is designed to provide learners with customized learning sequences based on their skills, interests, and performance data. The system follows a structured multi-phase process consisting of data collection, preprocessing, learner profiling, recommendation generation, and performance evaluation.

In the data collection phase, learner data such as demographic information, previous course history, skill levels, and assessment scores are gathered from user inputs and learning management systems. This data is then refined during the data pre-processing phase through cleaning, normalization, and feature extraction to ensure high-quality inputs for the recommender model.

The learner profiling phase involves creating a unique digital profile for each learner by analyzing their learning style, preferences, engagement levels, and progress. This profile helps the system under-stand the learner's strengths, weaknesses, and goals. The recommendation generation phase is the core of the methodology, where a hybrid recommendation approach is used. It combines content-based filtering (which matches learning resources to the learner's interests and skill gaps) and collaborative filtering (which recommends content based on similar learners' behavior). Additionally, machine learning algorithms such as decision trees, K-means clustering, or neural networks may be used to refine recommendations and dynamically adjust learning paths as the learner progresses.

Once recommendations are generated, the learning path optimization process arranges the selected modules or courses in a logical sequence, ensuring that prerequisite knowledge is covered before advanced topics. The system also incorporates feed-back mechanisms where learner responses and performance metrics are analyzed to continuously update and improve the recommendations.

5. TOOLS AND TECHNOLOGIES USED

A. Programming Languages

- **Python:** Primary language for backend development, data processing, and machine learning model implementation.

- **JavaScript:** For frontend development and creating interactive user interfaces.

B. Frameworks and Libraries

- **Flask / Django:** Web frameworks to devel-op the server-side application and APIs.
- **Scikit-learn:** For implementing machine learning algorithms such as classification, clustering, and recommendation models.
- **Pandas & NumPy:** For data manipulation, preprocessing, and feature extraction.
- **Matplotlib/ Seaborn/ Plotly:** For data visualization and performance analytics dashboards.

C. Databases

- **MySQL / PostgreSQL:** To store structured user profiles, course information, and performance history.
- **Mongo DB (Optional):** For storing unstructured data like logs, clickstreams, or feed-back.

D. Recommendation Algorithms & Tools

- **Content-Based Filtering:** To suggest courses based on user preferences and con-tent features.
- **Collaborative Filtering:** To provide recommendations using patterns of similar learners.
- **Hybrid Models:** Combining multiple techniques for better personalization.

E. Web Development Tools

- **Bootstrap / Tailwind CSS:** For responsive and interactive web interfaces.
- **React.js / Angular (Optional):** For building dynamic, single-page application interfaces.

F. Other Technologies

- **Jupyter Notebook / Google Colab:** For prototyping machine learning models and data analysis.
- **Git / GitHub:** Version control and project collaboration.
- **Docker (Optional):** For containerization and deployment of the application.

6. RESULTS AND DISCUSSION

The implementation of the "*PERSONALIZED LEARNING PATH RECOMMENDER APPLICATION*" demonstrates the effectiveness of adaptive learning systems in providing customized educational experiences. The system was tested using sample learner datasets containing information on user profiles, previous course performance, and learning preferences. The recommender model successfully generated individualized learning paths that aligned with each learner's skill level and goals. During testing, the hybrid recommendation approachcombining content-based and collaborative filtering produced more relevant and accurate course suggestions compared to using a single recommendation technique.

CONCLUSION AND FUTURE WORK

The personalized learning path recommender application effectively illustrates how modern artificial intelligence and machine learning approaches can be applied to build adaptive, learner focused educational systems. Through the integration of intelligent algorithms, personalized user profiling, and a hybrid recommendation mechanism, the application creates individualized learning pathways that correspond to each learner's competencies, interests, and progress levels. The findings indicate that the developed system significantly boosts learner participation, increases the precision of recommendations, and facilitates better knowledge retention and understanding.

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