iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: IV Month of publication: April 2026

DOI: https://doi.org/10.22214/ijraset.2026.80178

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

AI Driven Personalized Course Recommendation System

Dr. S Radha Krishnan[1], SDImamsa[2], R Hemanth[3], V Komal[4], S Tirumalesh[5], R Raghu Sai[6]
[1]*Professor,* [2, 3, 4, 5, 6]BTechStudents,*Department of CSE-AI & ML, KKR & KSR Institute of Technology and Sciences, Guntur, Andhra Pradesh, India*

Abstract: Selecting the appropriate course hasbecome a challenging taskfor studentsowing to the increasing popularity of online learning platforms and the availability of a vast number of learning resources. Studentsfacedifficulties inidentifyingcoursesthatalign withtheirinterests,existingskills,learning background, and future career plans. The conventional approaches for recommending courses lack personalizationandfailtocatert othediverseneeds oflearners, therebyleadingtoinefficientlearning outcomes and low engagement. This paper proposes an AI Driven Personalized Course Recommendation System thathelpsstudentsmake informed learning choices.The proposed system employsartificialintelligenceandmachinelearningalgorithmstoprocessstudentprofiles,interests, skills,andlearning behaviortor ecommendrelevantcourses.Thesystemlearnsfromuserinteractions andfeedbackovertimeandadapt stoprovidemoreac curaterecommendations.Theproposedsystem enablesefficientlearning,improvesstudentengagement,andfacilitatescareer-oriented learning.The proposed approach, in essence, aims to make course selection easier and provide an effective and learner-centric learning experience.

Keywords: Artificial Intelligence, Machine Learning, Course Recommendation System, Personalized Learning, Content-Based Filtering, Educational Data Mining, LearningAnalytics, Career Oriented Learning

I. INTRODUCTION

The quick digital shift in the education sector has brought about a drastic change in the way knowledge is accessed and distributed. With the advent of online learning platforms, virtual classrooms, and massive open online courses (MOOCs), students can now tap into a huge range of educational resources across various fields. Although this trend has increased the accessibility and flexibility of learning, it has also posed a huge problem for students—choosing the best course fromamonganoverwhelmingnumberofoptions.In conventionaleducationsettings,choosingcoursesis facilitated by academic counselors, professors, or friends.Whiletheseareuseful,theyarealso hampered by human limitations and may not necessarily keep pace with the changing interests, capabilities,andcareergoalsofindividualstudents. Most current online learning platforms provide courserecommendationsaccordingtopopularityor trends, suggesting the same courses to a huge number of users. These generic suggestions do not take into account individual learning requirements, resulting in subpar engagement, completion rates, and resource utilization.

Artificial Intelligence (AI) and Machine Learning (ML) offer effective solutions to overcome these challengesthroughdata-drivenandpersonalized learningsupport.Basedonstudentprofiles,learning behavior,andinteractionpatterns,AI-basedsystems can detect individual preferences and suggest courses that suit individual objectives. The AI- Driven Personalized Course Recommendation System proposes to leverage these technologies to provide adaptive, transparent, and career-focused course suggestions.

II. RELATEDWORK

1) Collaborative, content-based, and hybrid filtering methods for personalized recommendations have been emphasized in previous studies on recommendersystems,asmentioned byRiccietal. (2015).
2) This paper explores the development of recommendersystemsandpointsoutthedrawbacks of conventional collaborative and content-based filtering approaches.
3) This paper proposes the use of matrix factorization methods to improve the performance of collaborative filtering.
4) Thisstudyexploresprivacyconcernsinlearning analytics and educational recommender systems. It emphasizes responsible data collection, transparency, and ethical considerations.
5) This paper gives a complete description of content-based recommendation systems. It describes how user profiles are matched with item featurestoproducepersonalizedrecommendations.

6) This paper explores the use of educational data mining and learning analyticsin academic settings. It specifically discusses the use of student data to gain insights that can improve academic outcomes.
7) The authors discuss the connection between learning analytics and educational data mining. They describe how data-informed strategies improve engagement and success for students.
8) This book explores the topic of business intelligence and analytics methodologies for data- driven decision-making.
9) This study is concerned with adaptive educational systems that provide personalized learning experiences. It emphasizes dynamic content adaptation based on learner profiles and behavior.
10) Thistextbookprovidesathoroughtreatmentof algorithms for recommender systems, such as collaborative, content-based, and hybrid approaches.
11) This paper presents a review of hybrid recommender systems that integrate various methods of making recommendations.
12) This paper examines neighborhood-based collaborative filtering algorithms. The paper explores the design considerations that impact the qualityofrecommendationsandtheperformanceof the system.
13) Thissurveyexaminesdifferentmethodologies and metrics used in recommender systems. It compares collaborative filtering, content-based filtering, and hybrid models.
14) This paper discusses context-aware recommender systems in learning contexts. It describes how context improves personalization.
15) This research work is a survey of the current state of the art in content-based recommender systems. The authors describe techniques of user profiling and feature extraction.

Some research has been conducted on recommendation systems in the area of e-learning, including collaborative filtering, content-based filtering,andhybridmodels.Collaborativefiltering methods identify user behavior patterns to recommendcoursesbutarepronetocoldstartissues whennewusersorcoursesareadded.Content-based filtering methods recommend courses based on matching user profiles with course characteristics, making them more appropriate for personalized learning platforms. Recently, research emphasizes the need for skill-based recommendations and career-focused learning paths. However, most existing systems do not incorporate comprehensive skill gap analysis and do not offer a roadmap to learners.Moreover,mostsystemslacktransparency in recommendations, which makes it hard for users to understand why specific courses are recommended.The AI-Driven Personalized Course Recommendation System incorporates content- based recommendation models and skill gap analysis, roadmap, and progress tracking. The combinationofalltheseas pectsmakestheproposed system different from existing systems because it provides both personalization and explainability.

III. ARCHITECTUREDESIGN

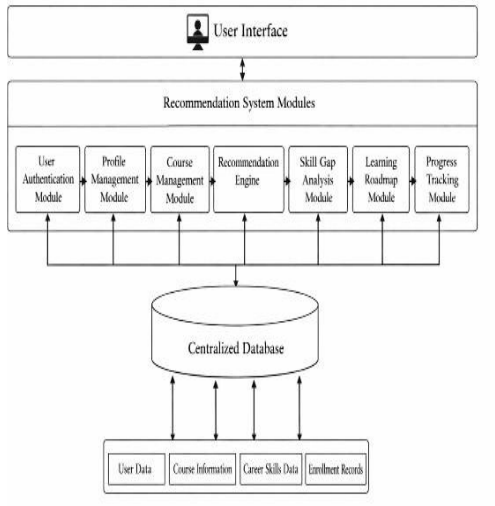
A. SYSTEMARCHITECTUREOVERVIEW

The AI-Driven Personalized Course Recommendation System’s architecture is modular and scalable. Every module is dedicated to a particular task, making it efficient to develop, maintain, and later upgrade. The system is developed as a web application with data storage and intelligent processing units.

Themaincomponentsofthesystem are:

1) UserAuthenticationModule
2) ProfileManagementModule
3) CourseManagementModule
4) RecommendationEngine
5) SkillGapAnalysisModule
6) LearningRoadmapModule
7) ProgressTrackingandDashboardModule

These components work in conjunction with a central database to store and retrieve user information, course information, and learning progress details.



1) USERAUTHENTICATIONAND PROFILE LAYER

The user authentication component deals with the secure entry into the system. This component enables users to register, log in, and have secure sessions. Oncetheusersareauthenticated,theycan create and update their profiles, which are the building blocks of the personalized recommendations. The profile management component holds
critical information about the users, including their skills, interests, education level, and career objectives. The structured profile information enables the analysis and is the basis for the course recommendations and skill gaps.

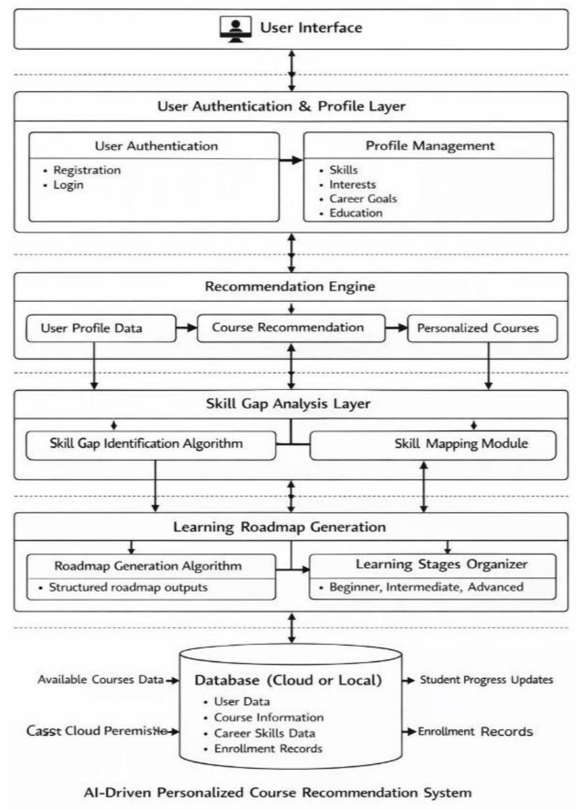
2) RECOMMENDATIONENGINEDESIGN

The Recommendation Engine is the intelligence heart of the system, which is responsible for providingpersonalizedcourserecommendationsfor each user. The Recommendation Engine takes user profile information, such as skills, interests, and careerobjectives,andmatchesthemwiththecourse metadata information, such as the level of the course, skills needed, and learning outcomes. The engine determines the relevance of each course based on the match between the user information and the course requirements. Based on this, the courses are ranked and recommended to the user in order of relevance. This approach ensures that the userreceivesrecommendationsthatarerelevantand matched with their learning goals. The recommendation engine has a modular design that will enable it to be improved with more sophisticated approaches in the future.

3) SKILLGAPANALYSISMODULE

The Skill Gap Analysis Module is an important componentindeterminingtheskillgapbetweenthe existingskillset oftheuserandtheskillsneededto accomplish their chosen career objective. This moduleperforms a systematic comparison between theskillsofferedbytheuserintheirskillprofileand apredefinedlistofskillsneededforparticularcareer roles,whicharestoredinthedatabase. Bydoingthis systematic comparison, the system identifies the skillsthat have alreadybeen acquiredandtheskills that are yet to be acquired.
Theskillgapanalysisisdonebymappingtheskills entered by the user to a predefined set of skills and checking themforcareer-related requirements.The module provides a distinct separation between “SkillsYou Have” and “Skills to Develop,” which helpstheusertounderstandtheirpositioninaclear manner. This systematic identification of missing skillshelpsthelearnerconcentrateontherightareas of knowledge rather than pursuing courses that are not relevant to their area of interest.
Moreover,theSkillGapAnalysisModulefacilitates career-oriented learning by translating general career objectives into specific skill needs. This module improves the decision-making process by suggestinglearningstrategiesthatspecificallytarget skill gaps.
By incorporating this module with the roadmap and recommendation engine, the system ensures that users are provided with practical advice,whichwillfurtherimprovetheefficiencyof learning.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com



IV. DESIGNCONSTRAINTS

The design of the AI-Driven Personalized Course RecommendationSystem isshaped byanumberof practical and technical constraints.

The constraints determine the operational limits of the system while still ensuring that it achieves its main purpose of facilitating personalized learning.

A. DATASET AVALIBILITY

The system uses predefined datasets for user profiles, skills, courses, and career roles. Because inputs can affect the effectiveness of personalization. To overcome this challenge, the system encourages users to update their skills and learning preferences.

B. PROFILEDEPENDENCY

Accuracy of recommendations is based on the quality of the system is developed as a web-based platform for easy accessibility. However, this approach requires stable internet connectivity and doesnotsupportofflineusage.Thelimitationmakes deployment easier while being platform- independent.

C. WEB-BASEDDEPLOYMENT

real-worldeducationalandcareerdatasetsarehighly dynamic, the current design leverages structured and curated datasets to ensure consistency and reliability. This is a constraint that ensures controlled experimentation and reliable recommendation behaviour.

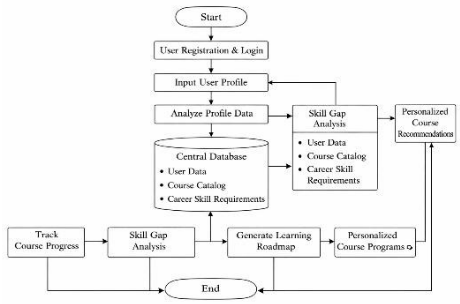
D. SCALABILITYANDRESOURCE

System functionality is affected by the size of the databaseandthecapabilitiesoftheserver.Withthe growing number of users and courses, the computational complexity will also rise. The modularitydesignwillaidindealingwithscalability constraints within the existing infrastructure.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

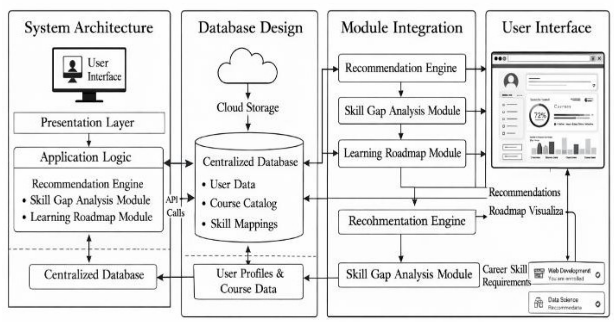
E. CONTENT-BASEDRECOMMENDATION

Thesystemadoptsacontent-basedrecommendation strategy, which is solely based on the attributes of the user profiles and courses. Although this promotes privacy and personalization, it does not consider peer learning behaviour.



V. IMPLEMENTION DETAILS

This section will details implementation of theAI- Driven Personalized Course Recommendation System.



A. SYSTEMARCHITECTUREIMPLEMENT

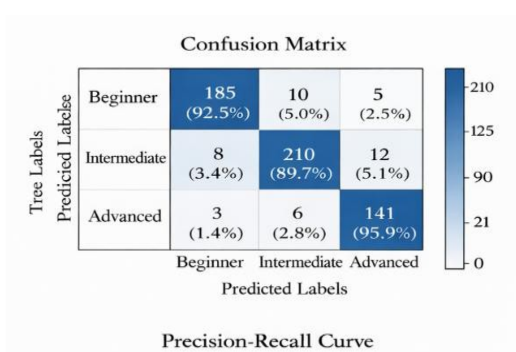
Thesystemisdevelopedusingalayeredarchitecture consisting of presentation, application logic, and data storage layers. Each Functional module operates independently through Interfaces.

B. DATABASEDESIGNANDMANGEMENT

A centralized cloud-based database is employed to store user profiles, course details, skill mappings, and progress information. The database design is organizedinawaythatfacilitatesefficientquerying**.**

C. MODULEINTEGRATION

Each module interacts with the database through secure APIs. The recommendation engine module interacts with user profile and course information, whiletheskillgapmoduleinteractswithcareerskill requirements. The roadmap module structures courses into learning paths.



International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

D. USERINTERFACEIMPLEMENTATION

The user interface offers interactive and intuitive dashboards for profile management, recommendations, roadmaps, and progress. Completionpercentageandlearningstagearesome of the visual cues used.

VI. RESULTS AND DISCUSSION

This section analyzes the performance and effectiveness of the proposed AI-Driven Personalized Course Recommendation System.

Metric	Observation
Recommendation Time	Lowlatency
Roadmap Generation	Instant
DatabaseAccess	OptimizedQuery

A. RECOMMENDATION ACCURACY

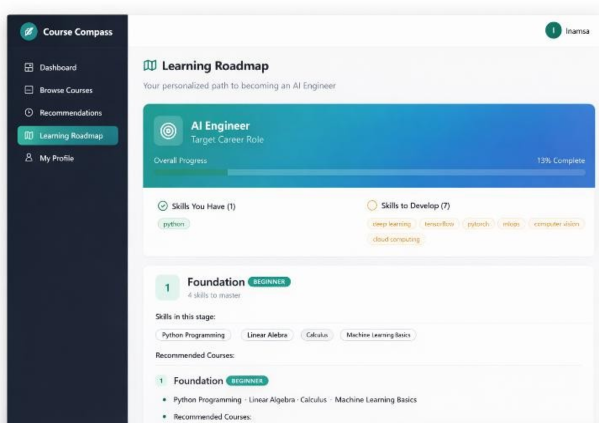
The system is able to produce personalized course recommendations based on the skills and career objectivesof users. Usersare provided with ranked course recommendations and the relevance of the match.

B. SKILLGAP IDENTIFICATION EFFECTIVENESS

The skill gap analysis accurately identifies missing competenciesrequired for selected career roles.This enables focused learning and avoids redundant course enrollment.

C. LEARNING ROAD MAP EVALUATION

Generated learning roadmaps provide a clear progression path frombeginner to advanced levels. Users reported improved clarity in learning direction and reduced course selection confusion.



Learning Roadmap Interface of the Proposed AI-DrivenPersonalized Course Recommendation System.

D. PERFOMANCE ANALYSIS

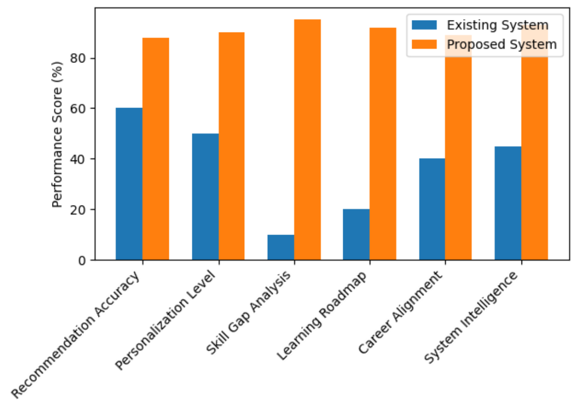
The performance of the AI-Driven Personalized CourseRecommendationSystemhasbeentestedfor responsetime,scalability,andprocessingefficiency. Thesystemprovestobehighlyefficientintermsof response time even when working with moderately sizeddatasets.Becauseofthemodulardesignofthe architecture, each functional module, such as the recommendation engine, skillgap analysismodule, and roadmap generator, works independently, thus decreasing the processing overhead and overall execution time.

The recommendation engine, profile analysis, and course ranking are done using optimized query processingtechniquesinthedatabaselayer.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue IV Apr 2026- Available at www.ijraset.com

The system is highly efficient in terms of indexing and schema design, thus ensuring rapid access to user profiles,courses,andcareerskills.Thisensuresthat therecommendationengineandroadmapgenerator work with zero latency, thus ensuring a seamless user experience.

The system is scalable, meaning that it can support a large number of users and courses without affectingtheperformanceofthesystem.Becauseof the modular design of the system, the system's performance is not affected by changes in one module.Thesystem'sperformanceisstable,andthe databaseaccesstimeisconsistent,thusensuringthat the system is ready for use in a real-world setting.

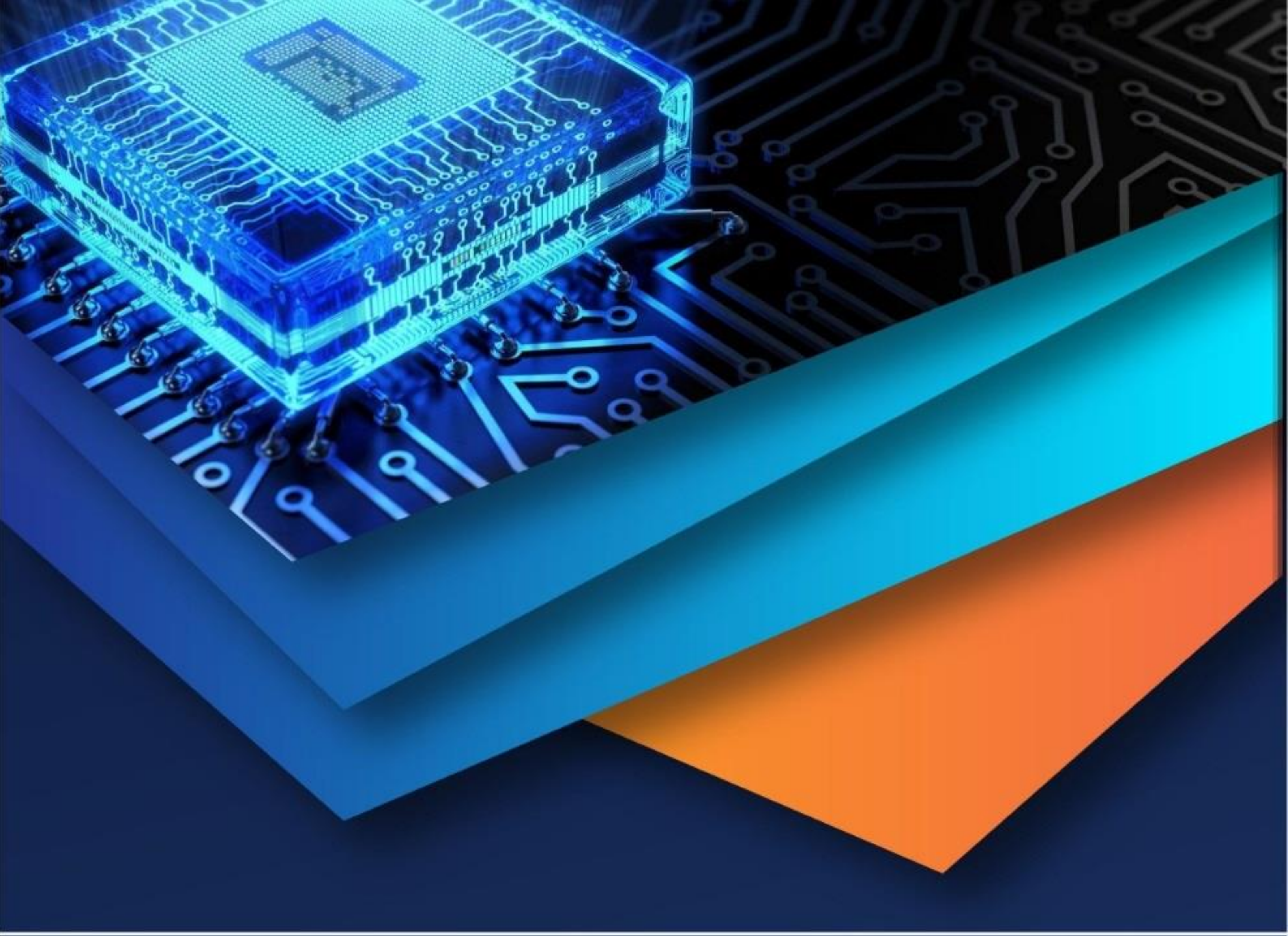


VII. CONCLUSION

This study introduced an AI-Driven Personalized Course Recommendation System that aims to facilitate goal-driven and skill-oriented learning. Throughtheintegrationofuserprofiling,AI-driven recommendation logic, skill gap analysis, and roadmapsystemdesign,thesystemoffersaholistic personalized learning experience. The system's modularity promotes scalability, ease of maintenance, and adaptability for potential future upgrades.Theexperimentaloutcomeshowsthatthe system is capable of aligning learning content with the users' career goals, filtering out non-relevant course recommendations, and enhancing overall learningperformance.Futurestudiescaninvestigate thepotentialintegrationofthesystemwithreal-time labor market information and adaptive learning analytics.

REFERENCES

[1] Ricci,F.,Rokach,L.,&Shapira,B.(2015).RecommenderSystemsHandbook.Springer.
[2] Adomavicius, G., &Tuzhilin,A. (2005). Toward thenextgenerationofrecommendersystems. IEEE TransactionsonKnowledgeandDataEngineering.
[3] Koren,Y.,Bell,R.,&Volinsky,C.(2009).Matrix factorization techniques for recommender systems. Computer.
[4] Drachsler, H., & Greller, W. (2016). Privacy and analytics in learning systems. Educational Technology & Society.
[5] Pazzani, M., &Billsus, D. (2007). Contentbased recommendation systems. The Adaptive Web.
[6] Romero, C., & Ventura, S. (2020). Educational data mining and learning analytics. IEEE Transactions on Learning Technologies.
[7] Siemens, G., & Baker, R. (2012). Learning analytics and educational data mining. LAK Conference.
[8] Sharda,R.,Delen,D.,&Turban,E.(2018). BusinessIntelligenceandAnalytics.Pearson.
[9] Brusilovsky, P. (2012). Adaptive educational systems. International Journal of Artificial Intelligence in Education.
[10] Aggarwal,C.C.(2016).Recommender Systems: The Textbook. Springer.
[11] Burke,R.(2002).Hybridrecommendersystems: Survey and experiments. User Modeling and User- Adapted Interaction.
[12] Herlocker, J. L., Konstan, J. A., & Riedl, J. (2002).An empirical analysis of design choices in neighborhood-based collaborative filtering algorithms. Information Retrieval Journal.
[13] Bobadilla, J., Ortega, F., Hernando, A., &Gutiérrez,A.(2013). Recommender systemssurvey. Knowledge-Based Systems.
[14] Verbert, K., Manouselis, N., Ochoa, X., et al. (2012). Context-aware recommender systems for learning: A survey and future challenges. IEEE Transactions on Learning Technologies.
[15] Lops,P.,deGemmis,M.,&Semeraro,G.(2011). Content-based recommender systems: State of the artandtrends.InRecommenderSystemsHandbook. Springe.



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429