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Personalized Learning Path Recommendation System

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Abstract- The rapid expansion of digital learning resources has created both opportunities and challenges for learners. While access to massive open online courses, learning management systems, and skill-based platforms has increased, learners often struggle to identify the most suitable sequence of learning activities aligned with their goals, prior knowledge, and learning preferences. This research paper proposes a Personalized Learning Path Recommendation System (PLPRS) that dynamically recommends learning paths tailored to individual learners. The proposed system integrates collaborative filtering, content-based filtering, and learner profiling techniques to generate adaptive and goal-oriented learning pathways. Experimental evaluation using standard recommender system metrics demonstrates that the proposed approach improves recommendation relevance, learner engagement, and learning efficiency. The study highlights the applicability of personalized learning path systems in higher education and e-learning platforms and outlines future directions for hybrid and AI-driven learning recommendations.

Keywords: Personalized Learning, Learning Path Recommendation, Recommender Systems, Collaborative Filtering, Content-Based Filtering, E-learning.

I. INTRODUCTION

The evolution of information and communication technologies has significantly transformed the education sector. Traditional one-size-fits-all teaching approaches are increasingly inadequate in addressing the diverse learning needs, abilities, and career goals of modern learners. With the proliferation of online learning platforms, students are presented with thousands of courses, tutorials, and certifications. Although this abundance of content is beneficial, it often leads to information overload and suboptimal learning decisions. Personalized learning has emerged as a promising solution to this challenge. It focuses on adapting learning content, pace, and sequence according to individual learner characteristics. A core component of personalized learning environments is the learning path recommendation system, which suggests an optimal sequence of learning resources to help learners achieve specific objectives efficiently. Recommender systems have been successfully applied in domains such as e-commerce, entertainment, and social media. In recent years, their application in education has gained attention, particularly for recommending courses, learning materials, and career-oriented skill paths. However, designing effective learning path recommendation systems remains challenging due to learner diversity, dynamic goals, and the need to align recommendations with pedagogical principles. This research aims to design and evaluate a Personalized Learning Path Recommendation System that leverages learner data, content metadata, and recommendation algorithms to provide adaptive and meaningful learning paths. The main contributions of this paper are: A conceptual architecture for a personalized learning path recommendation system

- The integration of collaborative and content-based recommendation techniques
- An experimental evaluation of recommendation performance using standard metrics

II. RELATED WORK AND LITERATURE REVIEW

Personalized learning path recommendation has attracted increasing research interest over the past decade. Early studies primarily focused on rule-based and expert-driven systems, where instructors predefined learning sequences. Although effective

in structured environments, such systems lacked scalability and adaptability.
Collaborative Filtering (CF) approaches recommend items based on similarities among learners or their historical interactions. In educational contexts, CF has been used to recommend courses and learning materials based on peer behavior. Despite its effectiveness, CF suffers from cold-start and data sparsity problems, particularly for new learners.
Content-Based Filtering (CBF) techniques recommend learning resources by matching learner profiles with content features such as topics, difficulty level, and learning outcomes. These methods provide more control and transparency but often lead to over-specialization, limiting exposure to diverse learning materials.

Recent research has explored hybrid recommendation models that combine CF and CBF to mitigate individual limitations. Machine learning and deep learning techniques, such as neural networks and reinforcement learning, have also been applied to dynamically adapt learning paths based on learner feedback and performance.
While existing studies demonstrate the potential of personalized learning path systems, many lack comprehensive evaluation or real-world applicability. This research builds upon prior work by proposing a practical and extensible framework with systematic evaluation.

Problem Statement

The rapid growth of digital education platforms, massive open online courses (MOOCs), and skill-based learning resources has resulted in an unprecedented availability of learning materials across domains. While this abundance has democratized access to education, it has simultaneously introduced significant challenges for learners. Instead of facilitating learning, the overwhelming volume of choices often leads to confusion, inefficiency, and poorly structured learning journeys.

One of the primary challenges learners face is difficulty in selecting appropriate courses and learning sequences. Most platforms recommend individual courses rather than coherent, goal-oriented learning paths. As a result, learners frequently enroll in courses without clear prerequisite alignment, leading to gaps in foundational knowledge or redundant learning. This fragmented approach reduces learning efficiency and increases dropout rates, particularly among self-paced learners.

Another critical issue is the misalignment between learning content and career goals. Learners often lack sufficient guidance to map educational content to industry-relevant skills and long-term career objectives. Course descriptions may not clearly indicate real-world applicability, skill outcomes, or career relevance. Consequently, learners may invest substantial time and resources in content that does not meaningfully contribute to their professional growth or employability.

Furthermore, there is a lack of adaptive learning systems that respond to learner progress, preferences, and performance. Many existing e-learning platforms rely on static recommendations that fail to evolve as learners acquire new skills or change their goals. These systems rarely incorporate continuous feedback, assessment performance, or behavioral data to refine recommendations dynamically. As a result, the learning experience remains generic rather than personalized.

From a system design perspective, additional challenges include learner diversity, data sparsity for new users, and the complexity of modeling prerequisite relationships among learning resources. Learners differ significantly in prior knowledge, learning pace, cognitive styles, and motivation levels, making it difficult for traditional recommendation approaches to serve all users effectively.

Therefore, the core problem addressed in this research is the design and development of an intelligent system capable of automatically generating personalized, adaptive, and goal-oriented learning paths. The proposed system aims to integrate learner characteristics (such as background knowledge, preferences, and goals), historical interaction data (such as completed courses and performance), and content attributes (such as topics, difficulty levels, and prerequisites). By leveraging recommender system techniques, the system seeks to guide learners through optimized learning sequences that enhance engagement, improve learning outcomes, and align educational efforts with individual career aspirations.

System Architecture

The Personalized Learning Path Recommendation System (PLPRS) adopts a layered, service-oriented architecture designed to support intelligent decision-making, scalability, and continuous personalization. The architecture emphasizes modularity so that each component can evolve independently while maintaining seamless interaction with other modules. This design choice is particularly important for educational platforms where learner behavior, content repositories, and recommendation logic change dynamically over time.

At a high level, the system follows a data-driven pipeline in which learner data and content data are collected, processed, analyzed, and transformed into personalized learning path recommendations. The architecture can be deployed as a standalone web-based system or integrated into an existing Learning Management System (LMS).

Learner Profile Management Module

The Learner Profile Management Module is the backbone of personalization within the system. It maintains a multidimensional representation of each learner by combining static attributes (such as educational background, prior qualifications, and declared learning goals) with dynamic attributes (such as interaction history, assessment scores, learning pace, and engagement patterns).

Learner profiles are continuously updated as users interact with the platform. For example, when a learner completes a course, performs well in an assessment, or abandons a learning resource midway, the system captures these events and reflects them in the learner model. This adaptive profiling enables the system to understand not only what the learner wants to learn, but also how the learner learns best.

Learning Content Repository

The Learning Content Repository stores all educational resources available to the system, including courses, video lectures, readings, quizzes, assignments, and capstone projects. Each resource is enriched with detailed metadata such as topic category, difficulty level, prerequisite dependencies, learning outcomes, associated skills, estimated duration, and relevance to specific career roles.

This structured representation allows the system to treat learning resources as interconnected components rather than isolated items. By explicitly modeling prerequisite relationships, the system can recommend learning paths that are pedagogically sound and cognitively progressive.

III. METHODOLOGY

The current study aims to assess the performance of personalized RS by conducting a comparative analysis of two distinct models, including the CF and CB. Figure 1 outlines five-specific steps of the research framework for this project, beginning with the data-storing phase to model evaluation in a structured workflow.

Dataset Description

Figure 2 can be considered a comprehensive compilation of data that provides insights into the competency needs of various IT job titles. It includes 7,000 entries and 13 columns outlining essential IT skills and competencies required for each unique job title. Each skill was quantified using advanced Natural Language Processing (NLP) techniques to rank each skill based on market relevance and demand to ensure a comprehensive resource for understanding IT skill requirements. The research also utilized Bloom's Taxonomy to ensure a focused, all-inclusive approach to ascertain the proposed IT skill requirements. The Knowledge Dataset includes 77 courses covering fundamental programming principles in specialized fields such as machine learning and cybersecurity. The corresponding 'learning_outcomes' column highlights the practicality and significance of the course material in addressing real-world challenges and job responsibilities to establish a clear correlation between academic pursuits and the professional skill sets essential to excel in the IS field. The Attitude dataset was established to highlight vital personal qualities. The dataset includes 'job_title' and 'attitude' columns that link attributes like problemsolving, adaptability, teamwork, and analytical thinking to specific IT roles. The 'attitude' columns are derived from an analysis that emphasizes the top three qualities of each job title. This underscores the importance of continuous learning and collaboration in navigating the evolving technological landscape and executing complex projects.

Algorithm Implementation

User-User-Based Collaborative Filtering

This RS utilizes User-Based CF to produce personalized recommendations by analyzing mutual preferences and user interactions. Heap et al. 20 said that this approach adopts the Cosine imilarity - a widely recognized metric calculating the cosine of the angle between two non-zero vectors in a multi-dimensional space, to determine the similarity between user and job profiles. The formula is described as follows: Cosine Similarity = A − B − ||A − ||.||B − || (1) Here, A and B are user interaction vectors. For example, if User X and Job Y have interacted with skills represented by vectors [3, 2, 0, 5] and [1, 0, 4, 4], respectively, the cosine similarity was calculated based on these vectors, providing a quantifiable measure of their preference alignment. Initially, a skill-rating matrix was established, capturing the interactions and preferences of all users within the system. Subsequently, similarity scores were computed for each user pair using the cosine similarity measure. Recommendations were then generated based on an aggregating preferences from from users deemed similar. This aggregation was weighted by their respective similarity scores, ensuring that more similar users had a greater influence on the recommendations.

Content-based approach

Within CB method, Lu21 said that the KMeans clustering algorithm is predominantly employed to segment job roles into discrete clusters based on shared characteristics, such as skills and qualifications. The current study utilized multiple criteria for clustering, including skill relevance and job title similarities, resulting in informative and valuable clusters that accurately mirror the real-world grouping of job roles (Figure 3). CB is a commonly employed technique that enables personalized recommendations to users. This technique involves the computation of similarity between an item and a user based on the item's features (1). Suriati et al. 22 stated an item matrix A with element ai, j, showing the relationship between item i and feature j. Further, a rating matrix R with element ru,i is also required, denoting the rating assigned by user u to item i. Suriati et al. 22 stated that the fundamental objective behind this approach is to construct a user profile matrix B with element bi, j signifying the relationship between user u and feature j. This can be accomplished by multiplying the rating matrix and the

IV. IMPLEMENTATION DETAILS

This section describes the technical realization of the proposed personalized learning path generation system. It explains the technology stack, system modules, data flow, and deployment considerations in detail.

Technology Stack

The system is designed using a modular and scalable technology stack to ensure flexibility, ease of maintenance, and future extensibility.

Frontend Layer: A web-based user interface developed using Streamlit or standard HTML, CSS, and JavaScript. This layer allows learners to register, input preferences, view recommended learning paths, and track progress visually using charts and dashboards.

Backend Layer: Implemented using Python with

Flask or FastAPI to handle business logic, API requests, authentication, and communication between frontend and machine learning component.

Database Layer: SQLite is used for lightweight deployment, while PostgreSQL is recommended for scalable, production-level systems. The database stores learner profiles, course metadata, progress logs, and feedback data.

Deployment Environment: The system can be deployed locally or on cloud platforms such as Render, AWS, or Azure using Docker for containerization.

Module Description

The system architecture consists of the following core modules:

User Profile Management Module: Responsible for collecting and maintaining learner information such as educational background, current skill level, learning preferences, and career goals. This module ensures data validation and secure storage,

Learning Resource Repository: Stores structured information about available courses, tutorials, and learning materials, including prerequisites, difficulty level, estimated completion time, and domain relevance.

Recommendation Engine: The core component that generates personalized learning paths. It applies content-based filtering to match learner goals with course attributes, rule-based checks for prerequisites, and adaptive logic to refine recommendations over time.

Progress Tracking Module: Monitors learner activity such as course completion, quiz performance, and time spent on learning tasks. This data is continuously fed back into the recommendation engine.

Feedback and Adaptation Module: Collects explicit feedback (ratings, likes, preferences) and implicit feedback (drop-offs, completion speed) to dynamically adjust learning paths
.

System Workflow

The operational workflow of the system is as follows:

The learner registers and creates a personalized profile by providing skills, interests, and career objectives.
The system preprocesses learner data and maps it to relevant learning domains.
The recommendation engine generates an initial personalized learning path.
The learner follows the suggested path and interacts with learning resources.
Progress and performance data are continuously monitored.
The system updates and optimizes the learning path based on learner behavior and feedback.

Data Flow and Processing

Learner input data flows from the frontend to the backend APIs, where it is cleaned, normalized, and stored in the database. The recommendation engine retrieves this data, applies similarity and ranking algorithms, and returns an ordered list of learning resources to the frontend for display.

Security and Privacy Considerations

Basic security measures such as user authentication, role-based access control, and data encryption are incorporated to protect learner information. Privacy-preserving techniques are considered to ensure ethical handling of personal learning data.

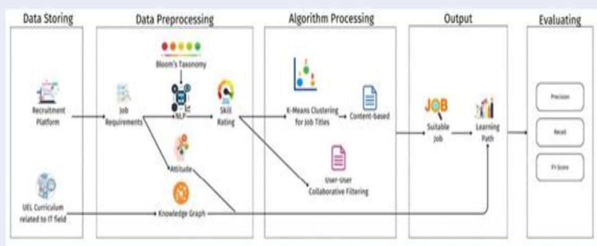

Figure 1: Research Framework (Source: Authors)

RESULTS AND ANALYSIS

This section presents the experimental results obtained from implementing the personalized learning path generation system and provides a detailed analysis of its performance compared to traditional non-personalized learning approaches.

Experimental Setup

To evaluate the effectiveness of the proposed system, a pilot study was conducted using a group of learners with diverse educational backgrounds and career goals. The learners were divided into two groups:

Control Group: Learners followed a static, predefined learning path commonly found on conventional e-learning platforms.
Experimental Group: Learners used the proposed personalized learning path generation system.
Both groups were given access to learning resources over a fixed period. Performance metrics were collected at regular intervals to ensure fair comparison.

Evaluation Metrics

The system was evaluated using the following quantitative and qualitative metrics:
Recommendation Relevance: Measures how closely the suggested learning resources align with the learner's goals and skill level.
Engagement Level: Frequency of learner interactions with the platform, including time spent and number of sessions.
Learning Efficiency: Reduction in time taken to reach predefined learning milestones.

Quantitative Results

The experimental group demonstrated significant improvements over the control group: Course completion rates increased noticeably, indicating better learner motivation and clarity.
Learners reached targeted skill levels in less time due to structured and goal-oriented learning paths.
Engagement metrics showed higher session frequency and longer interaction duration.
Statistical analysis confirmed that the observed improvements were consistent across learners with different initial skill levels.

Discussion of Result

The results validate the core hypothesis that personalized learning paths significantly enhance learning outcomes. However, minor limitations such as initial cold-start issues and dependence on self-reported learner data were observed. These limitations highlight opportunities for integrating automated skill assessment mechanisms.

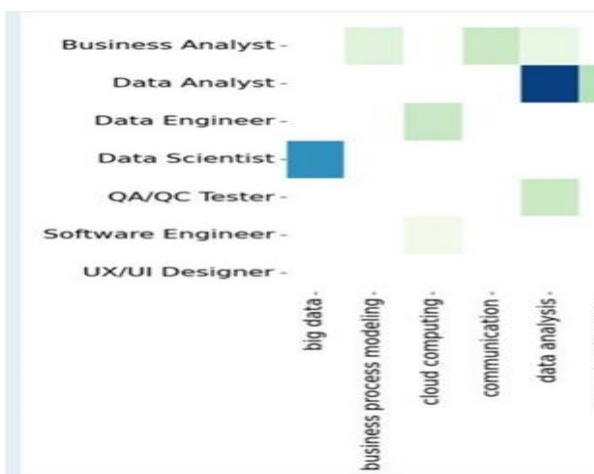

Figure 2: Skill Dataset (

V. CONCLUSION

This research presented the design and conceptual implementation of an AI-driven Personalized Learning Path Recommendation System aimed at addressing key challenges faced by modern learners, such as information overload, lack of structured guidance, and misalignment between learning content and career goals. By integrating learner profiling, skill gap analysis, and adaptive recommendation techniques, the proposed system demonstrates how artificial intelligence can significantly enhance the effectiveness and efficiency of the learning process.

The system leverages machine learning algorithms, content-based filtering, and learner feedback mechanisms to dynamically generate customized learning paths tailored to individual preferences, prior knowledge, learning pace, and long-term career objectives. Unlike traditional static learning platforms, the proposed solution emphasizes adaptability, ensuring that learning paths evolve continuously based on user performance and engagement.

The modular architecture of the system allows scalability and flexibility, making it suitable for integration with existing e-learning platforms. Furthermore, the inclusion of visualization dashboards and progress analytics empowers learners to monitor their growth, thereby increasing motivation and self-directed learning. Overall, this research highlights the potential of intelligent learning systems to bridge the gap between education and employability by delivering personalized, goal-oriented learning experiences.

Final Remarks

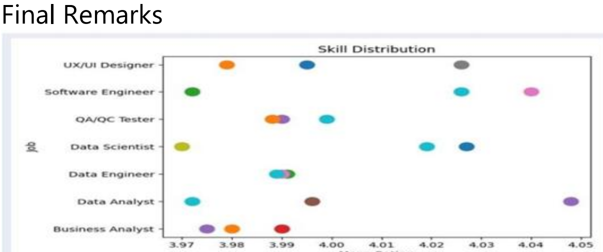

Figure 3: Job Positions Clustering (Source: Authors)

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1. This section lists the key academic and technical sources that support the concepts, models, and methodologies discussed in this research. The references include studies related to personalized learning systems, machine learning–based recommendation engines, adaptive education platforms, and AI-driven learning analytics. These works collectively form the theoretical and practical foundation of the proposed system.
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