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Systematic Review of AI and Non-AI Approaches for Personalized Learning Paths

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Abstract

/Personalized learning paths (PLPs) have emerged as a promising strategy to enhance student outcomes. These paths tailor educational content, pace, and assessment methods to meet individual student needs and learning styles, promoting deeper engagement and better knowledge retention. In this paper, we survey and analyze existing solutions, both AI-driven and non-AI approaches. AI-based methods leverage techniques such as machine learning, natural language processing, and recommender systems to dynamically adapt learning experiences. At the same time, non-AI solutions rely on rule-based systems, instructor-driven customizations, and predefined learning sequences. By comparing these approaches, we highlight their strengths, limitations, and applicability in the university STEM context. Our analysis aims to provide researchers, educators, and policymakers with insights into the current landscape of personalized learning path development and guide future research directions for integrating AI responsibly and effectively in higher education.

Keywords
Personalize Learning Path, Education, Knowledge Forest, Large Language Models, User Profiles

1. Introduction

The rapid evolution of Artificial Intelligence (AI), particularly the emergence of Large Language Models (LLMs), is transforming many fields, including higher education. One of the most promising applications of LLMs lies in the development of Personalized Learning Paths (PLPs) (Hu et al. 2024), particularly in Science, Technology, Engineering, and Mathematics (STEM). PLPs aim to tailor educational experiences to match the unique needs, preferences, and capabilities of each student, enabling more effective learning journeys. LLMs have the potential to play a central role across the entire PLP development pipeline, from the creation of domain-specific knowledge representations to the delivery of customized learning materials.

A critical first step in building a PLP is constructing a knowledge graph (or knowledge forest) that captures the structure of a course's content. This graph defines the key concepts, their interdependencies, and the logical progression a student should follow to master a subject (Ji et al. 2021). For example, in an Operating Systems course, the knowledge graph would represent topics such as process management, memory management, file systems, synchronization, and scheduling, showing how each concept builds upon the others. LLMs, with their advanced natural language understanding and generation capabilities, can assist in the automatic construction and refinement of such knowledge graphs. By analyzing course syllabi, textbooks, and lecture materials, LLMs can extract concepts, identify prerequisite relationships, and create modular learning paths that adapt to different levels of prior knowledge. In parallel, student profiling is a key element of personalized learning.

Understanding how students prefer to engage with course materials, whether through video lectures, interactive simulations, or traditional readings, as well as identifying their learning styles, cognitive strengths, and areas of difficulty, allows the system to further tailor their learning experiences. LLMs can help construct dynamic student profiles by analyzing learning management system (LMS) interactions, quiz performance, discussion forum contributions, and even direct feedback provided by students. These profiles evolve continuously, capturing both long-term learning preferences and short-term changes in engagement or comprehension (Sarkar et al. 2021). The integration of the knowledge forest with student profiles is where LLMs can add significant value. Thus, by matching students' current positions within the knowledge graph with their personal preferences and learning needs, LLMs can curate and recommend the most appropriate materials (Amin et al. 2023).

For some students, this may involve offering simplified explanations with extra scaffolding, while for others, it might mean providing advanced exercises or links to cutting-edge research papers. Importantly, LLMs can also adapt instructor-provided content to meet individual needs, enrich explanations, generate visual aids, summarize complex sections, or even transform text into videos, animations, or interactive exercises. This dynamic content generation not only addresses students' cognitive gaps but also maintains engagement by tailoring material to their preferred formats and challenge levels. Finally, seamless integration with Learning Management Systems (LMS) such as Canvas ensures that personalized materials are delivered just-in-time, appearing within the familiar learning environment of each student (Cai et al. 2019). By acting as a personalized content curator and tutor, the LLM continuously adjusts the materials, pace, and type of content delivered to each learner as they progress through the knowledge forest.

This paper explores the potential of LLMs to revolutionize personalized learning paths in STEM education by supporting every stage of the PLP pipeline: from building the knowledge graph to profiling students to dynamically adapting and delivering personalized learning content. Through this exploration, we highlight both the opportunities and challenges in integrating LLMs into university-level STEM education, including issues related to content accuracy, cognitive bias, instructor oversight, and the ethical implications of algorithmically shaping students' educational experiences. This exploration is carried out by surveying existing solutions, both AI-based and non-AI approaches, for the construction of PLPs. We review methods for building knowledge graphs, creating student profiles, and dynamically adapting educational content. By comparing traditional rule-based systems, instructor-led customization techniques, and the latest AI-enhanced methods, this survey provides a comprehensive overview of the current landscape, highlighting the opportunities, challenges, and future directions for personalized learning in STEM.

2. Review Strategy

To conduct a comprehensive review of personalized learning paths, we employed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach (Page et al. 2021), where we systematically analyzed research papers from five prominent academic databases; IEEE Xplore, ScienceDirect, PubMed, ACM Digital Library, and SpringerLink. These databases were selected because of their extensive coverage of research in education, artificial intelligence, and adaptive learning systems. A structured search strategy was used to identify relevant

literature with publication years ranging from 2021 to 2024. The strategy consisted of three major parts; applying the search query to the relevant databases, removing duplicate documents, and filtering based on inclusion and exclusion criteria. Table 1 summarizes the inclusion and exclusion criteria. The search query focused on the titles, abstracts, and key terms of the papers. Books, magazines, dissertations, review articles, and news reports were excluded.

Table 1. Inclusion and Exclusion Criteria

Inclusion Criteria		Exclusion Criteria
1.	conference proceedings, journal articles	1. books, magazines, and chapters
2.	well-defined framework or algorithm	2. theoretical/conceptual without empirical validation
3.	dedicated to higher education	3. review paper or survey rather than original research
4.	published in English	4. not published in English

We reviewed each article with regard to its relevance to the field of education, and the selected articles must have a well-defined framework or algorithm for the personalized learning or recommendation system and demonstrate effectiveness with test datasets. The five databases generated a total of 851 articles. 243 from SpringerLink, 20 from PubMed, 27 from ACM Digital Library, 122 from Science Direct, and 439 from IEEE Xplore. The total number of retrieved articles was 633 after duplicate articles from several databases were removed. 21 articles were finally selected after the articles had been reviewed using the inclusion and exclusion criteria.

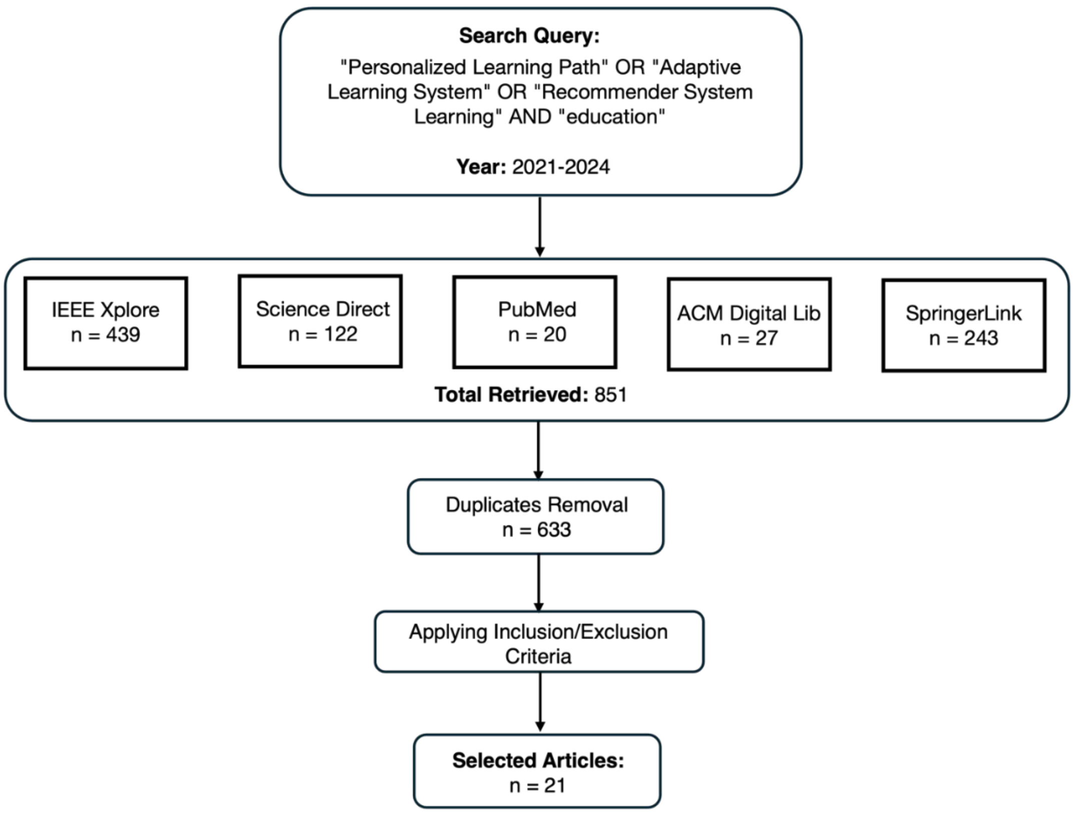

Figure 1. an overview of the review strategy.

3. Research Results and Literature Review

3.1 Personalized Learning Paths with AI

In this subsection, we discuss some papers that have leveraged the power of Artificial Intelligence in advancing PLP systems.

The Adaptive Learning Path Navigation (ALPN) system by Chen et al. (2023) integrates attentive knowledge tracking (AKT) to dynamically assess students' knowledge states and entropy-enhanced exponential policy optimization (EPPO) to optimize the recommendation of learning materials. Unlike traditional learning paths (Guri-Rosenblit and

Sarah 2005), the ALPN continuously updates learning paths based on real-time student performance, mitigating issues of learning disorientation and cognitive overload (Sun et al. 2008).

The experimental results show that the ALPN improves learning outcomes by 8.2% compared to previous models and offers a 10.5% increase in the diversity of the learning pathway, contributing to greater engagement and adaptability. The ALPN system builds on knowledge trace (KT) research, which aims to predict students' future performance based on historical interactions. Earlier KT models, such as Bayesian Knowledge Tracing (BKT) (Mayer et al. 2003) and Deep Knowledge Tracing (DKT) (Piech et al. 2015), lacked the ability to capture complex learning dynamics. The paper adopts Attentive Knowledge Tracing (AKT), which uses attention mechanisms to provide a more nuanced assessment of students' knowledge states (Ghosh et al. 2020). Furthermore, the system incorporates deep reinforcement learning (DRL) techniques (Lecun et al. 2015; Arulkumaran et al. 2017), specifically an improved version of Proximal Policy Optimization (PPO) (Schulman et al. 2017). This EPPO model improves exploratory learning by balancing short-term performance with long-term knowledge retention. Compared to previous reinforcement learning-based learning path optimization models (Cai et al. 2019), ALPN shows superior stability and efficiency in recommending learning materials.

Gao et al. (2023) explored the integration of large language models (LLMs) into recommender systems to enhance interactivity, explainability, and adaptability. Traditional recommender systems often struggle with challenges such as lack of user engagement, difficulty in explaining recommendations, and the cold-start problem for new users or items. The Chat-REC framework proposed by Gao et al. (2023) leverages LLMs such as ChatGPT to process user profiles and historical interactions as prompts, allowing dynamic context-sensitive recommendations. This approach allows the system to refine suggestions based on conversational feedback, improving personalization and making recommendations more interpretable. For their top 5 recommendations, the Normalized Discounted Cumulative Gain (NDCG) scores of the three GPT-3.5 models surpassed the baseline models (LightFM and LightGCN) with a score of 0.3802 (11.01%) higher than the baseline models.

Sajja et al. (2024) introduced an AI-powered Virtual Teaching Assistant (AIIA) system that integrates advanced AI, natural language processing (NLP) and large language models (LLM) to create an interactive and adaptive learning platform. The system aims to reduce cognitive load by offering real-time assistance, personalized learning pathways, quiz and flashcard generation, and automated assessment tools. The AIIA framework builds upon previous research in AI-based educational tools, including Virtual Teaching Assistants (VTAs) (Essel et al. 2022) and AI-enhanced learning environments (Huang et al. 2021). The system incorporates NLP models based on GPT-3.5, leveraging techniques such as short-shot learning, text embeddings, and cosine similarity for query interpretation and response generation. Additionally, Automatic Speech Recognition (ASR) technology (Whisper API) is used to transcribe and analyze classroom recordings, enabling multimodal learning support. Unlike previous chatbot-based tutoring systems (Neumann et al. 2023), AIIA focuses on context-aware responses and adaptive learning strategies, ensuring students receive highly relevant and structured educational support.

Nan Li (2025) explored how big data analytics and AI can improve personalized English learning. The study proposed a personalized learning path optimization model that incorporates collaborative filtering based on neural networks, cognitive level diagnostics, and dynamic learning path generation. This approach tailors learning sequences based on individual learner characteristics, such as knowledge background, mastery levels, and learning behaviors, ensuring more effective and targeted English language instruction. The research highlights that students who followed the optimized learning paths saw a significant improvement in performance, with experimental class scores increasing by 25.82 points, demonstrating the effectiveness of data-driven personalization. It integrates collaborative neurocognitive filtering, which refines learning recommendations by incorporating cognitive state analysis of the learner. In addition, a cognitive level diagnostic layer assesses the learner's proficiency, dynamically updating recommendations to suit individual progress. The study also applies hybrid collaborative filtering algorithms to overcome the limitations of traditional recommendation systems, such as data sparsity and cold start problems. The model proposed in the paper achieved the best NDGC@K metric performance of 0.352 and 0.465 on the ML-100K and ML-1M datasets respectively.

Hu and Wang (2024) introduce the FOKE (Forest of Knowledge and Education) framework designed to enhance personalized and explainable learning experiences by using large language models (LLMs), knowledge graphs (KGs) and prompt engineering to provide adaptive and interactive educational support. A key innovation of FOKE is the hierarchical knowledge forest, which structures domain knowledge dynamically, improving the organization and retrieval of educational content (Ji et al. 2021). Also, the framework employs multidimensional user profiling to tailor learning pathways based on individual learner characteristics, capturing learner attributes, behaviors, and learning trajectories (Bernacki et al. 2021). The paper demonstrates the applications of FOKE in programming education, intelligent homework assessment, and personalized learning path planning, showcasing its effectiveness in creating structured, personalized, and engaging learning experiences (Singla et al. 2021). Graph embedding techniques are used to integrate knowledge representation and user modeling, ensuring that learning recommendations remain contextually relevant (Singla et al. 2021). FOKE places a strong emphasis on explainability, allowing both learners and educators to understand the reasoning behind content recommendations and assessments. The Scholar Hero system, an implementation of FOKE, has been tested in real-world educational settings, highlighting the practical benefits of the framework (Devlin et al. 2019; Rajpurkar et al. 2016)

Sarkar and Huber (2021) introduced a framework that personalizes learning paths by leveraging Reinforcement Learning (RL) and Conditional Generative Adversarial Networks (CGANs). The approach seeks to optimize learner performance while minimizing direct student interaction during the system's training phase. By simulating student characteristics using CGANs, the model reduces the need for real-time student feedback, thereby minimizing negative experiences due to suboptimal learning paths. The system is built on the Felder and Silverman Learning Style Model (FSLSM) and Differentiated Pedagogy, ensuring that learning materials align with individual learning styles. This research highlights how AI-driven simulations can improve personalization in e-learning platforms, making them more adaptive to individual students' needs. The model consists of two main components: an RL-based learning path optimizer that selects the best learning objects (LOs) and a CGAN-based student simulation agent that mimics learner behavior. By training RL agents with synthetic learner profiles, the framework identifies optimal learning paths without excessive reliance on real student interactions. This approach infers student learning preferences (Graf et al. 2007), making it more seamless and adaptive. In addition, CGANs generate realistic learner behaviors based on limited observed data, improving the system adaptability compared to static learning path generation methods (Goodfellow et al. 2014). The experimental results indicate that the use of CGANs significantly reduces the number of real student interactions required, improving both learning efficiency and student satisfaction.

Amin et al. (2023) presented a system that personalizes learning paths using Reinforcement Learning (RL) and Markov Decision Processes (MDP). The system is designed to optimize student engagement and learning outcomes by dynamically adapting educational content based on student interactions. This framework uses Q-learning and sequential path recommendations (SPR) to provide real-time personalized learning paths. Experimental findings show that the system outperforms traditional methods by maximizing long-term learning rewards while minimizing frustration and disengagement. The proposed model consists of two key components: a reinforcement learning agent using Q-learning to optimize learning sequences and a state-transition mechanism based on MDP that determines the best educational content recommendations. The framework captures learner behaviors through sequential learning patterns, dynamically adjusting the difficulty of courses based on student progress (Pang et al. 2018). The system includes a reward-based feedback system, where students receive positive reinforcement for completing learning tasks and penalties for disengagement, aligning with previous work in RL-based recommender systems (Xian et al. 2019).

Yazdi et al. (2024) designed a recommendation system to improve personalized learning by predicting students' interests in educational resources. The model integrates BiLSTM (Bidirectional Long Short-Term Memory) networks to capture both long-term and short-term user interests, ensuring that recommendations remain relevant over time. The study demonstrates that BiLSTM’s gradual learning feature helps accommodate students' evolving interests, leading to an accuracy of 0.9978 and a loss value of 0.0051, making it superior to traditional filtering-based recommendation approaches. It integrates attention mechanisms to weigh user interactions based on time-sensitive factors, ensuring that recent behaviors have a stronger influence on recommendations. The system also incorporates Recurrent Neural Networks (RNNs), Multi-Layer Perceptrons (MLPs), and Gated Recurrent Units (GRUs) to refine the recommendation process.

Gomede et al. (2021) explore the use of deep autoencoders to create an adaptive e-learning recommendation system that personalizes content based on student interactions. The proposed model employs three types of deep autoencoders—Collaborative Denoising Autoencoders (CDAE), Deep Autoencoders for Collaborative Filtering (DAE-CF), and Deep Autoencoders for Collaborative Filtering using Content Information (DAE-CI) to refine learning object (LO) recommendations. The model operates using student interaction data collected from Massive Open Online Courses (MOOCs), capturing both implicit (clicks, time spent, navigation patterns) and explicit (ratings, feedback) user behaviors. The results show that DAE-CF provides the best adaptability and personalization, while DAE-CI improves content-based recommendations. Evaluation metrics such as Mean Average Precision (MAP), Normalized Discounted Cumulative Gain (NDCG), Personalization, Coverage, and Serendipity (SAUC) confirm that deep autoencoders significantly enhance the quality of learning path recommendations, making them more relevant and engaging for students.

Lin et al. (2021) introduce the CIEPA (Context-Integrated Explainable Path Attention) model that improves personalized learning by incorporating knowledge graphs (KG), item embeddings, and path attention mechanisms. The item embedding is used to capture latent relationships between learning objects, while the path attention mechanism refines the propagation of user preferences in the knowledge graph. Inspired by RippleNet and Deep Knowledge Graph Models (Dong et al. 2017), the system enhances the learning path recommendations by propagating historical learning interactions along the edges of the knowledge graph (Wang et al. 2019).

Gu and Runlong (2025) introduces a framework that leverages Graph Attention Networks (GAT) and Deep Reinforcement Learning (DRL) to enhance personalized learning path recommendations in e-learning. The system uses Graph Attention Networks (GAT) to capture relationships between learners and learning materials, while Deep Reinforcement Learning (DRL) refines learning path recommendations by continuously updating strategies through trial-and-error optimization (Arulkumaran et al. 2017). Experimental results indicate that the integration of GAT significantly improves the precision of recommendation, with test scores improving from 5.8 to 12.8 points and the precision of the model increasing by 5. 3% compared to traditional deep learning models. The study also incorporates a labeling feedback mechanism, which enhances the system's adaptability by adjusting recommendations based on user feedback and knowledge retention levels (Zhang et al. 2019).

Yun et al. (2024) propose a Doubly Constrained Deep Q-learning Network (DCQN), a novel offline reinforcement learning approach that operates solely on historical student interaction data, reducing the ethical concerns and computational costs associated with real-time data collection. DCQN model addresses extrapolation errors, a common issue in offline RL by implementing two generative models that constrain both policy selection and Q-value estimation, ensuring more stable and accurate learning path recommendations. The model builds upon existing research in adaptive learning path optimization, which has leveraged graph-based models (Liu et al. 2019), actor-critic reinforcement learning (Sutton and Richard 1988), to personalize education. However, traditional RL models require active interaction with students, leading to potentially suboptimal recommendations during training phases (Chen et al. 2021). To address this, DCQN integrates policy constraints (Fujimoto et al. 2019) and conservative value estimation (Kumar et al. 2020), ensuring that recommended actions remain within the distribution of observed student behaviors.

Alshmrany (2022) proposes an adaptive learning style prediction system based on a Convolutional Neural Network (CNN) optimized using the Levy Flight Distribution (LFD) algorithm. The CNN-LFD framework consists of two major components: (1) Feature extraction from MOOC datasets, where learning behaviors are mapped into structured sequences, and (2) Learning style classification using CNN with LFD-based hyperparameter tuning, which optimizes CNN's learning rate, kernel size, and dropout rate to prevent overfitting. The system classifies learners into four learning styles - Active/Reflective, Sensing/Intuitive, Visual/Verbal, and Sequential/Global - following the Felder-Silverman Learning Style Model (FSLSM). Experimental results indicate that CNN-LFD achieves a classification accuracy of 97.09%, outperforming traditional machine learning models. Table 2 summarizes the merits and demerits of some of the papers that used AI for developing the Personalized Learning Path, discussed in this section.

Table 2. Summary of Some Papers That Used Artificial Intelligence

Paper	**Dataset(s)**	**Method(s) Used**	**Strengths & Weaknesses**
Chen et al. (2023)	Junyi Academy Math Practicing Log	Attentive Knowledge Tracing, Entropy enhanced Proximal Policy Optimization, Deep Reinforcement Learning	8.2% improvement in out-comes; however, it focuses only on mathematics, limiting generalizability.
Sarkar and Huber (2021)	Synthetic learner profiles generated by CGANs	Reinforcement Learning, Conditional Generative Adversarial Networks (CGANs)	Minimizes student interaction fatigue; however, reliance on synthetic profiles may reduce real-world applicability.
Gao et al. (2023)	MovieLens 100k	GPT-3.5-turbo, text-davinci-003, text-davinci-002	Generates relevant recommendations for new users without requiring large prior interaction data but inherits biases from underlying language models
Yun et al. (2024)	JunYi Dataset, EdNet, Assistment datasets	Doubly Constrained Deep Q-learning Network (DCQN)	Mitigates extrapolation errors in offline RL; however, it does not integrate real-time feedback.
Ahmadian Yadzi et al. (2024)	OULAD Free University	Bidirectional Long Short-Term Memory, Recurrent Neural Networks	Captures both past and future user preferences but has high computational cost.

3.2 Personalized Learning Paths without AI

In this subsection, we discuss some papers that have the explored Personalized Learning Paths using non-AI or rule-based solutions. Yuhana et al. (2024) presents an approach that dynamically adapts to students' abilities. The study integrates Ant Colony Optimization (ACO) with Item Response Theory (IRT) to improve learning path recommendations based on students’ pretest scores, knowledge levels, and the difficulty of learning modules. The study involved 80 students, divided into two groups: one using ACO alone (Group X) and the other using the enhanced ACOIRT method (Group Y). The results showed that Group Y achieved a significant performance improvement (up to 127.8%), with a statistically significant p-value of 0.002, indicating the superiority of ACOIRT over conventional methods.

Liu (2024) explores the integration of Markov Chain algorithms and adaptive learning techniques to create a personalized recommendation system for English learners. By employing Markov Chains, the system models user learning behavior as a series of state transitions, allowing it to predict future learning needs based on past interactions (Wang et al. 2021). the proposed system ensures that each learner receives individualized recommendations, thereby increasing engagement and optimizing learning outcomes (Tang et al. 2019).Wang et al. (2024) presents a novel algorithm, Portfolio ST which uses Steiner Tree (ST) theory to build a knowledge graph, representing subject domains and their interdependencies, and then applies the Portfolio ST algorithm to determine the shortest and most efficient learning path between the current state of knowledge of the learner and the target competencies. The study focuses specifically on the finance domain, constructing a graph with 100 key financial concepts and 751 relationships, demonstrating that Portfolio ST outperforms traditional path optimization methods in both efficiency and adaptability. This model considers the non-linear relationships between knowledge points, ensuring a more efficient and personalized learning trajectory.

Phong et al. (2024) introduce a framework that uses User-Based Collaborative Filtering (CF) and Content-Based (CB) to provide personalized recommendations by analyzing mutual preferences and user interactions. It uses cosine similarity, to measure similarity between user and job profiles. The system first creates a skill-rating matrix to capture user preferences, computes similarity scores for each user pair, and then generates recommendations by aggregating preferences from similar users, with the aggregation weighted by the similarity scores. The Content-Based (CB) method uses KMeans clustering to segment job roles into clusters based on shared characteristics like skills and qualifications, improving the accuracy of job role grouping. Recommendations are made by predicting user ratings for items using the cosine similarity between the user and item vectors, with a score close to 1 indicating a strong match.

Luo (2021) explores the use of eye-tracking technology to identify learning styles within adaptive learning systems. The research uses the Felder-Silverman's learning style model (FSLSM) (Kuhlenschmidt 1988) as a framework, examining specific behavior patterns to identify learning styles through eye movement. Tobii eye-trackers are used to record participants' fixation data and eye-movement patterns and compares this data with self-reports from the Index of Learning Style (ILS) questionnaire (Soloman et al. 2005) to assess the accuracy of eye-tracking technology in identifying the four groups of learners in FSLSM model. A quasi-experiment was conducted with 30 university students. The findings suggest that eye-tracking can effectively identify learning styles with reasonable accuracy (63.50% to 84.67%), though several factors influence identification accuracy.

Meng et al. (2021) propose a novel learning path generating method named learning diagnosis-learning path (LD-LP), which is based on knowledge structure and learning diagnosis. The LD-LP method includes creating a student model based on students' behavioral information, status information, and achievement, constructing a knowledge model by marking the precursor knowledge, subsequent knowledge, and setting the initial difficulty, and generating learning paths using Euclidean distance to calculate the similarity between learner's ability and knowledge difficulty to adaptively select the next knowledge. The effectiveness of LD-LP was tested with mathematics students, and the experimental results demonstrate its high adaptivity and positive feedback.

Martinez-Carrascal et al. (2023) introduce a novel technique for modeling recommended learning paths (RLPs) and measuring student adherence to these paths using process mining and log skeletons (Verbeek et al. 2018). The method involves abstracting an event log, the necessary input for process mining algorithms, from raw data generated by the LMS, scoping the event log and select representative traces of the RLPs, generating log skeletons as modeling notation, and using conformance metrics to measure the similarity between the RLP model and the learning path followed by learners.

Zhang et al. (2024) propose a process-type learning path model and its recommendation approach. The approach presents a learning path in the form of a flowchart and dynamically recommends path branches according to the knowledge states of the learner during the learning process. Deep knowledge tracing is used to annotate the knowledge states of learners in historical logs, and process mining is used to generate a personalized process-type learning path that contains sequences, parallel relationships, and selection relationships between learning objects (Corbett et al. 1994). The correlation between the knowledge state and the selection of different branches of a learning path in historical logs can be obtained via decision mining. A branch recommendation model is trained and used to recommend a path branch in a process-type path with the highest probability of mastering the target learning object of the learner based on the learner's knowledge state. Table 3 summarizes the merits and demerits of some of the papers that used rule-based for developing the Personalized Learning Path, discussed in this section.

Table 3. Summary of Some Papers That Used Rule-Based Methods

Paper	Dataset(s)	Method(s) Used	Strengths & Weaknesses
Yuhana et al. (2024)	Pretest and Posttest data	Ant Colony Optimization, Item Response Theory	Improves student knowledge estimation, but the system cannot generate learning paths for students who score 100% on the pretest
Liu (2024)	User behavior logs	Markov Chain Algorithm	Enables real-time adjustments to learning paths; however, it does not explicitly account for student motivation or cognitive load.
Wang et al. (2024)	100 financial concepts	Steiner Tree Algorithm	Reduces redundant content traversal but does not integrate motivation or engagement tracking.
Zhang et al. (2024)	Historical logs	Deep Knowledge Tracing	Recommends path branches based on the learner's knowledge state but has a high computational cost.

6. Conclusion

This paper makes several significant contributions. To the best of our knowledge, it is the most recent survey that comprehensively examines the state-of-the-art methodologies in Personalized Learning Paths. We specifically focus on both AI-based and non-AI-based systems. In the AI category, we reviewed systems that used large language models (LLMs), reinforcement learning, deep learning methods, and other relevant approaches and in the non-AI category, we specifically reviewed papers that used rule-based and statistical approaches. To ensure a comprehensive analysis, we diversify our sources by including publications from reputable academic databases such as IEEE, ScienceDirect, PubMed, ACM, and SpringerLink. Consequently, this paper serves as a valuable resource for researchers and practitioners in both academia and industry who aim to develop or select tools for personalized learning paths.

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