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Ontology and Machine Learning-Based Recommender System for Teacher Resource Personalization

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Abstract: Teachers face challenges when conducting their jobs (stress, work overload, lack of resources, lack of time, etc.), which may lead them to psychological problems. With the current information overload and sparsity of resources, it can be challenging to find relevant educational resources promptly. Recommender systems are designed to address the issue of information overload by filtering relevant information from a large volume of data based on user preferences, interests, or observed behavior. A recommender system can help mitigate teachers' struggles by recommending personalized resources based on teachers' needs. This paper presents previous works related to recommender systems in education. It highlights their techniques and limitations. Some papers relied on machine learning and/or ontology for building recommender systems, while others relied on a hybrid system comprising several techniques. The most employed recommendation techniques include collaborative filtering (CF), content-based (CB), and knowledge-based (KB) approaches. Each approach has its advantages and limitations. To overcome these limitations, several advanced recommendation methods have been proposed, such as social network-based recommender systems, fuzzy recommender systems, context awareness-based recommender systems, and group recommender systems. Our analysis reveals that existing recommender systems are learner-centered, often lacking an understanding of the teacher's context. The continuous advancement of recommendation approaches and techniques has led to the implementation of numerous recommender systems and the development of numerous real-world applications. A context-aware personalized recommender system for teachers should consider personal and professional development goals and psychosocial state when presenting a recommendation. Years of experience, access to equipment, and commute time are some of the aspects that should be considered when designing such a system. Moreover, the studies surveyed provided detailed information about their evaluation methodologies. However, the evaluation of these systems is typically conducted using simulated or nonreal students, along with various assessment approaches such as algorithmic performance tests, statistical analysis, questionnaires, and qualitative observations.

Keywords: Recommender systems; Education; Teacher; Personalized recommendations

1. Introduction

Teachers may find a plethora of digital and physical content available as learning resources. It is often a challenge to find relevant information promptly. The material used by teachers should be suitable for their mental and physical state, available equipment, and teaching style, as these factors directly impact teaching quality and student outcomes. The system should consider both professional aspects and mental challenges. These factors may include stress, burnout, commute time, and mental and physical health. Hence, there is a need for a teacher-centric recommender system, which is a tool designed to assist educators in looking for and selecting the most appropriate learning resources. In recent times, a diverse range of recommender system software has been developed for various applications. Researchers and professionals acknowledge the significant opportunities and challenges that recommender systems present in business, government, education, and other domains. Real-world applications of recommender systems have demonstrated their effectiveness in addressing these challenges. The field of learning technology has experienced rapid growth and garnered substantial support from advancements in technology, online learning platforms, and various stakeholders with diverse requirements. Numerous organizations, researchers, and educators are actively developing learning technologies to cater to these evolving needs.

The research questions for this paper are as follows:

RQ1: What are the key challenges faced by teachers in their roles, and how can a personalized recommender system address these challenges effectively?

RQ2: How can context-aware recommendations be implemented to consider the living and working environments, as well as the psychological well-being of teachers, when making personalized recommendations?

RQ3: What are the limitations and challenges of existing e-learning recommender systems, and how can these limitations be overcome to provide more effective recommendations for teachers?

RQ4: What is the impact of a personalized educational resource recommender system on the overall satisfaction and well-being of teachers, and how can this impact be measured and evaluated effectively?

RQ5: How can user feedback and surveys be incorporated into the system to continually improve the quality and relevance of recommendations for teachers?

This paper is organized as follows: Section 2 discusses recommender systems and their various approaches. As well as challenges facing the implementation of such systems. Sections 3 and 4 examine the literature selection method and literature review. It also compares different techniques and different goals for each application of said technique. Section 5 goes through an analysis and discussion of previously surveyed techniques while highlighting a potential research gap. Finally, Section 6 presents the conclusion.

2. Recommender System

Recommender systems are designed to address the issue of information overload by filtering relevant information from a large volume of dynamically generated data based on user preferences, interests, or observed behavior (Lü et al., 2012). These systems aim to deliver personalized recommendations for online products or services, thereby tackling the growing problem of online information overload and enhancing customer relationship management. The primary feature of a recommender system lies in its ability to infer a user's preferences and interests by analyzing their behavior or the behavior of other users. This analysis serves as the basis for generating personalized recommendations.

Recommender systems gather pertinent user data to create a user profile or model that aids in prediction tasks. This user profile encompasses various aspects, such as user attributes, behaviors, and the content accessed by the user (Burke et al., 2011). A learning algorithm extracts and utilizes user features from the feedback collected during the information collection phase. The recommender system makes recommendations or predictions regarding the types of items that the user may prefer. The prevailing techniques employed at present include content-based, collaborative filtering, knowledge-based and hybrid approaches.

2.1 Content-Based Filtering

The content-based technique relies on domain-specific information and emphasizes the analysis of item attributes to generate predictions. In this technique, recommendations are made based on user profiles, utilizing features extracted from the content of items that the user has previously evaluated (Meteren, 2000). Content-based recommender systems play a vital role in information retrieval. Initially, the assignment of terms is done manually. This entails the selection of a technique that compares these terms with the information in the client's profile. Furthermore, a learning algorithm is chosen to execute these techniques and deliver relevant results to the client.

2.2 Collaborative Filtering

Collaborative filtering recommends items to a user that they have not rated before but have received positive ratings from users in their neighborhood. The recommendations produced by collaborative filtering can be in the form of predictions or recommendations. Prediction involves assigning a numerical value representing the predicted score of items for the user (Basilico & Hofmann, 2004). Recommendation, on the other hand, consists of a list of the top N items the user will likely enjoy.

Model-based approaches are considered a subcategory of collaborative filtering. Constructing a model for recommender systems involves utilizing a range of machine learning and data mining techniques. These techniques encompass diverse approaches, including Singular Value Decomposition (SVD) for reducing dimensionality, Matrix Completion techniques, Latent Semantic methods, Regression, and Clustering methods.

Some of the commonly used techniques are association rules, clustering, decision trees, artificial neural networks, link analysis, regression, Bayesian Classifiers, and matrix completion.

2.3 Knowledge-Based Recommendation

Knowledge-based (KB) recommendation systems offer item suggestions to users based on knowledge about the users, items, or their relationships. These systems typically maintain a functional knowledge base that describes how a specific item satisfies a particular user's needs. A common approach to KB recommendation is through case-based reasoning, where recommender systems represent items as cases and generate recommendations by retrieving the most similar cases to the user's query or profile (Tarus et al., 2018). Ontological recommendations are a subcategory of knowledge-based recommendations. An ontology-based recommender system serves as a formal representation of a knowledge domain (George & Lal, 2019), where the semantics are defined by the concepts and relationships within it. Ontologies enable the unambiguous expression of various elements. They act as conceptual models that describe a particular domain of discourse by employing a set of concepts and relationships.

2.4 Hybrid Recommendation Techniques

To enhance performance and address the limitations of traditional recommendation techniques, a hybrid recommendation technique has been developed. It is a special type of recommendation system that combines the most advantageous features of two or more recommendation techniques into a single hybrid technique (Burke, 2002).

2.5 Context-Aware Recommender System

A recommender system that is context-aware utilizes the sensing and analysis of user context to deliver personalized services (Raza & Ding, 2019). By leveraging information derived from the user's usage history, the system enhances the accuracy of its recommendations. Consequently, users receive recommendations that are customized and better aligned with their individual preferences and needs. The idea behind a context-aware recommender system is that the preferences and needs of users can vary depending on the context in which they are making decisions (Adomavicius & Tuzhilin, 2010). By incorporating contextual information, the recommender system can deliver more accurate and relevant recommendations to users. Contextual information can be obtained from various sources, including user profiles, usage, and behavior. This information is used to create context models that capture the relationships between contextual factors and user preferences (Villegas et al., 2018). Contextual information can be obtained explicitly, implicitly or inferring. Explicitly gathering contextual information involves directly approaching relevant individuals or sources, such as through web forms or specific questions, to provide access to specific web pages. Implicit contextual information, including changes in a user's location or transaction timestamps, can be provided by data or the environment. There is no interaction between the user and other sources as this information is accessed immediately. Inferring the context depends on the use of statistical or data mining methods. The quality of such a classifier is critical to the success of inferring this contextual information, and it varies widely between applications.

2.6 E-Learning Recommender Systems

The recommendations provided by e-learning recommender systems serve to facilitate efficient navigation of online materials by allowing learners to quickly find relevant resources through recommended shortcuts (Rahayu et al., 2022). This helps in enhancing the overall learning experience. Once a database of learning materials or activities is established and the learner's registration information is obtained, the Personalized Learning Recommendation System employs computational analysis models to identify the specific learning requirements of everyone (Tarus et al., 2018). Matching rules are then applied to generate personalized recommendations of learning materials or activities for each learner.

Recommender systems can address various challenges available in the e-learning system. Firstly, e-learning systems usually have enormous amounts of information, so it can sometimes be difficult for students to find the relevant information they need. This problem can be tackled by the recommender system, as it can analyze user behaviour and preferences to give personalized recommendations. Secondly, it can sometimes be challenging to design an e-learning system that is suitable for all students as they have different learning preferences and styles. This can be solved by customizing content recommendations according to the learner's desired format, speed, and resource type, recommender systems can guarantee a more efficient and individualized learning experience. Moreover, it can be difficult to maintain a student's motivation and engagement. To maintain students motivated and engaged throughout the course, recommender systems can make suggestions for cooperative activities, adaptive assessments, or gamified, interactive content. It can also be challenging for students and instructors to identify individual skills gaps. A student's performance and assessment data can be analyzed by recommender systems, which then indicate specific topics where students can benefit from further help or suggest skill-building modules. This means that personalized learning paths can be created. A sequence of courses is suggested that matches the student's goals and skill level. A better learning experience and a continuous improvement cycle can be ensured by providing feedback on the recommended content. Reinforcement learning-enhanced adaptive recommender systems are a possible approach since they interact with students to track and analyse their interests and maximise their satisfaction and engagement throughout the extended learning process (Zhang et al., 2021).

3. Phases of Recommender System

The utilization of semantic-based methods in recommendation systems remains prevalent, as it has been demonstrated to be a superior approach for item recommendations. We have divided the recommendation process into three phases accordingly.

3.1 Information Collection Phase

Recommender systems gather pertinent user data to create a user profile or model that aids in prediction tasks. This user profile encompasses various aspects, such as user attributes, behaviors, and the content accessed by the user. In the context of an e-learning platform, a user profile comprises a compilation of personal information linked to an individual user. It includes cognitive skills, intellectual abilities, learning styles, interests, preferences, and interactions with the system. The user profile serves as a valuable resource for retrieving relevant information and constructing a comprehensive user model.

3.2 Learning Phase

A learning algorithm is employed to extract and utilize user features from the feedback collected during the information collection phase.

3.3 Prediction/Recommendation Phase

The recommender system makes recommendations or predictions regarding the type of items that the user may prefer. This can be achieved either solely based on the dataset collected during the information collection phase, which can be memory-based or model-based, or through the analysis of the user's observed activities within the system.

4. Critical Analysis of Recommender Systems

The techniques previously mentioned have their obvious advantages and disadvantages. Each technique can be best deployed depending on a suitable use case. Below are the advantages and disadvantages of those techniques.

4.1 Advantages

Content-Based Filtering:

- Personalization: it provides personalized recommendations based on the user's preferences and the characteristics of items they have interacted with.
- Reduced Cold Start Problem: it is effective in addressing the cold start problem, as it can make recommendations for new items based on their content features.
- Transparency: it produces explainable results since they are based on specific item features that match the user's preferences.

Collaborative Filtering:

- Adaptability: it adapts to changing user preferences over time and incorporates a human feedback loop.
- Not relying on Metadata: it does not require metadata about items as it relies on behavioural patterns.

Knowledge-Based Recommendation:

- Explainability: it provides explainable recommendations by explaining why certain items are suggested based on explicit rules or domain knowledge.
- Customizability: it can be customized based on explicit user preferences or constraints.

Hybrid Recommendation Techniques:

- Flexibility: they can be adapted to different application scenarios by adjusting the weights of the combined recommendation approaches.
- Accuracy: they leverage the strengths of different recommendation techniques, leading to improved accuracy and robustness
- Avoiding cold start and data sparsity: by combining different methods and approaches, cold start and data

sparsity can be mitigated.

Context-Aware Recommender System:

• Relevancy: it considers the user's current context, leading to more relevant recommendations that align with the user's immediate needs.

• Adaptability: it can dynamically adapt to changes in the user's context, providing timely and appropriate suggestions.

4.2 Disadvantages

Content-Based Filtering:

• Restricted diversity: it can be difficult to introduce users to unexpected or diverse items since recommendations are based on known user preferences.

• Dependency on Metadata: limited item metadata can affect the quality of the recommendation output.

Collaborative Filtering:

Cold Start: it is difficult to provide reasonable recommendations for new users or items with little to no historical data.

Knowledge-Based Recommendation:

• Explainability: it provides transparent recommendations by explaining why certain items are suggested based on explicit rules or domain knowledge.

• Effectiveness: in domains with limited data, it can provide valuable suggestions based on available domain knowledge.

• Customization: it can be customized based on explicit user preferences or constraints.

Hybrid Recommendation Techniques:

• Accuracy: they can leverage the strengths of different recommendation techniques, leading to improved accuracy and robustness.

• Cold Start and Data Sparsity: they can combine different methods to mitigate challenges like the cold start problem and data sparsity.

• Flexibility: they can be adapted to different application scenarios by adjusting the weights of the combined recommendation approaches.

Context-Aware Recommender System:

Relevancy: it can consider the user's current context, leading to more relevant recommendations that align with the user's immediate needs.

5. Literature Review Method

We curated a bibliography by considering the quality of the publication venues and their relevance to the subject. The sources we utilized for this purpose were IEEE Xplore, ACM Digital Library, Springer, and Elsevier. Additionally, we expanded our search by using scholarly search engines such as Google Scholar, Web of Science, ResearchGate, and ArXiv. At first, we used the queries "recommender systems", "context-aware recommender systems", "collaborative filtering", "content matching" and "recommendations". This yielded literature that is generalized in recommender systems. We then shifted our focus to specific techniques. We used the terms "ontology-based recommender system", "hybrid recommender system" and "machine learning recommender system". Then, we narrowed down our focus by using search queries "teacher recommender systems", "e-learning recommender systems", "learning recommender systems" and "learner recommender systems". We focused on research between 2016 and 2022. Our search yielded 138 papers. We then narrowed it down to research that is relevant and yielded 38 papers in the recommender system field. Out of these, we chose 15 papers that focused on implementing eLearning recommender systems using various techniques. Those papers matched our core scope which focused on building teacher/learner focused recommender systems. They also implement various recommendation techniques. They also combine various techniques to formulate hybrid approaches that overcome technical challenges that faced prior techniques.

6. Literature Review

Garanayak et al. (2020) developed a recommender system that utilizes classification techniques "Random Forest Classification" and "KNN" which stands for K-Nearest Neighbours classification algorithms. The Random Forest algorithm employs a voting-based approach, while KNN searches for the nearest neighbor class to organize the given data. By combining time series forecasting and classification techniques, the proposed recommender system aims to provide accurate rank predictions and recommendations for undergraduate students seeking admission into engineering courses at the top IITs in India. Lalitha & Sreeja (2020) introduced a Personalized Self-Directed Learning Recommendation System that integrates classification, personalization, and recommendation models. The classification component merges content-based analysis with collaborative filtering techniques. Web mining methodologies are applied to collect pertinent data from web sources, and semantic analysis employing WordNet and ontology facilitates the categorization of materials by subject. Subsequently, the Random Forest algorithm is employed for clustering and categorizing materials into distinct proficiency levels, such as basic, moderate, and advanced. The personalization aspect of the system incorporates the use of the k-nearest neighbor algorithm and knowledge-based filtering to store user information. Lastly, for recommendation purposes, the system employs the association rule algorithm to extract patterns from a pattern model repository.

Bouihi & Bahaj (2019) presented an architecture for a semantic web-based recommender system as shown in Figure 1. This architecture builds upon the traditional 3-tiers web application architecture by incorporating an additional semantic layer. This semantic layer consists of two subsystems: an Ontology-based subsystem and SWRL (Semantic Web Rule Language) rules.

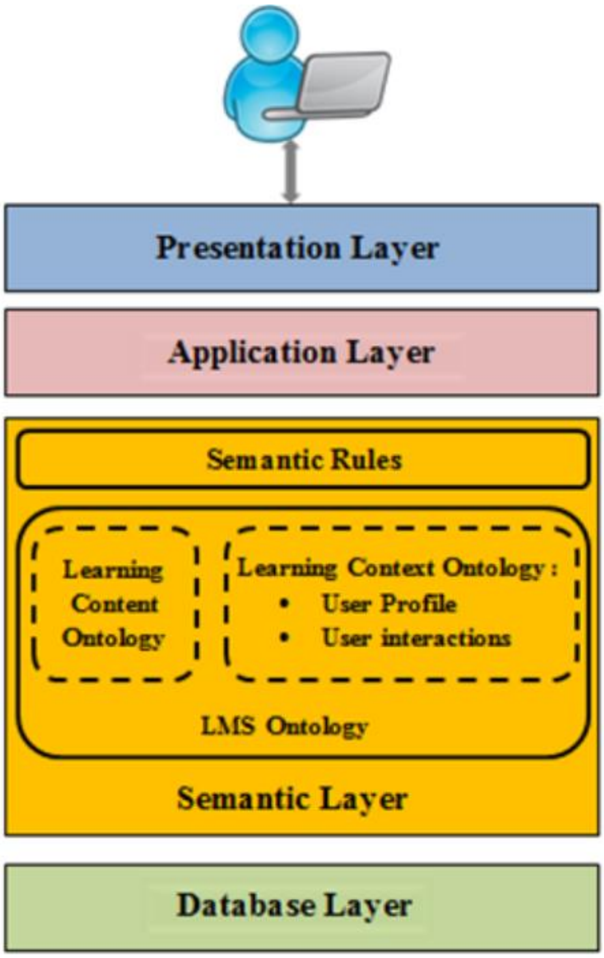

Figure 1. Semantic web-based architecture for an e-learning recommendation system

Obeid et al. (2018) developed semantic-based approach combined with machine learning for personalization. The system uses ontology in combination with clustering to create student profiles. Qomariyah & Fajar (2019) present an implementation design for an e-learning recommender system called APARELL (Active Pairwise Relation Learner) that utilizes a logic- based approach. The authors propose an ontology of material content that considers different learning styles. The system employs a graph-based recommender algorithm to search for e-learning material contents that match the rules generated by the learning algorithm. Furthermore, the user preferences are examined by obtaining a definition that describes the learning style not dominated by any other style within the given preferences.

De Medio et al. (2020) proposed MoodleRec, a hybrid recommender system implemented as a plug-in for the

Moodle Learning Management System. MoodleRec provides a ranked list of Learning Objects based on simple keyword- based queries. The recommender system operates on two levels, employing various recommendation strategies. Firstly, a ranked list of Learning Objects is generated, considering their relevance to the query and their quality as indicated by the repository of origin. Socially generated features are then utilized to showcase how the listed Learning Objects have been utilized in other courses, providing insights to teachers. The hybrid recommender system combines content-based similarity evaluation on Learning Objects with a collaborative filtering approach where it is based on a teacher model.

Bhaskaran et al. (2021) proposed a recommender system that utilizes a split-and-conquer strategy-based clustering approach to automatically adapt to the requirements, interests, and knowledge levels of learners. The recommender system analyzes and learns the individual styles and characteristics of learners. Furthermore, the study introduces a cluster-based linear pattern mining algorithm to extract functional patterns from the learners' data. These patterns are then used to provide intelligent recommendations by evaluating the ratings of frequent sequences. Jeevamol & Renumol (2021) focus on addressing the new user cold-start problem. authors study mitigates this problem by integrating additional learner data into the recommendation process. The recommendation model uses an ontology to represent the characteristics of the learner and the learning objects. The recommendation model incorporates both collaborative and content-based filtering techniques to generate the top N recommendations. Collaborative filtering leverages the ratings provided by other learners to identify similar users and suggest relevant content. Conversely, content-based filtering analyzes the learning objects' characteristics to make recommendations based on the learner's preferences.

Demertzi & Demertzis (2020) presented an Adaptive Educational eLearning System (AEeLS). AEeLS incorporates a Semi- Supervised Classification method for ontology matching and a Recommendation Mechanism that utilizes collaborative and content-based filtering techniques to offer a personalized educational environment for each student. (Dwivedi & Roshni, 2017) employed collaborative filtering-based recommendation techniques to suggest elective courses to students based on their grade points in other subjects. Authors utilized the Similarity Log-likelihood measure to identify patterns among grades and subjects. Das & Al Akour (2020) developed a personalized recommender system Their proposed model employed t-Distributed Stochastic Neighbor Embedding (t-SNE) and Principal Component Analysis (PCA) for selecting the most relevant features. PCA main objective is to convert a dataset containing potentially correlated elements into principal components - a new set of uncorrelated features. The first principal component explains the greatest variance in the data, the second principal component explains the second-highest variance, and so on. These principal components are linear combinations of the original features. For further enhancement, they adopted a Fuzzy Logic Classifier and optimized its membership limits using the Rider Optimization Algorithm (ROA).

Pariserum Perumal et al. (2019) utilized frequent pattern mining to refine content into three levels using fuzzy logic. Then, fuzzy rules are utilized to accommodate all types of learners by applying rules on the pattern tables. Agrebi et al. (2019) utilizes Deep Reinforcement Learning to suggest the most suitable course for learners based on their characteristics, including their profile, needs, and competencies. This approach considers each learner's specificities to provide tailored recommendations. Ansari et al. (2016) introduce a hybrid and context-specific recommender system called CodERS, designed for an interactive programming e-learning system. The system learns user behaviors and activities, particularly coding patterns, feedback, interactions, connections, and preferences, to identify their specific requirements and needs. Wan & Niu (2019) proposed a hybrid filtering recommendation approach called SI-IFL, which combines a learner influence model (LIM), a self-organization-based (SOB) recommendation strategy, and sequential pattern mining (SPM) for recommending learning objects (LOs) to learners.

There are some considerations and potential future directions that can be taken into consideration based on previous challenges such as enhancing the systems to consider various contextual factors such as time, location and social contexts. Further research can explore methods to integrate and modify recommendations based on dynamic user contexts. Recommender systems can be enhanced by focusing on developing interpretable models and designing efficient approaches to deliver the theory behind recommendations given to users, in other words conveying the black box nature of machine learning algorithms. An algorithm that keeps its inner workings hidden from the user is known as a "black box" algorithm. The systems can be adapted to include algorithms that understand and recommend the content of various forms of data, including text, audio, images, and video. One of the most important challenges that should be tackled is the cold start problem (Singh et al., 2021). This is when the recommender system struggles to provide correct and reliable recommendations for new users. Future methods for advancement might involve inventive approaches to managing sparse data and utilizing supplementary data to enhance suggestions for learners with limited interaction records. Different recommendations systems algorithms can be combined to form a hybrid recommendation system to leverage the benefits of multiple techniques, so more robust, reliable, and correct recommendations will be provided. Recommender systems often operate in dynamic contexts where user preferences fluctuate over time. Later studies could concentrate on creating real-time recommendation systems that can promptly adjust to evolving user preferences and behaviors.

Privacy and ethical considerations are important aspects while developing and implementing recommender systems. As discussed in previous sections they are designed to analyze the preferences and behaviours of the users to give personalized recommendations. Although these systems offer many advantages, they also raise significant concerns that are related to privacy and ethics. The following are some key issues on the significance of privacy and ethics.

- User privacy: To fully understand user preferences, recommender systems frequently gather and analyze vast volumes of user data. Prioritizing user privacy and ensuring that sensitive data is handled appropriately are essential. Unauthorized access to personal information may result in malicious acts such as stalking or identity theft. Paraschakis (2017) lists several risks, including invasions of privacy (through data breaches or unconsented data collection), breaches of anonymity, manipulation of user behaviour and biassed recommendations, content censorship, exposure to adverse effects, and unfair treatment of users in A/B testing that results in a lack of user awareness and distrust. To safeguard user data, developers must put strong security measures in place. The solution proposed revolved around a user-centered design approach that introduced adjustable tools for users to explain and control the method by which recommender systems use the personal information of the users.
- User control and customization: Giving users authority over their recommendations enables them to change settings and preferences. Users are now more empowered to actively shape their online experience. Privacy should be considered while designing customization options so customers can personalize recommendations without risking the security of their personal data.
- Data minimization: Only the required information for the recommender system to operate properly should be collected. Unnecessary information gathering should be prohibited to decrease privacy risks. Any irrelevant or outdated data should be deleted from the system.
- Informed consent: Users need to be provided the choice to give explicit consent and be made aware of the data collecting procedures used by recommender systems. The development of trust between users and system developers depends on open communication. It is important to have clear and easily accessible privacy policies that outline the uses, storage, and sharing of user data.

7. Synthesis

Table 1. Literature's objectives, focus and personalization comparison

Paper	Objective	Teacher/Learner Focused	Is It Personalized?
Dwivedi & Roshni, 2017	generate recommendations for students to choose electives	learner	✔
Das & Al Akour, 2020	predicts how many users have recommended LMS "E-khool"	learner	✔
Pariserum Perumal et al., 2019	classify the e-learning topics into levels: simple, medium, hard	learner	✖
Gomede et al., 2021	learn students' behavior, predict the probability of consuming determined learning objects	learner	✖
Agrebi et al., 2019	suggests courses according to user profiles	learner	✔
Bouihi & Bahaj, 2019	deliver suitable material to the learner by modeling learner's context	learner	✔
Obeid et al., 2018	aiding higher education students in choosing a study major by assessing their strengths, weaknesses, capabilities and interests	learner	✔
Ansari et al., 2016	evaluate user's programming skill and provide recommendations for courses and educational resources provide self- recommendations to improve the system itself	learners	✔
Wan & Niu, 2019	recommend open educational resources to university students	learner	✔
Qomariyah & Fajar, 2019	aid students in choosing learning materials according to their preferences	learners	✔
Garanayak et al., 2020	recommend engineering institutes for undergraduate students in India	learners	✔
De Medio et al., 2020	sort through learning repositories and suggest a raked list of learning material	teachers	✖
Bhaskaran et al., 2021	providing suggestions for learning activities based on their style of learning, preferences and characteristics	learners and teachers	✔
Jeevamol & Renumol, 2021	recommend content based on learner goals	learner	✔
Lalitha & Sreeja, 2020	provide self-directed learning strategy to tailor learning process according to needs and goals	learner	✔
Demertzi & Demertzis, 2020	create an adaptive eLearning system that adapts learning curriculum according to student skills	learner	✔

Table 1 illustrates the objectives of the literature. It shows whether it is teacher or learner focused. It also shows the personalization type presented.

Table 2 shows the techniques applied by the literature. It also shows the data it was applied to, in addition to the evaluation metrics and their respective scores.

Table 2. Literature techniques, evaluation metrics and performance comparison

Paper	Data	Ontology Based	Recommender System Technique	Technique	Evaluation Metric	Performance Evaluation		
Dwivedi & Roshni, 2017	School data from central board of secondary education in India	✖	✖	Item based recommendation, log similarity, log likelihood	Root mean square error	0.5		
Das & Al Akour, 2020	Ekhool e-learning app	✖	✖	Fuzzy logic classifier with rider optimization algorithm	FPR	0.079		
					F1	0.808		
					Sensitivity	0.888		
					MCC	0.758		
					NPV	0.92		
					Specificity	0.92		
					FNR	0.111		
					Accuracy	0.914		
					FDR	0.259		
					Precision	0.74		
Pariserum Perumal et al., 2019	Locally collected Documents representing e-learning topics	✖	✖	Fuzzy rules	Precision	0.012		
					Recall	0.0055		
Gomede et al., 2021	Massive Open Online Course (MOOC)	✖	✖	Collaborative Denoising Auto Encoders (CDAE), Deep Auto Encoders		CDAE	DAE-CF	DAE-CI
					MAP	0.22	0.22	0.23
					NDCG	0.366	0.346	0.417
					Personalization	0.735	0.872	0.851
					Coverage	0.672	0.111	0.095
					SAUC	0.014	0.0113	0.015
Agrebi et al., 2019	Custom dataset collected from e-learning platforms	✖	✖	Deep reinforcement learning	Precision	48		
					Recall	70		
Bouihi & Bahaj, 2019	Not specified	✔	LMS ontology, Learning context ontology, Semantic web rules	✖	Not specified	Not specified		
Obeid et al., 2018	Surveys and collected data from French and Lebanese universities' portals	✔	Higher education institution ontology, student ontology	K-mode, self-organizing map, hierarchical clustering	Not specified	Not specified		
Ansari et al., 2016	Data collected from CodERS platform	✖	✖	Collaborative filtering, content-based filtering, user behavioral analysis	Custom evaluation metric based on user's performance, acceptance rate and system maintenance	User satisfaction	Percentage	
						Imperfect	8.4	
						Low	25	
						Medium	41.6	
						High	8.4	
						perfect	15.6	
Wan & Niu, 2019	Undisclosed e-learning platform data from different	✖	✖	Learner influence model, self-organization based recommendation,	Anylogic modeling, matching degree, diversity, score, experience, human	Usefulness	4.4	
						Satisfaction	4.3	

	schools and universities			sequential pattern mining, fuzzy logic	surveying for effectiveness, efficiency and learner satisfaction	
Qomariyah & Fajar, 2019	Not specified	✔	Learning material ontology	Active pairwise relation learner, graph-based recommendation algorithm	Not specified	Not specified
Garanayak et al., 2020	Custom dataset collected from 2016 to 2018 about Indian institutes of technology	✖		Random forest, K-nearest neighbor classifiers	Random forest KNN	accuracy 80 94.11
De Medio et al., 2020	Data gathered from Moodle system log database	✔	Unspecified ontology	Hybrid recommendations using machine learning, collaborative filtering, content-based filtering	Precision Recall F1	0.22 0.39 0.28
Bhaskaran et al., 2021	Custom educational dataset that contains 1000 learner	✔	Learner model ontology, task ontology, teaching strategy ontology	Clustering based liner pattern mining algorithm	Recall Ranking score Precision	0.326 0.07 0.216
Jeevamol & Renumol, 2021	Dataset collected from India-Cochin university and APJ Abdul Kalam technological university	✔	Learner ontology, learner material ontology, learner log ontology	Collaborative filtering, content filtering,	Precision Recall	0.73 0.73
Lalitha & Sreeja, 2020	Not specified	✖		Random forest, k-nearest neighbor, association rule	F1-score, recall, precision, matrix factorization	Not specified

8. Analysis and Discussion

From examining the literature survey, we can deduce that most of the research focuses on enhancing the learning experience for learners. There is a notable gap concerning educators. There is a growing need for recommendations tailored to educators. An educator-focused recommender system can provide recommendations for material suitable for teaching and learning processes. Through such a system, teachers can be provided with suitable material and teaching resources, have equipment suggested to them, or even get connected to other educators with the knowledge they need. Previous research failed to consider the living, working, and mental environments. For example, a recommender system may recommend online material to teachers, such as digital books and online courses, without considering their ability to access the internet. A system may also recommend a learner join a learning group without considering the availability of such a group. The availability of equipment should not be considered a given. Access to computers, libraries, special equipment, or the Internet should be considered. A personal recommendation system should take these factors into consideration before producing any recommendations. Other previous work seen earlier focused on recommending universities to students based on their preferences and skills. These systems failed to consider socioeconomics. Another example is that a system can recommend a particular school to a student without considering their financial capacity to be admitted to such a school or commute time, which plays a key role in deciding whether to join said school.

Another key aspect to consider is the psychological state of the learner or teacher. A teacher may suffer from stress, burnout, or mental or physical impairment, which may impede their ability to learn. A recommender system may fail to recommend a suitable learning pace along with the material. From the literature survey, we can observe that previous work evaluation was based on quantitative evaluation with an obvious lack of qualitative one. Systems that relied on machine learning techniques were evaluated with machine learning metrics such as F1 score, mean average precision, recall, etc., while systems that relied on ontologies relied on ontological metrics such as competency, fluency, correctness, completeness, etc. Most literature failed to assess the overall system's ability to produce a recommendation that satisfied its user base. Jeevamol & Renumol (2021) surveyed learner satisfaction rates but failed to clarify whether this survey serves as a feedback loop to further improve the system.

Furthermore, the findings of the present study indicate that the recommender system generates recommendations without the direct involvement of educators. However, considering that education involves a dynamic interaction between educators and students, educators need to play a role in the recommendation process. Moreover, although students receive recommendations, they may encounter challenges in their learning journey (Konstan et al., 2015). Hence, educators must provide support to address motivational or competency-related issues faced by students.

Based on observations from the literature survey, we can conclude that personal recommendation systems can provide recommendations tailored to each specific learner. But they fail to be personal enough as they lack understanding of the living environment, working environment, personal and professional development goals, and psycho-social state. These aspects should be considered when building a personalized recommender system capable of tailoring its outcome to each learner. Also, there is an absence of recommender systems that focus on learners. A teacher-focused personal recommender system should be able to provide personally tailored recommendations. These recommendations should take into consideration all the personal and professional aspects of a teacher. A teacher has additional traits that should be considered when tailoring a recommendation. These traits include, but are not limited to, teaching style, years of experience, time availability, access to equipment, and much more. These traits can be collected using questionnaires that cover the personal and professional aspects of a teacher. Also, some of the traits can be indirectly inferred based on the answers provided to the questions. One such approach is called SWRL, which is an acronym for semantic web rule language. SWRL provides a way to express complex relationships and infer new knowledge based on existing information in ontologies. The new knowledge can be considered by the recommendation system to produce more personalized and tailored recommendations.

We propose a personalized recommendation system that focuses on teachers. The system does not only take into consideration their professional skills and professional challenges concerning personal development. But there are, socio-psychological risks associated with personal development. The system would rely on real-world data collected in the form of surveys from teachers from diverse backgrounds (urban and rural). The survey targets school and college teachers from Countries such as Egypt and France. The system's goal is to provide teachers with recommendations while considering all the risks that they may face. The survey covers a wide range of topics related to teacher profiles, living and working environments, personal and professional development, the advancement of students, psycho-social risks, and hostile behaviors. By collecting data on these aspects, the survey aims to gain a comprehensive understanding of the teachers' characteristics, experiences, and living conditions. Having a comprehensive model for a teacher aid in designing a context-aware recommender system that is tailored to each teacher. This results in a system that facilitates the acquisition of personalized material that is better suited to his/her needs.

The proposed personalized recommendation system for teachers, which integrates considerations of professional skills, socio-psychological risks, and challenges in personal development, exhibits promising features. However, several potential limitations need to be acknowledged. Privacy concerns loom large, particularly given the sensitivity of the information collected through surveys. The system's efficacy may be compromised by representation bias if the survey sample does not comprehensively mirror the diverse teacher population. Country-specific variability in socio-psychological risks introduces the challenge of ensuring the system's relevance across different cultural contexts. The dynamic nature of teaching environments poses another challenge, as the system must adapt to changing conditions over time. Ethical considerations arise when dealing with psycho-social risks and hostile behaviors, necessitating responsible and conscientious use of such information. While user engagement and acceptance hinge on factors like trust, transparency, and the interpretability of recommendations. Resource intensiveness, both in terms of survey participation and system maintenance, also presents a potential constraint. Addressing these limitations requires a holistic approach that considers ethical, legal, and technical dimensions, while remaining responsive to user feedback and the evolving educational landscape.

9. Conclusions

In conclusion, the analysis and discussion of e-learning recommender systems reveal several important insights and gaps in the existing literature. While considerable progress has been made in enhancing the learning experience for learners, there is a notable lack of focus on educators and their specific needs. Recommender systems should aim to provide personalized recommendations tailored to the characteristics, experiences, and challenges faced by educators. E-learning recommender systems have made progress in enhancing the learning experience, but there is still room for improvement. Future research should focus on developing personalized recommender systems that address the specific needs and challenges of both learners and educators, considering psychosocial factors, psychological well-being, and context. By bridging these gaps, recommender systems can play a more significant role in supporting teaching and learning processes and facilitating the acquisition of personalized and relevant learning materials. The study is limited to recommendation systems that cover the education field along with its subsidiaries. The study was not limited geographically or methodically. The literature covered spans across different geographical locations and different recommendation techniques.

In order to effectively traverse the complexity of personalized learning experiences, educators, technology developers, and the academic community must work together to adopt some measures such as establishing clear ethical guidelines for the development and deployment of recommender systems. This guarantees an ethical and reliable e-learning environment and includes clear data policies, user consent procedures, and proactive steps to reduce biases. Moreover, user feedback, preferences and concerns to create recommendation systems that enhance the student's experience must be prioritized. Instructors should be given the opportunity for professional development, so they understand and utilize recommender systems efficiently. Technology and education will work together effectively if instructors are equipped with the skills to understand and add to recommendations. Collaboration between different educational institutions can be promoted to share their insights, challenges and successful approaches related to the integration of recommender systems in an efficient way. The establishment of reliable and context-aware recommendation models can be significantly enhanced by this collaborative approach.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this paper.

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