STUDENT LEARNING AND CAREER GUIDANCE RECOMMENDATION SYSTEM: A REVIEW

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Abstract
Education is an essential factor in human life. Education enhances human with different perspective of life. In today dynamic landscape of education, career choices also affected. The utilization of different machine learning techniques in the dynamic landscape in education provide an effective helping hands in career planning to students. Proposed system of personalized career guidance systems that leverage the power of machine learning algorithms and psychometric test with various level of anxiety test using facial expression. The system leverages advanced technology to enhance the accuracy and effectiveness of career counseling. By incorporating psychometric tests, it analyzes individual traits, preferences, and strengths, while also factoring in anxiety levels through data collected from various sources, such as facial expressions and physiological responses. These inputs are processed by machine learning algorithms to identify correlations between psychological factors and career choices. The system then provides insightful and customized career guidance, helping individuals make informed decisions aligned with their abilities and comfort levels. This holistic approach not only addresses professional aspirations but also considers the emotional well-being of users. However, ethical considerations related to data privacy, user consent, and responsible AI implementation must be given priority to ensure the system's ethical and beneficial use.

Keywords:
career guidance, recommendation, machine learning, data analysis.

I. Introduction

The rapidly evolving landscape of education, technology, and the job market has brought forth an increasing need for personalized approaches to student learning and career guidance. As traditional career paths become less linear and more diverse, individuals face a complex array of choices that require careful consideration and informed decision-making. There is a growing demand for customized methods to learning and career advising. In response to this challenge personalized student learning and career guidance programs have evolved as creative responses to this issue, leveraging the power of technology and data-driven insights to help people navigate their professional lives.

The utilization of different machine learning techniques in the dynamic landscape in education provide an effective helping hands in career planning to students. This review paper aims to delve into the realm of personalized career guidance schemes, examining their significance, methodologies, technological foundations, and potential impacts to leverage the power of machine learning algorithms. These student learning and guidance systems have enormous potential. These systems have the ability to make recommendations that strongly align with a person's skills and goals by understanding the complex interactions between a person's traits and the changing requirements of the labor market.They may lessen the uncertainty surrounding professional decisions and lower the dangers brought on by a mismatch between a person's skills and the career route they have selected.

A comprehensive examination of machine learning algorithms like recommendation systems, clustering, and predictive modeling showcases their roles in generating insightful career suggestions. These algorithms take into account the multifaceted dimensions of an individual's profile, fostering an approach that moves beyond a one-size-fits-all strategy. The article explores various methodologies

employed in these systems, including data collection techniques, feature engineering, and algorithm selection. It delves into the challenges and opportunities of integrating diverse data sources, such as academic performance, personality traits, and labor market trends, to create holistic and accurate student profiles. Furthermore, the review highlights the ethical considerations and privacy concerns inherent in handling sensitive student data. Through a critical analysis of recent case studies and implementations, this review offers insights into the efficacy and limitations of existing systems. It also suggests future directions for research, including the integration of real-time labor market data, cross-cultural considerations, and the development of interactive platforms for students.

This paper presents a systematic review of the literature that analyzes the use of machine learning algorithms in career recommender systems and identifies new research directions. The goals of this study are to (i) identify trends in the use or research of machine learning algorithms in recommender systems; (ii) identify open questions in the use or research of machine learning algorithms; and (iii) assist new researchers to position new research activity in this domain appropriately.

This paper is organized as follows: Section 2 describes the theoretical background needed, Section 3 explains the systematic review protocol, and Section 4 explains the results of this study. Section 5 presents conclusions and future work.

II. Literature

Recommender systems (RSs) are used to help users find new items or services. These systems also play an important role in decision-making, helping users to minimize the risk. As the RS field evolved, researchers studied the use of algorithms from machine learning (ML), an area of artificial intelligence (AI). Popular machine learning methodologies like classification, clustering.

Many RS a proposed till date. this review article review few of them to better understanding and the research gaps. The eDoer is an data driven approach to the development of a personalized learning and career-oriented recommender system developed by M. Tavakoliet et al.[1] . eDoer utilizes different features such as Source, Format, Transcript, Rating, and View Count had already been extracted automatically. It also employ statically analysis of data. Imran ali et al. novel for the Recommender system (RS) which helps the learner to make appropriate choices for completing the enrolled course. There is tremendous scope and opportunities available for researchers to focus on this domain. An exhaustive analysis is required to spotlight the opportunities in this relation [2]. Sahraoui Dhelim et al. has tried to compare the main differences between conventional recommendation systems and personality-aware recommendation systems. Here the author has highlighted the existing personality-aware recommendation system based on the used recommendation technique. By taking sample reviews of the works the authors have tried to propose personality-aware recommendation systems [3]. Anirudh Som et al. used simple convolution neural network models for career guidance recommendation. It has used spatiotemporal representations of individual student roles and behaviour annotations as input for group collaboration assessment [4].M Qamhieh et al. have suggested a design that has considered high-school students in developing countries. where educational and professional guidance in schools is limited. It is a Personalized Career-path Recommender System (PCRS) to provide guidance and help high school students choose engineering discipline. The design of PCRS is based on the fuzzy intelligence of N-layered architecture and uses students' academic performance, personality type, and extra-curricular skills [5]. E K Subramanian et al. provides a perspective for students to select a specific program within a recommended study field. This novel aims E K Subramanian analyse personal information, academic history, hobbies, co-curricular involvement, extracurricular activities, interests, background, and individual aspirations to provide personalized course recommendations [6]. V Maphosa et al. utilises a lens AI based model that offers students an encompassing view of fifteen years of research in higher education recommender systems. This module explores current trends and outlines future directions [7]. Simon Fong et al. have developed a

software for students to automated university admission recommender system for secondary school students. It represents a hybrid model of neural network and decision tree classifier that serves as the core design for a university admission recommender system [8]. Jie Lu, this research has introduced a novel framework for a personalized learning recommender system designed to assist students in discovering relevant learning materials. The framework incorporates two interrelated technologies: firstly, a multi-attribute evaluation method is established to assess the specific requirements of individual students. Secondly, a fuzzy matching technique is developed to identify appropriate learning materials that align closely with each student's distinct needs. Through the deployment of this innovative personalized learning recommender system, online learning for students can be significantly enhanced, facilitating more effective engagement and aiding in the instruction of diverse, large-scale online classes encompassing students from various backgrounds [9]. Mack Sweeney et al. this novel has devised a system capable of forecasting students' grades for the upcoming enrolment term. This predictive model harnesses insights gleaned from historical transcript data, which is complemented by supplementary details concerning students, courses, and the respective instructors leading the courses. By amalgamating this wealth of information, we have constructed a framework that discerns patterns and trends, enabling us to anticipate the academic outcomes of students in the courses they are set to undertake in the subsequent enrolment period [10]. Nguyen Thai-Nghe et al. introduced an innovative methodology that harnesses the capabilities of recommender system techniques in the realm of educational data mining, specifically focusing on the prediction of student performance [11].

Table 1. shows a short represent review table for recommendation systems developed.

Sr.no	Reference	Objective	Limitation
1	M Tavakoli (2022)	Open, Personalized, labor market oriented learning RS	-Randomized Experiment -Only focus on data-science job.
2	I.Uddin(2021)	-Review of Massive online learning system RS. -Domain focus course choice RS	Review paper only concentrate on massive online learning systems only.
3	Sahraoui Dhelim(2021)	Provide extensive review of personalize aware systems.	Not address cold start and recommendation diversity papers. -Maintaining a high personality detection accuracy
4	Anirudh Som (2021)	Used CNN model to learn spatio temporal features from student Profile. Provide individual-level or group-level feedbacks.	-Model is less robust. -Only focus on quantitatively behaves, quality behavior was not address.
5	M.Qamhieh (2020)	-Model utilizes fuzzy intelligence of N-layered architecture and uses students' academic performance, personality type, and extra-curricular skills for RS. -Model is scalable.	Targeted to target Palestinian community and MENA region. Recommendation is done on base of small factors.
6	E K Subramanian (2019)	Model Utilizes personal information, academic details, hobbies, curricular activities, extracurricular activities and other activities interests, background, aims of the specific person.	-student dropout is not consider in RS

7	V. Maphosa (2023)	-Evaluate the development and growth of RS in higher education. -Analyze different article types, publication trends, top-cited articles and the most cited publications	Focus on USA, China, Taiwan data for RS
8	S .Fong(2009)	-RS mainly targeted secondary high school admission trends. -Uses Neural Network & Decision Tree for classification. -Consider student background for more accurate prediction.	-RS scope is limited to Macau city only. -Author fail to analysis the application on other area.
9	Jie Lu(2004)	-Help student to find the e-learning material resources. -multi attribute evaluation & Fuzzy matching method were used.	-Target limited no of student. -Achieve less accuracy as compared recent development
10	M. Sweeney (2016)	-Factorization Machines (FM), Random Forests (RF), and the Personalized Multi-Linear Regression model achieve the lowest prediction error. -Used to Predict student performance in Next Term.	-Less customized view. -cold-start problem in system.
11	N. Thai-Nghe (2010)	-Educational data mining approach for student performance prediction.	-Cold-Start problem. -Different combination of dataset were not tried.

III. Methodological Review

Recommender Systems Classification: RS are mainly categories into three main approaches as content-based, collaborative, and hybrid-based approaches [12].

III.1 Collaborative based approach: Collaborative filtering (CF) recommends items to targeted users by finding other users with similar interests. This approach uses user behaviour or user ratings to make recommendations on products liked by similar users. CF's foundation is that people with similar tastes will likely make similar choices in the future [13].The motivation is that users consider recommendations from family and friends whenever they decide on a career, investment or education. Thus, CF techniques begin by finding a group of users whose preferences are similar to the targeted user. All the items the group likes are recommended to the targeted user. A study to examine RS that assists students in choosing elective courses showed that the CF was the most widely used RS technique [14].

III.2 Content based approach: Content-based (CB) methods recommend items to the user based on historical data by learning the services or products the user acquired and then suggesting new items. This approach is widely used in e-commerce, social networks, and education, where product rating is a dominant attribute of this technique. Things that a user previously rated are used to build a user profile. CB approach is that recommendation is independent of the user but based on content attributes. CB inability of this technique to extend the user's current preferences or interests is another limitation.

III.3 Hybrid Based approach: Hybrid-based systems aim to get the best results by combining collaborative filtering and content-based recommendation methods. A hybrid approach is used to overcome the inherent limitations of the two major recommendation techniques, and it aggregates the two

techniques to develop other variations.

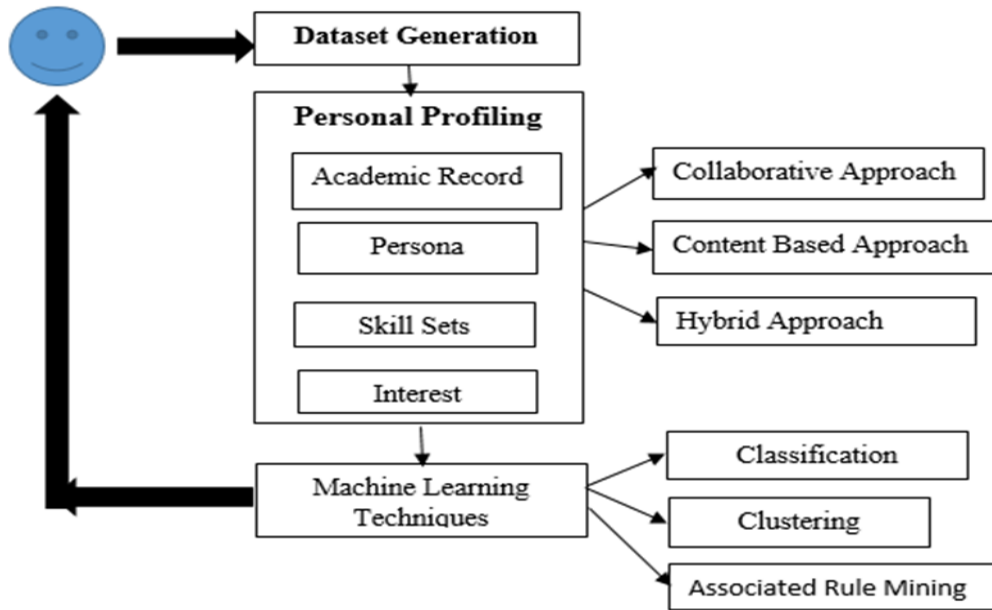Figure 1 shows the general outline structure of recommendation system for education sector

Figure 1: Education recommendation system general process architecture

Extensive review of many articles get published in last five year uses various machine learning techniques for analysis of student profile to provide a right career recommendation. Also many researcher employee various methods for personal profiling like CB, CS, or hybrid approach.

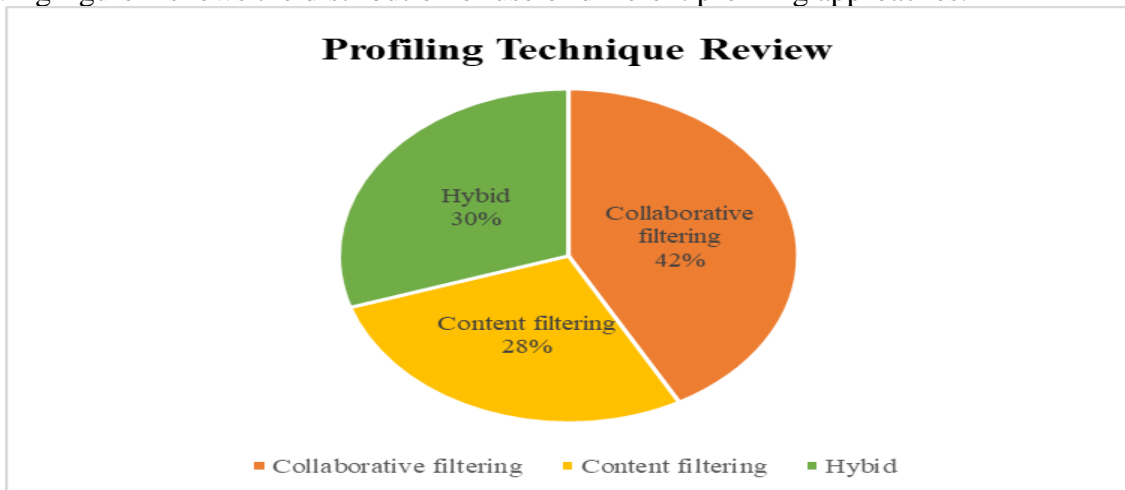Following figure 2 shows the distribution of use of different profiling approaches.

Figure 2: Distribution of use of different profiling approaches.

Figure 3 Representation of different machine learning techniques and deep learning techniques used in last five year by various research in education path planning RS.
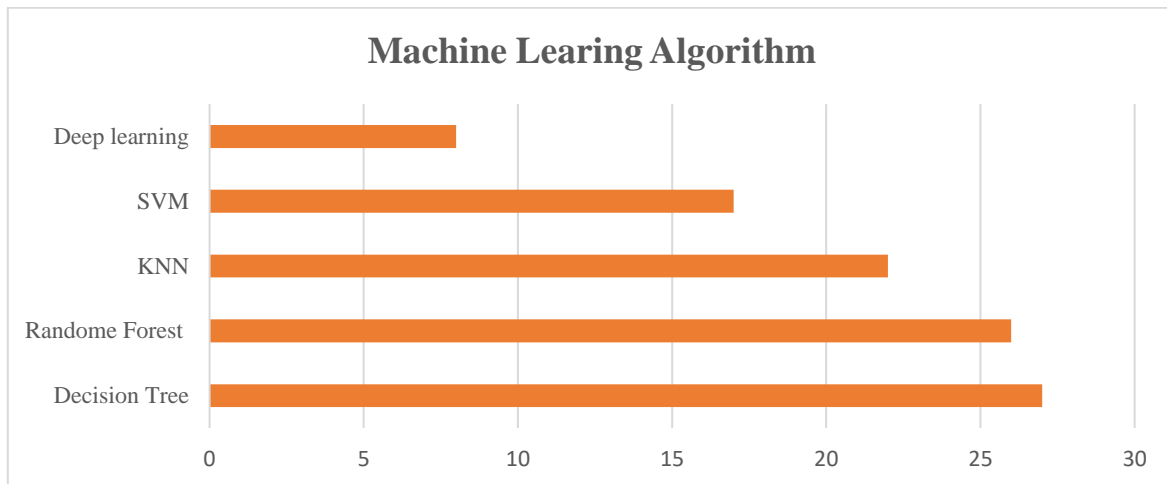
Figure 3: Use of different machine learning techniques in educational recommendation System.

In last five-year article review shows that decision tree is a popular machine learning algorithm in researcher. Some research also got good accuracy in career path prediction using random forest and support vector machine algorithm to develop a hybrid approach. Research focusses k-nearest neighbor algorithm for mainly grouping a similar interest student profile. In recent year convolution neural network (CNN) is also becoming a popular approach for career guidance RS.CNN basically used for feature extraction from student profile.

IV. Research Gaps:

Personalized career recommendation systems are a burgeoning area of research, aiming to provide tailored guidance to individuals seeking career paths that align with their skills, interests, and goals. Extensive literature review from past five year personalize career recommendation system author highlight some research gaps challenges in this field that you might consider exploring in project paper. These research gaps are as follows:

Data Quality and Diversity: Many pre-existing RS rely on historical job data and user profiles. However, the quality and diversity of these datasets can significantly impact the accuracy and fairness of recommendations historical job data might lead to skewed recommendations may mitigate these biases.

Dynamic Labor Market Trends: The job market is dynamic and constantly changing due to factors like technological advancements, economic shifts, and global events many system not able to accommodate this dynamic nature.

Incorporating Soft Skills and Interests: Personalized recommendations should not only consider hard skills but also incorporate soft skills and personal interests, which play a crucial role in job satisfaction.

User Context and Goals: Users' career goals, financial aspirations, work-life balance preferences, and geographical constraints can greatly influence their ideal career paths. Explore ways to capture and integrate this contextual information to provide recommendations that align with users' holistic career aspirations.

V. Discussion:

Research publication for RS in education system grow from 2017 onward. Due to covid19 scenario online education is a key motivation behind the personalize learning and career guidance recommendation systems. The development and implementation of a student learning and guidance recommendation system bring about a multifaceted discussion, encompassing various aspects that contribute to its significance and potential impact. We need to address research gap in the development of deep learning based personalize career recommendation system like personalized learning paths to enhance engagement and motivation, leading to more effective learning outcomes. RS need to offer holistic support by recommending resources for mental health, well-being, extracurricular activities, and career development.

System need to provide support with diverse range of learning resources like online courses, research papers, videos, and interactive materials. A well-designed system can aid in long-term skill development, not just for immediate academic needs but also for lifelong learning and adaptability in a rapidly changing job market.

VI. Conclusion

The landscape of personalized learning and career guidance recommendation systems is evolving rapidly, presenting a dynamic and promising avenue for reshaping how individuals navigate their professional trajectories. This review article has provided a comprehensive analysis of the current state of the field, identifying key advancements, challenges, and research gaps that underscore the need for further exploration. Achieving accurate recommendations hinges on fusing diverse data sources, understanding both hard and soft skills, and accommodating individual ambitions and contexts. The imperative for transparent algorithms aligns with broader AI ethics concerns, emphasizing user trust. The unceasing dynamism of the job market necessitates a system that not only adapts to emerging trends but also empowers users to anticipate and plan for evolving opportunities. Addressing the identified research gaps, such as data quality enhancement, robust skills mapping, and the integration of multidimensional user context, offers fertile ground for innovation and advancement.

The study gives essential insights into current and future research on RS in HE. This analysis helps researchers, policymakers, and practitioners better understand the development and trajectory of RS with possible practice implications. Therefore, this study recommends that developing such systems to improve learning and career guidance path.

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