

Adaptive Educational Recommendation Systems For Personalized Learning: A Review Of User Modeling And Machine Learning Approaches

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Abstract - The article explores a wide range of tools that are helpful in improving personalized learning, such as models, methods, and slants with an accent to the difficulties and successful moments in their application to the e-learning process. The widely used learning style models of user-centered approach like Myers-Briggs Type Indicator, Kolb's theory of Empirical learning,

Dunn and Dunn Learning Styles Model, Felder-Silverman Learning Style

Model were reviewed in detail. The technology-centered approach was discussed on the example "Protus" system. In addition, it was observed that the use of personalization methods in combination with technological advances leads to promising results, because these two approaches can cover each others shortcomings. For example, the Felder-Silverman model is flexible in meeting the diverse needs of students, while systems such as Protus demonstrate the effectiveness of modular and semantic technologies in adaptive learning. In the result were highlighted the role of clustering, data mining, and algorithms for recommendation to success in the delivery of educational content in the mode of real time. However, the paper highlights that ethical reasoning, issues of privacy, and the lack of standardized algorithms for recommendation remain the major problem. Future researches dedicated to the implication of hybrid models, which consider natural language processing and adaptive dynamic algorithms of personalization are very important for the further evolution of recommendation systems in education.

Keywords - Personalized Learning, Recommendation Systems, Adaptive Education, Machine Learning, User Modeling, Educational Data Mining, Hybrid Learning Models.

1. Introduction

Recent advances in education have placed increasing importance on personalized learning to enhance student achievement and engagement. Personalization of learning means the adaptation of the educational processes to individual learners, taking into account the learning styles appropriate to each single student according to their needs and goals. The variety of students and multitude of available resources make this approach important in the contrast with traditional approaches which comply with standards. Despite the fact that implementation of personalization is difficult, adaptation of teaching methods to individual peculiarities can improve motivation of learners and outcomes of educational process[1]. Personalized learning is based on educational recommendation systems which utilize user profiles and sophisticated algorithms to provide personalized recommendations. Such systems perform a wide range of functions, from providing relevant information in groups to planning training, providing additional materials, and determining and addressing knowledge gaps. The central place in these systems is occupied by the use of user models that contain information about the correspondence of learning styles preceding the educational and educational goals of students. The Felder-Silverman learning style model, which is the basis of learning style models, seems to be in the greatest demand due to its organized and

flexible way of addressing student needs [2, 3, 4, 5]. The development of adaptive e-learning systems largely depends on data collection and, as a result, the accuracy of algorithms. To do this, two methods are used: research and clustering, which identify learning styles that will then be integrated into the recommendation system. Despite the lack of a universal recommendation algorithm, progress in this area has been significant. Thus, systems like "Protus" have become the basis for the most of modern developments [6, 7, 8]. The improvement of mentioned technologies leads to the significant changes in the process of teaching and the outcomes of learning.

Making the studying process personalized has become a core of modern education, because it can allow to meet diverse needs and preferences of learners according to their goals and previous experiences. This way of transformation is especially important in the condition of rapidly changing needs and expectations of groups and individual learners, because the traditional, generalized approaches are getting ineffective. Moreover, personal treatment allows to widely reveal the potentials of learners [9]. However, the implementation of personalized learning faces many challenges. Some of them include difficulties related, in particular, to time constraints, lack of resources, as well as various levels of internal differences between developers. In spite of mentioned difficulties it is necessary to build effective systems which can ensure an individual approach to each learner, while have an ability of scalability and accessivity. The benefits of personalized learning in terms of motivation, engagement, and positive impact on students have been confirmed by numerous scientific studies.

Personalization succours active participation and sustained interest, making the learning process relevant to the entire interests and purposes of students and conveniently linking it to their lives, which ultimately leads to deeper involvement in the learning process. Educational systems which can offer satisfactory and decent recommendations play a key role in the success of personalized learning in the e-learning environment. These systems use sophisticated algorithms and custom models to provide guidance that match students' needs, preferences, and goals. The systems which offer courses that complement each other are good in identifying knowledge gaps and recommending remedial strategies. They are considered the foundation of adaptive e-learning systems, and create more effective and efficient learning experience. In section 2 we discuss the main approaches of recommendation algorithms, in section 3 we explored the results of applying recommendation algorithms and approaches, section 6 and 7 provide discussion and conclusion on the review.

2. Methods

Personalized type of learning has become the cornerstone of modern education, pursuing to meet the unique needs of students by tailoring educational content and strategies to the preferences, abilities, and objectives of individuals. This approach is more preferable in e-learning systems and environments which are accessible to wide range of students, because the traditional standardized approaches does not take into account the wide diversity of learning styles and the previous experiences of learners. Approaches of personalized learning have significant impact of educational theories, technological advances, data-driven systems on their improvement and evaluation. There are two approaches for the personalization of learning: user-oriented and technological[1]. The user-centered method puts the learners at the center of the personalization process, focusing on understanding and meeting of the individual needs, preferences, and styles of learning. A distinctive feature of this method is

the use of detailed student profiles which means the inclusion of information about their prior experience, knowledge, learning goals, preferred styles, etc.

These types of information are necessary to classify students based on their cognitive and behavioral patterns [10]. One of the examples is the Felder-Silverman model. The Felder-Silverman model has become widespread in e-learning systems due to its structure and discrete scale [11]. Researches have shown that this approach can significantly increase student motivation and engagement [12].

In contrast, technology-based approaches are about the integration of advanced personalization systems and algorithms. These approaches include the of artificial intelligence, machine learning, and data mining. For example, Protus was one of the first technology-oriented systems for personalized learning and probabilistic resource allocation [13]. Educational recommendation systems widely use this approach as a key tool which provides functionality such as:

- Offering additional resources to address knowledge gaps.
- Provision of individual content in groups depending on the level of knowledge.
- Identification of additional courses to improve learning trajectories [14].

Despite the fact that the focus is directed to the application of technology, the success depends on the integration of accurate and relevant user data, which highlights the importance of combining user-centric and technology-centric methods. The combined use of user-centered and technology-based approaches underpins modern educational recommendation systems. These systems use user-centric models which contain data about students' previous experiences, current knowledge levels, and future goals. The advanced algorithms then process this data to give the suggestions for individuals for improving learning effectiveness [15].

The detailed look at user-centered and technology centered approaches are provided in subsections A and B.

2.1. User-centered approach: Popular Learning Style Models

Understanding individual learning styles is crucial in the development of effective personalized learning systems. The next models: the Dunn and Dunn, the Myers-Briggs Type Indicator (MBTI) and Kolb's theory can serve as the basic tools for exploring and extracting an important information about students which can help with determining appropriate approach for their learning.

2.1.1. The Myers-Briggs Type Indicator (MBTI)

MBTI is a tool for psychological assessment. This model uses four dichotomies for classifying learners into 16 different personality types Extraversion – Introversion, Perception – Intuition, Thinking – Feeling, Judgment Perception. These combinations grant insight into how people perceive the universe and make decisions which play a key role on their learning preferences. For instance, sensory types of students may prefer concrete practical information, while for intuitive types abstract concepts may be sufficient. Understanding these peculiarities allows teachers and instructors to adapt teaching methods according to students' natural inclinations, thus increasing engagement and understanding [16].

2.1.2. Kolb's Theory of Empirical learning

David Kolb's Theory of Empirical Learning (ELT) considers the learning as a dynamic process that consists of four stages: concrete experience, reflective observation, abstract conceptualization, and active experimentation [17]. The cyclical model (**Figure 1**) assumes that personalized knowledge can be improved through effective integration at all four stages; this enables a person to grasp and interpret experience in the form of knowledge. The Kolb

model helps to identify four different learning styles, grouped according to preferences for each stage:

- Divergence: People demonstrate a swell ability to see situations from multiple diversity of aspects, and they prefer to observe instead of acting.
- Learners: this type prefers less active logical thinking, combining information of various kinds into reasonable, clear conclusions.
- Convergent: Students who are best suited to this combinative personality style are those who enjoy the practice-oriented artistic exploration of thoughts or ideas to solve problems.
- Compliance: People who receive information through observation or intuition, they prefer to complete tasks.

Kolb has developed a Learning Style Inventory (LSI) in order to measure learning styles. After several modifications of this tool have been developed in order to increase its validity and reliability. Since then, has been explored the internal validity and reliability of LSI, focusing on its factor structure and its consistency with different student groups. For example, Kayes (2005) investigated the internal validity of the revised LSI Flask (versions 2A and 3) with business students, which contributed to an understanding of its psychometric properties [19]. Many systematic review papers criticized the Kolb model and proposed changes which obviate its limitations it. The Morris Systematic Review (2019) proposes a revised empirical learning cycle, with an accent on broader experiences placed in a rich context, with vital reflexive moments that are important in learning [20]. Despite the fact that ELT developed by Kolb was useful, it

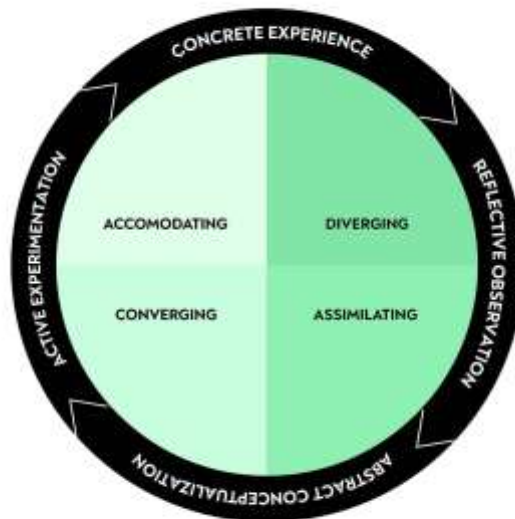


Fig. 1 Stages of Kolb's Theory of Empirical learning [18]

has been criticized due to its underlying theoretical foundations and practices. There were offers to rethink about the learning cycle to pay tribute to complex learning processes based on experience. For example, Seeman et al. (2017), revised the foundations of empirical learning, questioning an alternative prospective which expand its applicability [20]. Kolb's

theory can serve as a base for studying and understanding experimental approaches of learning. The model is still evolving and getting improved by exploring the possibility of applying it in different and varied contexts.

2.1.3. Dunn and Dunn Learning Styles Model

The Dunn and Dunn Learning Styles Model is a full-blown collection of 21 individual factors influencing one's learning preferences under five stimuli (**TABLE 1**): Environmental, Emotional, Sociological, Physiological, and Psychological. This model strongly promotes tailoring educational experiences in light of those divergent preferences, which, therefore, enhances the curve of learning[21].

The Learning Style Inventory (LSI) developed by Dunn and Dunn outlines a diagnostic tool which helps to disclosure individual learning preferences from all these data. After the assessment of each learner's learning style, teachers modify their instructional strategies and structure classroom environments to meet the diverse learning needs of students, ideally refining academic performance and satisfaction.

Table 1. Key Factors of the Dunn and Dunn Learning Styles Model

Category	Factors	Description
Environmental	Sound, light, temperature, seating design	Conditions in the learning environment that affect concentration and information retention.
Emotional	Motivation, persistence, responsibility, need for order	Internal emotional factors that influence learning success.
Sociological	Individual learning, group learning, authority figure interaction	Preferred ways of interacting during the learning process.
Physiological	Visual, auditory, kinesthetic learning style, time-of-day preference, mobility needs	Defines how learners best perceive and retain information.

Psychological	Global (holistic) vs. analytic (detail-oriented) thinking styles	Determines whether a learner processes information as a whole or in segments.
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2.1.4. Dominance of the Felder-Silverman Learning Style Model

Despite the opinion that no theory of learning differs from other theories, a significantly large part of the research (72.5%) was based on the Felder-Silverman model. Most researchers have justified the idea of using this model, since it has a discrete scale, which acquires various parts during the learning process [22].

The Felder-Silverman Learning Style Model (FSLSM) was developed in 1988 by Richard Felder and Linda Silverman. This learning style model can get popular in educational researches and applied to practical cases due to its detailed characterization of preferences of learners from four sides: active/reflexive, sensory/intuitive, Visual/Verbal, and Consistent/Global. This approach helps to understand the needs of students in-depth, to develop appropriate strategies of learning taking into account the mostly fitting learning styles.

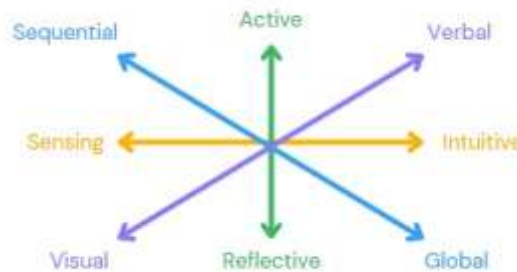


Fig. 2 Felder-Silverman learning style model.

Unlike other models that categorize students into broad categories, FSLSM provides a more detailed analysis of learning preferences. For example, while Kolb's theory of empirical learning focuses on a cyclical process involving concrete experience, reflective observation, abstract conceptualization, and active experimentation, FSLSM distinguishes between how students process information (actively/reflexively) and perceive information (Sensorially/Intuitively), prefer to receive information (visually/verbally) and understand information

(consistent/global). This detailed breakdown allows teachers to more accurately adapt their teaching methods to the individual needs of students. Although learning environments based on FSLSM technology have been reported to be particularly effective, research has shown that learning can be improved by integrating FSLSM into e-learning systems based on matching the learning content and the stated preferences of students. For example, a study conducted by Graf, Viola, and Leo (2007) showed that adaptive educational systems based on FSLSM promote different individual learning styles, increasing student satisfaction and academic

achievement [23]. FSLSM includes aspects of other established learning style theories, which contributes to the completeness of the model. The active/reflexive measurement corresponds to the stages of active experimentation and reflexive observation of Kolb, while the Sensory/The intuitive dimension corresponds to Jung's psychological types. Thus, with proper use of FSLSM, a wide variety of different learning styles can be viewed through the lens of other learning style theories. Being universal, FSLSM has an undeniable advantage for teachers [24]. In some classes, according to various studies, FSLSM was effective in various contexts. For example, a study conducted by Zywno (2003) confirmed the reliability and validity of the Learning Styles Index, an FSLSM-related tool for assessing student learning preferences. In addition, Felder and Spurlin (2005) have published a comprehensive review of FSLSM applications, highlighting their usefulness in improving learning structure and student engagement. Due to its detailed and integrative approach, the learning styles model developed by Felder and Silverman has many advantages over other learning styles models. The theoretical foundations, together with past work experience, now position FSLSM as a valuable tool for any teacher seeking to improve teaching effectiveness while taking into account the needs of each individual student or group. The first versions of Protus focused on identifying student styles and recommending content for their use. The system used adaptive hypermedia methods to create rich and diverse content, presenting interactive materials appropriate to the individual nature of learning. This was done in order to ultimately interest the student and conceptually provide the opportunity to learn in different styles.

2.1.5. Theory and Practice

However, it needs to be cited that instructional methods that are in alignment with the identified learning styles of students can bring improved academic achievement and attitude towards studies. A meta-analysis by Lovelace (2005) found that educational interventions in agreement with the Dunn and Dunn model had an effect size of moderate-to-large on student outcomes with practical or educational significance[25]. Other studies show that when the lessons are based on the learning styles preferences of the learners, increase motivation, hence, discipline. An extraordinary example is a study carried out on fourth-grade students with language processing difficulties by Oweini and Daouk (2016) regarding the Dunn and Dunn Learning Styles Model's impact on reading comprehension and motivation. It revealed significant improvements in both when instruction is tailored to the learning style of the student [26]. Though its usage is wide in scope, the Dunn and Dunn model has been under severe criticism with regard to its complexity and the validity of the assessment tools. It seems that in the overly lengthy list of the model, some researchers express that its application could be very difficult when working on lots of educational settings. The reliability of the Learning Style Inventory has also been questioned due to some concerns about its psychometric properties [27]. The broader concept of learning styles is termed a "neuromyth," with studies showing that a considerable number of educators still believe in and implement learning styles because little empirical evidence prevails regarding their effectiveness. A systematic review by Newton and Salvi (2020) found the belief in learning styles among educators to be high, indicating the importance of continued research and best practice training to overcome such misconceptions [28].

2.1.6. Integrating Learning Styles into Personalized Learning Systems

Utilizing the models in personalized learning systems provides the basis for the development of adaptive personal learning experiences. Assessing individual learning preferences using tools like the MBTI or Kolb's LSI allows the e-learning system to provide different types of content delivery: illustrative materials for visual learners or interactive simulations for

kinesthetic learners. This congruity not only supports a more robust analysis but also promotes motivation and engagement with respect to individual learning dispositions. The differences of learning styles are such as MBTI, Kolb's Experiential Learning Theory, and the Dunn and Dunn Learning Styles Model. They must be recognized and appropriately addressed if a personalized education is to be effective. The examinations will empower educational institutions and e-learning teachers to develop bespoke instructional methods to advance learning performance and attend to the needs of learners.

2.2. Technology-centered approach: Historical Foundations.

2.2.1. Development of recommendation system "Protus".

"Protus"[29] is the information system for learning, which served as a basis for later recommendation systems. Many e-learning systems adopted its design and architecture, specifically modules for recommendation and learning. The development of this system had a big impact on the evolution of personalized type of learning. "Protus" stands for the expression "PRogramming TUtoring System" which was initially developed for assisting the learners who were studying Java language, exactly the basic concepts of this language. Its architecture integrates adaptive hypermedia and recommendation systems to deliver personalized educational experiences. Early iterations of Protus were concentrated on identifying learners' styles and recommending content for doing the same. The system employed adaptive hypermedia methods for the rich and various forms of content presenting interactive materials aligned with the individual learning nature. It was intended to ultimately engage the learner and conceptually enable learning across different styles. A mark into version 2.0 was an enhanced offering due to the introduction of ontology-based semantic recommendations. The latter was used to semantically describe learning materials and learner profiles by the means of ontologies and allow more contextual and relevant recommendations to be made. Main overall improvements involved the incorporation of the semantic web technologies, therefore enhancing the pertinence of recommended learning resources for a personalized experience[30].

Further contouring proceeded to give form to Protus 2.1 [31], which included collaborative tagging techniques, a system of strategies/improvements oriented to bolster the recommendations provided. This way, learners were enabled to annotate educational content with tags, forms of evidence developing consensus on the best recommendations suggested to the system from that collective intelligence equation. It thus provided Protus 2.1 with a focus on refining recommendations relative to changing needs and preferences of the learners.

The architectural design of Protus 2.1 should be modular and adaptable so that various personalization strategies could be additionally incorporated. The architecture also permits integrating the addition of learning materials of new capabilities and adaptation rules so that the tutoring system would also grow in correspondence with educational requirements and technologies under development continually[32].

The evolution of Protus from one release up to 2.1 is reflective of the dynamic nature of educational systems of recommendation. Protus improves personalized learning experiences through integration of semantic web technologies and collaborative tagging. These endeavors bring to mind the ability intelligence tutoring systems have to adapt to very personal learner profiles, thus benefiting in maximizing the level of engagement and learning.

2.2.2. Adoption of "Protus" architecture in modern e-learning systems.

The key feature of Protus 2.1 consists of a modular architecture, which includes components such as the learner model, the domain ontology, and the teaching strategy modules. This structure allows dynamic adaptation of content based on real-time analysis of learner interactions and preferences. Such modular frameworks have found adoption in modern learning systems to facilitate scalability and flexibility of personalized content delivery. For instance, the WBT-Master learning management system architecture employs CDAT architecture including Controller, Data, Activity, and Template emphasizing the modularity and adaptability of the e-learning environment [33].

The ontological approach applied in Protus 2.1 to semantically represent learning materials and learner profiles helped refine accuracy of content recommendations. This semantic representation approach gives a better understanding to relationships between different learning objects and learning requirements formulated, thus achieving more precise and context-sensitive personalization [34].

Furthermore, the inclusion of collaborative tagging in Protus 2.1 enables learners to annotate content, creating collective intelligence to fine-tune the recommendation system. This sustains the participatory approach used at modern e-learning platforms to leverage user-generated information to enhance personalization and promote a more engaging learning environment. The user-centered design and analytics, brought into synergy in adaptive learning systems, have substantively supported scholars in the acquisition of complex cognitive skills [35].

Architectural principles of Protus-2.1, particularly the modular design, semantic representation, and collaborative features, have indeed been very influential in the development of common current e-learning systems. By adopting these principles, the latter have increased their capacity to create personalized, engaging, and efficient learning pathways.

3. Results of complex application of user-centered and technology-centered approaches

3.1. Educational Recommendation Systems.

In personalized learning, an Educational Recommendation System (ERS) acts as a link between user-centered and technology-centered approaches and have next key capabilities:

- Delivering targeted knowledge in group settings.
- Scheduling learning activities and complementing course selections.
- Offering additional learning resources.
- Identifying knowledge gaps and suggesting corrective strategies.

The systems are built to address the specific needs and preferences of the learner while using advanced technologies to provide the learner with personalized educational experiences. A user-centered approach, on the one hand, would focus on building a profile of each learner, identifying personal goals and multiple assurances with regard to learning likes, dislikes, and preferences, so as to come up with precise recommendations. The technology-centered approach, on the other hand, uses automated recommendations by way of algorithms, data mining, and artificial intelligence, among other means. This has led ERS to fit snugly into modern learning environments, providing dynamic and adaptive solutions with enhanced engagement and impact. This section casts a brief glance at the traditional functionalities of the ERS, such as specifically targeting knowledge within group dynamics, scheduling learning activity, supporting resource proffers, and identifying and filling knowledge gaps. These

features combine the principles of user-centeredness and technology-centeredness, which permits an individualized and effective educational experience.

3.2 Development of Adaptive E-Learning Systems: Learning Style Techniques and Recommendation Algorithm Identification .

ERS can form cohorts of learners having a set goal, study levels, or different learning styles to conduct collaborative learning. This approach increases peer interaction and knowledge exchange. For example, Bahargam et al. (2017) developed some algorithms to assemble groups of learners and schedule instructional material delivery in massive online classes, thus improving learning outcomes [36]. 2. Scheduling Learning Activities and Complementing Course Selections ERS would assist the learners to map their educational trajectory by recommending courses and scheduling learning activities according to their goals and prior knowledge. A systematic review done by Rahayu et al. (2022) elaborated on the role played by the learning path recommender systems guiding the learners in psychological educational sequences to augment learning [37]. 3. Offering Additional Learning Resources On the basis of learners' interactions and preferences, ERS suggests additional study materials, articles, videos, or exercises to clarify understanding. Deschênes (2020) remembers: Recommender systems provide most of the learning resources, which support learners' agency and learning goals in technology-enhanced learning environments [38]. 4.

Identifying Knowledge Gaps and Suggesting Corrective Strategies ERS would indicate where the learners are weak and propose targeted interventions to handle those gaps. Khosravi et al. (2017) developed RiPLE, a system to identify learners' knowledge deficiencies and interests, thus providing personalized recommendations to facilitate effective learning [39]. In general, educational recommendation systems improve individual learning by purposefully providing knowledge, planning courses, additional resources, and eliminating knowledge gaps, which contributes to more effective and engaging learning.

3.3 The role of user models.

User models in educational recommendation systems are crucial for implementing a personalized learning process based on different student characteristics. Such models usually include learning style, previous experience, goals, and demographic information. Learning styles are defined here as the ways in which a person prefers to process information, including visual, auditory, or kinesthetic methods. Learner preferences incorporated into ERS will enhance student engagement and comprehension since teaching will be done in the learning styles preferred by the learner. Prior experience [40] is the meta-knowledge and skills already possessed by the learner, which would help the system determine the complexity and depth of the materials recommended since such materials should suit the learner's ability levels. Goals [41] are learning objectives, such as competencies acquired or certification; hence the ERS uses these to prioritize recommendations that directly serve those aims. Further demographic information [42] such as age, education background, and language proficiency further polishes the personalization process by including the learners' characteristics that could affect their learning preferences and needs. The e-learning systems need more efficient user modeling. The diversity of learner profiles necessitates the construction of models which capture a variety of backgrounds, objectives, and preferences better. The construction of a universal model encapsulating such variation, therefore, is complicated; not so generalized that it betrays some of the individual's aspects, nor too detailed such that operations tend to be somewhat gargantuan and difficult to handle. Moreover, changeability of learning preferences requires technology to keep monitoring users at times in order to update them continuously, which will claim many resources and

may demand some sophisticated mechanisms during the process as well. The most important things are data privacy and ethical considerations. Collecting and utilizing personal data for user modeling raises concerns directly, concerning all aspects of privacy and consent-based issues. Thus, e-learning systems should be cautiously devised in order to assure trust and compliance with legal standards, which, in return, in some limited scope, restricts the amount of data collected and analyzed. Furthermore, it remains technically challenging to assemble multidimensional data, such as behavioral patterns, assessment results, and demographic features, into a unified user model. It

interfaces with high-driven engineering that processes different types of complex datasets to formulate actions, including recommendation formation. Finally, the big challenge is scalability. Implementing detailed user models across large e-learning platforms requires solutions that will handle vast amounts of data and provide real-time recommendations without degrading their performance.

Addressing these challenges is of utmost importance for effective deployment of user models in ERS, as they call for the systems' mettle in providing personal and meaningful learning encounters. Working towards the consideration of matching technical sophistication, while also ensuring ethical issues are given their worth, as well as scalability, recommends being accurate, relevant, and firmly flexible concerning the student's needs. For the detailed and complete overview of the needs and challenges involved in designing recommender systems for e-learning environments, the reader is to consult a survey article by Klačnja-Milicević et al. [40].

3.4 Development of Adaptive E-Learning Systems: Learning Style Techniques and Recommendation Algorithm Identification.

Thus, data collection should precede the development or selection of a recommendation algorithm for an adapted e-learning system. Choosing the right data collection methodology and its subsequent use in the recommendation algorithm gives an impetus to the creation of a good learning theory. The learning style can be determined using the following methods: questionnaires, data mining, a rule-based approach, and fuzzy arithmetic mean. The questionnaire is the most frequently used and best suited for new e-learning systems. However, for systems currently in operation, a data mining method may be applicable, which can be implemented by analyzing log data in these systems.

3.4.1. Questionnaire-based methods.

Questionnaire-based methods are considered the basis for determining learning style in educational systems for a long time. They include structured surveys and, often, self-assessment tools that systematically gain insight into individuals' preferences regarding the processing and preservation of information in the learning process. Due to their simplicity in development, accessibility to everyone, and scalability they were very attractive to educators which were interested in the improvement of the personalization of learning process. Questionnaires basically contain multiple-choice questions which are directed to retrieve an information about the emotional, cognitive, and behavioral senses of students by providing answers about different situations. Students are classified into learning style groups on the base of collected answers. The students can be grouped like reflective-active, analytical-global, visual-auditory or kinesthetic. This grouping can help educators to adapt teaching methods to individual learners in order to increase the involvement of students to studying process. These methods not only provide a standardized way to understand student diversity by offering a variety of customized educational strategies, but they are also claimed to enhance engagement, learning motivation, and academic achievement by carefully aligning

learning strategies with student preferences. The materials presented below demonstrate their real advantages in terms of applying questionnaire-based approaches to achieving personalized learning to create a decent educational environment.

1. Ease of implementation: The questionnaires are easy to use, which makes them an excellent choice for both teachers and educational institutions. They can be presented in various ways, such as paper, online forms, or two platforms integrated into e-learning systems. 2. Standardization: Questionnaire-based methods often rely on well-established tools such as ILS or LSI, which are often thoroughly reviewed and widely recognized in the field of educational research. This also makes them standardized and very consistent in measuring learning styles [43]. 3. Scalability: Tools of this type have a high degree of scalability due to the extremely large number of samples used, which makes them suitable for use in regular classrooms, in training courses, or even in online e-learning courses for various groups of students. 4. Adaptation: Identifying individual learning preferences through questionnaires helps to identify learning paths and environments appropriate to those preferences. For example, students with visual perception can receive diagrams and videos, while students with kinesthetics can perform practical tasks.

The questionnaire-based approach, like all others, has its advantages and limitations (Table II). Its disadvantages include subjectivity, static nature, excessive generalization and verification restrictions. 1. Subjectivity: Students sometimes misjudge or fail to express their preferences and allow bias in their responses. 2. Static: Questionnaires capture a specific moment in the formation of student preferences, which can be crucial for the development of preferences or other situational learning needs. Real-time results are rarely taken into account. 3. Excessive generalization: Assigning students to certain categories based on the survey results can lead to a generalization of complex individual learning processes. Critics argue that such classifications do not take into account the contextual or flexible nature of the learning process. 4. Verification restrictions: Although many survey-based tools have been validated to a greater or lesser extent, some tools have not been supported by convincing empirical evidence, and because of this, some of them may be less reliable or valid than others for use with different populations.

Table 2. Questionnaire-based methods advantages and limitations

Advantages	Limitations
Ease of implementation	Subjectivity
Standardization	Static
Scalability	Excessive generalization
Adaptation	Verification restrictions

3.4.2. Data mining approaches

Data mining points out various sequences in which learning styles operate. Behavioral analysis finds itself leveled at how learners act-time on task, paths they pass through, quiz answers, and amount of interaction frequency. Take, for example, a student continuously stopping and rewinding some video content. This might indicate a crossroad for visual learning. Some clustering algorithms that may help in grouping learners with similar

behaviors and preferences perceived to best correlate with specific learning styles include k-means and hierarchical clustering. They optimize their prediction further using classification techniques, usually covering decision trees and neural networks, by sorting learners into pre-defined learning-style categories using their history of actions [44]. There is also association rule mining, which identifies relationships between behaviors and learning styles (e.g., preference for interactive exercises associated with kinesthetic learning). Sequence pattern mining reveals information about the order of learning activities, exposing tendencies such as reflective learning for those learners who review content before being tested. But, this approach has disadvantages. Unlike static questionnaires, dynamic and real-time insights allow continuous adaptation to changing learner behaviors and preferences, assuring that recommendations stay relevant and effective. It is also an objective way of dealing, leaving no room for the subjectivity affixed to self-reported questionnaires, hence providing prediction of learning styles that are more reliable. On a higher-level degree of granularity, data mining scales in a manner that suits the usage of very large amounts of data, something that is at least considered for such large-scale applications to date, like MOOCs. In addition, it merges nicely with adaptive learning systems [45], allowing for personalization based on current user activities in real time. However, the approach has its challenges. The collection of data about learners by questionnaires, from system logs for analyzing and determining their preferences lead to issues related to ethical concerns and individual privacy. Data collection process needs compliances with legal rules and standards like General Data Protection Regulation (GDPR). Some institutions can have problems with implementing sophisticated data mining and analyzing algorithms, because this process needs not only expertise in computer science and algorithms, machine learning, also expensive computing resources. There is also the risk that inferred learning styles may oversimplify individual preferences, leading to overgeneralizations that do not fully capture the complexity or variability of learners [46].

3.4.3. Rule-based and fuzzy clustering methods.

Clustering algorithms have a central role in educational data mining, pushing students into distinct clusters on the basis of common properties with the aim of facilitating personalized experiences for students. Among these methods rule-based and fuzzy clustering methods have recently gained prominence for their greater potentials for analyzing complex educational datasets.

3.4.4. Rule-Based Clustering Methods.

Among these methods, rule-based clustering methods are very effective in the grouping of students on the basis of explicitly defined "if-then" rules, which in turn helps in personalized learning experiences. These rules are usually devised from a domain viewpoint or obtained using algorithms like association rule mining. For instance, students can be grouped according to setting criteria such as level of performance, learning behaviors, demographic factors, etc. The interpretability of this approach allows the educators to understand and validate the clustering results more readily and ensure that the clustering fits within educational contexts. The success of rule-based clustering relies mainly on the quality of the rules and the comprehensiveness of the rules, which in some cases are not able to capture the complete complexity of student behaviors.

The study [47] surveyed the application of clustering algorithms in educational data mining and emphasized the considerable degree of attention that should be paid to the selection of appropriate methods for specific educational datasets. Their further endorsement of rule-based methods marks their advantage in clarity and simplicity over

other complex methods; however, there are more chances for rule-based methods to be used in a less effective way if rules are not well defined.

Work of Agrawal and Srikant [48] on association rule mining gives the first insight on how to find relationships between the variables in a large dataset, which allows for effective rule-based clustering in educational contexts.

3.4.5. Fuzzy Clustering Methods.

Fuzzy clustering techniques are best placed to satisfactorily deal with the vagaries and overlaps of student learning behavior in educational data mining. Unlike traditional clustering techniques that assign a data point to one cluster only, fuzzy clustering allows for degrees of membership across multiple clusters-an aspect that reflects the complicated relationship between varying learning preferences.

3.4.6. Fuzzy C-Means (FCM) Algorithm.

Primal among fuzzy clustering methods is the Fuzzy C-Means (FCM) algorithm. With this algorithm, a level of membership is assigned to each data point with respect to a particular cluster, thus indicating how strongly it is associated with that cluster. This approach is particularly suited for the educational context, where students may show some properties that are aligned with many learning styles. For example, one student can tend to learn visually and kinesthetically at the same time. The overlap between learning styles being captured using the FCM algorithm allows for highly personalized forms of instructional settings. In his research, Hogo (2010) clearly demonstrated how FCM was used to gauge online learners' involvement by clustering students into categories that represent distinct learning profiles. The study showed that fuzzy clustering represents learners' behaviors in a more accurate form than does crisp clustering, with the two behaviors reaching a match percentage of 78. Fuzzy clustering methods are used in adaptive learning systems to either detect or classify learning styles. For instance, research by Yelalliou et al. (2018) proposed a fuzzy classification approach for predicting learning styles based on web usage mining. The approach extracted learning sequences from server log files, clustering them according to particular learning style models using clustering algorithms, including FCM [50]. Agbonifo and colleagues (2018) similarly used FCM to identify students' preferred modes of studying in online settings by utilizing Honey and Mumford's learning styles as a research vehicle. It emphasized the efficiency with which FCM remained able to capture the nuances of individual learning preferences; thus, personalized learning experiences are built around the learning needs of each learner [51]. Fuzzy clustering techniques work best where the uncertain and overlapping aspects of human learning behavior are to be modeled. That is, they allow for a partial membership across several clusters and give an effective representation of student profiles, enabling teachers to set up interventions that meet the divergent and overlapping learning demands of learners. In addition to such advantages, application of the fuzzy clustering methods provides with attendant challenges. These include - but are not limited to - a high demand for significant amounts of computing resources in some instances, as well as difficulties to interpret membership degrees. In addition, the effectiveness of this technique rests on the appropriate selection of parameters and the quality of input data. Thus, teachers and researchers should take these factors into account when applying fuzzy clustering techniques in educational settings.

3.5. Algorithmic requirements.

Success of Educational Recommendation Systems (ERS) is contingent upon ability of algorithms to process this data in an efficient way, model user behavior efficiently, and make appropriate personalized recommendations. Such algorithms have to be focused on the

inherent complexity of high learning settings which cater to diverse individual learner needs aligned within a set boundary of system goals. The well-chosen algorithm provides the grounds for scalable, relevant, and adaptable recommendations for individual learners' needs overtime. To ensure that the recommendations suggested to learners remain effective and relevant. But since the latter might mislead their design, then they will fail to adapt to the learning experience of the user and through collaboration of various filtering styles; for instance, collaborative filtering algorithms will analyze different patterns exhibited by learners demonstrating a similar behavior to personalize the suggestions that will be recommended to their learning experiences [44]. Scalability is one of the most critical considerations, especially in large-scale implementations of MOOCS. In such environments, algorithms must process much data while not compromising on computational efficiency. Matrix factorization, among other techniques, is thus suitably applied in this context as handling large datasets is its cardinal virtue, though modifications may be invoked to ensure real-time efficiency of applications using them [52]. The adaptability feature remains important in the ERS for the learners, for their aims towards their learning activity, their distinct learning styles, and the amount of earlier knowledge is different too. By supporting an adaptive approach through algorithms like decision trees and ensemble methods, systems can dynamically model with hierarchies so that they meet each learner's particular needs. Their adaptability provides personalized recommendations relative to a dynamic learning experience [53]. Another vital requirement of ERS algorithm is that they develop dynamically over time to adapt to changing learner behavior and preference. Reinforcement learning and recurrent neural networks (RNNs) are some companies that show great promise in this regard. They allow for systems to persist in learning and updating recommendations in real-time so that the learner is able to receive the most relevant suggestions as the profile of the learner appears to develop in real-time[54]. Managing uncertainties and incomplete datasets is a pervasive challenge in the educational domain. Algorithms effectively dealing with missing data and uncertainty use techniques such as Imputation and Probabilistic Modeling. Fuzzy clustering offers recommendations with the robustness and accuracy that remains quite high, even in its incomplete state, as does Bayesian networks [44]. Lastly, there is always the question of algorithmic complexity and interpretability itself. Although advanced techniques, for example, a deep neural network, could give exceedingly accurate recommendations, their inability to be transparent is a drawback where trust or clarity in educational scenarios are most desired. In such cases, simpler algorithms like k-nearest neighbors (k-NN) or rule-based systems might be preferable for being easier to understand and implement [55].

3.6.Recommender Algorithms in E-Learning.

3.6.1. Overview of existing algorithms: Capabilities and limitations.

Aimed at rich personal learning experiences through advice on relevant content, resources, and learning strategies, recommender algorithms are crucial in the educational recommendation systems (ERS). Recommender algorithms analyze several learner data types, including behavior, preferences, and learning goals to increase engagement, optimization of learning paths, and enhancement in knowledge retention. For e-learning, several types of recommender algorithms have been put to practical use; each is endowed with different abilities and reasons for failure.

3.6.2. Recommendation systems based on Content-Based Filtering and Collaborative Recommendation

Algorithms which, as per Lops et. al., while generating, do target advice based on items that are akin to those an exact user has preferred in the past, collaborative recommendation systems first and foremost pin the users who share likenesses.

3.6.3. Content-based filtering utilizes attributes of learning materials and user profiles to supply recommendations.

Often used techniques for text-based content analysis are TF-IDF (Term Frequency-Inverse Document Frequency) and cosine similarity [56]. It works efficiently when much information about learning materials and user preferences are respectively available. However, this sort of filtering may also yield the over-specialization aspect in narrowing recommendations so that they are repetitive.

Collaborative filtering is one of the most widely used methods in e-learning recommendation systems. It is to generate suggestions by recognizing the similarities between learners' behaviors and preferences. CF can be divided usually into user-based CF and item-based CF methods. User-based CF recommends resources by users that have similar interaction patterns [57]. On the other hand, item-based CF recommends new content by deriving similarities between already accessed materials [58]. Whereas CF is a winner in the accuracy and diversity of recommendations, it is criticized for its cold-start problem with new users and items regarding insufficient interaction data [59]. Meanwhile, an appropriate selection of pedagogical factors could yield solutions to this type of problem [59]. Hybrid recommender systems leverage both methods in conjunction with any other additional methods, combining content-based and collaborative approaches, thus balancing their respective strengths and weaknesses. For hybrid systems, at least one of either content-based filtering (CBF) or collaborative filtering (CF) is compulsory. Any combination of collaborative filtering and content-based filtering methods may be employed and called: CF-X, CF-CBF, CF-CBF-X, item-item CF and user-user CF, CBF-X where X = Demographic Filtering, Knowledge-Based Filtering, Data Mining(DM), and Machine Learning (ML) among others. Such systems find a specific use in e-learning environments where various data sources are available. Most of the studies state that hybrid models perform better with respect to accuracy and user satisfaction compared to single-method models [60].

4. Research Methodology

This study uses the literature to examine the current state of educational recommendation systems designed to support personalized learning, with a particular focus on approaches relevant to school-age students. Considering the growing demand for adaptive and individualized learning environments. The purpose of this review is to provide a consistent synthesis of models, algorithms, and user modeling strategies.

To ensure a systematic and reproducible approach, the review uses recommendations for a structured analysis of literature in the field of educational technology. Five main academic databases were used to search for relevant literature: Scopus, Web of Science, IEEE Xplore, SpringerLink, and Google Scholar. The search queries included such combinations of terms as "educational recommendation system", "personalized learning", "adaptive learning", "learning styles", "student modeling" and "hybrid recommendation".

The selection process took place in three stages: first, titles and keywords were checked for relevance to the research topic; second, annotations were checked to exclude unrelated or insufficiently detailed works; third, full-text articles were checked for methodological

clarity, direct relation to personalization in learning systems, and the availability of evaluative data or system design. As a result of this process, 56 high-quality sources were identified and included in the final analysis.

Each selected article was analyzed in order to extract the main characteristics of the presented system or model. These include the type of recommendation algorithm used (content-based, collaborative, hybrid), the structure of the learner's model (for example, learning styles, prior knowledge, motivation), and the technological basis of the system (for example, fuzzy clustering, semantic representation, neural networks). In addition, information about assessment methods, such as accuracy indicators, user engagement data, or learning outcomes, was recorded. The final summary of the results is based on a thematic classification of the described systems and methods in order to identify trends, gaps and best practices in using ERS to personalize education.

5. Research Questions

The following research questions were formulated as a guideline for the review:

- What methods of personalized learning are used in educational systems?
- How are the individual characteristics of students represented and implemented in these systems?
- What hybrid approaches to personalization have been proposed to improve the adaptability and accuracy of training recommendations?
- How are educational recommendation systems used to support adaptive learning for school-age students?

6. Discussion

Personalized learning has evolved through a variety of approaches, including user-centered, technological, and hybrid methods, each focusing on different aspects of student adaptation and engagement. Learning styles, goals and preferences of individual learners are natural for user-centered approaches, while the application of computational approaches, machine learning algorithms, deep learning architectures for data mining and automatization for the personalization of educational process are natural for technological methods. Hybrid models combine both approaches, providing a balance between automated adaptation and meaningful student engagement. An effective personalized learning system should include several key functions. These include comprehensive user modeling, which collects and analyzes students' preferences, previous knowledge, and learning goals. Adaptive content provision provides dynamic customization of educational materials in accordance with individual learning trajectories. Tracking the learners' progress in real time and giving timely feedback make learning process effective, determining knowledge gaps and increasing attention and retention of students. Additionally, these systems should not force students to keep exact paces, students should have ability to choose comfortable learning mode in accordance with their suitable style of learning. To achieve effective personalization in e-learning systems, recommendation algorithms must be adaptive and constantly evolving. One way to accomplish this task is to use hybrid recommendation models that combine content analysis and collaborative filtering methods. In addition, algorithms should include machine learning and real-time behavior analysis to adjust recommendations based on changing student profiles. Personalization mechanisms should also take into account ethical aspects, ensuring the protection of data privacy and providing accurate and relevant recommendations. The key factors like relevance, accuracy, scalability, transparency and

robust security play significant role in the effectiveness of recommendation systems in electronic learning. The relevance and accuracy mean that proposed material meet the need of learners and fit their capabilities. The importance of scalability can be explained by the amount of data to be processed and variety of user types and transaction preferred by them. Transparent algorithms makes students to trust the system, used for their education. The implementation of security measures allow to comply with local and global security rules, also saves from the risk of personal data leakage. E-learning systems uses various algorithms for recommendation, despite the fact that each of them has their own pros and cons. Content-based filtering is based on an analysis of educational resources and user preferences, but may limit the variety of recommendations. Collaborative filtering identifies patterns based on interactions with other users, but faces challenges such as a cold start for new users. Hybrid approaches combine several techniques to improve the accuracy of recommendations, but often require more computing resources. The recommendations based on the knowledge of area experts can be used to generate appropriate suggestions, but they can suffer from the low level of adaptation to the dynamic process of learning. Reinforcement learning and dynamic deep learning can handle this problem, but they require extensive computational resources and constantly extending set of data. The combined use of analyzed approaches in the implementation of e-learning platforms can result in sufficiently outstanding personalized recommendation system which can improve academic success of students.

7. Conclusion

This document provides an overview of several models, methods, styles, and approaches to learning, their challenges, and successes. Various distinctive features can be identified; among them is the Felder-Silverman model, which demonstrates attention to program design and offers flexibility in meeting the needs of different students, while Protus has to date proven the value of modular and semantic technologies in the process of personalized technology-based learning. The results highlight the importance of hybrid models combining personalization and technological improvements. Those who use clustering, data mining, and algorithmic recommendations will be able to customize adaptive systems that provide educational content in real time. As tempting as these advances may seem, challenges remain, such as ethical considerations, privacy issues, and the lack of a standard recommendation algorithm. To eliminate these obstacles, further research on hybrid models using natural language processing and adaptive dynamic personalization algorithms will be required. Advanced personalized learning systems will eventually enter the scene and transform education into a more effective and engaging learning process.

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