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Review Article

Recommendation Algorithms for Educational Systems

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Abstract *- This study offers an in-depth review of techniques and tools used in supporting personalized learning in e-learning environments. The techniques and tools discussed in this study include user-centric and technology-centric techniques, such as several popular models of learning styles, including the Myers-Briggs Type Indicator, Kolb's theory of experiential learning, Dunn and Dunn's learning style model, and Felder-Silverman's learning style model. The technological aspects discussed in this study include an overview of the Protus system, which is used as an example of how adaptive hypermedia and semantic technologies can be used in supporting personalized learning. The combination of user modeling and recent advances in technology highlights the limitations of both techniques when used in isolation. The limitations discussed in this study include ethical concerns, data privacy, and the lack of standardization in recommendations. The analysis ends with an overview of future research possibilities, such as using natural language processing in combination with adaptive personalization techniques.*

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

1. Introduction

In recent times, the construct of personalized learning has emerged with significant prominence in the literature on educational improvement and practice. Personalized learning is defined as the customization of learning content, instructional approaches, and delivery to match the needs, wants, and goals of an individual student [1]. In other words, while the traditional approach to teaching and learning is one-size-fits-all, personalized learning aims to address the diversity of students by recognizing their unique learning styles, learning experiences, and learning expectations [2, 3].

The academic interest in this domain is increasing at a markedly rapid pace. As of September 2025, a search on ScienceDirect for publications related to the terms "Personalized Learning" and "Recommendation Systems" indicates a substantial increase in publications over the last two decades (Figure 1). The publications for the year 2025 alone have exceeded 184 publications, compared to 15 publications in the year 2018 and merely 3 publications in the year 2003 (Figure 1). This indicates a rising interest in Educational Recommendation Systems (ERS) and the need for a comprehensive and structured review that addresses the models, efficacy, and integrative potential of ERS [4-6]. Educational Recommendation Systems (ERS) are a critical tool for the facilitation of personalization, and this is done with the help of user profiling and sophisticated algorithms [7]. The success of ERS relies on the accurate modeling of the user, including their learning style preferences, existing knowledge, and mental processing.

Adaptive e-learning systems are related to the advancements in data collection methods, the emergence of clustering methods, and the progression of educational data mining technology [8]. E-learning systems like Protus make use of semantic web technology and a modular design to automatically align the content with the learner's profile [6]. Empirical research indicates that personalization leads to increased learner motivation and interest, which are responsible for enhanced learning outcomes [9].

This research fills a gap in the existing literature by exploring the integration of theory-based foundations and implementation aspects of personalized recommender systems, as opposed to isolated research in user modeling and algorithm development. The existing literature lacks a systematically updated review of style learning theories and their association with existing recommender algorithms such as fuzzy clustering, neural networks, and hybrid filtering. As such, there is a deficiency in the existing understanding of the integration of machine learning and psychological theories in an adaptive learning environment.

The main aim of the review is to fill the existing gap by providing a systematic evaluation of user-centered (theory-based) and technology-centered (algorithm-based) aspects of personalized learning in an educational context. The review will cover existing style learning theories such as MBTI, Kolb, Dunn and Dunn, FSLSM, and existing systems such as Protus, as well as existing methods of recommendations. The existing issues and potential future prospects of hybrid models of personalized learning will be addressed. Through this approach, the study makes an important contribution to the synthesized body of research that can be used to inform the design and evaluation of recommender systems, especially those that require scalability-based personalization.

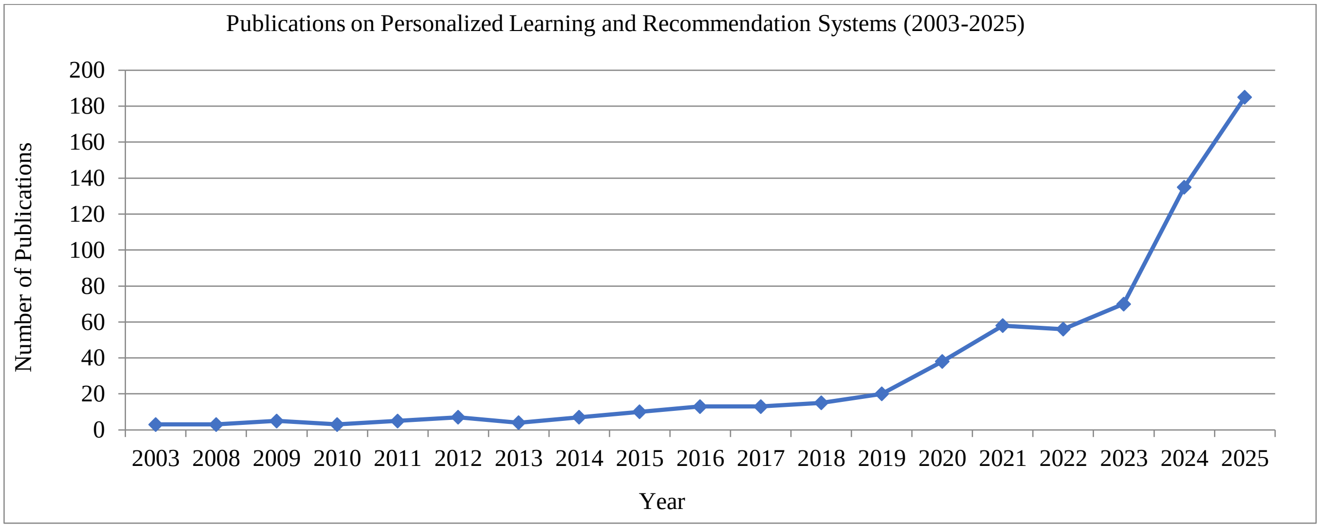

Fig. 1 Number of publications on "Personalized Learning" and "Recommendation Systems" in ScienceDirect (2003-2025, as of September)

2. Methods

Individualized learning continues to be one of the core elements of modern pedagogy, which seeks to cater to the requirements of individual learners by adapting and modifying the learning materials and methods according to their tastes, skills, and goals. This feature proves to be highly beneficial in online learning platforms where a large number of learners from diverse backgrounds are present. Conventional learning styles often fail to meet the requirements of different learning styles, experiences, and cognitive skills, making individualized learning a vital component of online instruction.

Significantly, the advancements in the field of personalized learning have been largely influenced by the ongoing developments in educational theory, technology, and data-based systems. On a general note, two major approaches have been identified in the context of personalization: the user-based approach and the technology-based approach [1].

In the learner-centered approach to personalization, the learner is considered the center of attention. As such, there is a need to take into consideration individual differences in terms of learning style, motivation, and prior knowledge. The defining feature of the learner-centered approach is the integration of comprehensive learner profiles, which may include information regarding prior academic achievement, current knowledge levels, learning objectives, and media preferences. The profiles allow for the grouping of learners based on cognitive and behavioral patterns, thereby allowing for more effective methods of instruction to be employed [10].

A good example of a user-centered approach is the Felder-Silverman Learning Style Model, which has been widely applied in adaptive e-learning environments due to its highly structured, scalable design [11]. Empirical research suggests that this approach significantly increases student motivation and interest when applied in learning environments [12].

On the other hand, the technology-based approach emphasizes the use of new computational tools such as artificial systems, machine learning, and data mining in the personalization process. Such systems are good examples of this approach, as they utilize probabilistic algorithms and semantic technologies to match the distribution of study materials with student profiles based on their observed behavior [13].

The most common functionalities that are usually available in education-oriented recommender systems that are compatible with a technology-centric approach are as follows [14]:

- Providing supplementary materials to fill gaps in knowledge;
- Providing personalized content to cohorts of learners based on their performance levels;
- Providing additional courses to best support individual learning paths.

While technological advancement remains at the heart of this approach, it remains contingent on access to quality data from learners. This requirement thus underscores the importance of a hybrid approach that incorporates user-centered and technology-centered approaches.

Current pedagogical recommendations are increasingly informed by a hybrid model, in which user-generated data such as historical performance, learning style, and objectives are processed via complex algorithms to produce unique outputs [15].

An overview of user-centered and technology-centered methodologies is discussed in the following subsections.

2.1. User-Centered Approach: Popular Learning Style Models

The issue of understanding the learning style of individual students constitutes a critical concern when developing effective personalized learning systems. Various theoretical frameworks have been widely used to identify and categorize the different learning styles of students, offering valuable insights into the manner in which students perceive and process information. Some of the most widely quoted theoretical frameworks regarding learning styles include the Myers-Briggs Type Indicator, Kolb's Experiential Learning Theory, and the Dunn and Dunn Learning Style Model.

2.1.1. The Myers-Briggs Type Indicator (MBTI)

The Myers-Briggs Type Indicator (MBTI) is a psychological test used to divide the personalities of individuals into one of sixteen different types, depending on their responses to different dimensions:

- Extraversion/Introversion (E/I)
- Sensing/Intuition (S/N)
- Thinking/Feeling (T/F)
- Judging/Perceiving (J/P)

Personality type definitions give one an idea about the perceptions of students, decision-making, and information acquisition. For example, sensing-oriented students might be interested in examples and applications, whereas intuiting-oriented students might be interested in theories and concepts. Knowing these cognitive styles can help teachers match their teaching styles with those of their students, which can increase their interest and understanding [16].

2.1.2. Kolb's Theory of Empirical Learning

David Kolb's Experiential Learning Theory (ELT) is based on a transactional, cyclical model of learning, comprising four successive learning steps:

- Concrete Experience
- Reflective Observation
- Abstract Conceptualization
- Active Experimentation [17]

As shown in Figure 2, following this model, effective learning occurs when all four steps of the experiential learning process are combined, resulting in the conversion of direct experience into structured knowledge. The ELT has been used to guide the development of learning environments, allowing for individualized instruction by identifying each student's optimum learning mode.

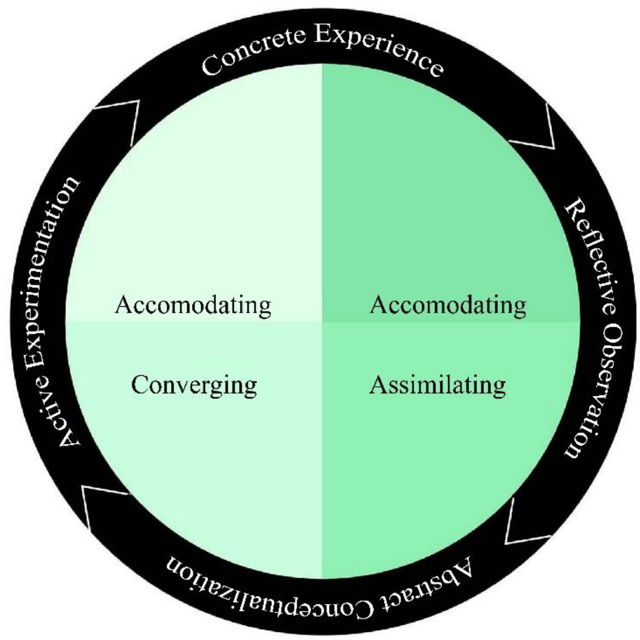

Fig. 2 The Experiential Learning Cycle and Four Learning Styles (adapted from Kolb) [18]

Based on the learners' distinct preferences, as reflected in this learning cycle, Kolb has identified the following main learning styles:

- Diverging: Learners with this style tend to have a talent for viewing situations from various points of view. These learners tend to be more reflective than active, with a greater inclination towards observation than engagement.
- Assimilating: This group of learners is more logical, with a greater emphasis on conceptual learning, a preference for abstract ideas, and a need to structure knowledge.
- Converging: These learners tend to have a problem-solving approach to learning, with a greater inclination towards technical tasks, displaying competence in applying ideas to real-world situations.
- Accommodating: Learners with this style tend to be more intuitive, experiential, with a need for active experimentation, a willingness to take risks, and to make quick decisions.

Kolb's theory provides an original model for personalized learning that has been developed through a series of theoretical and empirical refinements and validations within a wide range of teaching situations. To assist with the identification of learning styles, Kolb developed the Learning Style Inventory (LSI) to act as a diagnostic tool, which has been through a number of revisions to improve its reliability and validity. For instance, a study by Kayes (2005) assessed the internal structure of a revised LSI (versions 2A and 3) within a study of business students to evaluate the subject matter [19].

The ELT model has been subject to criticism regarding its applicability to real-world contexts and its theoretical underpinnings. For example, Morris (2019) suggested that the model should be adapted to highlight the role of contextually rich experiential encounters and reflexivity within the process [20]. Similarly, Seeman (2017) suggested a reconceptualization of experiential learning to address the complexities found within real-world contexts.

2.1.3. Dunn and Dunn Learning Styles Model

The Dunn and Dunn Learning Styles Model provides a comprehensive framework with 21 different factors that influence student learning styles. These factors are grouped into five major domains: environmental, emotional, social, physiological, and psychological stimuli (Table 1). The model suggests that the learning process should be adjusted to accommodate different learning styles in order to enhance student outcomes and the acquisition of knowledge [21]. The Learning Styles Inventory (LSI), which was created by Dunn and Dunn, serves as a diagnostic tool for determining individual student learning styles. Once this data is available, educators are encouraged to adjust their approach to teaching and structuring their lessons to meet the needs of their individual students. This approach is intended to increase student outcomes and satisfaction with their educational experience.

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

Category	Factors	Description
Environmental	Sound, light, temperature, and seating design	Conditions within the learning environment that affect focus and information retention.
Emotional	Motivation, persistence, responsibility, need for order	Internal emotional attributes that influence learning effectiveness.
Sociological	Individual learning, group learning, and authority figure interaction	Preferred social contexts for learning interactions.
Physiological	Visual, auditory, kinesthetic learning style, time-of-day preference, mobility needs	Sensory modalities and physical conditions that affect how information is best processed.
Psychological	Global (holistic) vs. analytic (detail-oriented) thinking styles	Cognitive processing styles that determine whether information is perceived holistically or sequentially.

The Dunn and Dunn model can be enhanced by the acknowledgment and incorporation of the multidimensional nature of learner variability. This not only makes the learning environment inclusive but also efficient.

2.1.4. The Felder–Silverman Learning Style Model (FSLSM)

In terms of learning style theories, the most popular and prominent model used is the Felder-Silverman Learning Style Model (FSLSM). This model is used because of its practical applicability and ease of understanding, especially when used in adaptive learning systems. A significant percentage of recent research on personalized learning systems, up to 72.5%, utilizes FSLSM as a major theoretical construct [22].

The framework was initially developed by Linda Silverman and Richard Felder in 1988. The Felder-Silverman Learning Style Model (FSLSM) categorizes students on four bipolar scales:

- Active vs. Reflective
- Sensing vs. Intuitive
- Visual vs. Verbal
- Sequential vs. Global

All four categories are related to specific cognitive and perceptual attributes that affect the way students receive, perceive, and understand information, as depicted in Figure 3. The Felder-Silverman model allows teachers to implement teaching methods that are more consistent with the student's cognitive style, thereby increasing understanding, motivation, and learning efficiency.

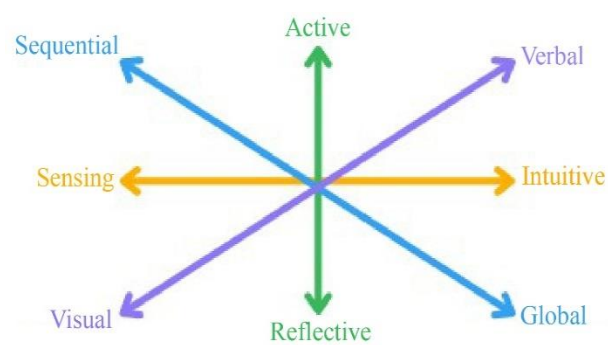

Fig. 3 The four dimensions of the Felder-Silverman Learning Style Model [18]

FSLSM offers a detailed description of learning style, unlike more general and classifiable concepts found in some models. Unlike Kolb's Experiential Learning Theory, which proposes a model of learning consisting of a four-part cycle, FSLSM offers differences along the following dimensions:

- Information processing (active vs. reflective),
- Information perception (sensing vs. intuitive),
- Information input modality (visual vs. verbal), and
- Information understanding (sequential vs. global).

This model offers individualization at a small scale, both in traditional and computer-assisted learning. From a practical perspective, it is interesting to note that FSLSM can be used to describe stimuli offered by rival models, e.g., active/reflective corresponds to Kolb's active experimentation and reflective observation, while sensing/intuitive relates to Jungian psychological typology.

Studies have proven that the application of FSLSM leads to a number of favorable outcomes in adaptive learning environments. For instance, Graf, Viola, and Leo (2007) established that e-learning environments developed with reference to FSLSM significantly improved learner satisfaction and learning outcomes [23]. The robustness of the model has been proven through extensive research in psychometrics. For instance, Zywno (2003) validated a revised Index of Learning Styles (ILS) instrument developed from FSLSM as a reliable diagnostic tool [24]. Felder and Spurlin (2005) also conducted extensive research on the applicability of the model across a broad range of disciplines and levels [25].

Considering the modular and integrative design of FSLSM, it is particularly suited for implementation in adaptive hypermedia environments such as Protus, an antecedent system for user modeling using FSLSM. The initial versions of Protus focused on identifying student preferences on the FSLSM dimensions and then delivering content in accordance. The system successfully supported Diverse learning styles through adaptive navigation and interactive learning objects, thus increasing student engagement and achievement. Considering its adaptability, empirical validity, and compatibility with methodological approaches to personalization in instruction, FSLSM is arguably one of the most valuable models in modern learning systems.

2.1.5. Theory and Practice

Despite the popularization of martianological learning style models, there are divergent views regarding the integration of these models into instruction design. However, research findings suggest that there is a need to align instruction methods with students' self-identified learning styles, which can result in improved academic achievement and motivation. In her meta-analysis, Lovelace (2005) showed that learning style-based education programs have a moderate to large effect on students' attainment; the effect size is also statistically significant [26]. Oweini and Daouk (2016) also examined the effect of learning style-based teaching on fourth-grade students with learning difficulties in language comprehension. They showed that teaching aligned with students' most suitable teaching modality significantly enhanced students' motivation and comprehension in reading [27]. Nevertheless, despite these positive findings, the implementation of the Dunn and Dunn model, especially with reference to learning styles, has been extensively evaluated. In this regard, there are issues with the complexity of the Dunn and Dunn model, especially with reference to the 21 factors included in the learning styles component of the model. In addition, issues with the reliability and validity of the Dunn and Dunn Learning Style Inventory (LSI) have been raised, especially with reference to inconsistent empirical support [28].

Learning style has been described as a "neuromyth," which is defined as "a popular but empirically unsupported assumption or belief." Learning style is an assumption that is not empirically supported but is nevertheless commonly held. In spite of the absence of empirical support for learning styles, many educators continue to support learning style instruction. For example, in a systematic review of the literature on learning style instruction, Newton and Salvi (2020) reported that despite the empirical evidence against learning style instruction, the level of support for learning style instruction by teachers remained high [29].

2.1.6. Integrating Learning Styles into Personalized Learning Systems

The integration of learning style models into adaptive and personalized learning environments offers an essential foundation for the implementation of learner-centered adaptive learning experiences. An individual learner's predispositions may be evaluated using standardized measures such as the Myers-Briggs Type Indicator (MBTI) or Kolb's Learning Style Inventory (LSI), thus facilitating an e-learning platform in meeting the cognitive and perceptual needs of the learner.

The alignment of learning style models with learner modeling not only facilitates an accurate learner modeling experience but also offers an essential foundation for learner motivation through the recognition of individual differences. Learning style differences defined by the MBTI, Kolb's Experiential Learning Theory, and Dunn & Dunn Learning Styles Model need to be recognized and strategically addressed for an effective learner-centered learning experience. The systematic implementation of learning style models facilitates educational institutions and e-learning practitioners in developing learner-centered learning approaches. By basing these approaches on empirical measurements of learner predispositions, learning experiences may be enhanced for the needs of contemporary learners.

2.1.7. Comparative Overview of Learning Style Models

Table 2 below is a summary of the prominent features of the most popular learning style models that have been reviewed in this paper.

The table is a comparison of the principal dimensions of these models, teaching strengths, weaknesses/limitations, and the instruments commonly used in implementing these models.

Table 2. Comparative Summary of Popular Learning Style Models

Model Name	Dimensions / Types	Advantages	Limitations	Tools / Inventories Used
Myers-Briggs Type Indicator (MBTI)	4 dichotomies: Extraversion–Introversion, Sensing–Intuition, Thinking–Feeling, Judging–Perceiving	Offers deep psychological profiling; widely used in education and business	Lacks strong empirical support in educational contexts; static classification	MBTI Questionnaire
Kolb's Experiential Learning Theory (ELT)	4 stages: Concrete Experience, Reflective Observation, Abstract Conceptualization, Active Experimentation; 4 styles: Diverging, Assimilating, Converging, Accommodating	Emphasizes learning as a cyclical process; dynamic and experience-based	Criticized for limited validity and over-simplification of complex behaviors	Learning Style Inventory (LSI)
Dunn and Dunn Learning Styles Model	5 categories with 21 factors: Environmental, Emotional, Sociological, Physiological, Psychological	Highly detailed and holistic; emphasizes environmental and emotional variables	Complex for implementation; some tools lack psychometric robustness	Dunn and Dunn LSI
Felder-Silverman Learning Style Model (FSLSM)	4 dimensions: Active-Reflective, Sensing-Intuitive, Visual-Verbal, Sequential-Global	High granularity; well-suited for adaptive learning systems; strong adoption in e-learning	May oversimplify learning preferences; primarily self-reported	Index of Learning Styles (ILS)

2.2. Technology - Centered Approach: Historical Foundations

2.2.1. Development of Recommendation System "Protus"

Protus (PRogramming TUtoring System) is one of the first intelligent tutoring systems that played an important role in the creation of modern intelligent learning recommendation systems [30]. Initially designed as a tool to help students learn the basics of the Java programming language, it was later developed as a prototype for modern adaptive e-learning platforms with integrated recommendation and adaptive hypermedia technologies.

The initial iterations of Protus focused on satisfying student preferences and offering personalized content through adaptive hypermedia. Various types of content and interactive materials were offered in accordance with the unique learning styles of the students, thus increasing student engagement and supporting multiple cognitive modalities. One of the major breakthroughs in the evolution of Protus was the development of Protus 2.0, which introduced ontology-based semantic recommendation techniques. The upgrade enabled the system to semantically describe both the learning resources and student profiles, thus making recommendations more contextual and precise [31]. The introduction of semantic web technologies represented a major leap in terms of both precision and personalization in the offered learning content.

The incorporation of tools for social tagging within the Protus 2.1 release allows for the creation of a shared knowledge base through the categorization of information with keywords. The tags developed by the students encapsulated a collective understanding regarding educational resources and aided in the refinement of recommendations through ratings obtained via surveys [32]. The incorporation of a social layer within the system, to address the changing needs and preferences of students, led to the incorporation of an adaptable component within the system. This led to a higher degree of responsiveness within the system. The modular nature of the Protus 2.1 release demonstrated its scalability and flexibility, thereby allowing for the incorporation of new personalized methods, additional learning content, and adaptation rules. This led to the updating of the system to accommodate emerging technologies and new requirements for instruction [33].

The progression of the system from its initial prototype to the current release, i.e., Protus 2.1, can be seen to have demonstrated the concept of personalized learning from a technological perspective as a dynamic process. The incorporation of semantic technology and collaborative intelligence within the system led to the creation of a basic prototype for an intelligent tutoring system that could adapt to a learner's individual profile, thereby increasing their motivation, performance, and relevance of the subject matter.

2.2.2. Adoption of "Protus" Architecture in Modern e-Learning Systems

A notable feature of Protus 2.1 is that it has a modular structure with different components, such as the learner model and domain ontology, among others. This structure allows for dynamic adaptation of content based on real-time observation of user interactions and their preferences. The modularity of this structure makes it highly advantageous in creating contemporary e-learning platforms.

Similar architectural concepts are found in different contemporary platforms. For instance, the WBT-Master learning management system utilizes the CDAT architectural model, which consists of controller, data, activity, and template layers. It supports the concept of separation of concerns and customization of learnable paths, similar to adaptability innovations applied in Protus [34]. Another long-lasting feature of Protus is the ontological modeling of learning content and learner profiles. Such semantic modeling allows for a more accurate evaluation of relationships between learning objects and learner goals, thus improving the accuracy and contextuality of content presentation to learners [35].

The social tags incorporated within Protus 2.1 feature as a vital component of modern systems. They allow students to provide tags for the material, which enables a body of metadata to improve the refinement of recommendation systems. This social feature encourages active participant engagement and supports collective knowledge development through an online learning experience. The application of modularity, semantic representation, and group-based features, along with modern adaptive e-learning systems, has increased their potential for providing learners with effective, efficient, and appropriate learning experiences [36].

2.2.3. Summary of the Technology-Centered Approach

The union of advanced computational technologies and adaptable system configurations has produced impressive changes in the technology of personalization. The initial technologies, such as Protus, incorporated adaptive hypermedia, semantic ontologies, and social tagging, thereby providing the foundation for current learning technologies.

The types of content and major components of the approach are:

- Flexible system architecture that can be extended to incorporate new learning strategies.
- Semantic student profiles and educational content to facilitate accurate student recommendations.
- Collaboration capabilities that utilize user information to enhance the quality of student recommendations by providing an environment that is conducive to collaborative learning.

The major components of such technologies are capable of adapting to individual students' interests, cognitive abilities, and knowledge levels, thereby increasing the power, motivation, and significance of online learning.

Despite all this, there are some challenges remaining, which are mostly related to the need for quality annotated data, ethical issues related to user profiling, and technical difficulties related to implementing algorithms of real-time adaptation. Nonetheless, technology-driven approaches continue to function as a major engine of e-learning infrastructures, facilitating data-informed personalization and scalability of learning interventions.

3. Results of the Complex Application of user-Centered and Technology-Centered Approaches

3.1. Educational Recommendation Systems

In the context of a Personalized Learning Environment, ERS operates as an interface between user-centric and technology-centric philosophies. ERS encompasses a broad range of capabilities, which can be summarized as follows:

- The delivery of content to individuals and groups.
- The scheduling of individual courses.
- The provision of auxiliary learning materials.
- The detection of knowledge gaps and the determination of appropriate remedial action.

ERS is expected to meet the variety of individual preferences, cognitive styles, and learning demands, while utilizing the capabilities of current technologies to automate and assist a personalized approach to instruction.

The user-centric component of Educational Recommender Systems (ERS) aims at creating detailed student profiles. The profiles combine different types of data, such as past learning experiences, objectives, attitudes and preferences, and behavior, to provide personalized recommendations that meet the unique needs of individual learners. On the other hand, the technological component utilizes data mining, machine learning, and artificial intelligence to process large volumes of data and provide real-time adaptive recommendations.

With the support of these two components, responsive learning environments allow contemporary ERSs to operate as dynamic systems. While the humanistic component ensures pedagogical relevance, the technological component provides scalability, accuracy, and adaptability. As a result, learners enjoy increased engagement, motivation, and academic performance.

The above discussion reveals critical features of ERSs, such as personalized learning, adaptive instruction, additional resources, and identifying knowledge gaps. This demonstrates the integration of instruction and cutting-edge computation in contemporary educational environments.

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

Adaptive e-learning systems utilize Educational Recommendation Systems (ERSs) to recommend learning content to learners, tailor their learning paths to ensure optimum performance, and support their learning with tailored feedback. Adaptive e-learning systems' functionality includes creating clusters of learners based on their goals, educational level, and/or learning styles to promote collaboration and co-learning. For instance, Bahargam et al. (2017) developed clustering algorithms that cluster students and their materials for large-scale online courses, which improved their learning outcomes significantly [37].

Apart from clustering algorithms, ERSs help learners develop their learning path by recommending appropriate courses and adapting their learning activities to match their prior knowledge and goals. Rahayu et al. (2022) conducted a systematic review that demonstrates the efficacy of learning path recommender systems in supporting learners as they progress through a sequence of content based on psychological and pedigree concepts [38].

Another prominent feature of ERSs is their capability to recommend additional materials for study, such as articles, videos, and exercises, based on the activities and predispositions of learners. According to Deschênes (2020), such systems enhance learners' autonomy and support learners in matching their goals with available learning materials in technologically mediated environments [39].

ERSs are also instrumental in identifying gaps in learners' knowledge and providing appropriate interventions. For example, Khosravi et al.'s (2017) RiPLE system identifies gaps in learners' knowledge as well as their interests to provide highly personalized recommendations, thus enhancing efficient and meaningful learning [40].

Adaptive e-learning systems, which utilize learning style identification and powerful recommendation algorithms, are now able to provide learners with highly personalized and engaging learning experiences. Such systems enhance learners' motivation, increase their ability to retain content, and support long-term learning that leads to academic achievement.

3.3. The Role of user Models

User models are an integral component of educational recommender systems, serving as a baseline for providing students with a tailored educational experience based on an individual student profile. The user model is normally based on several factors, including the student's learning styles, pre-experience, learning objectives, and demographic information. Learning styles are defined as the style in which an individual processes information, which can be visual, auditory, kinesthetic, or a combination of all three. The integration of learning styles is expected to improve student engagement and information comprehension by matching the information to the student's preferred style of learning.

Pre-experience refers to the knowledge and skills that an individual already possesses. The integration of pre-experience is expected to allow the system to recommend tasks that are challenging enough to prevent redundancy and are matched to the student's cognitive ability. For example, a student who is already conversant with the basics of programming is expected to gain more from higher-level tasks than from the basics [41].

The learning objectives, which cover the achievement of certain competencies or certifications, further personalize the recommendation process. In this regard, the recommendation engine would favor activities or content that directly correspond with a learner's declared objectives, thus improving the outcomes of goal-based learning [42].

Furthermore, age, education, and language proficiency provide another aspect of personalization. In this case, learners' objectives would be clarified by providing contextual information, which may influence learners' preferences or the availability of resources [43].

The building of custom models faces various challenges, the first of which is the mixed nature of learners' profiles, making it challenging to build a model of a learner. This is because of its generalist nature, focusing on students as learners. A model that is overly specialized may be too narrow and difficult to manage, while one that is overly general may not capture learners' most significant attributes.

The ever-changing nature of learning styles requires constant evaluation and updating of user models within the system. Real-time updating requires sophisticated monitoring technology and algorithms, hence the creation of more complex systems and an increase in the complexity required for computations.

Ethical considerations and data confidentiality are integral parts of the model. The collection and utilization of personal information have to comply with confidentiality regulations and ethical limitations on the scope of information collection, with strict adherence to consent protocols. Trust and transparency are essential components for any system to effectively model user behavior.

Furthermore, there are technical difficulties associated with developing a model from which a multidimensional dataset can be constructed to include information on user behavior, test scores, and demographics. Sophisticated data processing methodologies are required to ensure that the system works with quality datasets and provides reliable recommendations.

Scalability is another key challenge. The challenge in maintaining accurate user models for tens of thousands or even millions of users without compromising system performance arises from varying sizes of user bases and scalability requirements of e-learning systems.

These challenges need to be overcome to ensure further progress in educational recommendation systems. To ensure accurate user modeling, there is a need to amalgamate technical and ethical considerations and provide efficient, fair, and accurate personalized learning recommendations. The challenges and considerations in user modeling for e-learning are discussed in detail in the survey by Klašnja-Milićević et al. [41].

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

The beginning of the development of adaptive e-learning systems starts with data collection, which is used as a basis for choosing or creating a suitable recommendation algorithm. The quality of the collected data directly affects the adaptability of the e-learning system to the learner's requirements, hence improving learning outcomes. An important aspect of this process is identifying the learning style of a particular learner, which can be achieved using questionnaires, data mining, rule-based systems, or fuzzy logic.

In particular, questionnaire-based methods have been the most popular up to now, especially during the initial phase of implementing e-learning systems. In existing e-learning systems, data mining methods, including analyzing user interactions, become applicable, allowing for modeling learners' preferences.

3.4.1. Questionnaire-based Methods

The use of questionnaire-based methods has traditionally been viewed as an essential methodology for identifying learning styles within the framework of an educational system. These questionnaires, administered as pre-determined tools, have proved to be an essential source of information regarding the learning styles of students. The popularity of this methodology can be traced to its ease of use, accessibility, and flexibility. It is also highly appreciated by educators for facilitating the application of a variety of personalized learning techniques.

In this methodology, questionnaires have typically been developed to help identify students' emotional, cognitive, and behavioral characteristics. These questionnaires have helped students to be categorized according to their learning styles, such as reflective or active, visual or auditory, or analytical or global, based on the data received. This has helped to facilitate a more precise personalization of content to suit students' learning styles.

The advantages of this methodology can be identified as follows, as illustrated in Table 3:

Table 3. Advantages and Limitations of Questionnaire-Based Methods

Advantages	Limitations
Ease of implementation	Learners may misinterpret or inaccurately report preferences (Subjectivity)
Standardization	Fixed questionnaires may not reflect evolving learning needs (Static nature)
Scalability	Broad categorizations can oversimplify complex behaviors (Overgeneralization)
Adaptation	Some tools lack consistent empirical validation (Verification constraints)

Questionnaire-based methods have some advantages in terms of standardizing the collection of learner information, allowing for the efficient segmentation of large groups of students, and providing an initial foundation for more personalized interventions. The commodity-grade questionnaires, such as the Index of Learning Styles (ILS) and Kolb's Learning Style Inventory (LSI), have been heavily researched by scholars [44].

However, there are some disadvantages to the use of questionnaire-based methods. The results obtained by such methods can be based upon the respondent's interpretation of the results and can be influenced by the respondent's perceptions of the researcher's expectations. The results can be based upon a snapshot of the student's behavior, which is fixed and does not take into consideration the dynamic nature of the student's behavior. The results can be based upon an overgeneralization of the student's behavior, which is based upon a rigid classification of the student's behavior without regard to context. Further, while survey methods are used by many researchers, some of these methods do not have substantive research backing, which can limit the reliability of such methods across different population groups. In light of the disadvantages of the questionnaire-based methods, it is recommended that more dynamic methods of modeling student behavior, such as data mining, be used to improve the accuracy of more responsive methods of adaptive technologies.

3.4.2. Data Mining Approaches

Data mining provides an active and scalable approach to the identification of learners' learning styles, unlike the conventional methods that are based on questions. Data mining uses behavioral indicators such as time spent on activities, navigation, quiz answers, and frequency of usage to identify patterns that reveal learners' implicit tendencies and preferences.

For instance, learners who rewind and pause video materials may have a strong preference for visual learning, while learners who engage with interactive simulations may have a preference for kinesthetic learning.

For instance, several techniques are used in data mining to identify learning styles, such as:

- Clustering Algorithms: Clustering techniques, such as k-means clustering and hierarchical clustering, group students who show similar behavioral patterns, which often correspond to one of the learning style categories.
- Classification Techniques: Classification techniques, such as decision trees and neural networks, classify students according to predefined learning style categories, using historical student behavioral data [45].
- Association Rule Association rule mining creates rules to predict student behaviors, among other things.
- Sequential Pattern Analysis: The technique examines student interactions with content, such as reflexive learning, where students review content before an assessment.

Advantages of Data Mining Approaches

The main advantage of data mining is the potential for objective information to be provided in real time. In comparison with self-report methodologies that are potentially inaccurate and outdated, student behavior is updated automatically through data-driven models on which these approaches are based. This allows for real-time recommendations throughout the learning process.

In addition, data mining approaches are highly scalable and are potentially useful for online learning environments, such as MOOCs. They are also potentially easy to incorporate into adaptive learning environments that meet the varied activities of individual students [46].

Limitations and Challenges

Despite its advantages, data mining techniques face several challenges:

- Confidentiality and Ethical Concerns: The continuous collection of user data faces an ongoing challenge in terms of protecting user confidentiality and ensuring ethical considerations. These systems must comply with regulations such as GDPR.
- Technical Complexity: The application of effective data mining techniques requires knowledge in machine learning, data analytics, and software engineering, in addition to access to sufficient computer resources.
- Oversimplification of Patterns: The patterns learned may not necessarily represent an individual's practice in all cases or as it may change in their life context [47].

3.4.3. Rule-based and Fuzzy Clustering Methods

The clustering techniques are an important aspect of the data mining applications in education, as these help in classifying students on the basis of their behavior and creating clusters. The most commonly used clustering techniques include rule-based clustering and fuzzy clustering.

Fuzzy Clustering Methods

Unlike hard cluster-based approaches, which assign a learner to a specific cluster, fuzzy cluster-based methods allow a learner to show characteristics within multiple clusters. This offers a better and more accurate representation of the varied and sometimes overlapping nature of learners and their characteristics. For instance, a learner could show characteristics of a visual and a kinesthetic learner.

Fuzzy cluster-based methods have been found to be effective when used in educational settings where learners show ill-defined or dynamic preferences. The fuzzy C-means method is a popular cluster-based technique for finding ill-defined clusters. These methods are effective for developing a personalized experience for learners with complex and multidimensional student profiles.

However, fuzzy cluster-based methods have to be carefully tuned to ensure proper and accurate cluster formation. Incorrectly tuned parameters can result in ambiguous and incorrect cluster assignments. Moreover, fuzzy cluster-based methods have a lower interpretability compared to rule-based cluster methods, which could limit the educator's potential for taking corrective action.

Rule-Based Clustering Methods

Conversely, in rule-based clustering, students are grouped according to rules that are well specified and are based on if-then statements. Such rules could either be manually specified by experts in the domain or could be derived from data-centric approaches such as association rule mining.

The major advantage of rule-based clustering stems from its ability to provide clear explanations. Such clustering provides ease in terms of verification and modification of rules to ensure proper correspondence with instructional objectives. It also facilitates differentiation since conditions leading to a specific group are easily identifiable.

However, the efficacy of such clustering largely depends on the quality and comprehensiveness of the rules applied. For instance, simple rules might not adequately account for complex dynamics in student behavior and cognition. Such rules might also result in inappropriate groupings, thus negating personalization objectives.

The research described by [48] emphasizes the need to ensure that clustering schemes are chosen based on the level of specificity represented by the educational data sets. It illustrates the benefits of employing rule-based approaches, including ease of interpretation, while also noting the drawbacks of these approaches when not adequately addressed.

The research by Agrawal and Srikant on mining association rules, as described by [49], was a starting point for exploring meaningful relationships between different variables within a data set. This approach can be used to automatically develop rules for educational clustering.

Fuzzy and rule-based clustering approaches are critical for customization of learners within adaptive learning systems. Fuzzy clustering is useful for dealing with the fuzziness of representation, while the use of rule-based clustering provides a transparent approach to clustering. The use of a combination of these approaches or choosing the best approach based on the learning context can result in better outcomes for learners.

3.4.4. Fuzzy Clustering Techniques in Learning Style Identification

Fuzzy clustering techniques have been found to be effective tools in modeling complex, uncertain, and overlapping aspects of student learning behaviors in educational data mining. Unlike crisp clustering, in fuzzy clustering, data points, such as students, can simultaneously be members of more than one group. The ability of fuzzy clustering techniques to allow data points to simultaneously be members of more than one group is particularly useful in an educational setting, where it is likely for an individual to simultaneously possess characteristics of more than one learning style.

Fuzzy clustering techniques capture the dynamic nature of human learning. For instance, it is possible for an individual student to simultaneously possess strong visual and kinesthetic learning styles. Thus, it would be reductive to strictly classify such an individual. By allowing an individual student to simultaneously be members of more than one learning style category to a limited degree, fuzzy clustering techniques provide a more realistic modeling of student learning behaviors. Thus, it enables more personally relevant and substantively more effective instruction. Of all the fuzzy clustering techniques, Fuzzy C-means (FCM) clustering holds a prominent position. FCM clustering assigns a membership value to each data point for a cluster, thus identifying the degree of association between the learner and a specific group of learners with regard to a specific learning style under investigation. FCM clustering is highly relevant to developing adaptive e-learning systems that utilize the varied and dynamic natures of learners to enhance their learning experience by presenting content in a manner most suited to their requirements.

A study undertaken by Hogo (2010) proved the efficacy of FCM clustering in identifying online learners based on their requirements, as depicted by their activity profiles. The study established a match rate of 78%, thus showing that FCM clustering accurately captures online learners' behavior compared to traditional clustering techniques [50]. This shows the promise that fuzzy clustering holds in developing a system that can address issues in e-learning. The efficacy of FCM clustering was further established in a study undertaken by Elallui et al. (2018), where Internet usage was studied to identify learners' styles.

The authors later improved their system to develop a fuzzy classification model to validate their approach. The FCM database and server data were used to efficiently group learners according to their styles and thus facilitate adaptive learning [51]. Learning style classification according to learners' perceptions, as described by Honey and Mumford, was used to identify online learners' preferences with regard to FCM clustering, as described by Agbonifo et al. (2018). The study established the efficacy of FCM clustering in identifying learners' online learning styles and thus validating FCM clustering as a tool for developing adaptive e-learning systems [52].

However, there are some problems with Fuzzy C-means (FCM) clustering. First of all, it is known to be an effective technique, but it is very computationally intensive, especially if it is to be used with large educational data sets, such as those produced by MOOCs or university LMS systems. Secondly, it is found to be difficult for individuals who do not have formal knowledge of mathematical models to understand the results of FCM. Thirdly, it is found that the quality of the learning data used is an influential factor in the results of the FCM technique. FCM is found to be more vulnerable to a decline in the quality of results because of inappropriate parameter selection.

The fuzzy clustering technique is found to be able to reduce the inherent uncertainty and heterogeneity of learners. As such, it can be used to develop an adaptive learning environment that can enhance the results of the learning process by allowing for more interactive experiences for the students, which can lead to a higher level of subject matter expertise.

3.5. Algorithmic Requirements

The effectiveness of learning recommender systems depends on algorithms that analyze the information of the users to make appropriate learning recommendations that suit the behavior of learners. This can help to mitigate the limitations of the learning environment, as the objectives and interests of learners, particularly for new learning, can be divergent, yet they need to be addressed with regard to higher learning objectives.

One of the key factors of algorithms, particularly for remote sensing, is relevance and efficiency. This means that algorithms need to make appropriate recommendations to learners at the right time without creating infrastructural challenges to the system. This is particularly applicable to algorithms for collaborative filtering, which is based on the behavior of humans while also considering the interests of other learners with similar interests [45].

Scalability is a key aspect, particularly for algorithms to be applied to MOOC environments, as it involves a huge number of learners. This is particularly applicable to algorithms such as matrix factorization, as it can help to reduce dimensions for real-time recommendations to learners [53].

Adaptability represents another fundamental attribute. This attribute is a result of realizing that there is a need to change over time. In this case, algorithms and decision trees are appropriate, as they are used in scenarios where there is a change over time concerning students' requirements, with adaptable and hierarchical structures defining students' objectives [54].

As a result, there is a need for a learning system to enable real-time learning. Reinforcement learning algorithms, as well as algorithms based on recurrent neural networks, enable the system to improve its learning with each interaction, hence allowing adaptation of recommendations according to students' responses [55].

In view of the uncertainties and incompleteness of training datasets, remote sensing initiatives must be robust despite the presence of missing information. This can be achieved through algorithms that can work effectively despite the presence of uncertain and/or incomplete information, such as fuzzy clustering algorithms and Bayesian networks [45].

Finally, interpretability is seen as an important factor. Transparency is essential for building trust in educational settings. While deep learning approaches (for example, neural networks) may be optimal in terms of accuracy, if not transparent, then they may not be applicable in cases where teachers and students need an explicit understanding of the rationale for a recommendation. In such cases, less complex approaches such as k-nearest neighbors (k-NN) or rule-based approaches are more desirable because of the explicit nature of the recommendation logic [56]. In order to provide an overall summary of the trade-offs between the most popular Educational Recommender System (ERS) approaches, Table 4 provides an overall comparative summary of the main performance characteristics.

Table 4. Comparative Summary of Algorithms

Algorithm Type	Accuracy	Interpretability	Scalability	Adaptability
Collaborative Filtering	High	Medium	High	Medium
Matrix Factorization	High	Low	Very High	Medium
Decision Trees	Medium	High	Medium	High
Ensemble Methods	High	Medium	High	High
Reinforcement Learning	Very High	Low	Medium	Very High
Recurrent Neural Networks (RNNs)	Very High	Low	High	Very High
Fuzzy Clustering	Medium	Medium	Medium	Medium
Bayesian Networks	High	Medium	Medium	High
k-Nearest Neighbors (k-NN)	Medium	High	Low	Low
Rule-Based Systems	Medium	Very High	Low	Low

3.6. Recommender Algorithms in E-Learning

Recommender systems are the core component of Educational Recommendation Systems (ERS), which help learners have a personalized experience with the help of recommendations for educational materials and methods that match the learner's profile. The systems analyze a variety of information related to the learner, such as behavior, preferences, and goals, to increase learner engagement and retention. Various types of recommender systems are used for e-learning platforms, each with its pros and cons.

Content-Based Filtering (CBF) is one of the simplest forms of recommendation systems for educational content. This approach works on the assumption that the learner will be interested in learning materials that are similar to the ones he/she has liked or accessed previously. In CBF, learner profiles are used along with item attributes to provide recommendations. Text analysis algorithms like Term Frequency-Inverse Document Frequency (TF-IDF) and Cosine Similarity are commonly used while implementing CBF recommendation systems [57].

CBF is said to work best in scenarios where there is an abundance of metadata available for both the learning content and learner profiles. However, CBF faces the drawback of over-specialization, wherein the recommendation may become too narrow and mundane, thereby restricting the learner experience. Collaborative Filtering (CF) is a widely accepted standard methodology that, while providing recommendations, focuses on identifying patterns within a group of users. Unlike traditional approaches, CF does not take into account content attributes, focusing instead on user activities. CF is broadly classified into two categories:

- User-Based CF, which offers recommendations based on identifying users with similar interaction patterns [58].
- Item-Based CF, which offers new items based on similarities to previously accessed items.

The CF methodology offers varied and appropriate recommendations. However, it faces a major drawback, known as the cold start problem, which arises when new users or items, with limited interaction, need to be recommended. This drawback can be addressed only to a certain extent by using pedagogical metadata and learner profiles together.

Hybrid Recommender Systems have emerged with increased recognition to address the limitations associated with singular methods. Hybrid Recommender Systems combine two or more methods, including Content-Based Filtering (CBF) and Collaborative Filtering (CF), and can further include other methods like demographic filtering, knowledge-based systems, and machine learning-based methods. Hybrid Recommender Systems can be defined as:

- CF-CBF (Collaborative Filtering and Content-Based Filtering)
- CBF-X or CF-X, where X can be Demographic Filtering, Data Mining (DM), or Machine Learning (ML).

Hybrid Recommender Systems leverage the power of each component to improve the quality and accuracy of recommendations and increase user satisfaction. Hybrid Recommender Systems are best suited for a dynamic e-learning environment, where data are collected from multiple sources like quizzes, courses, discussion forums, and student activities. Empirical studies have confirmed that hybrid systems perform much better compared to other methods with respect to effectiveness and student engagement.

To summarize, e-learning recommender systems need to balance personalization, diversity, scalability, and robustness. While content-based and collaborative filtering methods have inherent advantages, a hybrid model is more comprehensive to meet the diverse needs of learners, which is a typical aspect of modern electronic training environments.

4. Comparative Analysis of Educational Recommendation Approaches

Empirical evaluations of the efficacy of different educational recommender systems have been conducted. In one such study, Graf et al. [23] integrated the Felder-Silverman Learning Style Model into an adaptive learning scenario and found that it resulted in increased student satisfaction by 14%, with tangible performance improvements in terms of assessment results compared to traditional content presentation methods.

Bahargam et al. [37] used clustering techniques to cluster students in a MOOC setting, aiming to provide individualized learning content. The system resulted in an increase in completion rates and improved student performance, particularly among those who were not as proficient in the subject matter.

Another study on an educational recommender system, called RiPLE, developed by Khosravi et al. [40], showed that it was possible to identify knowledge gaps in learners as well as their interests, thus increasing the quality of peer recommendations in peer learning.

The above examples demonstrate the capabilities of user modeling combined with intelligent algorithms. It is difficult to compare different systems, as there are different evaluation criteria, target groups, and infrastructures used. Table 3 shows a summary of the main advantages and disadvantages of the most popular recommendation methods.

The present survey provides a technical and theoretical integration of personalized learning systems, although it does not provide new empirical research or experiment-based evaluation. Further research should be based on extensive experiments, including comparative research, user trials, or simulation-based experiments.

5. Research Methodology

This study aims to perform a structured literature review to evaluate the current state of Educational Recommendation Systems (ERS) developed to enable personalization within the educational domain, with specific emphasis on ERS developed for school-going ages. This study, like previous literature reviews such as Kidanemariam's investigation into the impact of learning styles and materials on academic performance for preparatory school students in Ethiopia, aims to build upon the synthesis of previous research. This study hopes to address the emerging need for personalization within the educational domain by facilitating a holistic integration of models, algorithms, and user modeling within the current ERS.

In order to maintain methodological consistency, this review follows the guidelines for conducting a well-structured literature review, particularly for the domain of educational technology. Literature for this review has been retrieved from a database consisting of five main academic networks, namely Scopus, Web of Science, IEEE Xplore, Springer Link, and Google Scholar. The search strategy for this review consists of a combination of the following terms: “educational recommendation system,” “personalized learning,” “adaptive learning,” “learning styles,” “student modeling,” and “hybrid recommendation”.

The article selection process involved three steps:

1. Evaluation of relevance to the topic based on title and keyword filtering.
2. Abstract-level filtering to check for articles that are not related or do not have sufficient detail.
3. Full-text filtering to check for articles that have sufficient methodology, direct relevance to personalization within learning systems, and the inclusion of evaluative data or system design.

Out of this process, sixty quality articles were identified for use in the subsequent analysis.

Each of the selected studies is analyzed to identify its main specifications of the proposed system or model. The main specifications of ERS are as follows:

- Recommendation algorithm type (content-based, collaborative, or hybrid);
- User model structure (learning styles, prior knowledge, or motivation);
- Technological basis (fuzzy clustering, semantic representation, or neural networks).

Moreover, where possible, there was documentation of information concerning system evaluation procedures, including accuracy, user behavior, or learning outcomes. Thematic synthesis was used to classify systems and methods, with the objective of identifying major trends, research gaps, and effective ways of using Educational Recommender Systems (ERS) to personalize education.

6. Research Questions

To assist in the systematic review and to facilitate a more focused analysis, the following research questions have been identified:

1. What forms of personalized learning are currently employed in school recommendation systems?
   This research question is intended to provide an overview and classification of the different forms of personalization techniques employed to personalize learning content and learning experiences to meet the needs of individual learners.
2. How do learners’ individual characteristics feature in these educational recommendation systems?
   This research question is intended to provide an understanding of how learning styles, preconditions, learners’ motivational factors, and learners’ demographic factors feature in these educational recommendation systems and the role they play in personalizing learning experiences for learners.
3. What hybridization techniques have been developed to improve the flexibility and accuracy of educational recommendation systems?
   This research question is intended to provide an understanding of the different forms of hybridization techniques employed to improve the accuracy and flexibility of educational recommendation systems, which results in better performance in ERS.
4. How do educational recommendation systems feature in the provision of adaptive learning for school learners?
   This research question is intended to provide an understanding of the localization of ERS to meet the needs of learners in the school context.

7. Discussion

Personalized learning has developed along a spectrum of conceptual and technological models, which may be broadly categorized as user-centric, technology-centric, and mixed models.

The learner-centric models are based on the individual attributes of learners, which include style, experiences, goals, and preferences. The main idea of these models is to deliver learning material in a manner that is compatible with the cognitive and emotional requirements of learners, with the objective of enhancing learners’ motivation and productivity.

The technology-centric models depend on various technologies of machine learning, including deep learning and data mining, to carry out automatic processes of personalization, which allow individual learners to gain access to and interact with products and/or services.

Hybrid models, in their turn, are designed to bring about an amalgamation of the advantages of distinct approaches through the combination of user modeling and algorithmic analytics. As such, it can be concluded that such models bring about an effective compromise between meaningful, human-centric design and automated personalization, thus allowing for an effective and more engaging learning environment.

Key functional components necessary for the effective functioning of a personalized learning system:

- Comprehensive user modeling;
- Adaptive content delivery;
- Real-time tracking and feedback, identifying knowledge

gaps;
- Learner autonomy;

An important prerequisite for deep personalization is scalability, accompanied by continuous adaptation of referents. The application of hybrid recommender systems, which bring about an amalgamation of content-based filtering and collaborative filtering, is particularly beneficial in such an instance. The application of real-time monitoring, in combination with machine learning, further enhances the system's adaptability.

Algorithmic bias is one of the major concerns in the development of recommendations in an educational setting. Such biases may arise from performance-related data or learners' usage metrics used in the system, underlying assumptions in the algorithmic framework, such as the assumption of linear development of human skills from simple to complex tasks, or major differences in user profile data.

Algorithmic environments may be biased towards educationally successful learners or against those who are part of underrepresented groups. Finally, "black-box" algorithmic configurations may not help educators to grasp the underlying logic of particular algorithmic recommendations. To mitigate algorithmic bias, it is not sufficient to simply develop algorithmic guidelines. Instead, it is necessary to design interventions to improve the development of such guidelines.

In addition, it is necessary to take into consideration ethical aspects, such as data confidentiality, informed consent, and transparency, in the design of personalization mechanisms. Trust in the system is of primary importance in an educational setting, in which learners and teachers must trust the system.

Five main factors affect the efficiency of recommendation systems in the electronic learning domain. These factors are:

1. Relevance;
2. Accuracy;
3. Scalability;
4. Transparency;
5. Security;

Suitable combination and adaptation of these factors in accordance with the particular domain can lead to the development of efficient adaptive e-learning systems. The efficiency of properly applied educational recommendations can be quite substantial.

8. Conclusion

The current study provides a thorough examination of theoretical frameworks, personalization methods, and algorithmic approaches used within ERS for personalizing learning. It assesses the effectiveness and limitations of both user-centered and technology-centered perspectives and illustrates the potential for learner attributes, including learning styles, goals, and mental activities, to be formally constructed for improving the flexibility of online learning tools.

An examination of some of the most popular learning style models and recommendation algorithms is presented by analyzing the differences between each model or algorithm with regard to scalability, interpretability, and accuracy. The Felder-Silverman Learning Style Model (FSLSM), for example, is one of the most popular theoretical frameworks due to its systematic derivation and applicability to real-world scenarios.

The Protus system, for another example, illustrates the potential for modular systems and semantic technologies to improve the flexibility of online learning tools. Table 3 offers a summary of the most important trade-offs for each algorithm with regard to real-world applicability.

While it is based on existing knowledge from the relevant literature, it does not include original research in the form of empirical research experiments and system evaluation. The practical viability of the presented models and algorithms will need to be further validated. The realization of truly adaptive and impactful Educational Resource Systems (ERS) still faces several critical challenges:

- Ethical and privacy concerns related to data collection, user profiling, and transparency of algorithms used;
- The risk of algorithmic bias, which might result in the perpetuation of educational inequality and the use of incomplete and/or biased information to draw unfair inferences.
- The lack of evaluation frameworks and algorithmic benchmarks;
- The lack of integration of real-time personalization mechanisms to dynamically respond to changing user profiles.

To this end, it is recommended that future research should focus on developing hybrid approaches that combine learning analytics, natural language processing, and behavior monitoring technologies. Such approaches should be highly scalable and have explainability and ethical compliance to ensure trust and a significant impact on learners' performance.

Learning recommendation systems have tremendous potential to revolutionize online learning environments. This is because such systems have the ability to match learners with their needs and preferences, thus making online learning personalized, inclusive, and efficient, especially in online and large-scale environments.

Conflicts of Interest

The authors declare that there are no conflicts of interest related to the publication of this article.

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