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A review of literature on Recommender Models for career pathway selection in Competency-Based Education

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ABSTRACT

In Competency-based Education (CBE), learners acquire skills and knowledge through a personalized and flexible learning path, based on their prior knowledge and skills. To support learners in selecting career pathways that match their interests and competencies, recommender models are widely used. Recommender models (RM) analyze learners' competencies, interests and goals to suggest career pathways suited for them. This paper reviews literature by analyzing recommender models used for career pathway selection in CBE through desk study. First, it explains the concepts of CBE. Secondly, it discusses the types of recommender models used for career pathway selection in CBE. Lastly, it discusses various recommender models developed for career pathway selection highlighting their strengths and weaknesses. Findings from the review reveals that hybrid recommender model is popularly employed for career pathway selection compared to content-based, knowledge-based, and collaborative filtering recommender models as it gives a higher level of accuracy in the recommendation. Overall, this review paper contributes to the growing body of literature on recommender models for career pathway selection in CBE. In addition, it provides valuable insights for practitioners, researchers and emphasizes the need for future research to address the challenges associated with recommender models for career pathway selection in CBE.

Introduction

An individual's major and or minor decision has historically been based on recommendations. When an opinion comes from an experienced person or when two or more people recommend the same, an individual is most likely to accept it.. Unfortunately, these well-intentioned suggestions are often ineffective, as peoples tastes and preferences are not the same (Singh et al., 2021).

The ever growing technology advancements and the expansion of online services have enabled quick access to immense quantities of online information (Roy & Dutta, 2022).This makes it difficult for users to filter the information, and extract the most essential details, resulting in information overload (Fayyaz et al., 2020). It would be of great assistance if there was a personal advisor who would assist in making decisions by recommend-

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ing the optimal course of action. Thankfully, there is one in the form of the Recommender Model (RM), a web application (Singh et al., 2021).

Recommender models are software tools and procedures that provide recommendations for a variety of decision-making processes, including selecting career pathways, merchandise to buy, music to listen to, films to watch, or online information to read-all of which may be matters of interest to a specific consumer (Ricci et al., 2015). Recommender models reduce the time and effort required by users to search for relevant online information and provide recommendations based on their interests (Roy & Dutta, 2022). In the final decade of the 20th century, modern recommender models emerged as a remedy for information overload and content personalization in today's world of big data (Pavlidis, 2019). In the education sector recommenders, can be advantageous to learners as they are faced with a difficult decision when choosing subjects, programs, courses, and career pathways.

In the development of recommender models, certain data mining techniques are applied which include clustering, classification and association rule mining. Clustering is used by RM to identify the group of persons who have the same tastes and to increase the recommender system's effectiveness (Amatriain & Pujol, 2015). Classification creates a model, or classifier that can be applied to new items based on training data.

Competency-Based Education (CBE) is an approach to learning that focuses on student mastery of specific competencies or skills, rather than on the traditional fixed-time model where all students progress at the same pace (Wyne et al., 2021). Concept of CBE programs was first introduced in the area of teacher education in the late 1960s and later quickly progressed through applications to other professional education programs as well in USA in the 1970s (Wyne et al., 2021).

Methods

The paper is a review of literature on Recommender Models including their application, strengths and weaknesses in relation to career pathway selection in CBE. The following databases were used to search studies: Scopus, IEEE Xplore, ACM Digital Library, Science Direct, Springer Link, ELSEVIER and any other peer reviewed journal related to the theme. The targeted search items were journal papers, conference papers, and articles. Automatic search was used to perform the search, in the selected databases by entering search strings on the search engines of the electronic data source, and finally the relevant studies were selected. The search string "Recommender Models", "Competency-Based Education" and "Career Pathway" were used and articles and publications from Scopus, IEEE Xplore, and ACM Digital Library papers with high number of citations were preferred.

Inclusion criteria was based on

i) Studies written only in English;
ii) Studies referencing any of the subjects related to Recommender Model, Competency-Based Education and Career Pathway Selection
iii) Peer reviewed journal papers, conference papers, articles, and workshop papers.
iv) Exclusion criteria was:
v) Repeated studies found in different search engines only one study was considered;
vi) Duplicate studies reporting similar results the most complete study was considered;
vii) Inaccessible papers and books.

Concepts of Competency-Based Education (CBE)

Competency-based education (CBE) originated from the "behavioral objectives movement" in the 1950s in the USA, aiming to enhance student achievement and teacher training by structuring learning outcomes (Mulenga & Kabombwe, 2019). In response to economic challenges, the UK and Europe shifted towards vocational education with a focus on competency-based qualifications, seeing education as a catalyst for economic regeneration. Similarly, in Germany, CBE emerged in the 1970s, emphasizing specialization and ab-

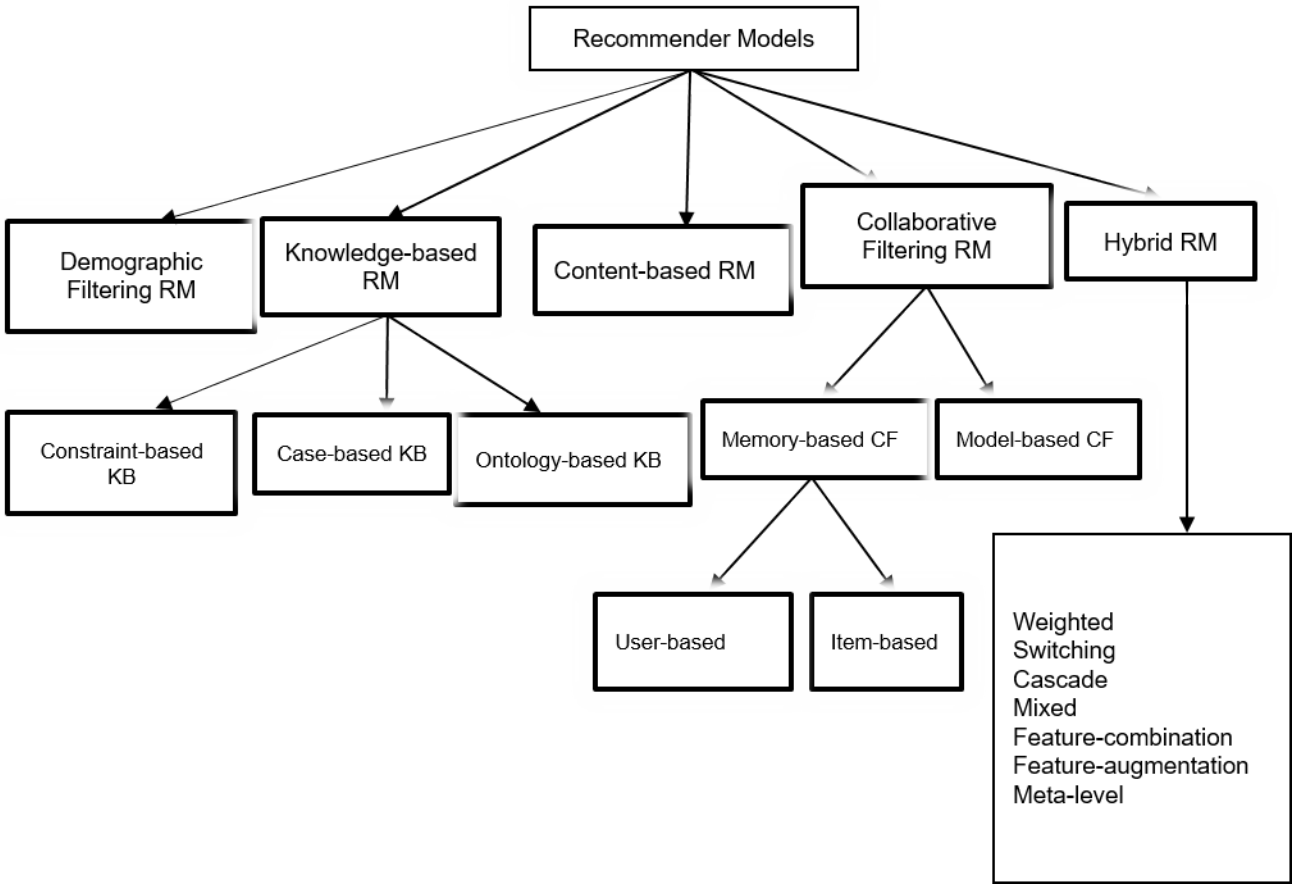

Figure 1: *Recommender Model Taxonomy*

stract knowledge, and later adopting an action competence approach in vocational education, encompassing vocational, personal, and social competences. These approaches underscore the significance of learners acquiring specific knowledge, skills, values, and attitudes for success in their professional and social contexts. The United States of America (USA), the United Kingdom, Australia, Germany, South Africa, Tanzania, Rwanda, and Kenya are among the countries that have adopted CBE (Mulenga & Kabombwe, 2019).

CBE enables multiple learning pathways which allows students to pick and choose the career pathways that are most useful to them in achieving their desired professional goals (Wyne et al., 2021). CBE focuses on student's demonstration of desired learning outcomes as central to the learning process. To become competent in a specific career, a learner needs to: know something about it, have the skills to apply the knowledge and have the right attitudes that ensure s/he will do it well (Mulenga & Kabombwe, 2019). In the context of CBE, competencies refer to the ability to perform a specific task by applying the knowledge, skills, and attributes associated with specific subject area which is further divided into smaller units to facilitate implementation (Wyne et al., 2021).

According to their profile or state, learners also have specific learning needs and competencies (Yago et al., 2018). Traditional recommender systems only consider the items that the user interact with, and then recommend the next item that the user may be interested in, without fully considering the user's personalized preferences (Lu, 2022).

Types of Recommender Models for Career pathway selection in Competency-Based Education

Recommender models are categorized according to the methods they use for suggestion and the types of data they utilize for prediction, which

are user-item interaction and user-item characteristics information (Burke, 2002). The main components of a RM are users, items and ratings (Vaidhehi & Suchithra, 2019). The next section discusses Content-based recommender model, Collaborative filtering recommender model, Knowledge based recommender model, and Hybrid filtering recommender model as recommender models that have been used for career pathway selection in CBE.

Content-based Recommender Model (CBRM)

The Content-based Recommender Model (CBRM) works with the data provided by the user collected either explicitly by rating or implicitly by clicking a hyperlink. It is closely linked with supervised machine learning that recommends an item to a user based on a description of the item and a profile (Ochirbat et al., 2018). The CBRMs function is to find products with the same content to suggest to the active users. This recommender system compares the user's items ratings with items he or she did not rate and then computes the similarities (Obeid et al., 2022). The system learns to recommend items that are similar to the ones that the user liked in the past. The similarity of items is calculated based on the features associated with the compared items. For example, if a user has positively rated a movie that belongs to the comedy genre, then the system can learn to recommend other movies of this genre (Singh et al., 2021). A graph-based cross-domain recommendation that leverages massive education and career data via community-based data fusion is proposed by (Zhu et al., 2020). It recommends rank-ordered courses or jobs for a student (or junior employee) by considering his/her education/career history and leveraging a heterogeneous graph that integrates education and career data. They conducted an experiment using college students. However, there were fewer overlapping skills across jobs and courses in that only 79 of the 376 skills identified in the course data could be mapped to skill terms listed in job advertisements.

A Personalized Career-path Recommender System (PCRS) is proposed (Qamhieh et al., 2020) to provide guidance and help high school students choose engineering discipline. The design of PCRS is based on fuzzy intelligence using students' academic performance, personality type, and extracurricular skills. An experiment was conducted using 177 engineering college students and a slight agreement between the recommendations of PCRS and the actual career choice was proved based on an evaluation sample. They proposed an increase in the evaluation sample so as to enhance the agreement results of the evaluation test in future (Qamhieh et al., 2020).

A career recommendation system for engineering students using content-based filtering using a dataset of 20000 entries was proposed by (Yadalam et al., 2020). The framework provides extra abilities to undergraduates required for related employment opportunities. Users can give their feedback and criticism dependent on their experience on various parameters. However, other streams can be included and the student's profile handled in a more secure way in the future. In addition the system can be implemented using collaborative approach.

Knowledge based recommender model (KBRM)

Knowledge-based recommender model generates appropriate recommendations based on explicit and implicit knowledge about the users and items. This technique integrates knowledge such as users' characteristics, preferences, interests, or needs (Obeid et al., 2022). Knowledge-based RM provide a recommendation based on additional knowledge model related to the relationship between the present user and items. Case-based reasoning technique is a common feature of KBRSs that divides the user's need into multiple cases, depending on various criteria and provide recommendations that closely matches to user's likely preference (Bridge et al., 2005). Another type of KBRM, known as constraint-based RS that works as per the user's preference and recommends items that match the preference (Felfernig

and Burke, 2008). If no such item is available, then a set of alternative items that are close to the preferred item is recommended (Singh et al., 2021). Using knowledge based recommender model (Verma et al., 2017) proposed a Student career path recommendation in engineering stream based on three-dimensional model.

Collaborative Filtering Recommender Model (CFRM)

Collaborative Filtering Recommender Model (CFRM) is based on the notion that if some users have the same preferences in their history, they will share mutual preferences in the future (Obeid et al., 2022). It encompasses two essential types namely the Memory-based and Model-based collaborative filtering recommender (Ricci et al., 2015).

Memory-based collaborative filtering recommender model computes the similarity between users based on users' activities, ratings, or selected items to generate appropriate recommendations. Thus, it integrates users and items' dataset to generate predictions. Memory-based CFRM can be further divided into two categories item-based and user-based depending on the method of similarity computation (Al-Shamri & Al-Ashwal, 2014. In item-based, similarity is computed among a set of items while in user-based, similarity is computed based on the similarity values of users (Singh et al., 2019).

Model-based collaborative filtering recommender model calculates the similarities between users and/or items, then saves them as a model, and then implements the saved similarity values to generate recommendations. The Model- based CFRM implements several algorithms such as clustering algorithm, matrix factorizations, Bayesian network or regressions (Obeid et al., 2022). In cases where the model is built on basis of the training set, Model-based CFRM is more scalable (Mudita & Gupta, 2021).

The philosophy followed by CFRM is based on the idea that a person's interests can be inferred by the company they keep. Therefore, if CFRM finds that two or more users had similar interests in the past, it assumes that their interests will continue to match in the future (Singh et al., 2021). CFRM integrates users' preferences, interests, and actions to suggest products to users based on the match between users' profiles. CFRM offers several benefits, including its simplicity, accuracy, and the ability to make recommendations without evaluating the content of the recommended systems. It also addresses scalability, sparsity, and other challenges effectively, resulting in improved prediction performance. However, CFRM has limitations such as the requirement for a large dataset of users and items to start, the reliance on standardized merchandise, performance degradation in the presence of sparse data, and the issue of cold start, where new users without prior data may receive poor recommendations (Melo, 2018) .

A collaborative filtering recommender model was designed for university elective courses, where course recommendations are made based on the similarity between students' course templates (Bhumichitr et al., 2017). The system employed two widely used algorithms: collaborative filtering using Pearson Correlation Coefficient and Alternating Least Squares (ALS). The performance of these algorithms was compared using a dataset consisting of academic records from university students. The experimental findings demonstrate that ALS outperforms collaborative filtering based on Pearson Correlation Coefficient in this particular domain, achieving an accuracy rate of 86 percent.

In their study, (Singh et al., 2021) describes a collaborative recommender system that recommends university optional career pathways to students based on career pathways taken by other like students. The proposed approach employs an association rules mining method as an underlying strategy to find patterns between career pathways. Experiments with real datasets were conducted to assess the overall performance of the proposed approach. It recommends career pathways and describes the expected grades for these career pathways. As a result, the student may en-

roll in a system-recommended career pathway and earn a passing grade.

According to (Mondal et al., 2020), they proposed a recommendation system that utilizes a machine learning approach to suggest suitable courses to learners based on their past learning details and performance. The model employed a K-Means clustering algorithm to classify students according to their performance ratings. Collaborative filtering techniques were then applied to the clusters to identify appropriate courses for each student. This study revealed the need to enhance the system by incorporating a knowledge base to uncover shared characteristics among students. This would enable the identification of more students with similar areas of interest and target needs.

In their research, (Ogunde & Idialu, 2019) developed a recommender model to aid prospective students in choosing appropriate IT businesses in Nigeria. They collected data through an online survey, receiving 200 responses, and employed the C4.5 method to classify the dataset and generate a decision tree model for collaborative filtering recommendations, achieving an accuracy of 78.84 percent.

Based on previous research, the limitation of the RM can be circumvented by combining two methods (hybrid) to improve the recommendations with the help of machine learning techniques (Nouh et al., 2019).

Hybrid Filtering Recommender Model (HFRM)

Hybrid filtering recommender models leverage a combination of two or more techniques to enhance their performance. These models aim to address the drawbacks inherent in individual techniques by integrating them strategically (Fayyaz et al., 2020). By blending different approaches, hybrid models seek to achieve improved recommendation accuracy and effectiveness by capitalizing on the strengths of each technique while mitigating their respective weaknesses (Obeid et al., 2022).

According to (Burke, 2002) hybrid RM techniques are classified into seven hybridization strategies namely; weighted, switching, mixed, feature-combination, feature- augmentation, cascade, and meta-level.

In their study, (Ochirbat et al., 2018) introduces a recommender called Occupation Recommendation (OCCREC) that aims to assist students in determining their career paths at an early stage. OCCREC is a hybrid system that combines content-based filtering and collaborative filtering approaches. The model incorporates various information sources, including student profiles, student interests, and behavioral data.. The performance of the system is evaluated through experimentation, yielding significant results.

In their research, (Idakwo John, Babatunde Joshua Agbogun & Taiwo, 2022) proposes the development of a hybrid student's career path recommender system using Ensemble technique , taking into account individual's personal interests and academic records to recommend correct Computer Science career path that would be best suited for them.

A recommendation model by (Al-Dossari et al., 2020) called CareerRec was proposed, which uses machine learning algorithms to help IT graduates select a career path based on their skills. CareerRec was developed and tested using a dataset of 2255 employees in the IT sector in Saudi Arabia. A performance comparison between five machine learning algorithms was conducted to assess their accuracy for predicting the best-suited career path among three classes. The experiments demonstrate that the XGBoost algorithm outperforms other models and gives the highest accuracy (70.47%).

Discussion

Content-based recommender models (CBRM) focus on finding similar items based on the user's preferences and ratings. These models compare the user's item ratings with unrated items to compute similarities and make recommendations (Obeid et al., 2022). Knowledge-based recommender models leverage knowledge graphs and

Author, Year	Recommender Model	Dataset	Machine Learning Algorithm	Metric	Method
(Idakwo et al.,2022)	Hybrid Filtering Model	700 students	Ensemble	Accuracy	Experiment
(Ochirbat et al., 2018)	Hybrid(CBRM+CFRM) Model	612 students	Pearson correlation	Accuracy	Experiment
(Haritha, 2021)	Hybrid filtering model	1000 records	Logistic Regression Linear Discriminant Analysis	Accuracy	Survey
(Zhu et al., 2020)	Content based filtering	7824 college students	Text mining	Mean Average Precision = 0.64	Experiment
(Ibrahim et al., 2019)	Hybrid (CBRM+CFRM) Model	200 college students	Ontology K-Nearest Neighbour (OKNN)	Performance accuracy : Rank 84 % Recovery 70 % Precision 92 %	Experiment
(Son et al., 2021)	Knowledge based filtering	169 Coursera's courses, 342 learning outcomes 18 jobs	Genetic Algorithm (GA), Ant Colony Algorithm (ACO)	Time processing : GA=34 seconds ACO=162 seconds	Experiment
(Verma et al., 2017)	Knowledge based filtering	180 students and graduates	Fuzzy logic	Students response: 95%	Experiment
(Comendador et al., 2020)	Knowledge based filtering	93 Senior high school students	Fuzzy logic	Functionality 83% level of acceptance	Survey
(Qamhieh et al., 2020)	Content-based filtering	177 university engineering students	Fuzzy logic	Satisfaction Cohen's Kappa (κ=0.23, 95 % CI, p < 0.05)	Experiment
(Yadalam et al., 2020)	Content-based Filtering	20000 entries	K-means Cosine similarity	Not specified	Not specified
(Al-Dossari et al., 2020)	Hybrid filtering model	2255 records	XGBoost	Accuracy	Survey Experiment
(Hernandez & Atienza, 2021)	Hybrid filtering model	1500 students records	Decision Tree, Deep Neural Network	Accuracy	Experiment
(Bhumichitr et al., 2017)	Collaborative Filtering Model	423 students records	Pearson correlation Alternating Least Squares	Accuracy	Experiment
(Singh et al., 2021)	Collaborative filtering model	Not specified	Association rule mining	Not specified	Experiment
(Mondal et al., 2020)	Collaborative filtering model	300 students records	K-means clustering	Accuracy	Experiment
(Ogunde & Idialu, 2019)	Collaborative filtering model	200 respondents	C4.5 algorithm	Accuracy	Survey

Table 1: *Summary of reviewed articles that have used in recommendation approaches for career pathway selection*

multi-objective optimization to generate appropriate recommendations based on the user's background and goals (Son et al., 2021).

Collaborative filtering recommender models (CFRM) utilize user preferences and actions to suggest products based on similarity between users' profiles. CFRM offers simplicity, accuracy, and scalability but requires a large dataset and may suffer from performance degradation in the presence of sparse data or new users (Singh et al., 2021). Hybrid filtering recommender models aim to combine different techniques to enhance recommendation accuracy and effectiveness (Fayyaz et al., 2020). These models leverage the strengths of different approaches, such as content-based filtering and collaborative filtering, to overcome their limitations and improve recommendations (Ochirbat et al., 2018).

The studies also emphasize the importance of incorporating additional data and utilizing different algorithms to enhance the performance of recommender systems. Ensemble techniques and machine learning algorithms, such as XGBoost, have been utilized to develop hybrid models that recommend suitable career paths and occupations (Idakwo John et al., 2022; Al-Dossari et al., 2020).

The limitations of the reviewed recommender models include the need for large datasets, the challenge of system initialization for new users, and the construction of knowledge graphs. Future research directions include expanding the evalua-

tion sample, considering new types of recommendations, and addressing security concerns in handling student profiles. Additionally, the inclusion of descriptions, explanations, and feedback mechanisms can enhance the user experience and confidence in the recommendations (Yadalam et al., 2020).

Conclusion

Recommender models are key in competency based education as they provide learners with recommendations on career pathways, career guidance, and job opportunities. Different types of recommender models, including content-based, knowledge-based, collaborative filtering, and hybrid models, have been proposed and studied.

Content-based recommender models focus on finding similar items based on user preferences, while knowledge-based models leverage knowledge graphs and optimization techniques to generate personalized recommendations. Collaborative filtering models use user preferences and actions to suggest items based on similarity between user profiles, and hybrid models combine multiple techniques to enhance recommendation accuracy and effectiveness.

The studies highlight the need for incorporating additional data, utilizing different algorithms, and addressing challenges such as system initialization for new users and constructing knowledge graphs. Enhancements such as including descriptions, explanations, and feedback mechanisms can improve the user experience and confidence in the recommendations. Overall, the aim of recommender systems is to provide accurate and personalized recommendations to users while addressing limitations and challenges specific to each model. Future research directions include expanding evaluation samples, considering new types of recommendations, and ensuring the security and privacy of user profiles. The goal is to continually improve the performance, reliability, and user-friendliness of recommender systems to provide accurate and personalized recommendations to users across domains like career pathways.

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