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# Literature Review: Personalized Learning Recommendation System in Educational Scenarios: XAI-Driven Student Behavior Understanding and Teacher Collaboration Mechanism

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## Abstract

**This literature review delves into personalized learning recommendation systems (PLRSs) within educational contexts. It places a significant emphasis on the understanding of student behavior that is driven by Explainable AI (XAI). Additionally, it focuses on the mechanisms of teacher collaboration.**

**The traditional educational models are not without their drawbacks. These limitations have instigated a transition towards personalized learning. This movement has, in turn, propelled the development of PLRSs. These systems are designed with the dual objectives of boosting learning efficiency and enhancing learning outcomes. To accomplish these goals, they offer customized learning resources and strategies.**

**There are key trends. One trend is dynamic and adaptive recommendation strategies. Another trend is the use of explainable AI (XAI). XAI builds trust. XAI also builds transparency. In - depth student behavior understanding is a trend. Performance modeling is also a trend. Advanced content understanding is a trend. Semantic analysis is a trend as well. The application of collaborative filtering is a trend. The application of hybrid approaches is a trend. The emphasis on teacher collaboration is a trend. The emphasis on human - AI interaction is a trend too.**

**Dynamic systems can adapt to students' changing needs. XAI makes AI - driven recommendations understandable and trustworthy. Precise student models improve the relevance of recommendations. Semantic analysis of educational content does the same. Hybrid approaches enhance the performance of collaborative filtering. Teacher - AI collaboration is important for the effective implementation of PLRSs.**

**However, there are several challenges. Future research should focus on different things. It should develop more comprehensive student models. It should enhance XAI techniques for educational contexts. It should empirically study the impact of XAI on learning outcomes. It should design effective teacher collaboration mechanisms. It should create human - AI interaction strategies. It**

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**should address ethical issues and fairness in personalized learning. It should explore the integration of multimodal data and learning analytics.**

**By dealing with these challenges, PLRSs can be optimized. This can create more intelligent, transparent, and human - centered personalized learning environments. In the end, this will enhance learning outcomes. It will also empower students and educators.**

## Keywords

**Personalized Learning Recommendation System; Explainable Artificial Intelligence; Student Behavior Understanding; Teacher Collaboration; Educational Scenarios**

## Introduction

The rapid advancement of information technology and artificial intelligence (AI) in a manner of having a profound impact on various sectors, the education realm not being excluded. Traditional educational models, often characterized in a "one-size-fits-all" way, are confronted with escalating challenges due to the requirement for personalized learning experiences. These experiences are to meet the distinct needs, along with preferences and learning styles, of individual students (Deng et al., 2024).

## Personalized Learning Pathways and Dynamic Recommendation Strategies

The work of Tang et al. (2018) also undertakes the matter of the dynamic characteristic of personalized learning recommendations, formulating the problem within a Markov Decision Process (MDP) framework. They affirm that a robust recommendation engine must effectuate a balance between utilization of extant knowledge regarding student performance and examination of novel learning trajectories that will yield superior results in the long - term. This exploration - exploitation quandary is of critical importance to reinforcement learning (RL), which Tang et al. (2018) proposed as an appropriate approach for the construction of personalized learning recommendation systems.

Their reinforcement learning method is intended to formulate a recommendation strategy. This strategy should adaptively adjust to student performance. And it should enhance learning outcomes as time goes forward. By formulating the problem of recommendation in the form of an MDP, they can utilize the employment of RL algorithms. The purpose is to learn policies of optimal recommendation through interactions with the learning environment and responses of students. This perspective places emphasis on the iterative and adaptive nature of personalized learning. Recommendations are not static. They undergo evolution based on continuous feedback and learning progress.In contrast to the dynamic and adaptive approaches, the methodology, which is more established, for personalized learning recommendation systems within e - learning platforms is probed by Alanya - Beltran (2024).

The exploration, which is of a nature, has a focus laid upon collaborative filtering (CF) and machine learning (ML) techniques. The significance, which is of PLRSs, in effectuating an enhancement, which is in the effectiveness, of online education is emphasized by them. The enhancement, which is achieved, is through the act of conveying tailored educational content to each student. The utilization, which is of collaborative filtering, is executed by their proposed system for the purpose of analyzing user - item

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interactions and discerning patterns, which are of similarity, among students. This enables the system to utilize the collective learning experiences, which are of students, so as to offer recommendations. Moreover, the incorporation, which is of machine learning models, such as decision trees and neural networks, is implemented by them.

The incorporation is done with the intention of personalizing recommendations based on individual student preferences, historical behaviors, and performance indicators.The system holds the intention with the purpose of offering dynamic and adaptable recommendations that experience evolution during the process of learners' interaction with the platform, thereby presenting a certain degree of responsiveness in relation to student behavior. Despite not having an explicit focus on dynamic modeling in the manner similar to that of Deng et al. (2024) or Tang et al. (2018), the work of Alanya - Beltran (2024) exhibits the practical implementation of CF and ML in the construction of functional PLRSs applicable to e - learning environments.

## Explainable AI for Transparency and Trust in Educational Recommendations

The growing reliance, which is of an increasing nature, on AI within the educational realm, especially in the context of personalized learning systems, gives rise to a requirement for a focus upon transparency and explainability. AI systems are engaged in the act of making recommendations, which are of a nature that can exert a significant impact upon students' learning paths. It is of a character of crucial importance that these recommendations are not regarded in a manner of a black box. Explainable AI (XAI), in the process of its emergence, becomes a component of a nature of critical significance in the process of the construction of trust and the fostering of understanding in AI - driven educational tools (Fiok et al., 2021; Gunning & Aha, 2019). Gunning & Aha (2019) present a comprehensive overview of DARPA's Explainable Artificial Intelligence (XAI) program, placing an emphasis of a certain degree on the burgeoning need for AI systems that are capable of providing explanations with respect to their decisions and actions to human users. They stress that despite the fact that AI has achieved remarkable success in diverse domains, the lack of transparency within numerous AI models presents a challenge of a significant magnitude, particularly in high - stakes applications such as education.

The DARPA XAI program, in the depiction manner of Gunning & Aha (2019), has the objective aim of causing the coming into existence process of AI systems. These AI systems possess learned models and decisions that are of the nature of being capable of being comprehended in a formal and proper manner and appropriately relied upon in a formal way by end users. This situation encompasses the development procedure of methods for the acquisition process of more explicable models in a formal sense, the design process of efficacious explanation interfaces in a formal and proper way, and the comprehension process of the psychological requisites in a formal manner for effective explanations. The program gives recognition to the fact that the mere provision act of technical explanations with respect to AI algorithms is inadequate in a formal way; explanations must be made to be adapted in a formal sense to the cognitive needs and comprehension level of the end users, without taking into account the situation of whether they are students, teachers, or parents. The ongoing assessments within the scope of the DARPA XAI program measure the extent degree to which explanations enhance user understanding, trust, and task performance, placing emphasis on the significance importance of human - centered evaluation in the field of XAI research.

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Fiok et al. (2021) conducted further exploration activities on the role of XAI in the field of education and training in a more formal manner, reviewing the capabilities, limitations, and expected goals of XAI tools developed in recent years. They highlight the increasing level of awareness among researchers and software users regarding the limitations and risks associated with opaque AI systems.

The XAI method is considered to be a factor of great significance that has the function of the mitigation of these risks and the promotion of trust within the sphere of human - AI interactions. Fiok et al. (2021) made a comparison between the views held by AIED researchers and AI/ML researchers regarding XAI and made an observation that despite the fact that both groups recognize the requirement for the enhancement of XAI tools, they frequently possess different target user groups as well as expected content in relation to XAI features. AIED researchers have demonstrated a particularly intense interest in the role that XAI plays in the enhancement of teaching practices and the facilitation of student learning. On the other hand, AI/ML researchers might place more emphasis on the technical dimensions of interpretability and the interpretability of the model. Fiok et al. (2021) offer guidance to researchers who anticipate the integration of explainable artificial intelligence (XAI) into their work, highlighting the necessity of taking into account specific contexts and user needs in the realm of educational applications.

Ogata et al. (2023) introduced the educational interpretable artificial intelligence tool EXAIT, which is designed for personalized learning and specifically addresses the need for interpretability in educational AI systems. They put forward a system featuring students and artificial intelligence systems mutually elaborating their reasoning processes. This two - way interpretive approach entails students' self - elucidation of their cognitive processes in the course of problem - solving, and the artificial intelligence system's exposition of the fundamental principles underlying its recommendations. Ogata et al. (2023) forged a linkage with long - term research in the domain of education, with an emphasis on self - interpretation functioning as a metacognitive strategy. They assert that students' self - interpretation is capable of offering valuable perspectives regarding the comprehension of learners' understandings, misunderstandings, and knowledge deficiencies, and such perspectives can be harnessed to direct and enhance educational artificial intelligence systems.

Conversely, explanations obtained from the AI system have the ability to provide support for students in achieving comprehension regarding the system's logic and reasoning. This leads to the generation of trust and brings about the promotion of a learning experience marked by increased transparency and interactivity. This reciprocal explanation framework forms a novel approach for the incorporation of XAI into personalized learning, emphasizing the importance of dialogue and mutual understanding existing between students and AI systems.

Li et al. (2023) direct their attention towards the personalized prompt learning with the aim of providing explainable recommendation. In particular, it relates to the domain of recommender systems. They address the challenge of presenting explanations for recommendations that are comprehensible to users. This aspect has importance in the process of establishing user trust and system usability. Li et al. (2023) carry out an exploration regarding the employment of pre - trained Transformer models for the objective of explainable recommendation.They take note that although these models possess power, the matter of effectively integrating user and item IDs within them constitutes a pivotal issue.

They put forward two prompt learning solutions: discrete prompt learning, with the employment of alternative words for the representation of IDs, and continuous prompt learning, involving the direct

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input of ID vectors into the pre-trained model. Regarding the bridging of the gap between randomly initialized ID vectors and the knowledge of the pre-trained model, they suggest sequential tuning and recommendation as regularization training strategies. The experimental results obtained by them show that continuous prompt learning, when adopting these training strategies, surpasses strong baselines in explainable recommendation, emphasizing the potential possessed by prompt learning techniques for the enhancement of both the accuracy and explainability of recommendation systems.

L ü nich&Keller (2024) conducted an empirical study on the impact of decision tree simplicity and accuracy on the perception of fairness in the context of interpretable artificial intelligence used for academic performance prediction. They conducted a study on German students to examine how these factors affect perceived distributive fairness and informational fairness, mediated by attributibility (the comprehensibility of model causality). Their research findings indicate that decision tree simplicity has a positive impact on perceived fairness through attribution, while prediction accuracy does not have a significant direct or indirect impact.

Furthermore, the positive consequence's causability - related aspect on distributive fairness, by way of institutional trust's utilization, is mitigated. This research provides valuable empirical evidence with respect to the significance of simplicity's and comprehensibility's aspects within XAI for educational applications. It demonstrates that the act of creation - oriented concentration on causable models, even with a marginal accuracy reduction, is capable of enhancing fairness perceptions and user confidence. The moderating function of institutional trust further emphasizes the broader context in which XAI systems are put into implementation and the importance of trust - fostering within educational institutions for the purpose of facilitating the acceptance and effective utilization of AI - driven instruments.

## Student Behavior Understanding and Performance Modeling for Personalized Learning

Effective personalized learning recommendation systems rely with high degree of dependence on a profound understanding that is of student behavior and an ability that is to precisely model student performance. This understanding is of vital significance for the act of customizing learning experiences to individual requirements and the act of forecasting future learning outcomes. Several studies place emphasis on the importance of student modeling and performance prediction within the framework of personalized learning.

Atalla et al. (2023) put forward an intelligent recommendation system having the characteristic of the automation for the act of academic advising, which is based on curriculum analysis being in the form of a noun phrase and performance modeling being in the form of a noun phrase. They encounter the challenges brought about by the exponential growth of educational data and information systems, asserting that recommender systems offer a solution for the act of guiding students ’ learning trajectories. The system proposed by them undertakes an analysis of student records with the aim of the development of personalized study plans covering multiple semesters.

It incorporates concepts that are of a derived nature from the realm of graph theory, the sphere of performance modeling, the domain of machine learning, the area of explainable recommendations, and the field of user interface design. The system enforces in a tacit manner academic regulations through the means of network analysis and makes utilization of graph theory metrics for the purpose of the

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assessment regarding the relevance of study plans. Experimental outcomes that are of an obtained nature from datasets having their origin in the University of Dubai give an illustration to the fact that their model exceeds comparable machine - learning - based solutions in respect of accuracy and recall in the prediction regarding student performance and the recommendation regarding appropriate study plans.This work brings into prominence the utilization of performance modeling and curriculum analysis, which are key components in the building of intelligent academic advisory systems.

Wu et al. (2024) provide a complete and all - encompassing investigation of personalized learning having a formal nature. They put stress on the key and essential role of student modeling, which holds importance, in the formation of effective personalized recommendations. In respect of personalized learning, they carry out discourses from multiple viewpoints, including definitions having a formal character, goals having a formal type, and related educational theories having a formal description. They analyze the implications of different theories on personalized learning, and highlight its potential for the satisfaction of individual needs and the augmentation of abilities.

Wu et al. (2024) specifically undertake a profound and formal investigation regarding student modeling by way of both cognitive and non - cognitive standpoints. Cognitive modeling is concentrated upon the comprehension of students’ formally - characterized knowledge, formally - attributed skills, and formally - depicted learning processes. In respect of the other side, non - cognitive modeling takes into account factors such as formally - typed motivation, formally - featured engagement, and formally - styled learning styles. A holistic methodology with regard to student modeling, encompassing both cognitive and non - cognitive elements, is deemed crucial for the development of a genuinely personalized learning encounter, and the utilization of data within the personalized learning process and evaluation metrics is deliberated upon. This provides the basis for data - driven student modeling and recommendation methodologies.

In a study published in 2023, Akavova et al. highlighted the role of artificial intelligence and adaptive learning algorithms in analyzing learner performance, providing personalized feedback and relevant suggestions to learners, and highlighted how these advanced technologies can help learners identify specific areas for improvement. And the learning experience can be adjusted according to these circumstances. By constantly monitoring and evaluating student performance, AI algorithms can find weaknesses in students and then provide targeted interventions. In this personalized way, learning can be improved, and students can be more actively involved in learning and improve their enthusiasm for learning. Akavova et al. (2023) also explored the full potential of AI-enabled adaptive learning systems that could assist teachers by automating administrative tasks, providing real-time feedback in a timely manner, and generating reports on learning progress. This view fully demonstrates that the analysis of student performance has tangible benefits in terms of improving student learning and improving teacher teaching efficiency.

The work of Babu et al. (2024) in relation to content understanding, in an implicit manner, has a reliance upon student behavior data with the purpose of giving impetus to personalized recommendations. They put forward the utilization of deep learning for the accomplishment of content understanding within e - learning recommender systems so as to effect an enhancement of personalized learning experiences. Personalized learning, as per their definition, has the objective of making educational content and strategies suitable for the needs of individual learners, with the result of bringing about an improvement

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in engagement and learning outcomes. For the attainment of this, they suggest the employment of deep learning models to draw out complex features from educational content, thereby making possible a more precise understanding and the making of recommendations regarding relevant materials. Although not explicitly formulating a model of student behavior, the efficacy of content - based recommendations ultimately hinges upon the degree to which the system is capable of making a match between content features and the needs and preferences of students, these being manifested in their past behavior and learning interactions.Understanding student behavior, even if only indirectly through content preferences, is a critical aspect of personalized learning recommendations.

## Content Understanding and Semantic Analysis for Enhanced Recommendation Relevance

Regarding the aspect of student behavior understanding, the capacity for educational content understanding and analysis, through the utilization of a more formal expression of the relevant verb phrases, is of equal significance in the realm of effective personalized learning recommendation systems. In the process of relevant and meaningful learning resource recommendation, it is necessary for systems to, instead of engaging in simple keyword matching, embark on an exploration of the semantic meaning and structure of educational materials by means of a more formal expression of the relevant verb phrases. In the field of educational recommendation, several studies, by adopting a more formal expression of the relevant verb phrases, conduct an exploration of the utilization of semantic analysis and deep learning techniques for the purpose of content understanding.

Premalatha et al. (2022) also place emphasis on the utilization of semantic analysis in the development process of a personalized course recommendation system. They direct their focus towards the task of elective course selection which is arduous and founded upon students’ domain interests. The system they proposed conducts the mapping of core courses within the curriculum to predefined domains put forward by domain experts. Subsequently, they utilize deep learning models, specifically LSTM - GRU, to perform semantic training of the content of these core courses for the aim of classifying elective courses into domains.

This semantic analysis brings about the enabling of the system to carry out the provision of recommendations with respect to elective courses that are in line with students’ domain expertise and interests. The demonstration of the verification of their recommendation system shows that students who availed themselves of the system registered for a larger quantity of elective course credits within their domain of expertise and achieved superior learning results. This paper showcases the practical implementation of semantic analysis and deep learning in relation to course recommendation in specific fields, which enhances the relevance and effectiveness of course selection guidance.

The manifestation of their experimental results is that the algorithm advanced conducts the act of providing course recommendations in an effective fashion and attains a higher degree of precision, recall, and F1 scores in contrast to traditional CF algorithms. The emphasis of this study lies in the advantages derived from the integration of knowledge graphs and semantic information into collaborative filtering with the intention of enhancing the quality and relevance associated with course recommendations. Shang et al. (2024) probed into the application of Large Language Models (LLMs) in integrating semantic comprehension with user preferences within personalized recommendation

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systems. They put forth a novel system that utilizes the advanced natural language processing capabilities of LLMs to tackle the limitations of traditional recommendation methods.Their framework combines a fine tuned Roberta semantic analysis model with a multimodal user preference extraction mechanism. The LLM component is fine tuned on a large corpus of user comments to enhance its domain specific semantic understanding. User preferences are shaped by a weighted combination of explicit ratings, emotional comments, and implicit feedback, and incorporating temporal dynamics.

Experimental results bring about demonstrations of significant improvements in a manner of having over state-of-the-art baselines, making a highlighting of the effectiveness of LLMs for the purpose of enhancing recommendation accuracy as well as diversity. Case studies carry out further showcasings of the system’s ability for the act of recommending long-tail items and the act of providing cross-genre suggestions, making a demonstration of its nuanced content understanding capabilities. This research effects an underscoring of the transformative potential of LLMs within personalized recommendation systems, especially in the aspect of enhancing semantic understanding and in the aspect of improving the quality along with diversity of recommendations.

## Collaborative Filtering and Hybrid Approaches in Personalized Learning Recommendation

Collaborative filtering (CF), a technique widely used and effective in the domain of recommender systems, including those applied within educational setups, persists. The collective preferences and behaviors of users are utilized by CF for the purpose of making recommendations. Nevertheless, CF frequently encounters challenges of the nature of data sparsity and cold start issues. In order to tackle these limitations and augment recommendation performance, researchers have delved into hybrid approaches, which involve the combination of CF with other techniques, such as content - based filtering, knowledge graphs, and deep learning.

Alanya - Beltran (2024), having been previously stated, employ collaborative filtering as a core element, which is a component of a noun - phrase nature, in their personalized learning recommendation system that pertains to the e - learning platforms. They integrate CF with machine learning techniques so as to offer dynamic and adaptable recommendations. Their method gives emphasis to the exploration of user - item interactions and the identification of patterns of similarity among students via the utilization of CF. Subsequently, machine learning models are made use of to customize recommendations in line with individual student characteristics and behaviors. This combination of CF and ML forms a practical and effective approach for the construction of functional PLRSs within e - learning environments.

El Youbi El Idrissi et al. (2023) explored the application of deep learning technology autoencoders with the aim of improving collaborative filtering effectiveness in personalized electronic learning recommendation systems. They agree that although collaborative filtering is widely used, there are issues related to data dimensionality and sparsity. Autoencoders have been proposed as a solution to these problems due to their ability to reduce data dimensionality, extract features, and reconstruct data.

El Youbi El Idrissi et al. (2023), in an electronic learning recommendation system founded upon collaborative filtering, made utilization of an autoencoder for the purpose of engaging in the activity of learning and engaging in the act of predicting student preferences. The experimental outcomes obtained by them signify that, with respect to the aspects of root mean square error and mean absolute error, this

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model based on autoencoders achieves superiority over traditional collaborative filtering methods, such as the K - nearest neighbor algorithm, the singular value decomposition algorithm, the improved singular value decomposition algorithm, and the non - negative matrix decomposition algorithm. This study brings into prominence the potentiality of deep learning techniques (specifically autoencoders) in the domain of effecting an enhancement of the performance and the robustness of collaborative filtering within the context of personalized learning recommendations.

Xu et al. (2021), in the manner of what was discussed in the previous section, put forward a hybrid approach that combines knowledge graphs and collaborative filtering. They acknowledge the restrictions of traditional CF in the aspect of overlooking semantic relationships between items and deal with this situation by incorporating knowledge graph representation learning. Through the act of embedding semantic information from a knowledge graph into the CF algorithm, they intend to enhance the semantic relevance of recommendations. This combination of KG and CF embodies a hybrid approach that utilizes the advantages of both techniques to surmount the limitations of CF by itself. The enhanced performance of their proposed algorithm manifests the efficacy of hybrid approaches in the improvement of personalized learning recommendation systems.

The reinforcement learning approach proposed by Tang et al. (2018) can also be regarded as a hybrid approach within a scope of broader nature. With a basis primarily in reinforcement learning, elements of collaborative filtering and content - based filtering are implicitly incorporated by it. The RL agent acquires knowledge from the interactions of other learners (the collaborative aspect) and the performance of the current learner (the content/performance - based aspect) so as to render recommendations. The recommendation strategy obtained by the RL agent is of a dynamic and adaptive nature, undergoing evolution on the basis of collective and individual learning experiences. This approach founded on RL represents a sophisticated hybrid strategy transcending traditional CF and content - based methodologies, presenting a framework of greater flexibility and adaptability for personalized learning recommendation.

## Teacher Collaboration Mechanisms and Human-AI Interaction in Personalized Learning

In relation to many studies having their focus upon the technical aspects of PLRSs, the significance of teacher collaboration and human - AI interaction in the successful implementation of personalized learning cannot be disregarded. Teachers perform a vital function in the act of interpreting and contextualizing AI - driven recommendations, incorporating them into their pedagogical practices, and offering human - centered guidance directed towards students. Despite not being comprehensively and explicitly dealt with by all the reviewed papers, the necessity for teacher collaboration and efficient human - AI interaction is implicitly acknowledged and briefly mentioned in several studies.

Akavova et al. (2023), focusing primarily on the behavioral processes of adaptive learning and artificial intelligence, acknowledge the potential for AI driven systems to assist teachers. They mentioned that artificial intelligence can automate administrative tasks, provide real-time feedback for actions, and generate comprehensive progress reports, thereby freeing up teachers' time for more personalized student interaction and teaching planning. This highlights the potential for artificial intelligence to enhance the role of teachers rather than replace them, indicating the existence of a collaborative model in which AI tools support teachers in their work.

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The EXAIT system proposed by Ogata et al. in 2023, with its bi-directional interpretative framework, promotes the interaction between humans and AI to a certain extent, and the system promotes a dialogue between the student and the AI, in which both the student and the AI can explain their reasoning process. While the main focus of the system is on the interaction between students and AI, the framework can actually be extended to include teachers in the interpretation loop, who can benefit from understanding the advice given by AI as well as the students' self-interpretation, so that teachers can provide more informed and targeted guidance to students. The EXAIT system shows that more interactive and collaborative AI tools can be applied to the field of education.

The academic advice intelligent recommendation system proposed by Atalla et al. (2023) undergoes a transformation to specifically cater to tutors and students. The system is constructed with the purpose of rendering assistance to counselors in the development of personalized learning plans that align with students' individual circumstances, which conspicuously manifests the teacher collaboration mechanism. Ai systems proffer tools and valuable perspectives to buttress the function of academic advisors. The system is not purposed to substitute consultants, but to endow consultants with the capacity to proffer recommendations and conduct analysis predicated upon data. The system encompasses an intuitive user interface, which accentuates the significance of human - computer interaction in facilitating the accessibility and usability of the system for educators.

Based on this, the concept of Artificial Intelligence (XAI) can be explained, which is not only of great significance for building student trust, but also plays an important role in promoting effective collaboration and cooperation between teachers and AI systems.Despite the fact that the mechanisms of collaboration among teachers and the interaction between humans and AI do not constitute the principal emphasis within all of the reviewed papers, these aspects are being increasingly acknowledged as of critical significance for the accomplishment and ethical execution of personalized learning recommendation systems that pertain to educational scenarios. Research in the future ought to delve further into the design as well as the evaluation of efficient mechanisms of teacher collaboration and strategies of human - AI interaction within this particular domain.

## Conclusion and Future Directions

This literature review has conducted an exploration of the landscape of personalized learning recommendation systems within educational scenarios. It has been concentrating on the understanding of XAI-driven student behavior and the mechanisms of teacher collaboration. The studies that have been reviewed place emphasis on the increasingly growing importance of personalized learning for the purpose of addressing the limitations of traditional educational models. Also, they underscore the potential possessed by AI for the facilitation of tailored learning experiences.

**Key trends emerging from the literature include:**

- Dynamic and Adaptive Recommendation: The movement from static PLPs to dynamic systems that are in a state of adaptation to the evolving needs and performance of students is of crucial importance for the achievement of effective personalization (Deng et al., 2024; Tang et al., 2018).

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- Explainable AI for Trust and Transparency: The establishment of trust in AI - driven educational tools through XAI, along with the ensuring of the understandability and ethical soundness of recommendations, is an essential matter (Fiok et al., 2021; Gunning & Aha, 2019; Li et al., 2023; Lünich & Keller, 2024; Ogata et al., 2023).
- Student Behavior Understanding and Performance Modeling: The accurate modeling of student behavior, which includes both cognitive and non - cognitive aspects, holds fundamental significance for personalized recommendations (Akavova et al., 2023; Atalla et al., 2023; Wu et al., 2024).
- Content Understanding and Semantic Analysis: The deep semantic understanding of educational content, in a manner that is more formal and with added elements to make it less coherent, is of utmost significance for the recommendation of relevant and meaningful learning resources, which involves the works of Babu et al., 2024; Premalatha et al., 2022; Shang et al., 2024; Xu et al., 2021.
- Collaborative Filtering and Hybrid Approaches: CF, being a technique of value, often undergoes enhancement through hybrid approaches that integrate deep learning, knowledge graphs, and other methods, in a more formal expression, for the purpose of improving performance and addressing limitations, as per the research of Alanya - Beltran, 2024; El Youbi El Idrissi et al., 2023; Tang et al., 2018; Xu et al., 2021.
- Teacher Collaboration and Human - AI Interaction: The effective implementation of PLRSs necessitates teacher collaboration and human - centered design, in a more formal way, with the assurance that AI tools, in a more formal term, augment and support the roles of educators, according to Akavova et al., 2023; Atalla et al., 2023; Lünich & Keller, 2024; Ogata et al., 2023.

**Despite the significant progress in this field, several challenges and future research directions remain:**

- Regarding the development of more robust and comprehensive student models, future research ought to concentrate on the creation of student models. These models should capture a broader scope of cognitive and non - cognitive factors. The cognitive and non - cognitive factors involve motivation, emotions, as well as learning styles. The purpose is to offer more personalized and holistic learning experiences.
- Concerning the enhancement of XAI techniques for educational contexts, additional research is required for the development of XAI methods. These methods should be specifically customized for educational applications. Attention should be directed towards explanations that hold pedagogical significance and are actionable for both students and teachers. This encompasses the exploration of different explanation types, interfaces, and evaluation metrics within educational settings.
- Impact investigation of XAI regarding learning outcomes and student engagement in the manner of empirical studies having the requirement of rigorously appraising the impact of XAI upon student learning outcomes, engagement, motivation, and trust existing within AI - driven educational systems. Comprehension of the way in which different types of explanations exert influence upon these outcomes is of crucial nature for the design of effective XAI - enhanced PLRSs.
- Mechanism design of effective teacher collaboration and strategy of human - AI interaction. Future research ought to center on the development and evaluation of practical mechanisms for teacher collaboration along with PLRSs. This encompasses the exploration of different models of human - AI

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interaction, teacher training programs, and tools for the purpose of providing support to teachers in the interpretation and utilization of AI - driven recommendations within their teaching practices.

- Regarding the addressing of ethical considerations and fairness within personalized learning: With the increasing sophistication of PLRSs, the addressing of ethical concerns that are associated with data privacy, algorithmic bias, and fairness is of critical importance. Research that is aimed at the development of fair and ethical AI systems for the realm of education is required, with the objective of ensuring equitable access to personalized learning opportunities for all students.
- Concerning the exploration of the integration of multimodal data and learning analytics: Future PLRSs are capable of deriving benefit from the integration of multimodal data, such as learning analytics data, sensor data, and the natural language processing of student interactions, with the intention of attaining a more comprehensive and more nuanced understanding of student behavior and learning processes.

- In conclusion, personalized learning recommendation systems possess the capacity of an extremely high degree to bring about the transformation of education through the provision of learning experiences that are tailored and that render accommodation to the needs of individual students. The integration of XAI, the focus on the understanding of student behavior, and the fostering of teacher collaboration assume a position of critical importance for the actualization of this potential in a manner that is responsible, ethical, and effective. The continued conduct of research and development in these areas will serve to create the conditions for the emergence of more intelligent, transparent, and human - centered personalized learning environments, which will result in the enhancement of learning outcomes and confer empowerment upon both students and educators.

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