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RESEARCH ARTICLE

Recommender System in Academic Choices of Higher Education: A Systematic Review

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ABSTRACT Recommender systems have gained significant attention as powerful tools for supporting decision-making processes in various domains. However, the understanding of their impact and application in the field of academic choices in higher education remains limited. This systematic review aims to provide a comprehensive summary of the current knowledge regarding recommender systems utilized in the context of academic choices and advising in higher education. The study is based on the systematic analysis of a set of primary studies (N = 56 out of 1578, published between 2011 and 2023) included according to defined criteria. The articles were categorized based on specific criteria, and their findings were analyzed and synthesized. Results show that the hybrid strategy has been the most effective method for producing recommendations. Evaluation measures such as offline experiments and case-study validation were prominently observed in the empirical studies, providing insights into the effectiveness of recommender systems. The findings reveal that the design of recommender systems in higher education is context-specific, with researchers considering various parameters to tailor recommendations to individual needs. However, most of the selected articles relied on lab-based studies rather than real-world applications, indicating a need for further research in practical settings. This systematic review also identifies future research directions, including the incorporation of deep learning technologies and the analysis of personality traits. By providing a comprehensive overview of the current state of recommender systems for academic choices in higher education, this review offers valuable insights for researchers and practitioners, guiding the development of more effective and personalized recommendation systems to unlock the full potential of individuals in their academic journey.

INDEX TERMS Academic choices, higher education, recommendation systems, course recommendation systems, holland code assessment, systematic literature review.

I. INTRODUCTION

In recent years, recommender systems have emerged as powerful tools for aiding decision-making processes across various domains. These systems have been extensively studied and applied in areas such as e-commerce [1], [2] entertainment (YouTube [3]), (Netflix [4]), and personalized content recommendations. However, their potential impact and application in the field of academic choices and advising in higher education have received limited attention. Understanding how recommender systems can support students' academic decision-making processes is crucial for providing effective guidance and enhancing educational outcomes. Recommender algorithms can be used to make smart decisions in complex information systems and help the users decide upon useful materials [5]. The purpose of this systematic review is to provide a comprehensive summary of the current knowledge regarding the utilization

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of recommender systems in the context of academic choices and advising in higher education. The review categorizes the selected articles based on specific criteria, allowing for a structured analysis of the various dimensions and approaches adopted in the design and implementation of recommender systems for academic choices. Notably, the articles primarily focus on three distinct domains of academic choices, with course recommendation being the most prevalent area of interest.

Students' often get confused while choosing the most suitable course in higher education that meets their requirements. This confusion arises due to the vast array of available courses and the complexity of educational systems. To address this challenge, recommender systems have emerged as valuable tools for supporting students in making informed decisions about their academic choices in higher education. Recommender systems utilize advanced algorithms and techniques, such as machine learning and data mining [6], to analyze relevant data and generate personalized recommendations for students. By considering factors such as students' preferences, academic performance, career aspirations, and feedback from previous students, these systems can assist in identifying the most suitable courses that align with individual requirements. The benefits of recommender systems in academic choices are manifold. Firstly, they save students time and effort by providing them with tailored recommendations, eliminating the need for extensive manual research. Secondly, they enhance the accuracy of decision-making processes by considering a wide range of relevant information and filtering out irrelevant options. Moreover, these systems promote personalized learning experiences, enabling students to explore courses that align with their interests and goals, Recommender System (RS) can contribute to their academic performance and motivation by indicating personalized learning content [7].

However, there are challenges associated with the development and implementation of recommender systems in the context of academic choices. Difficulties arise from differences in learner's educational interests and needs [8]. These challenges include data sparsity, cold start [7], privacy concerns, ensuring diversity in recommendations, and addressing biases that may arise from the data used to train the system. The approach utilized to produce recommendations is also an example of difficulties. For instance, the way content-based recommender systems manage data is inextricably linked to overspecialization [9], [10]. Accurately identifying user expectations and recommendations is one of the main challenges [11]. Differences in learners' educational preferences and needs lead to challenges [8]. There are questions about how to assess the effectiveness of RS from an educational perspective. Applying the classic recommender evaluation methodologies is a common strategy to assess the quality of educational recommenders [12]. This method evaluates the performance characteristics of the system, such as its precision and prediction accuracy. However, system effectiveness in the educational setting must take into account students' learning progress. This feature adds significant challenges to how to assess RS effectively from an educational perspective. The scientific community has become increasingly interested in RS [13], and in recent years, substantial study has been done to solve these concerns [6], [14], [15], [16]. Data mining, information filtering, education and information technologies, machine learning, and other computational approaches are only a few examples of how RS has evolved into an area of application [6] in education [17].

Despite these challenges, recommender systems hold great potential to revolutionize the course selection process in higher education. The efficient design of the recommender system in education will help the students by generating the appropriate recommendations [18]. As technology advances and more data becomes available, it is expected that recommender systems will become even more accurate and effective in providing personalized recommendations to students. In addition, recommender systems offer valuable support to students facing the daunting task of choosing the most suitable courses in higher education. By leveraging advanced algorithms and analyzing relevant data, these systems can alleviate confusion, save time, and enhance the accuracy of decision-making. As research and development in this field continue to progress, recommender systems will play an increasingly vital role in helping students navigate the multitude of course options [19], ensuring they make well-informed choices that align with their academic and professional aspirations.

This review article is organized as follows: In Section II, related works are presented. Section III describes the protocol applied to conduct the systematic literature review. Section IV presents a synthesis of the important results guided by research questions. Section V highlights the comprehensive outcome of this review and identifies some research gaps and possible solutions. Section VI describes future research direction in this field. Section VII represents the practical uses of course recommendation system. Finally, Section VIII concludes this review.

II. LITERATURE REVIEW

Recommender systems (RSs) have gained significant interest in education as technologies supporting personalized teaching and learning experiences. Over the past 12 years, research efforts have focused on mapping and summarizing various aspects of RSs in education. By exploring RSs in education, researchers aim to enhance teaching and learning by tailoring educational content to individual learners. The scientific community's attention to RSs reflects a growing interest in utilizing technology to improve educational experiences through personalized recommendations.

In [20] a comprehensive review of technology-enhanced learning recommender systems was carried out. The authors analyzed 82 recommender systems from 35 different

TABLE 1. Research questions that are the focus of this systematic review.

ID	Research Questions	Rationale
RQ-1	What are the various purposes of RS in higher educational admission?	Overview of the key areas in higher educational advising. Thus, possible findings from this question will recognize areas of academic advising where RS is applied.
RQ-2	What approaches are utilized in developing higher education admission RS?	This research question seeks to get insights into the most commonly used techniques, methods, or algorithms in recommendation systems in educational choices.
RQ-3	What types of parameters are used in the design of RS?	This question aims to explore the specific parameters used in designing each RS.
RQ-4	Which platform is used for the deployment of recommender system?	This question aims to find whether the RS has been deployed in a web/mobile environment or proposed model/framework.
RQ-5	What types of evaluation strategies are applied to RS?	The goal of this query is to analyze validation criteria utilized in this domain.
RQ-6	What are the outcomes of this recommender system in education?	It is crucial to explore whether the proposed RS has any educational outcome.
RQ-7	What parameter's hierarchy should follow in the design and development of course recommendation system?	The parameters hierarchy ensures a nuanced and personalized approach, aligning academic suggestions with individual preferences, strengths, and aspirations for an effective and satisfactory user experience.
RQ-8	What are the significance and relevance of each parameter in the course recommendation System?	Understanding the significance and relevance of each parameter in the course recommendation system is essential to tailor recommendations based on diverse factors, ensuring a comprehensive and personalized approach that meets the unique needs and preferences of individual users.
RQ-9	How holland tratis can help in course recommendation system?	Holland traits can aid in a course recommendation system lies in leveraging vocational preferences to provide tailored academic suggestions, aligning educational paths with individual strengths and inclinations for an enhanced and personalized learning experience.

countries published from 2000 to 2014 and provided an overview of the area. This study explores various aspects of recommender methods, information sources, and assessments in education and information technologies. It categorizes selected publications using a provided framework.

In [21], Rivera et al. conducted a systematic mapping to present a comprehensive overview of the ERS (Educational Recommender Systems) domain. Their study covered a broad range of papers and aimed to identify global characteristics in ERS research. Similarly, Pinho, Barwaldt, Espíndola, Torres, Pias, Topin, Borba, and Oliveira (2019) performed a systematic review of ERS, focusing on different questions and utilizing different repositories. Both works shared a common concern in providing insights into the evaluation methods of these systems and the main techniques employed in the recommendation process.

In their research, [22] focused on course recommendation systems and conducted a comprehensive review of techniques and parameters used in this type of Educational Recommender Systems (ERS). Additionally, they defined a taxonomy of the factors considered in the course recommendation process. On the other hand, in [23], the authors conducted a review on affectivity based ERS. Their study presented a macro analysis, identifying key authors and research trends while summarizing various aspects of recommender systems related to affectivity. These aspects included the techniques employed in affectivity analysis, the sources of affectivity data collection, and the methods used to model emotions. In [16] the authors present a systematic literature review on recommender systems in the educational domain. They analyzed 16 out of 756 primary studies, published from 2015 to 2020. The review reveals the dominance of the hybrid approach for recommendation production and the

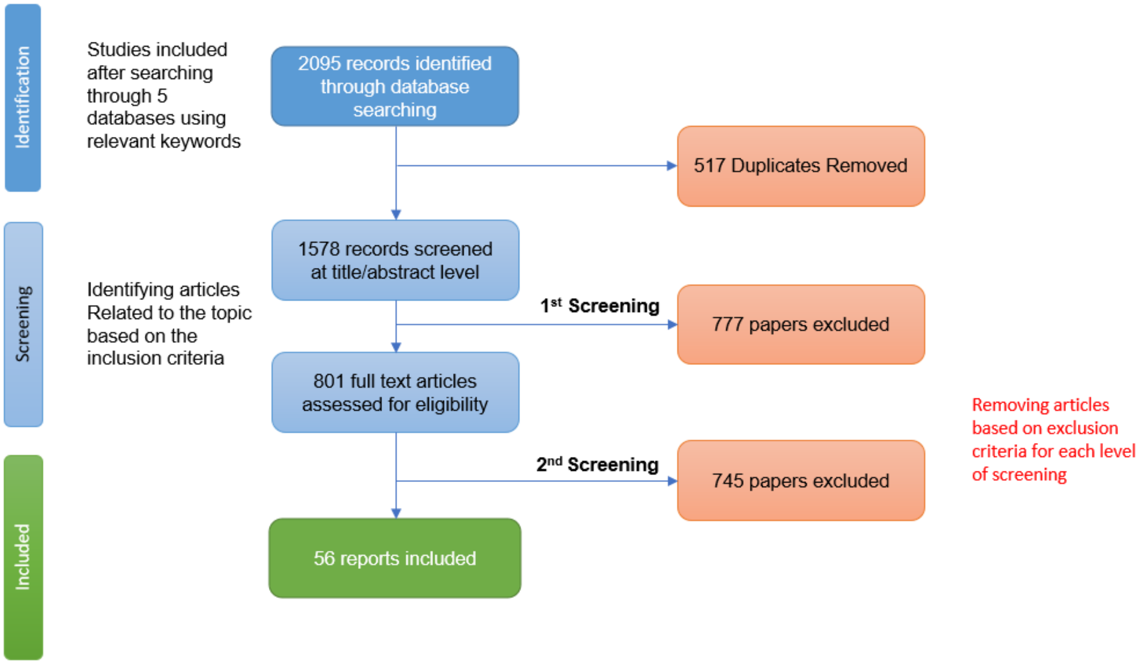

FIGURE 1. **Detailed workflow of the systematic search, based on the PRISMA workflow guidelines.**

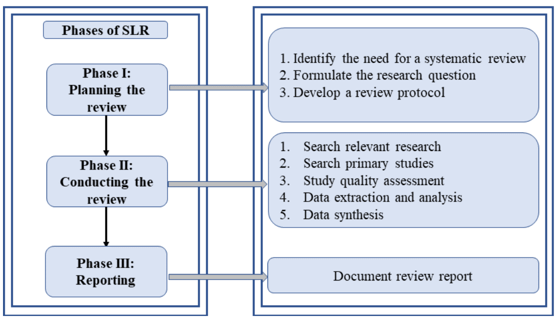

FIGURE 2. **Stages undertaken for crafting the systematic literature review (SLR).**

limited focus on accuracy in evaluation studies. It emphasizes the need for multidimensional evaluation frameworks to assess the pedagogical effectiveness of recommenders. The paper also identifies and discusses key limitations, highlighting areas for future research to enhance recommender systems in education.

III. METHODOLOGY

A systematic literature review (SLR) primarily includes a comprehensive and rigorous plan and search strategy to minimize bias by defining, assessing, and categorizing all related research studies on a specific topic, providing answers to particular research questions [24], [25]. Although conventional reviews aim to summarize the findings of several studies, systematic reviews use precise and strict guidelines to select, critically analyze, and summarize all research on a specific topic. We have performed a systematic literature review by considering the methods outlined in [24] to obtain a synopsis of recommendation systems regarding higher educational academic choices. Our pipeline involves several stages to conduct the systematic literature review, divided into three phases, each producing an output [25] and summarized in Fig. 2. Details concerning the steps of our systematic review are described in the following subsections:

A. REVIEW PLANNING

The first phase involves defining the underlying need for systematic review, formulating research questions (RQs) to guide the work, developing the research protocol, which involves identifying the keywords and operators, exploring literature sources, defining inclusion and exclusion criteria, and establishing a search strategy.

1) SEARCH, SELECTION, AND EXTRACTION

The second phase includes searching for and identifying relevant research, selecting research articles, analyzing quality by applying criteria, retrieving and monitoring data, synthesizing observations, and identifying possibilities for future research.

B. RESEARCH QUESTION

Formulating the research question(s) (RQ) is the critical component of any systematic review, as it focuses the study, determines the methodology, and guides all the stages of analysis and reporting [24]. Our research purpose is to examine an overview of the related work in using recommender systems regarding higher educational course advising systems. Therefore, to achieve a better understanding of the current literature, it is vital to formulate a series of research questions, each one addressing various facets of RS in higher educational choices. Table 1 outlines all the research questions of this review along with their rationale.

C. SEARCH STRATEGY

In this systematic literature review, we employed a well-structured search strategy in two stages. Firstly, we identified digital repositories for searches, including ACM Digital Library, IEEE Xplore, Science Direct, and Semantic Scholar, conducted through Google Scholar. Secondly, we defined keywords and combined them with Boolean operators to create search strings. The list of keywords and corresponding search strings used for each digital library is presented in Table 2 and Table 3, respectively. The search resulted in an initial set of 1578 potential primary studies for assessment of eligibility and inclusion.

D. SELECTION CRITERIA AND SCREENING PROCESS

To ensure that selected research articles meet the scope of this systematic review, we applied an inclusion-exclusion criterion to the initially obtained studies to determine whether a paper should be included in the final review. Therefore, the inclusion and exclusion criteria are defined as Table 2. We performed preliminary selection, defined the inclusion and exclusion criteria, and appraised the initially selected papers. Paper titles, abstracts, and keywords were screened by the authors to apply the inclusion criteria. A total of 1578 studies were included for full paper reading, where we applied the exclusion criteria. Among the screened publications, 56 research articles were sorted for this study. Fig. 1 demonstrates the detail of the initially found studies from each digital library and selected primary studies.

E. DATA EXTRACTION AND ANALYSIS

We extracted data by splitting each research question into precise parameters for determining a range of potential scopes.

Selected papers have been thoroughly read, analyzed, and categorized based on the various scopes of each criterion. Table 4 delineates possible answers to each research question along with the possible features extracted from the criteria.

IV. RESULT

A. AREAS IN HIGHER EDUCATION

Although the demands of the recommendation systems span across several domains of education, a few areas are addressed in terms of the academic choice sector. RQ1 seeks to know the main points of interest in the research on higher educational advising. After extracting studies from Table 3 based on the features of RQ1, the purpose of the reviewed papers is to provide recommendations mainly in three areas of educational choices. This includes predicting an institute (college, university, or graduate school), an academic discipline or degree program, and lastly, an academic course suitable for a student. From Table 3, it is apparent that the predominant area is course recommender systems; 37 papers, comprising 66.07% of the reviewed articles, recommend appropriate academic compulsory or elective-specific courses in an undergraduate or graduate program according to the student's goals, success rate, or preferences. In some studies [26], [27], [28], the authors exert grade forecasting, which specifies the success rate for future course selection and thus recommends the best possible courses.

Areas of higher education advising are not confined to course recommendations and go beyond advising suitable universities, colleges, or even degree programs for the students. According to extracted data, another significant use of the recommender system in 12 studies is to provide recommendations on specific or best-fitted colleges or universities. Most studies [29], [30], [31], [32], [33], [34], [35], [36], [37], [38] predict a set of most suitable universities or colleges for the admission of the new students. Only one study [39] determines the educational institution befitting university students.

However, a few studies, representing 8.9% of all primary ones, have been focusing on suggesting the candidate's most suitable degree programs. Included studies either recommend a suitable study track or department [31], [40], [41] or provide a list of probable majors depending on a student's interest [30], [32]. Besides, the following two studies have focused on multiple areas: [35] proposes an automated multidimensional framework for recommending a suitable program, relevant courses, and appropriate instructor for each student, and [41] provides a conceptual ontology-based recommendation framework to help students select both universities and majors that conform to their preferences.

B. RECOMMENDER SYSTEM APPROACHES

The purpose of research question 2 is to classify the nature of the approaches to the recommendation systems yielded in these literatures.

1) HYBRID APPROACHES

From Table 6, it is observed that 24 papers, comprising 43% of the reviewed literature, are based on the combination of different recommender types, known as hybridization. Decision trees are frequently employed in hybrid approaches. The authors of [29] use hybrid methods of a decision tree and association rules to recommend a specific institute. In [31] and [39] the authors propose a hybrid framework for university admission by integrating the back-propagation neural network algorithm and the C4.5 decision tree. Similarly, [37] focuses on a combined method of random forest and Multivariate Adaptive Regression Splines (MARS) to predict a list of the best colleges. Wakil et al. [41] proposes a hybrid web recommender system by combining neural networks (NN) and decision tree (DT). Reference [61] focuses on recommending an appropriate

TABLE 2. Definition of inclusion and exclusion criteria.

Criteria	Sl. No	Definition
Inclusion Criteria	IC1	Papers supporting formal educational choices and advising by using a recommendation system.
	IC2	Full papers, academic journals, and conference proceedings studies.
	IC3	Literature published in the field of recommender system, last 13 years (2011 – 2023)
Exclusion Criteria	EC1	Any other literature review regarding academic choices and admission is excluded from this review
	EC2	Papers that are focused on other areas of educational recommender system
	EC3	Studies include non-formal education (e.g., Virtual learning environments, MOOCs)
	EC4	Publications that do not clearly state the algorithm/approaches being used are excluded
	EC5	Papers that are not written in English

TABLE 3. List of search strings.

Digital Library	Search String
ACM Digital Library	(acmdlTitle: (“Recommender System/s” “Recommendation System/s”) OR recordAbstract: (“Recommender System/s” “Recommendation System/s”)) AND ((acmdlTitle: (“higher education”) OR recordAbstract: (“higher education”)) AND ((acmdlTitle: (“university”) OR recordAbstract: (“university”)) AND ((acmdlTitle: (“program”) OR recordAbstract: (“program”)) AND ((acmdlTitle: (“course”) OR recordAbstract: (“course”))
IEEE Xplore	(“Recommender System/s” OR “Recommendation System/s”) AND (“higher education”) AND (“university” OR “program” OR “course”)
Science Direct	(“Recommender System/s” OR “Recommendation System/s”) AND (“higher education”) AND (“university” OR “program” OR “course”)
Semantic Scholar	(“Recommender System/s” OR “Recommendation System/s”) AND (“higher education”) AND (“university” OR “program” OR “course”)
Web of Science	recommender system in higher education for course selection

elective course by determining a successful relationship between previous courses taken by Computer Engineering students.

The system analyzed transcripts of 100 students to categorize mandatory and elective courses. It calculated the effect rate between courses and extracted rules using the C5.0 decision tree, finally developing a fuzzy logic model based on these rules.

In article [30], the authors combine a hybrid approach of multiclass Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) to recommend appealing graduate programs. A. Ragab proposes in [34] and [35] a recommender system comprising two cascading recommenders and a predictor to provide university recommendations and predictions. Both track and college recommenders use knowledge discovery rules, while the predictor compares current and previous student data available in the system, forecasting the most fitting college for a student.

Another choice of hybridization technique involves combining collaborative filtering (CF) and content-based filtering (CBF). In [40], CF and CBF techniques are combined, where CF computes user similarities using Euclidean distance, and CBF calculates student interest in academic tracks to recommend a suitable diploma track. Reference [26] presents a two-stage collaborative filtering approach, employing an Artificial Immune System to predict course grades and make recommendations. Reference [49] combines Alternating Least Square (ALS), a model-based CF algorithm, with TF*IDF, a popular content-based filtering approach, to recommend suitable courses for college students. In [58], personalized elective course recommendations are proposed, with two preference estimations calculated based on student and course information separately, and a genetic algorithm configures the relevance of each criterion to provide user-specific suggestions. In [59], a course recommendation system measures similarity of course topics, matches

TABLE 4. Criteria and features extracted from each RS.

RQ ID	Criteria	Scopes	Description
RQ1	C1. Areas in higher education	Recommendation of college/university	Feature describes if the study recommends a/or list of institutes
		Recommendation of degree program	Feature describes if the study recommends a/list of suitable degree/s
		Recommendation of course/curriculum	Feature describes if the study recommends suitable primary/elective courses
RQ2	C2. RS approach	Clustering based recommendation	Feature determines if the proposed solution of the primary study is based on model (clustering) based recommendation approach
		Classification/Rule based / Neural Network	Feature determines if the proposed solution of the primary study is based on model (classification/Rule based/Neural network) based recommendation approach
		Collaborative Filtering	Feature determines if the proposed solution of the primary study is composed of collaborative filtering recommendation approach
		Hybrid Approaches (combination of the above)	Feature determines if the proposed solution of the primary study is composed of collaborative filtering recommendation approach
		Content based recommender system	Feature determines if the proposed solution of the primary study proposes a content based recommendation approach
RQ3	C3. Identifying and categorizing specific parameters	Explore parameters for a detailed understanding.	This research question seeks to delineate the specific types of parameters employed in the design of university course recommendation systems, contributing to a nuanced comprehension of the system's architecture and functionality.
RQ4	C4. RS development	Algorithms	Feature denotes whether the study proposes an algorithm or series of algorithms
		Methods	Feature denotes whether the study proposes a series of procedures for recommendation
		System	Feature denotes whether the study is deployed in a platform (web, App)
		Framework	This feature denotes that if the study purposes has a framework
RQ5	C5. RS empirical validation	Experiment	Feature implies that the proposed solution has been assess with some experiments
		Academic	Feature implies that the proposed solution has been analyze with academic case study
		Survey	Feature implies that the proposed solution has been evaluate with online/pen paper survey
		Not validated	Feature implies that the proposed solution has not been validated
RQ6	C6. RS educational outcome	Yes	Feature determines if the primary study has an educational outcome, i.e. study has been used in real life environment to recommend educational choices
RQ7	C7. Establishing an effective parameter hierarchy to align course recommendations	Defining a structured hierarchy for course recommendation system	This research question aims to determine a hierarchical arrangement of parameters in course recommendation systems for personalized and user-centric academic suggestions.
RQ8	C8. Assessing the importance of each parameter	Evaluating the significance and relevance of parameters	This research question aims to highlight the importance of each parameter in the course recommendation system for tailoring personalized recommendations to diverse user needs and preferences.
RQ9	C9. Exploring the contribution of Holland traits	Investigating how leveraging Holland traits enhances educational path alignment	This research question explores using Holland traits in a course recommendation system to enhance personalized learning by aligning suggestions with individual strengths and inclinations.

TABLE 5. Areas of academic choices.

Scopes: Domain	Publication	Total
Recommendation of college/university	[29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [42]	12
Recommendation of degree/program	[37], [41], [42], [43], [44]	5
Recommendation of course/curriculum	[26], [27], [28], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70], [71]. [72], [73], [74], [75], [76], [77]	37

descriptions and tags between courses and users' profiles and level, and analyzes course sentiments using Linear discriminant analysis (LDA), word-correlation factors, and SentiWordNet score respectively. It predicts ratings using Matrix Factorization and generates a single score denoting the degree of suitability of a course for target students using Backpropagation. Furthermore, [60] utilizes an ontology-based hybrid filtering framework comprising CB and CBF filtering, with CBF measuring similarities between user preferences and courses, and CF observing user-user similarities in the system. The recommendation list is then generated by combining the scores of CF & CBF. Besides, model-based CF is another choice for implementing the RS framework. Reference [27] applies a CF RS using K-means clustering to cluster similar students and find similarity between target students and cluster groups by utilizing the N-nearest neighborhood technique, and generates a list of elective course recommendations along with the expected grade by applying the association rule mining algorithm. Reference [66] aims to provide a 4-year study strategy by considering multiple constraints. The authors propose a hybrid model in which the min-cost-max-flow algorithm is used to solve credit constraints and evaluate the usefulness of courses by combining the scores of Course registration possibility by matrix factorization, student performance prediction by CBF, career interest ratings, and interest levels on skills thus generating a learning plan by sorting a list of courses into a directed graph and determining the priorities of courses.

2) COLLABORATIVE FILTERING

Collaborative filtering is a traditional filtering approach for information filtering, which represents 20% of the total of the studies. Paper [36] represents Multi-Criteria Collaborative Filtering (MC-CF) along with Dimensionality Reduction techniques to yield university or college recommendations. Reference [47] proposes a web-based course advising system using model-based CF (K-means algorithm), whereas study [48] represents a framework for university elective courses utilizing Pearson Relationship Coefficient and Alternating Least Square (ALS). The authors in [50] also recommend a course with CF based Bayesian Personal Ranking Matrix Factorization (BPRMF) algorithm, whereas the authors in [52] recommend suitable study programs using item-based CF algorithms. Reference [54] outlines a design of a recommendation system based on the 28 graduating attributes (developing values) of students. Lastly, [56] predicts master's course remarks, thus recommending a suitable course to students' using singular value decomposition (SVD) and CF.

3) CLASSIFICATION / RULE-BASED / NEURAL NETWORK

Supervised learning methods such as classification and rule-based schemes are also employed to recommend. Seven papers, representing 16% of the total studies, are based on different classification and rule-based techniques. Reference [33] implements the K-nearest neighbor (KNN) algorithm to recommend a list of graduate schools to the users. Moreover, [38] uses K-nearest Neighbor, Random Forest, SVM separately on the training data and founds SVM performs better than the other two. Similarly, [57] compares the performance of the Linear Regression Model, Naïve Bayes, Support Vector Machine, K-Nearest Neighbor, and Decision Tree Classifiers to identify appropriate courses goes with students' grade. However, [45] involves extracting rules from the preferences of previous students and thus recommending by checking the similarity between the courses pursued by the students and the precedents of the rules. Besides, Neural networks are also popular, and their usage is reported to be promising for both hybrid and single methods. Specifically, the proposed framework, intelligent recommendation system (IRS) [51] employs multi-layered feed forward NN to recommend the appropriate courses where success chance is higher, and [55] recommends courses at the graduate level by applying feed-forward neural networks.

4) CLUSTERING

A few studies—less than 0.7%—refer to using a clustering-based approach. Reference [32] designs a college recommender system by utilizing a weighted clustering process, WCLUSTER. The authors in [41] propose an ontology-based framework to distinguish students' interests and skills in order to provide a recommendation for a university. However, the proposed framework needs to be evaluated. Moreover, a framework to recommend course enrollment based on clustering techniques is explored in [44]. Apart from that, [28] applies a K-means clustering strategy with different numbers of clusters using Principal Component Analysis (PCA) to identify students with similar preferences and behaviors, followed by converting variables into fuzzy variables and mining fuzzy association rules in each cluster, yielding course selection rules to recommend courses along with the predicted scores for a student.

5) EXPERT SYSTEMS

A few studies, comprising 5% of the total papers, focus on developing expert systems for course advising. For instance, [78] suggests a rule-based expert system by employing Oracle Policy Automation (OPA) software to assist undergraduate students in academic course selection. Reference [63] proposes an educational advisory system by employing fuzzy logic into an expert system, and [65] presents the Course Advisory Expert System (CAES), consisting of rule-based reasoning (RBR) and case-based reasoning (CBR).

6) SWARM INTELLIGENCE

Among all the studies only one study [64] compares five different swarm intelligence algorithms, e.g., Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Intelligent Weed Optimization (IWO), Bee Colony Optimization (BCO), and Bat Algorithm (BA) for student course recommendation. Among them, ACO applies a hybrid CF and content-based filtering approach, whereas others depend on CF.

7) SEMANTIC ANALYSIS AND GRAPH-BASED APPROACH

Alternatively, [79] involves a series of algorithms, including TF-IDF, word2vec, latent semantic analysis (LSI), and Doc2vec utilized for similarity analysis based course recommendation. Course Rank [80], provides course recommendations based on the Ford-Fulkerson max-flow algorithm with constraints (e.g., prerequisites, requirements, etc.) focused on satisfying the degree program requirements at each semester. Moreover, [81] proposes a Personalized Forecasting Model (N-PSEF and BPSEF), a personalized recommendation system for academic curriculum paths based on performance traits, learning styles, and cognitive traits for each individual.

TABLE 6. Approaches used in developing recommendation system.

Scopes: Approach	Publication	Total
Clustering	[32], [42], [44]	3
Classification/ Rule based Neural Network	[33], [38], [43], [45], [51], [55], [57], [67], [82], [83], [84], [85], [77], [86]	13
Collaborative Filtering	[36], [46], [47], [48], [50], [52], [53], [54], [56]	9
Similarity Analysis	[79], [74]	2
Expert Systems	[62], [63], [65]	3
Swarm Intelligence	[64]	1
Graph - Based	[80], [87], [76]	3
Hybrid Approaches (Combination of the above)	[29], [39], [30], [31], [34], [35], [40], [37], [41], [26], [49], [58], [59], [60], [61], [27], [28], [66], [88], [89], [72], [74], [73], [90]	24

C. TYPES OF DATA SOURCES USED RS

RQ3 seeks to know the types of input parameters that are used in developing RS. As seen in Table 7, various input feature groups are used in the design of RS. All the research articles comprised at least two groups of parameters. Predominantly, 23 studies, representing 41% of the total studies, combine more than one type of data in designing RS. Academic data comprises university/college major, GPA, course grades, and entrance score. Demographic Data such as age, gender, and ethnicity are proven to be crucial parameters in these studies. Moreover, 12 primary studies use one or more demographic parameters. Furthermore, the course recommender system mainly comprises course data, e.g., name, type, credit, department, description, instructor information, and ratings of each course enrolled or preferences. These data categories represent 36% and 14%, respectively.

Recommenders for graduate school are mainly taking into account Performance data (standard test scores (GRE, TOEFL), research publication, work experience) and Institute Profile (location, type, ranking, safety, facility, admission requirements), which comprise only 3 studies. In some studies (around 13% of all studies), RS are designed based on ratings of user interest (personal, academic, or professional) and several aspects of an institute's profile, such as location, facilities, and faculties. A few studies utilized parameters from more than two categories. Reference [43] uses user interest, GPA, and test scores. Reference [36] combines personality type with other parameters, and [18] consists of data like the skills of learners, family income, and institute profile. In [28], the authors utilize age, gender, high school GPA, and the score of seven subjects on the university entrance exam, along with the university elective course description and grade. In this study, we have observed that, total 24 parent parameters was used in the course recommendation system. The parent parameters are: self-regulatory learning strategies, user interest, approach towards learning, performance data, psychosocial contextual factors, institute profile, personality dimensions, skills of learners, motivational factors, academic data, cognitive preferences, ratings, learning styles, entrepreneurial spirit & service orientation, demographic data, study preferences, goal orientation, communication style, multilingual proficiency, technology adoption, cultural preferences, time management, prioritization skills, course data. In Table 7 and 8 we have shown each of these parameters significance and relevance in the establishment of course recommendation system. In the previous studies each of these parent parameters was splitted into several child parameters. For each of those child parameters a test was conducted. The parent parameter's score was the summation of corresponding child parameters scores.

Let's denote:

P as the parent parameter's score,

C_i as the score of the i^{th} child parameter.

The mathematical equation representing the summation of the child parameters' scores for the parent parameter would be:

$$P = \sum_i C_i \tag{1}$$

This equation expresses that the parent parameter's score (P) is the sum of the scores of all corresponding child parameters (C_i).

In Table 9, 10, 11, 12, 13, 14 and 15 we have represented each of the parent parameter's corresponding child parameters.

D. DEVELOPMENT PLATFORM OF RS

RQ4 seeks information on whether the proposed solutions in primary studies are an algorithm/series of algorithms, a web- or mobile-based application, or a framework. The analysis of RQ4 in Table 8 illustrates that most reviewed papers propose systems, which represent 39.3% of the total of the studies, followed by studies corresponding to methods, with 38.81% then studies comprised frameworks, with 19.7%, and finally algorithms, with 19% of the total primary studies. Some of the studies have deployed the recommendation systems on specific platforms. The web is the most widely adopted platform for developing a recommendation system. 11 studies

TABLE 7. Significance and relevance of each parameter in the course recommendation System.

Parameters	Significance	Relevance
Self-Regulatory Learning Strategies	Indicates the student's ability to regulate their own learning processes, including goal-setting, self-monitoring, and self-reflection.	Courses that encourage self-directed learning and provide opportunities for reflection may be recommended.
Approach Towards Learning	Reflects the student's general attitude and style in acquiring knowledge and skills.	Helps in recommending courses that align with the preferred learning style, whether it's through hands-on experiences, theoretical analysis, or creative exploration.
Psychosocial Contextual Factors	Takes into account the social and psychological aspects influencing learning, including family support, peer relationships, and external stressors.	Recommends courses that consider the student's overall well-being and align with their social and psychological context.
Ratings	Ratings data gauges quality and satisfaction, informing future recommendations in a course system.	Ratings data shapes a dynamic system, enhancing precision and relevance for improved learning experiences in recommendations.
Skills of learners	Learners' skills feature is significant for precise alignment in course recommendations.	Skills of learners contribute to a personalized, skill-focused system for an effective educational journey.
Personality Dimensions	Assesses various personality traits that can impact academic preferences and performance.	Courses can be recommended based on how well they match the student's personality, ensuring a better fit for their individual strengths and preferences.
Performance data	Performance data, including test scores and work experience, is significant for precise university course recommendations.	Performance data shapes a targeted course recommendation system based on individual aptitude and experiences.
Motivational Factors	Identifies what drives the student to learn, whether it's intrinsic passion or extrinsic rewards.	Recommends courses that align with the student's motivations, whether they are driven by personal interest or future career prospects.
Institute data	Institute data tailors course recommendations based on unique attributes of institutions.	Institute data shapes a context-aware recommendation system, aligning suggestions with institution features for informed decision-making.
Cognitive Preferences	Highlights the student's preferred thinking and problem-solving approaches.	Recommends courses that cater to the student's cognitive strengths, such as analytical or creative thinking.
Learning Styles	Identifies how the student best absorbs information, whether visually, auditorily, or kinesthetically.	Recommends courses with teaching methods that align with the student's preferred learning style.
Demographic data	Demographic data tailors academic suggestions based on individual backgrounds, enhancing the system's adaptability.	Demographic data contributes to a personalized and inclusive course recommendation system, aligning with unique user needs and socio-economic contexts.
Entrepreneurial Spirit & Service-Orientation	Indicates the student's inclination towards innovation, risk-taking, or a desire to make a social impact.	Recommends courses that foster entrepreneurial skills or align with service-oriented professions.
Academic data	Academic data shapes recommendations based on strengths and study preferences in a course system.	Academic data shapes a precise course system, aligning with study programs, academic achievements, and preferences.
Study Preferences	Reflects whether the student prefers independent study or collaborative research.	Recommends courses that match the student's study preferences, promoting a conducive learning environment.

TABLE 8. Significance and relevance of each parameter in the course recommendation System.

Parameters	Significance	Relevance
Goal Orientation	Identifies the student's short-term and long-term goals.	Recommends courses that contribute to the achievement of the student's goals, whether they are immediate objectives or future aspirations.
User interest data	User interest data tailors suggestions, fostering engagement and satisfaction in a course system.	User interest data creates a personalized, user-centric system for an engaging educational experience.
Communication Style	Assesses the student's comfort with verbal and written communication.	Recommends courses that align with the student's communication strengths, be it through spoken or written expression.
Multilingual Proficiency	Highlights the student's language skills and interest in multicultural communication.	Recommends language-related courses or courses that involve cross-cultural perspectives.
Technology Adoption	Assesses the student's comfort with technology and adaptability to technological changes.	Recommends courses that leverage technology or match the student's preference for traditional or online learning.
Course data	Course data shapes tailored suggestions aligning with academic offerings in a recommendation system.	Course data ensures a comprehensive recommendation system, finely tuned to details and contributing to informed decision-making for students.
Cultural Preferences	Identifies the student's cultural sensitivity, global awareness, and interest in cultural studies.	Recommends courses that incorporate diverse cultural perspectives or align with the student's cultural interests.
Time Management	Assesses the student's ability to manage time effectively.	Recommends courses that consider the student's time management skills and preferences for flexible schedules.
Prioritization Skills	Reflects the student's ability to prioritize tasks and manage multiple responsibilities.	Recommends courses that align with the student's prioritization skills, ensuring a balanced workload.

TABLE 9. Parameters hierarchy table of motivational factors, cognitive preferences fators for course recommendation system.

Motivational Factors		Cognitive Preferences	
Parent Parameter	Child Parameters	Parent Parameter	Child Parameters
Intrinsic Motivation	Passion for the subject	**Analytical Thinking**	Problem-solving capability
	Personal interest		Logical reasoning
	Love for learning		Critical thinking
Extrinsic Motivation	Career prospects	**Creative Thinking**	Out-of-the-box thinking
	Financial incentives		Idea generation
	External rewards		Innovation

deployed the RS framework on a web platform, and in [29], [33], and [49] the authors deployed their system into Android apps.

E. EMPIRICAL VALIDATION OF RS

RQ5 examines the validation criteria used in these selected studies, which may be theoretical or experimental. Among the validation categories, 4 distinct classes have been identified, and 86% of all the studies are validated in some way. Table 9 depicts that 22 papers, which represent 50% of the total studies, conducted experiments to assess the efficacy of a recommender system.

1) EXPERIMENT

For validating models through experiments, some studies consider comparing models with related or previous models.

TABLE 10. Parameters hierarchy table of personality dimensions, learning styles factors for course recommendation system.

Personality Dimensions		Learning Styles	
Parent Parameter	Child Parameters	Parent Parameter	Child Parameters
Openness to Experience	Curiosity	**Independent Study**	Self-directed learning
	Imagination		Autonomy
	Aesthetic appreciation		Research interests
Interest in Leadership	Desire for managerial roles	**Visual Learner**	Preference for visual aids
	Leadership potential		Graphic learning
	Decision-making preferences		Diagrams and charts
Conscientiousness	Organization	**Auditory Learner**	Preference for listening
	Detail-oriented		Verbal instructions
	Dependability		Group discussions
Extraversion	Sociability	**Kinesthetic Learner**	Hands-on activities
	Assertiveness		Physical involvement
	Energy level		Experiential learning
Agreeableness	Cooperation	**Entrepreneurial Spirit**	Risk-taking propensity
	Empathy		Innovation
	Patience		Business acumen
Neuroticism	Emotional stability	**Service-Oriented**	Desire to make a social impact
	Stress tolerance		Helping professions
	Resilience		Volunteerism

TABLE 11. Parameters hierarchy table of time management, cultural preferences factors for course recommendation system.

Time Management		Cultural Preferences	
Parent Parameter	Child Parameters	Parent Parameter	Child Parameters
Time Management Skills	Ability to meet deadlines	**Cultural Sensitivity**	Appreciation for diversity
	Time allocation for studies		Global perspectives
	Punctuality		Cross-cultural communication
Flexible Schedule Preferences	Desire for flexibility	**Local vs. International Focus**	Interest in local vs. international issues
	Part-time vs. full-time studies		Global awareness
	Work-study balance		Cultural immersion
Prioritization Skills	Ability to prioritize tasks	**Interest in Cultural Studies**	Courses related to culture
	Juggling multiple responsibilities		Anthropology
			Sociology

Reference [29] measures instrument performance by showing accuracy, precision, and recall. References [31] and [39] evaluate their proposed hybrid classifier by using real student data for accuracy and time performance and also compare error rates among the proposed classifier, back-propagation, and c4.5 algorithms. The authors in [30] compare performance measurements, e.g., precision, recall, f-measure, and accuracy, with the values of the other four admission recommendation systems and also conduct an online user study. Moreover, [32] compares the K-means clustering algorithm with the proposed W-clustering algorithm in terms of execution time and number of clusters. The results show

TABLE 12. Parameters hierarchy table of goal orientation, technology adoption and communication style factors for course recommendation system.

Goal Orientation		Technology Adoption		Communication Style	
Parent Parameter	Child Parameters	Parent Parameter	Child Parameters	Parent Parameter	Child Parameters
Long-Term Goals	Vision for the future	**Tech-Savvy**	Comfort with digital tools	**Verbal Communication**	Comfort with spoken communication
	Career aspirations		Online learning preferences		Public speaking
	Graduate studies		Technical skills		Verbal expression
Short-Term Goals	Immediate objectives	**Traditional Learner**	Preference for traditional classrooms	**Written Communication**	Writing skills
	Skill development		Paper-based resources		Essay preferences
	Certifications		Face-to-face interactions		Documentation abilities
Task-Orientation	Focus on completing tasks	**Adaptability to Technological Changes**	Willingness to embrace new technologies	**Multilingual Proficiency**	Number of languages spoken
	Focus on achieving goals		Resistance to technological change		Interest in learning new languages
	Balance between task orientation & goal orientation		Tech curiosity		Multicultural communication

TABLE 13. Parameters hierarchy table of demographic, academic and course data factors for course recommendation system.

Parent Parameter	Child Parameters	Parent Parameter	Child Parameters	Parent Parameter	Child Parameters
Demographic data	Age	Academic data	Study Program	Course data	Course Level
	Gender		GPA		Course Duration
	Ethnicity		Academic Scores in Specific Subjects		Prerequisites
	Location		Research Experience		Course Format
	Family Income		Internship/Work Experience		Credit Hours
	Educational Background		Academic Achievements		Instructor Experience
	First-generation College Status		Extracurricular Activities		Student Reviews
	Language Proficiency		Study Abroad Experience		Textbook/Reading Materials
	Accessibility Requirements		Specialized Skills		Lab or Practical Component
	Parental Educational Background		Professional Certifications		Course Syllabus

that the W-clustering algorithm is scalable to the maximum extent. In [36], the authors compare their proposed HOSVD PCA algorithm with MC-IB CF and Higher-order singular value decomposition (HOSVD) algorithms by measuring

TABLE 14. Parameters hierarchy table of performance, institute data and user interest factors for course recommendation system.

Parent Parameter	Child Parameters	Parent Parameter	Child Parameters	Parent Parameter	Child Parameters
Performance data	Standardized Test Scores Breakdown	Institute data	Ranking in Specific Programs	User interest	Personal Interests
	Subject-Specific Test Scores		Facility Breakdown		Academic Preferences
	Entrance Exam Section Scores		Location Attributes		Career Aspirations
	Research Publications		Teacher Profiles		Preferred Learning Style
	Work Experience Details		Program-Specific Requirements		Extracurricular Involvement
	Internship Details		Extracurricular Opportunities		Preferred Teaching Methods
	Professional Certifications		Internship Placement Record		Professional Development Goals
	Project Contributions		Alumni Success Stories		Industry Interests
	Leadership Roles		Collaborative Research Initiatives		Preferred Work Environment
	Conference Presentations		Accreditation Information		Technology Interests

TABLE 15. Parameters hierarchy table of ratings and skills of learners factors for course recommendation system.

Parent Parameter	Child Parameters	Parent Parameter	Child Parameters
Ratings	Course Ratings	Skills of learners	Presentation Skills
	Teacher Ratings		Technical Skills
	Institution Ratings		Soft Skills
	Course Difficulty Ratings		Analytical Skills
	Relevance Ratings		Language Proficiency
	Feedback on Assignments		Research Skills
	Accessibility Ratings		Creativity
	Interactive Component Ratings		Leadership Skills
	Collaborative Project Ratings		Adaptability
	Recommendation Effectiveness		Project Management Skills

precision, recall, F1 metric, and execution time and observe that the model performs better among them as well as handles scalability issues efficiently. Reference [43] evaluates several classification models (with or without feature selection) based on accuracy. In [45], the authors compares their course recommendation system, RARE, with the other two course recommendation systems (SCR and AACORN) for evaluation and finds that their system performs better under the cold start problem compared to the two previous systems. In [59], the authors compared their proposed model and other recommendation approaches by average precision and mean reciprocal rank (MRR). Moreover, [60] compares the traditional CBF, CF, and proposed OPCR algorithms by three performance measure metrics: recovery, accuracy of relevance, and rank accuracy for online evaluation to assess the results obtained from the participants. Conversely, [33] evaluates the system by measuring its accuracy with the variation of training and test data. Similarly, [47] performs descriptive analysis on the experiment results, while [49] evaluates their mobile-based college recommender with RMSE and accuracy metrics. Studies [51] and [54] utilize mean square error (MSE) to define the accuracy

TABLE 16. Types of features used in designing recommendation system.

Scopes: Features	Publications	Total
Demographic data	[29], [39], [43], [45], [47], [30], [33], [36], [28], [89], [91]	11
Academic data	[39], [31], [33], [40], [38], [41], [43], [46], [26], [47], [48], [79], [52], [55], [56], [57], [63], [28], [65], [92], [70]	21
Course data	[45], [50], [79], [53], [54], [59], [60], [61], [62], [63], [27], [28], [65], [66]	14
Performance data	[33], [38], [46], [81], [69], [70], [71]	7
Institute profile	[29], [30], [32], [36], [51]	5
User interest	[41], [42], [44], [55], [67], [82], [69], [70], [89]	9
Ratings	[49], [54], [56], [58], [59], [60]	7
Skills of learners	[29], [81], [67], [82], [69], [70], [84]	7

TABLE 17. Types of features used in designing recommendation system.

Scopes: Features	Publications	Total
Algorithm	[32], [33], [52], [54], [81], [70], [91], [85], [72], [74], [77], [90]	12
System	[29], [33], [34], [35], [36], [41], [45], [47], [49], [57], [60], [62], [63], [65], [80], [81], [82], [89]	18
Framework	[39], [31], [40], [46], [26], [50], [79], [51], [58], [66], [92]	11
Method	[30], [37], [38], [43], [44], [48], [53], [55], [56], [59], [61], [27], [64], [28], [67], [84], [73], [75], [76]	19

of the models, whereas [52] measures the performance of the rating matrix using domain knowledge with precision. Reference [56] uses a statistical accuracy metric, the mean absolute error (MAE) between the predicted and the real values, to analyze the error in prediction. Reference [57] measures the accuracies and RMSE of the four different classification models. In [58], the authors examine the model by comparing it with related work. In [61], the performance of the model is measured using ROC analysis, and using the parameters of the analysis, accuracy (.73), sensitivity (.68), and specificity (.88) values are computed. The root mean squared error (RMSE) is used to evaluate the models in [81].

2) ACADEMIC CASE-STUDY

Another important category is validating a proposed method using an academic case study, which represents 26.7% of all the studies. Reference [46] uses evaluation based on real data from students with respective letter grades for courses. Also, [26] validates the system through a case study using MAE and confusion matrix analysis. In [48], the authors evaluate the performance of their proposed solution using a dataset of academic records of university students. Using Area under the ROC Curve (AUC) as a performance metric, [50] compares their proposed BPR-MF solutions with four different sets of models, such as baseline, memory-based, graph-based, and ensemble of different types of solutions, using a real-world course registration dataset. In [53], the authors use an enrollment dataset from a university to compare the accuracy of the proposed Markov-based model with item-based and matrix factorization-based course recommenders. The evaluation of this proposed model in [27] is performed using a real course dataset of graduate electrical engineering students by computing the precision and recall of different variations of the following parameters: minimum confidence, minimum match, minimum specified grade, and minimum support. Conversely, Sobecki et al. [64] compares the performance of the 5 SI algorithm by utilizing a course-grade dataset using the following metrics: Mean Absolute error (MAE), Normalized Mean Absolute Error (NMAE), and prediction accuracy (PA). ACO performed best with 0.88 PA. Reference [66] uses the RMSE score to evaluate the student performance prediction model and the Simple Matching Coefficient (SMC) as the study-path recommendation model's efficiency evaluation. In [80], the authors involve 558 undergraduate students at Stanford to evaluate their package recommendations based on Precision. More specifically, we can say that the researchers around the world are interested in educational recommendation system, mostly in USA, India, China, Saudi Arabia, and Thailand.

3) SURVEY

Some studies—around 17.6% of all studies—validate the RS through a survey. For instance, [34] and [35] conducted a survey where students compared their admitted college results with the proposed system prediction. Also, [46] conducted a survey to determine the satisfaction of the students upon seeing the recommendation to measure the effectiveness of the system. Some studies not only used performance metrics to evaluate the systems but also validated them using surveys. The effectiveness of [59] was measured using 1,000 test cases by comparing the Top-3 courses generated by their proposed recommender with three

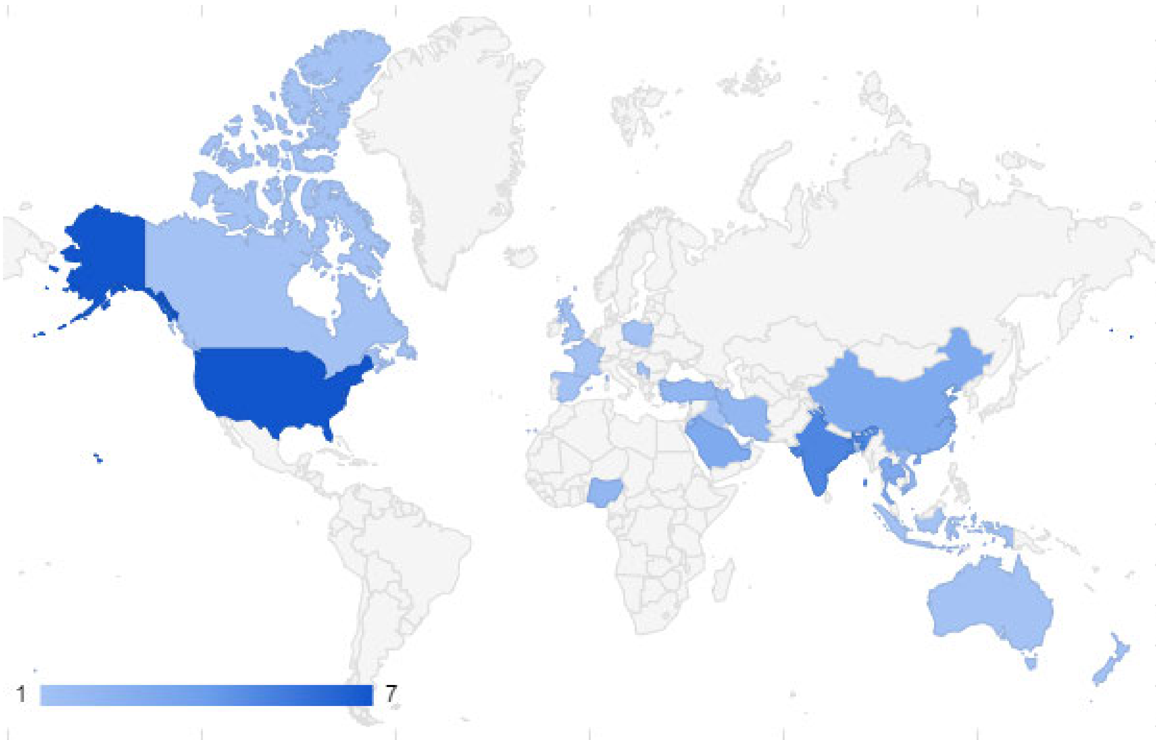

FIGURE 3. Geographical distribution of selected articles.

other popular courses. Another study, [60], was also evaluated by a group of university students. Following the evaluation, students ranked user satisfaction level and recommendation quality. Besides, in [62], the authors "Rule-based expert systems for supporting university students" is tested by Oracle Policy Automation (OPA). Finally, evaluation of the intelligent advisor (CAES) [65] is carried out by human advisors, who rate the CAES recommendation on a Likert scale of 0–5 to determine the degree of reliability. Results illustrate a mean satisfaction level of 3.89 out of 5.0, which indicates 77.8% user satisfaction.

However, a number of studies [37], [38], [40], [42], [44], [79] did not validate their proposed solutions.

F. OUTCOME OF RS

RQ6 aims to discover studies that are not only implemented, but also assist students in making informed decisions by providing real-life academic recommendations. Some studies within the course recommendation domain are successful platforms. They are used by several universities to provide students with personalized and appropriate recommendations. They require planning their academic path. For example, RARE [45] an association rule-based course recommender system, is used at the University de Montréal. Also, CourseRank [80], a personalized Stanford University Curriculum, now provides course-related services, e.g., choosing the right courses for each student at many universities throughout the United States. Another one is a personalized forecasting model, a performance prediction system, and a course recommendation system used at CanTho University [81].

V. RESULT SYNTHESIS

Within the educational domain, recommender systems serve numerous purposes by generating meaningful recommendations from an abundance of information. In this study, we surveyed the state-of-the-art within the domain of mainstream educational choice recommendation systems over the last ten years. Applying systematic review methodology, a total of 56 research papers were identified and examined from an initial set of 1578 studies. This section presents the empirical findings of this review and provides insights based on the overall analysis of the selected papers. The findings have outlined three distinct vital axes of empirical research on academic choices: university selection, program selection, and course selection. We have inspected the frequency of educational choice articles and domains from Table 6 and found that among the disciplines of educational preferences discussed in this review, course recommendation is a demanding research area, as extensive research has been carried out in this field [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59]. However, it is noted that research work towards recommending universities or study programs is minimal; only 7 studies were found over the last 13 years. Therefore, major/program recommendation after high school/college needs a significant focus.

TABLE 18. Evaluation criteria's of RS.

Scopes: Evaluation	Publications	Total
Experiment	[29], [39], [30], [31], [32], [33], [36], [43], [45], [47], [49], [51], [18], [54], [56], [57], [58], [59], [60], [61], [62], [81], [82], [54], [89], [73], [74], [75], [76], [77]	29
Academic	[30], [46], [26], [48], [67], [50], [53], [27], [64], [66], [80], [93], [85], [72]	13
Survey	[34], [35], [46], [59], [60], [65], [84]	7
Not validated	[40], [37], [38], [42], [44], [79]	6

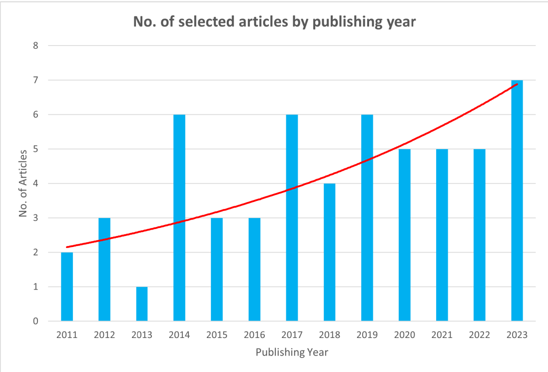

FIGURE 4. Number of selected papers by year.

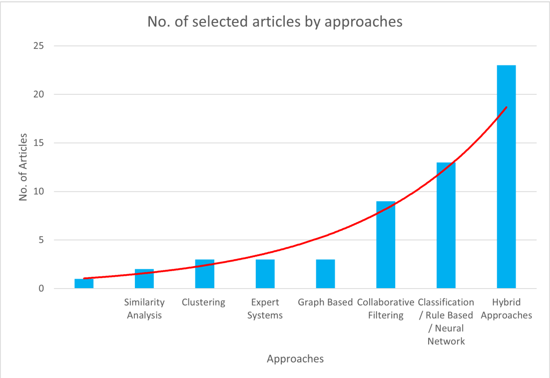

FIGURE 5. Number of selected papers by approaches.

Another crucial objective of this review was to probe the approaches applied in this field to develop better systems. We observed that hybrid recommender systems are well suited since these mechanisms enable systems to accommodate changes as well as resolve problems like sparsity and cold start [6]. The literature indicates that predominantly hybridization of CBCBF [27], [40], [49], [58], [59], [60] or combinations of machine learning and data mining approaches [28], [29], [30], [31], [34], [35], [37], [39], [41], [61] are used in this domain. Several studies proposed classification-based recommendation approaches such as Decision Tree, SVM, KNN, NN, Linear Regression [33], [38], [47], [51], [55], clustering (k-means) [31], [41], [43], and rule-based approaches [45]. In some studies, authors proposed Neighborhood-based CF [36], [79] or model-based CF (Matrix Factorization [48], [50], SVD [56], Markov chain [34], Non-parametric approach [47]) based models. Few studies include rule-based expert systems [62], [63], [65], swarm intelligence [64], or graph-based [80], [81] algorithms. Another prime aspect was exploring the parameters utilized in the design of RS. For recommending courses or curriculum, studies prioritize academic subjects and rating parameters, i.e., ratings of different courses, user feedback, academic grades, and subject interests. Academic and institute profiles were taken into consideration when recommending a university or academic field. Only two studies focus on learners' skills [29], [81]. Nevertheless, input attributes, such as socio-environmental factors and psychometrics, are not addressed, which prove to be crucial parameters for producing tailored recommendations in other domains [94]. The majority of studies used real-life academic cases in training and testing recommender systems. Prediction accuracy, recall, and precision were used as evaluation metrics in about 39% of the reviewed papers. These papers are grouped according to the recommender's approaches. They are compared by the average accuracy (calculated from the lowest to the highest range of accuracy) achieved by each group to understand the performance. Table 10 illustrates the average group accuracy achieved by these studies based on their approaches. While comparing the classification accuracy of model-based recommendation approaches, we noted that Hybrid techniques yield better accuracy over 88% and scalability than all other approaches. After Hybrid methods, various collaborative filtering algorithms were used in domains of academic preferences and achieved about 81% average accuracy. CF-based recommendations achieved an average of 85%. However, a simple classification-based recommendation system achieves an average of 67.9% accuracy. Besides, several studies validate their system using MAE, NMAE, and RMSE as performance metrics with the aim of enhancing the RS model. The review process also yielded some articles that conducted online experiments and surveys to substantiate the efficiency of their proposed systems. Studies examined in this review mostly propose a framework, method, or algorithm, comprising a total of 68% of all articles, rather than employing them on platforms. Only a few studies implemented their proposed system on web or mobile platforms. Therefore, only some studies have an impact on real-life students' successful learning outcomes [79], [80], [81] and provide a recommendation service to enable students to make informed academic decisions.

Additionally, the findings of this study have disclosed some limitations in the existing literature and outlined some research paths that may help foster research on this topic. For example, this review observed a notable paucity of empirical research in the academic program recommendation domain. To date, program/major recommendation has not been extensively studied. Assisting students to make an informed decision to determine suitable higher study options means encouraging students to explore and determine strategies befitting their overall career and educational goals. Therefore, researchers should consider conducting extensive research in this particular domain. Researchers have integrated a broad range of techniques, such as machine learning, information filtering algorithms, data mining, and others, for designing educational recommender engines. Yet, deep learning is a promising alternative for enhancing performance and managing the uncertainties of preference modeling. Finally, the majority of the studies provide a conceptual method or framework rather than deploying it on a platform. Developing a system within a dynamic real-world environment can provide valuable feedback on current approaches while assisting prospective students in making well-informed academic choices.

VI. FUTURE RESEARCH DIRECTION

Despite the advancements in recommender systems for academic advising in higher education, several research gaps and future directions remain to be explored.

A. APPLICATION OF HOLLAND CODE ASSESSMENT IN UNIVERSITY COURSE RECOMMENDATION SYSTEM

After meticulously examining all of the research papers explored in this study, we have observed that all of these course recommendation system follows some non-standard systems relying on individual characteristics testing. As a standardized approach, Holland code assessment can be employed to recommend courses.

The integration of the Holland Code assessment in course recommendation system, offers a comprehensive solution to the challenge of selecting perfect courses. Through a meticulous mathematical analysis, the system can provide tailored recommendations, empowering students to make informed decisions about their academic paths. Applying Holland Code assessments in university course recommendation system involves of assessment outcomes with the individual student's academic and career preferences. The Holland Code, also known as the **RIASEC** model, categorizes individuals into six personality types:

R Realistic
I Investigative
A Artistic
S Social
E Enterprising
C Conventional

$$\textbf{Courses}\begin{bmatrix} \boxed{\mathbf{R}} & \boxed{\mathbf{I}} & \boxed{\mathbf{A}} & \boxed{\mathbf{S}} & \boxed{\mathbf{E}} & \boxed{\mathbf{C}} \end{bmatrix}$$

FIGURE 6. Matrix to map RIASEC factor values to corresponding courses.

In below, we have explained the steps how the Holland Code assessment could be use in university course recommendation system.

1) ADMINISTER THE ASSESSMENT

In the initial phase of the Holland Code Assessment process, students are presented with a set of carefully crafted questions intended to discern their preferences across the Realistic (R), Investigative (I), Artistic (A), Social (S), Enterprising (E), and Conventional (C) categories of the RIASEC model. This assessment can take the form of an online questionnaire or a traditional paper-based tool, offering a comprehensive approach to capturing the diverse facets of a student's personality. After completion of the assessment, each student's responses can be transformed into a mathematical representation known as a vector. In this context, a vector is a multidimensional entity where each dimension corresponds to one of the RIASEC categories. For each question, the system captures the student's response and updates the corresponding dimension in the vector. For example, the vector representation like [R, I, A, S, E, C].

Vector normalization for Consistency – Vector normalization ensures the vectors maintain consistent scales and do not introduce biases due to variations in response intensity. The process involves adjusting the values in each vector to a standard range (between 0 and 1). This guarantees that the overall magnitude of the vector does not influence the subsequent analyses. The Normalized Value (NV) can be calculated using the below equation:

$$NV = \frac{\text{Max Value} - \text{Min Value}}{\text{Original Value (OV)} - \text{Min Value}}$$

2) COURSE MAPPING

Align Courses with Holland Codes – In the course mapping phase, the objective is to establish a connection between each course in the curriculum and the relevant Holland Codes. This alignment is crucial for understanding the compatibility between the content of a course and the corresponding personality types identified by the Holland Code assessment.

Relevance Score: Assigning Scores for Alignment – As part of this process, a relevance score is assigned to each course for each Holland Code. This score serves as a quantitative measure of how well a particular course aligns with the characteristics associated with each Holland Code. Typically, this score is normalized to a scale from 0 to 1, where 0 indicates no alignment, and 1 signifies a perfect match.

TABLE 19. Comparative accuracy analysis for various approaches.

Approaches	Studies	Average accuracy
Hybrid Approach of machine learning algorithms (Decision Tree, Random Forest, Regression Analysis, Association rules, SVM, KNN, Fuzzy Logic, Neural Network)	[29], [39], [30], [82], [31], [41], [61], [70], [72], [73], [74], [75], [76], [77]	88.25% (70%-98%)
Hybrid Approach of collaborative and content-based filleting	[26], [60], [93]	81% (76.8%-84.5%)
Classification	[33], [38], [43], [45], [55], [57]	67.9% (50%-90%)
Collaborative Filtering	[36], [48]	85%

TABLE 20. Significance and relevance of Holland code assessment's RIASEC factors in course recommendation system.

Factor name	Significance	Relevance
Realistic	Realistic traits favor hands-on activities, ensuring recommendations suit those inclined towards applied and skill-based courses.	In course recommendations, Realistic traits guide towards programs with tangible skills, like vocational training or technical courses.
Investigative	Investigative traits emphasize analytics, guiding recommendations for courses that cultivate critical thinking and problem-solving skills.	Investigative traits are pertinent for suggesting programs in scientific research, data analysis, or disciplines requiring analytical thinking.
Artistic	Artistic traits favor creativity, enhancing the system's significance by suggesting courses in fine arts, design, or creative disciplines.	Artistic traits guide towards programs nurturing creative talents and artistic expression.
Social	Social traits stress interpersonal skills, holding significance in recommending courses involving teamwork, communication, and community engagement.	Social traits are relevant for suggesting programs in fields like psychology, sociology, or any discipline requiring strong interpersonal skills.
Enterprising	Enterprising traits signify leadership and business acumen, adding significance by recommending courses aligned with entrepreneurial pursuits and leadership development.	Enterprising traits are pertinent for suggesting programs in business, management, or entrepreneurship.
Conventional	Conventional traits stress organization and detail orientation, providing significance in recommending courses with structured tasks and attention to detail.	Conventional traits are relevant for suggesting programs in fields like finance, administration, or any discipline requiring organizational skills.

The implementation involves constructing a matrix where each row represents a course, each column corresponds to a Holland Code, and the entries signify the relevance scores. If M is a matrix, where M_{ij} represents the relevance score for the i-th course and j-th Holland Code.

3) FEEDBACK LOOP

In the dynamic landscape of a university course recommendation system, user feedback plays a pivotal role in refining and enhancing the accuracy of the system over time. This process involves actively encouraging users to provide feedback on the recommended courses. The feedback gathered is then systematically integrated into the system to adjust weights, relevance scores, and prediction models, fostering continuous improvement. This iterative optimization process will fine-tune various components of the recommendation system.

Adjusting Weights: – For each trait category in the Holland Code assessment, adjust the weights based on the feedback received. Here W_i represents the weight for the i-th trait category. The updated weight W_i' can be calculated as:

$$W_i' = W_i + \alpha \times \text{Feedback}_i$$

Here, α is a learning rate, and Feedback_i is the feedback received for the i-th trait category.

Relevance Score Adjustment: – Modify the relevance scores for courses based on user feedback. This adjustment can be implemented by updating the relevance scores using the feedback.

Here, R_{ij} be the relevance score for the i-th course and j-th Holland Code. The updated relevance score R_{ij}' can be computed using the below equation:

$$R_{ij}' = R_{ij} + \beta \times \text{UserRating}_{ij}$$

Here, β is a learning rate, and UserRating_{ij} is the user's rating or feedback for the alignment of the i-th course with the j-th Holland Code.

The integration of the Holland Code assessment in course recommendation system, offers a comprehensive solution to the challenge of selecting perfect courses. Through a meticulous mathematical analysis, the system can provide tailored recommendations, empowering students to make informed decisions about their academic paths.

B. ADDRESSING COLD START PROBLEM

One critical research gap is finding effective strategies to address the "cold start" problem, where recommender systems struggle to provide accurate recommendations for new students with limited or no historical data. Future research can focus on developing innovative approaches, such as knowledge transfer techniques, to tackle this challenge and enhance the usability of recommender systems for all students [95].

C. INTEGRATING INTERDISCIPLINARY DATA

Most existing recommender systems in higher education primarily focus on academic data, such as course histories and grades. However, to provide truly holistic and personalized recommendations, future research can explore the integration of interdisciplinary data, such as co-curricular activities, extracurricular interests, and career aspirations. This will enable recommender systems to cater to the diverse needs and goals of students beyond their academic pursuits [96].

D. LONG-TERM IMPACT ASSESSMENT

Evaluating the long-term impact of recommender systems on students' academic performance, career outcomes, and overall learning experience is a crucial research area. Future studies can employ longitudinal data and conduct follow-up assessments to understand how students' choices and academic trajectories are influenced by recommender system recommendations over time [97].

E. FAIRNESS AND BIAS MITIGATION

As recommender systems play an influential role in shaping students' academic decisions, it is essential to address issues related to fairness and bias. Future research can focus on developing fairness-aware algorithms and mitigation strategies to ensure equitable and unbiased recommendations for students from diverse backgrounds [93], [98].

F. INCORPORATING USER FEEDBACK AND EXPLAINABILITY

Enhancing the transparency and interpretability of recommender systems is critical for building trust and acceptance among users. Future research can explore ways to incorporate user feedback into the recommendation process and provide meaningful explanations for the recommendations, enabling students to understand and trust the system's suggestions [99].

G. PERSONALIZED LEARNING PATHWAYS

Going beyond course recommendations, future research can explore the development of recommender systems that support personalized learning pathways for students. These systems can provide tailored learning resources, study materials, and skill development opportunities based on individual learning styles and preferences [100].

H. EFFECTIVENESS ACROSS DIVERSE EDUCATIONAL SETTINGS

Most existing research focuses on recommender systems in traditional higher education settings. Future research can investigate the effectiveness of these systems in diverse educational contexts, such as online learning platforms, vocational training programs, and lifelong learning environments [20].

I. HYBRID MODELS WITH USER COLLABORATION

While hybrid recommender systems show promising results, there is a research gap in understanding how user collaboration and input can be effectively integrated into the hybrid models. Future research can explore innovative ways to leverage user feedback and preferences to improve the accuracy and relevance of recommendations [71].

In conclusion, addressing the identified research gaps and exploring the suggested future research directions will advance the field of academic advising through recommender systems, leading to more accurate, personalized, and meaningful recommendations for students in higher education. Moreover, considering the ever-evolving educational landscape, continuous research and innovation are essential to ensuring that recommender systems remain relevant, trustworthy, and supportive tools in empowering students to make well-informed choices for their educational and professional success.

VII. PRACTICAL USES OF COURSE RECOMMENDATION SYSTEM

Course recommendation systems are essential tools for individuals navigating the complex landscape of career path selection. These systems provide personalized guidance by leveraging advanced data analytics and machine learning algorithms to analyze individual preferences, skills, and career aspirations. By offering tailored recommendations for courses and educational pathways, they assist users in exploring diverse career options and identifying the most suitable educational opportunities. Furthermore, course recommendation systems help bridge the gap between individuals' current skills and the requirements of various industries by suggesting courses that align with emerging trends and workforce demands. This proactive approach ensures that users acquire the necessary expertise to succeed in their chosen fields and remain competitive in the job market. Additionally, these systems facilitate lifelong learning by encouraging users to continuously update their skills and knowledge, enabling them to adapt to evolving job requirements and pursue career advancements effectively. Overall, course recommendation systems play a vital role in empowering individuals to make informed decisions about their career paths, facilitating professional growth, and enhancing overall career satisfaction and success. Here, we have discussed various practical uses of course recommendation system in personalized career path selection process.

A. PERSONALIZED LEARNING PATHS

Tailoring course recommendations based on individual student preferences and academic goals enables students to pursue a curriculum aligned with their interests and career aspirations. This fosters a sense of ownership over their education, increasing motivation and engagement.

B. IMPROVED STUDENT ENGAGEMENT

By suggesting courses that align with students' interests, learning styles, and career goals, course recommendation systems can enhance student engagement. When students are genuinely interested in the material, they are more likely to actively participate in class discussions, complete assignments, and seek out additional learning opportunities.

C. RETENTION IMPROVEMENT

Course recommendation systems can contribute to higher student retention rates by guiding students towards courses that match their academic strengths and interests. When students feel supported in their academic journey and see a clear path towards their goals, they are less likely to drop out.

D. REDUCED DROPOUT RATES

Decreasing dropout rates is a key benefit of course recommendation systems. By helping students choose courses that align with their abilities and interests, these systems can prevent academic overwhelm and increase the likelihood of successful course completion.

E. COURSE DIVERSITY PROMOTION

Promoting diversity in course selection is essential for providing a well-rounded education. Course recommendation systems can achieve this by suggesting a variety of options from different disciplines, cultures, and perspectives, encouraging students to explore new subjects and broaden their horizons.

F. ADDRESSING CURRICULUM GAPS

Course recommendation systems can identify gaps in the curriculum and suggest supplementary or complementary courses to fill those gaps. This ensures that students receive a comprehensive education that covers all necessary topics and prepares them for future academic or professional endeavors.

G. OPTIMIZING COURSE LOAD

Helping students optimize their course load is crucial for academic success. Course recommendation systems can suggest a balanced mix of core, elective, and prerequisite courses, taking into account students' schedules, academic goals, and extracurricular commitments.

H. ADAPTIVE LEARNING SUPPORT

Adaptive learning environments require personalized instruction tailored to each student's needs. Course recommendation systems play a key role in supporting adaptive learning by recommending courses that adapt to students' evolving knowledge and skill levels, ensuring they receive appropriate challenges and support.

I. CAREER PATH PLANNING

Course recommendation systems can assist students in planning their career paths by recommending courses relevant to their chosen professions or industries. By aligning coursework with future career goals, these systems help students make informed decisions about their education and career trajectory.

J. GUIDANCE FOR COURSE PREREQUISITES

Prerequisite courses are essential for building foundational knowledge and skills in a particular subject area. Course recommendation systems can recommend prerequisite courses necessary for students to succeed in advanced or specialized coursework, ensuring they have the necessary background knowledge to excel.

K. EXPLORING NEW SUBJECT AREAS

Encouraging students to explore new subject areas or interdisciplinary fields is essential for fostering creativity, critical thinking, and innovation. Course recommendation systems can achieve this by suggesting relevant introductory courses outside students' usual areas of study, sparking curiosity and encouraging intellectual exploration.

L. ALIGNMENT WITH LEARNING OBJECTIVES

Course recommendation systems must align with institutional learning objectives and academic standards to ensure that students receive a high-quality education. By recommending courses that meet these objectives, these systems contribute to the overall effectiveness and reputation of the institution.

M. INTEGRATION WITH ACADEMIC ADVISING

Integrating course recommendation systems with academic advising services enhances the guidance and support available to students. Academic advisors can use course recommendation data to provide personalized advice, helping students make informed decisions about their course selection and academic pathway.

N. EARLY WARNING SYSTEMS

Early warning systems leverage course recommendation data to identify students at risk of academic underperformance and provide timely interventions. By analyzing students' course selections, performance metrics, and engagement levels, these systems can flag potential issues and connect students with the resources and support they need to succeed.

O. SUPPORT FOR TRANSFER STUDENTS

Transfer students often face unique challenges when transitioning to a new institution. Course recommendation systems can assist transfer students by recommending courses that align with their prior coursework and academic background, ensuring a smooth transition and maximizing credit transfer opportunities.

P. CUSTOMIZED DEGREE PLANNING

Customized degree planning is essential for helping students navigate the complexities of higher education and achieve their academic goals. Course recommendation systems can recommend courses that fulfill specific degree requirements and elective preferences, empowering students to create a personalized academic pathway tailored to their interests and aspirations.

Q. CROSS-INSTITUTIONAL COLLABORATION

Course recommendation systems can facilitate cross-institutional collaboration by sharing anonymized course recommendation data. By pooling data from multiple institutions, these systems can improve the accuracy and effectiveness of course recommendations, benefiting students across different educational contexts.

R. INSTRUCTOR COURSE ASSIGNMENT

Assigning instructors to courses is a critical task for academic institutions. Course recommendation systems can assist in this process by matching instructors' expertise and preferences with course needs, ensuring a well-qualified and motivated teaching staff.

S. CONTINUOUS IMPROVEMENT

Course recommendation systems must continuously evolve and improve to meet the changing needs of students and academic institutions. By leveraging feedback mechanisms and performance metrics, these systems can identify areas for improvement and refine their algorithms and models accordingly.

T. ENHANCED LEARNING ANALYTICS

Course recommendation data provides valuable insights into student learning behaviors, preferences, and academic outcomes. By analyzing this data, academic institutions can generate actionable insights to inform instructional design, curriculum development, and institutional improvement initiatives.

U. FACULTY DEVELOPMENT INITIATIVES

Course recommendation systems can support faculty development initiatives by identifying areas where additional training or resources may be needed. By analyzing course recommendation data, institutions can identify trends and patterns that may indicate areas for improvement in teaching and learning practices.

V. PREDICTIVE ANALYTICS FOR ENROLLMENT MANAGEMENT

Predictive analytics techniques can be applied to course recommendation data to forecast future enrollment trends and student demand. By analyzing historical enrollment data and course recommendation patterns, institutions can make more informed decisions about course offerings and resource allocation.

W. PERSONALIZED LEARNING MATERIALS

In addition to recommending courses, course recommendation systems can also suggest personalized learning materials, such as textbooks, articles, videos, and online resources. By curating a selection of relevant materials tailored to each student's needs and preferences, these systems support self-directed learning and independent study.

X. ALIGNMENT WITH STUDENT LEARNING OBJECTIVES

Course recommendation systems can ensure that recommended courses align with students' learning objectives and educational goals. By considering factors such as learning style, academic interests, and career aspirations, these systems help students make choices that are meaningful and relevant to their personal and professional development.

Y. ALIGNMENT WITH INSTITUTIONAL RESOURCES

Course recommendation systems must take into account institutional resources and constraints when making course recommendations. By considering factors such as class size, faculty availability, and facilities, these systems ensure that recommended courses are feasible and practical for both students and the institution.

Z. INTEGRATION WITH LEARNING MANAGEMENT SYSTEMS

Integrating course recommendation systems with learning management systems (LMS) streamlines the course selection process for students and faculty. By providing seamless access to course recommendations within the LMS interface, these systems improve usability and accessibility for all users.

1) ACCESSIBILITY AND INCLUSIVITY

Course recommendation systems can promote accessibility and inclusivity by recommending courses that accommodate diverse learning needs and preferences. By considering factors such as language support, accommodation services, and alternative formats, these systems ensure that all students have equal access to educational opportunities.

2) FEEDBACK MECHANISMS FOR IMPROVEMENT

Course recommendation systems should incorporate feedback mechanisms to gather input from students, faculty, and administrators. By soliciting feedback on course recommendations, these systems can identify areas for improvement and refine their algorithms and models to better meet the needs of users.

3) LONGITUDINAL TRACKING OF STUDENT PROGRESS

Course recommendation data can be used to track students' progress over time and identify trends in course selection and academic performance. By analyzing longitudinal data, institutions can gain insights into student behavior and outcomes, informing strategic planning and decision-making.

4) ETHICAL CONSIDERATIONS AND PRIVACY PROTECTIONS

Course recommendation systems must adhere to ethical guidelines and privacy regulations to protect students' sensitive information. By implementing robust data security measures and transparency practices, institutions can build trust with users and ensure the responsible use of course recommendation data.

5) COST-EFFECTIVENESS AND RESOURCE OPTIMIZATION

Course recommendation systems can help institutions optimize resource allocation and minimize costs by recommending courses that maximize student enrollment and faculty utilization. By analyzing historical data and forecasting future demand, these systems support efficient planning and decision-making.

6) ALIGNMENT WITH INDUSTRY NEEDS

Course recommendation systems can align course offerings with industry needs and workforce demands. By analyzing labor market trends and employer feedback, institutions can identify areas of growth and opportunity and tailor course recommendations accordingly.

7) SUPPORT FOR ACADEMIC PLANNING COMMITTEES

Academic planning committees rely on course recommendation data to make decisions about curriculum development, program evaluation, and resource allocation. By providing timely and accurate course recommendations, these systems support the work of academic planning committees and help institutions achieve their strategic goals.

8) INTEGRATION WITH STUDENT SUPPORT SERVICES

Course recommendation systems can integrate with student support services, such as tutoring, advising, and counseling, to provide holistic support to students. By identifying students who may benefit from additional assistance and connecting them with the appropriate resources, these systems contribute to student success and well-being.

9) INTERNATIONALIZATION AND GLOBAL ENGAGEMENT

Course recommendation systems can support internationalization efforts by recommending courses that reflect diverse perspectives and global trends. By exposing students to a variety of cultural and linguistic experiences, these systems prepare them to thrive in an increasingly interconnected world.

10) ALIGNMENT WITH ACCREDITATION STANDARDS

Course recommendation systems can help institutions demonstrate compliance with accreditation standards and quality assurance measures. By ensuring that recommended courses meet established criteria for rigor, relevance, and effectiveness, these systems support accreditation processes and institutional accountability.

11) FACULTY COLLABORATION AND PROFESSIONAL DEVELOPMENT

Course recommendation systems can facilitate faculty collaboration and professional development by providing insights into teaching and learning practices. By analyzing course recommendation data, faculty can identify areas for improvement and share best practices with colleagues, fostering a culture of continuous improvement and innovation.

12) ALIGNMENT WITH INSTITUTIONAL MISSION AND VALUES

Course recommendation systems should align with the institutional mission and values to ensure that recommended courses reflect the institution's educational philosophy and goals. By incorporating institutional priorities and priorities into course recommendations, these systems contribute to the overall coherence and integrity of the academic program.

13) SUPPORT FOR TRANSFER ARTICULATION AGREEMENTS

Course recommendation systems can support transfer articulation agreements by recommending courses that meet transfer requirements and articulation guidelines. By facilitating the transfer process for students, these systems promote seamless pathways to degree completion and academic success.

14) COMMUNITY ENGAGEMENT AND OUTREACH

Course recommendation systems can engage the broader community, including alumni, employers, and industry partners, in the educational process. By soliciting input and feedback from external stakeholders, institutions can ensure that course offerings are relevant, responsive, and aligned with community needs and priorities.

These are some practical uses highlighting the multifaceted impact of course recommendation systems on student success, institutional effectiveness, and educational innovation. By leveraging data-driven insights and personalized recommendations, these systems support informed decision-making, enhance learning experiences, and promote equitable access to educational opportunities for all students.

VIII. CONCLUSION

In recent years, the field of tertiary education has witnessed a notable surge in interest in developing recommender systems for making informed decisions. This systematic review aimed to investigate the trends and techniques employed in recommendation systems within the context of higher educational academic advising. By analyzing 56 selected studies, we gained valuable insights into the utilization of recommender systems in six key aspects driven by research questions, including the purpose, development approach, incorporated features, deployment, validation criteria, and educational outcomes. The findings revealed that course recommendations emerged as the most prominent area of focus, accounting for approximately 53% of the papers. Notably, hybrid strategies constituted the primary development technique across the analyzed studies. However, it was observed that there is no one-size-fits-all generic model or framework for recommending educational choices, as each recommender system is tailored to its specific context and data type. As a conclusion, this systematic review sheds light on the growing importance of recommender systems in academic advising in higher education. The identified trends and techniques can guide future researchers in developing innovative approaches to unlock the full potential of academic advising and enhance student learning experiences. By effectively leveraging recommender systems, educational institutions can offer personalized guidance to students, leading to more informed and successful academic decisions. The comprehensive understanding gained from this review can pave the way for the continuous improvement and implementation of recommender systems in tertiary education, contributing to the advancement of the field and ultimately benefiting students' academic journeys.

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