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# Transforming Education with AI: The Development of a Personalized Learning Algorithm for Individual Learning Styles

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## ABSTRACT

The evolving educational landscape requires innovative teaching methods to enhance learning and accommodate diverse styles. Technologies like artificial intelligence (AI), machine learning (ML), and the Internet of Things (IoT) are transforming education by improving student performance and engagement. This research introduces an Artificial Intelligent Personal Recommender System Algorithm (AIPRS) that focuses on individual learning styles and interests to recommend customized learning programs. Unlike traditional methods, AIPRS personalizes education by analyzing learners' backgrounds and preferences, utilizing AI, ML, and IoT. This tailored approach marks a significant shift from conventional systems, emphasizing the importance of individual learning styles to improve the overall educational experience. The study highlights the potential of personalized education, offering a solution to efficiently deliver knowledge and enhance student satisfaction.

*Keywords:* Personalized Recommender Learning Algorithm, Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), Educational Technology, Learning Styles

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## 1 Introduction

Application of artificial intelligence (AI) and internet of things (IoT) in education has shown remarkable potential in personalizing learning experiences, improving teaching methods, and offering individualized learning opportunities [1,2]. By integrating program details, instructional data, and student learning styles, AI can provide customized course recommendations, adaptive learning paths, and personalized support, enhancing knowledge uptake and retention [3]. Furthermore, machine learning (ML) can play a significant role in improving the quality of education through personalized learning, early identification of at-risk students, and enhancing teaching methods, enabling educational institutions to predict student performance and tailor teaching approaches to individual needs [4,5,6,7].

Diagnosing a student's learning style involves analyzing student profile data, including academic records, interests, and questionnaires, using machine learning (ML) algorithms [8,9]. This process aids in determining the most effective learning style for each student, as learning styles encompass the various preferences individuals have in learning and processing information. While people may not fit neatly into one learning style category, understanding these styles can help educators tailor their teaching methods to better meet the needs of their students [10].

This research study highlights the importance of designing and constructing an intelligent system that can enhance teaching management by offering personalized adaptive learning systems that can identify the unique learning styles of each student. This system has the potential to significantly improve the quality of learning in higher education, as it can be effectively used for university planning, teaching management, and student management, including evaluating learning outcomes.

The proposed system is leveraged on large amounts of data to identify patterns and performance trends of students, providing valuable insights to improve teaching strategies and learning materials. Additionally, an intelligent system can help promote educational justice. The integration of IoT and ML can address many challenges in online education that each technology alone cannot. Furthermore, AI can significantly improve the quality of education by providing personalized learning experiences, identifying critical factors affecting student success rates, and creating intelligent learning support systems.

Machine learning plays a vital role in these systems, revolutionizing how educational institutions monitor student performance and identify areas for improvement. Personalized learning approaches, powered by machine learning, contribute to creating a more inclusive, accessible, and engaging education system. However, successful implementation requires addressing potential challenges related to privacy concerns, ethical considerations, accurate interpretation of training data, biases, and the possibility of information misuse. Additionally, the challenges associated with introducing new technology into classrooms, particularly the need for professional development around AI, must be addressed [11,12].

This study employs a descriptive-exploratory research design and an algorithmic-practical approach to investigate and introduce an intelligent system for educational data recommendations.

The primary objective is to explore the opportunities and challenges that emerge in the teaching-learning process when leveraging such a system. The research design involves a brief review on the application of artificial intelligence, machine learning, internet of things, and learning styles in education, providing a theoretical foundation. Additionally, the study involves the design and development of a prototype intelligent system that can analyze learner profiles, preferences, and requirements to generate personalized recommendations for educational resources and activities. By adopting this multifaceted methodology, the research aims to offer valuable insights into the strategic implementation of data-driven, personalized learning solutions to improve educational outcomes and promote inclusive learning environments.

## 2 Research Background

### a. Transformative Potential of AI, ML, and IoT in Higher Education

The integration of AI, ML, and IoT in education enhances the accessibility and effectiveness of learning resources, fostering a dynamic and adaptive learning environment [2,13]. Artificial intelligence and machine learning enables teachers to deliver more intelligent and targeted teaching, providing faster feedback and tailored learning experiences that meet students' individual needs and preferences. By analyzing students' learning behaviors and styles, AI can create personalized learning experiences that improve overall education quality and support diverse learners' needs [3].

In higher education, AI and ML have significant potential in enhancing the quality of learning by optimizing campus planning and management, leading to more efficient and intelligent learning environments. AI-optimized design for school management can improve efficiency, accuracy, and decision-making through better data analysis, resulting in superior education quality and improved academic performance [14]. However, the quality of the data used by AI systems is crucial for their effectiveness. Poor data quality can lead to inaccurate predictions and recommendations, which can negatively impact learning outcomes [15,16].

Furthermore, industry-relevant learning is critical in higher education, particularly in fields such as engineering, and understanding student perceptions is crucial for the effective integration of work-related activities [17]. IoT technologies, such as videoconferencing applications, have been widely accepted and used in higher education, especially in the context of remote learning, significantly improving the accessibility and flexibility of higher education [18]. Internet of Things has the potential to enhance higher education in various ways, such as providing personalized learning experiences through educational chatbots that can boost confidence, motivation, self-efficacy, learner control, engagement, knowledge retention, and access to information [19]. IoT devices can also collect more accurate and reliable information to improve the learning experience [20], enhance educational infrastructure and learning experience [21], and offer real-time feedback and assessment to improve the quality of teaching [22].

## b. Personalized Learning Systems and Intelligent Education

Personalized learning systems (PLS) have been instrumental in creating and monitoring individualized learning programs. These systems encompass the development of customized programs, content, tools, and data necessary to facilitate high-quality, personalized learning experiences for both educators and students [23]. By tailoring the learning journey to students' unique characteristics and needs, PLS have demonstrated successful results in enhancing the learning outcomes for individuals [24].

Pioneering work in PLS includes Seel's 2011 study, which leveraged AI and ML to adapt the learning experience for students based on their individual characteristics and requirements [23]. Building on this, Rani et al. (2016) presented an automatic web-based system that streamlined academic and administrative tasks, facilitating information management, notifications, and performance tracking. Furthermore, Pandey et al. (2017) introduced a smart library management system utilizing IoT technologies to effectively control and optimize library-related information, benefiting both staff and students [25]. Importantly, PLS can also provide real-time feedback and instructional support to learners, assisting them in improving their skills.

The combination of personalized learning programs with AI technologies, automated web-based systems, competency-based learning, and IoT has led to the development of intelligent systems that provide personalized training data based on program details and learning history [25]. These systems offer tailored learning experiences, support decision-making processes, and enhance administrative efficiency. By enabling the analysis of diverse learning materials and providing a comprehensive understanding of inclusive progress, personalized learning programs empower educators to identify individual strengths and weaknesses, allowing them to customize learning experiences accordingly [25].

Competency-based learning, often integrated with personalized approaches, connects K-12 experiences with graduate programs, emphasizing the mastery of specific skills and aligning educational experiences with personalized goals [26]. Artificial intelligence technologies, such as ChatGPT, can further enhance the learning experience by providing personalized and efficient support, enabling quick feedback and assisting in assessing student performance, empowering teachers with valuable insights [13,27]. Additionally, AI is increasingly utilized in online distance education to identify and predict student behaviors, facilitating adaptive and personalized learning [28].

Zaman et al. (2023) explored the use of machine learning to improve education quality, utilizing geospatial AI modeling to identify critical factors affecting student success rates and creating a microanalysis school education tool for stakeholders [29]. This study highlights the potential of machine learning to provide valuable insights that can enhance the quality of school education. Additionally, the Xinchuang Education Intelligent Evaluation System leverages AI technology to automate tasks such as scoring, evaluation, learning content recommendation, personalized learning, intelligent teaching and learning assistance, and student behavior analysis, ultimately enhancing the quality of education and promoting personalized and intelligent evaluation [30].

The integration of automated web-based systems, personalized learning programs, competency-based learning, AI, and IoT technologies enables the creation of smart personal recommender systems. These systems leverage learners' backgrounds and styles to design personalized and inclusive experiences. By harnessing these technologies and methodologies, intelligent systems can provide tailored education, support decision-making, and enhance administrative efficiency, ultimately promoting more effective and inclusive learning environments.

Several models are commonly used to categorize learning styles, with notable examples including the VARK model, KOLB learning style model, and the Honey-Mumford model [8, 9]. The VARK model classifies learners into four sensory modalities: Visual (prefer to learn through visual aids, images, and videos), Auditory (prefer to learn through listening and verbal explanations), Reading/Writing (prefer to learn through written text and information), and Kinesthetic (prefer to learn through hands-on, practical experiences) [31,32].

The KOLB learning style model categorizes learners into four distinct styles based on their preferences for perceiving and processing information: Diverging (concrete experience, reflective observation), Assimilating (abstract conceptualization, reflective observation), Converging (abstract conceptualization, active experimentation), and Accommodating (concrete experience, active experimentation) [33,34].

The Honey-Mumford model, on the other hand, identifies four learning types: Theoretical (prefers to learn through understanding underlying theories and concepts), Pragmatic (prefers to learn through practical application and problem-solving), Activist (prefers to learn through hands-on experiences and experiments), and Reflective (prefers to learn through observation and contemplation) [35]. Understanding a learner's preferred style within these models can help educators tailor instructional methods, learning activities, and educational resources to better match the individual's strengths and preferences, ultimately enhancing the effectiveness of the learning process.

## 3 Intelligent Recommender System for Personalized Learning

It is indeed possible to implement an intelligent system for educational data that focuses on learning styles. Such a system can involve the integration of various technologies and methods to enhance the learning experience. Figure 1 shows an example of a system using this logic. A smart learning system is designed to help users choose a lesson and request to learn a specific subject. Once the request is made, the system offers a personalized combination of educational content, such as videos, books, PowerPoint presentations, assignments, and tests, based on the user's learning style and previous records. If the user has a preference, such as learning through movies, the system adapts accordingly.

The user's test results and content-related data are stored in a database as raw data. This data is then analyzed using data mining techniques to identify patterns in the user's previous records, learning styles, and educational content. A proper machine learning algorithm leverages this information to determine the optimal combination of content for each individual learner and creates new content for future training stages based on the evaluations.

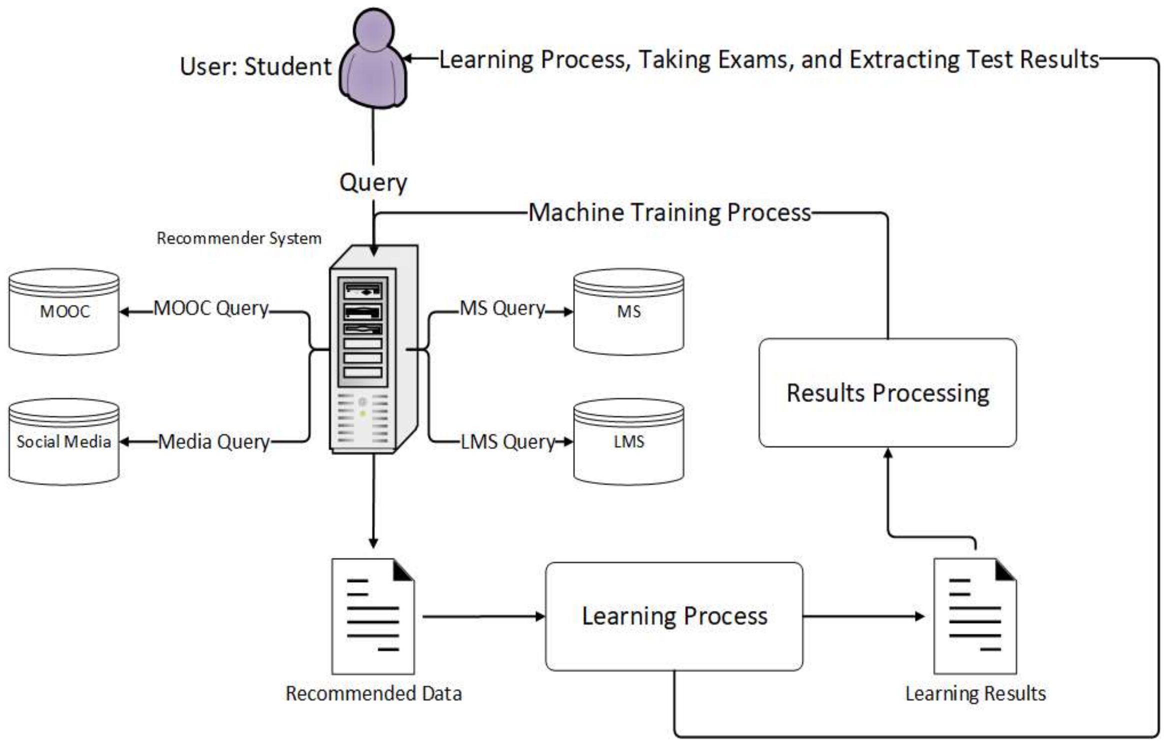


Figure 1: An example of the Intelligent Teaching Systems. First, based on the user's course request, learning style and material preferences, some offers such as MOOC, Media, MS, and LMS, are given for the educational content. Then, the user's content-related and test data are stored and analyzed to identify the best pattern for his learning style. Next, a proper Machine Learning algorithm is employed to determine the optimal combination of material contents for the user.

The recommender system then utilizes the stored test and educational records to provide the most suitable content to the learner, tailoring the experience to their specific needs and learning preferences. This personalized approach helps the learners achieve their desired learning outcomes while ensuring an engaging and effective learning experience.

Educational data mining, big data analysis, and adaptive learning technologies are crucial in modeling intelligent learning processes and enabling personalized online learning systems. These tools leverage data analysis to gain insights into students' learning behaviors, preferences, and styles, allowing the systems to adapt the learning experience to better suit individual needs. By understanding learners' characteristics, the systems can offer personalized support, such as providing additional resources or modifying content presentation for students struggling with specific topics. Educational data mining helps explore patterns in learning data to facilitate personalized approaches aligned with individual styles, as emphasized by Mitrofanova et al. [36].

Similarly, big data analysis in online learning, as highlighted by Dahdouh et al. (2018), enables the understanding of learners' behaviors and preferences, enabling customized experiences [37]. Adaptive learning technologies, as discussed by Chytas et al. (2022), further enhance the personalization of educational materials and activities based on students' individual learning needs and preferences [38]. This comprehensive approach to personalization optimizes the learning experience for each student.

Smart classroom environments equipped with Internet of Things (IoT) systems leveraging cloud computing technology enable the collection and analysis of real-time data to provide diverse, personalized educational services [39]. Learning Management Systems (LMS) further enhance this personalization by accommodating different learning styles and offering various content delivery options, such as text, video, and interactive quizzes, as well as collaborative learning tools for group work and discussions. Additionally, artificial intelligence (AI) algorithms can analyze how students interact with the system to determine their preferred learning styles, whether visual, auditory, or kinesthetic, and then adapt the content presentation accordingly. This comprehensive integration of IoT, LMS, and AI technologies facilitates personalized and context-aware learning experiences, optimizing the educational process for individual students.

The comprehensive integration of educational technologies, including recommender systems, feedback mechanisms, educational data mining, adaptive learning, big data analytics, IoT, LMS, and AI, enables the provision of truly personalized and optimized learning experiences. Regular feedback, facilitated through automated assessments, helps students understand their strengths and weaknesses, allowing them to adapt their learning strategies. Recommender systems can then provide personalized suggestions for learning resources and activities tailored to individual needs and preferences. By leveraging these advanced technologies, educational institutions can create intelligent systems that accommodate diverse learning styles, offering customized support for both students and faculty. This holistic approach, encompassing data-driven insights, adaptive content delivery, and real-time contextual awareness, empowers learners to thrive and maximizes the efficiency of the overall educational process.

## 4 Suggested Algorithm for Intelligent Recommender System

Figure 2 shows the key components of the proposed intelligent algorithm, called artificial intelligent personal recommender system (AIPRS).

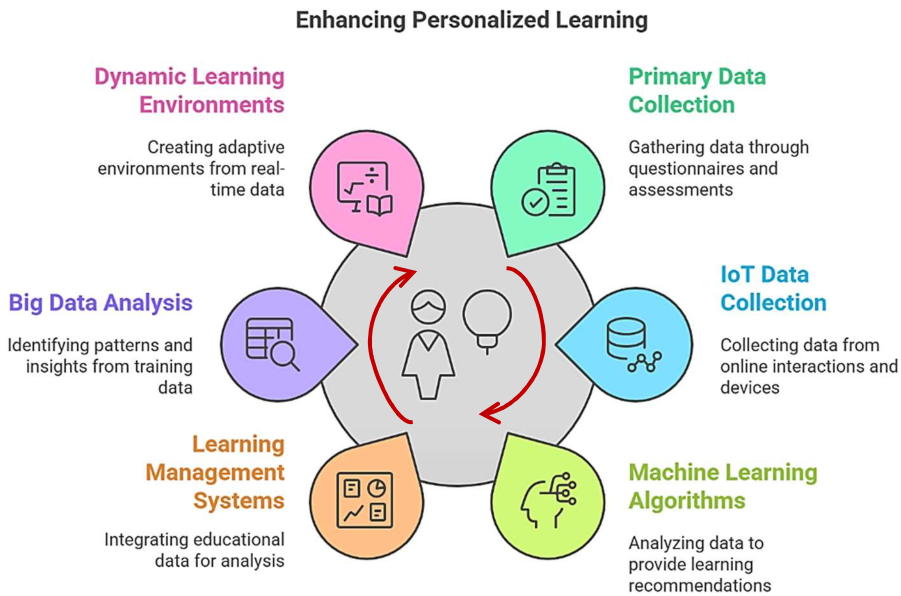


Figure 2: Main components of the AIPRS algorithm

The algorithm works in the following steps:

**Step 1:** Primary data collection and analysis:

- Student's primary data, including learning styles, is collected through questionnaires and assessments.
- Data from student's learning environment, such as interactions with online resources and devices, is collected using the IoT.

**Step 2:** Personalized learning with artificial intelligence:

- A proper machine learning algorithm is utilized to analyze the student's data and provide personalized learning recommendations.
- AI Chatbots is developed to offer students personalized support and learning assistance.

**Step 3:** Integration with a learning management system:

- The algorithm is integrated with the LMS to access and analyze educational data.

**Step 4:** Big data analysis:

- The collected training data is analyzed using big data techniques to identify patterns and gain insights.

**Step 5:** Internet of things for the learning environment:

- The data collected through the IoT is used to create a dynamic and adaptive learning environment based on real-time student interactions.

**Step 6:** Recommender system for course recommendations:

- The system utilizes machine learning to recommend courses based on student profiles and learning styles.

The implementation of the algorithm involves gathering student information, such as academic records, interests, and preferences, through assessments and surveys. The system then uses AI to identify the student's learning style and transmits the data to the recommender system. With the assistance of machine learning, the system provides training content that best aligns with the learner's identified learning style. The system evaluates the student's progress and provides appropriate feedback. Both training data and IoT data are utilized for instruction purposes, and the process continues until the system ensures the learner has achieved a satisfactory level of training. All steps are stored within the system and are accessible to students, teachers, and the system itself as educational records. By merging these key elements, the intelligent algorithm provides a comprehensive solution for enhancing the learning process through the use of artificial intelligence, machine learning, and the Internet of Things.

To better understand the proposed algorithm, a flowchart is presented in Figure 3. The proposed algorithm integrates a multi-phase adaptive learning framework designed to personalize educational content delivery. Initially, learner-specific data—encompassing academic history, preferences, and interests—are input into the system via a structured query interface. Artificial intelligence (AI) algorithms then analyze this data to identify the student's optimal learning style. Subsequently, the derived insights are transmitted to a machine learning (ML)--driven recommender system, which dynamically curates and delivers pedagogical materials tailored to the detected learning preferences.
Following content delivery, the system employs evaluative metrics to assess the learner's proficiency. Should performance metrics fall below predefined acceptability thresholds, the system generates targeted feedback for the learner and initiates an iterative retraining protocol. This involves recalibrating the instructional content and integrating supplementary data from Internet of Things (IoT) sensors or devices to refine contextual relevance. The recommender system subsequently redistributes the updated materials for further learner engagement.

This cyclical process persists until the system validates the attainment of competency through quantitative performance benchmarks. All procedural data—including input parameters, AI-driven learning style analyses, content recommendations, evaluative outcomes, and feedback iterations—are systematically archived within a centralized database. These records are accessible to stakeholders (learners, instructors, and administrators) for monitoring progress, informing pedagogical adjustments, and ensuring accountability. The framework thus exemplifies an adaptive, closed-loop system leveraging AI, ML, and IoT integration to optimize individualized learning trajectories while maintaining comprehensive auditability.

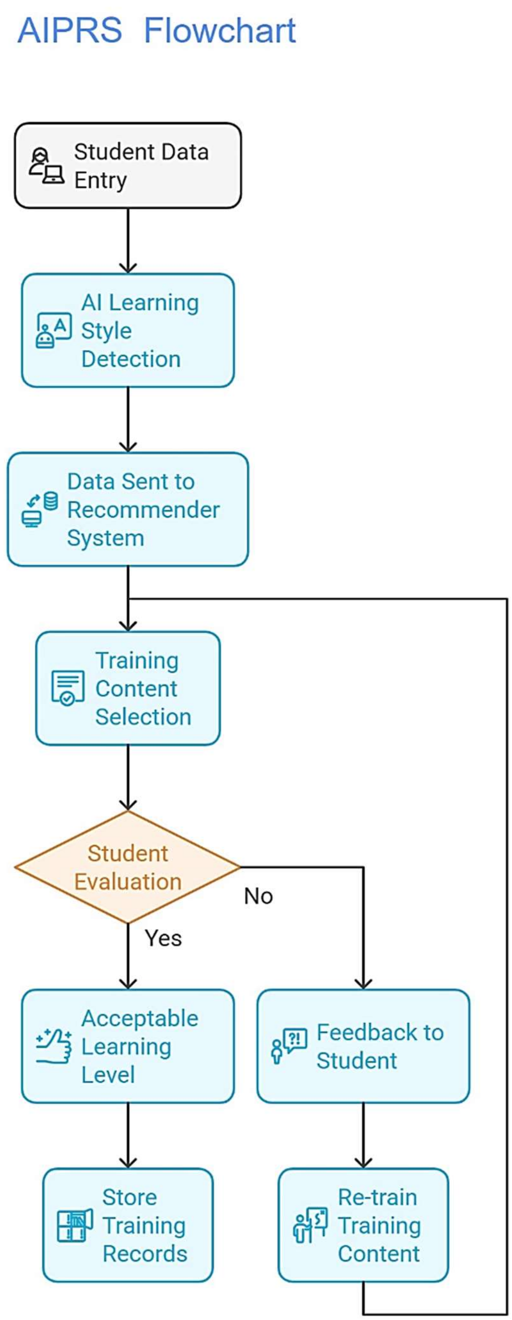


Figure 3: The flowchart associated with the AIPRS Algorithm. This flowchart demonstrates the steps for implementation of the AIPRS algorithm.

## 5 Key Data Sources for Intelligent Course Recommender System

The intelligent recommender system for educational data relies on integrating various technologies and different data processing methods. To personalize course recommendations for students, the system can utilize:

1. Learning Style Data: Information on students' visual, auditory, or kinesthetic preferences can guide recommendations for courses aligned with their learning styles [40].

2. Academic Performance Data: Student grades, test scores, and course completion rates can help identify appropriate courses based on their current knowledge and skills. Providing clear guidelines can assist students in staying on track with their academic schedules.
3. Learning Behavior Data: Insights into student behavior, such as time spent on tasks, interaction patterns, and study habits, can inform recommendations for courses that match their learning pace and habits [41]. This helps students stay on track with the optimal curriculum and make necessary corrections.
4. Personal Interest Data: Information about students' interests, hobbies, and subject preferences can be leveraged to recommend courses aligned with their personal interests and career aspirations [40].
5. IoT Data: Data collected from IoT devices, such as interactions on online learning platforms, can provide insights into student learning behaviors and preferences, enabling personalized course recommendations [41]

By analyzing these diverse data sources, the intelligent recommender system can tailor course recommendations to each student's unique needs and preferences, enhancing their educational experience.

## 6 Discussion

The integration of ML-based personalized approaches is reshaping educational experiences, fostering inclusivity, accessibility, and engagement. Intelligent educational systems leverage learners' specific data, including educational backgrounds and learning styles, to deliver personalized learning experiences. These systems, known as Intelligent Personal Learning System (IPLS), harness artificial intelligence (AI) and machine learning to customize the learning journey according to each learner's unique characteristics and requirements. By analyzing learners' backgrounds and learning styles, recommender systems and machine learning algorithms discern the most suitable activities for individual learners.

Providing quality education is a costly and long-term task for educational systems worldwide. However, using an intelligent system can be a great opportunity to reduce the resources, cost, and time required for education, while improving the quality of learning. The presented algorithm suggests that the system continues the process of providing the best combination of educational content for the learner until it is confident that the learning has been completed well and the student has reached the desired level of knowledge. This approach has the potential to save time and money while ensuring that students can access the most suitable educational content based on their learning style.

Despite the significant benefits of integrating intelligent systems in education, there are also technological challenges that need to be addressed. These challenges include privacy concerns, bias and unfairness, the balance between quantitative and qualitative factors, misinterpretation of data, and the potential for increased stress and pressure on students. To address privacy concerns, it is crucial to implement robust security measures and adhere to best practices in data handling and storage, ensuring compliance with data protection regulations and safeguarding student privacy [42]. Addressing bias and unfairness requires proactive measures, such as employing fairness-aware algorithms, conducting regular audits, and promoting diversity and inclusion in the development and training of the intelligent system [43].

Relying solely on quantitative performance data may overlook important qualitative aspects of students' learning, such as creativity, critical thinking, and problem-solving skills. Adopting a holistic approach that considers both quantitative and qualitative factors is necessary for accurate and well-rounded course recommendations. This can be achieved by incorporating multiple data sources and utilizing assessment methods that capture a wide range of competencies [44].

The risk of misinterpreting student performance data can lead to incorrect recommendations. To mitigate this, it is essential to employ robust data analysis methods and ensure that the insights derived from the data are valid and reliable. This can involve employing statistical techniques, conducting rigorous validation, and involving domain experts in the interpretation of the data [45].

Finally, personalized course recommendations based on performance data may unintentionally contribute to increased stress and pressure on students. It is crucial to strike a balance between personalized recommendations and fostering a supportive and nurturing learning environment that prioritizes student well-being and holistic development [40]. By addressing these technological challenges and adopting a balanced and ethical approach, the integration of intelligent systems in education can unlock the full potential of personalized learning, enhancing the overall quality and accessibility of education.

## 7 Conclusion and Future Work

This research introduces an innovative Artificial Intelligent Personal Recommender System (AIPRS) algorithm that prioritizes learners' individual styles and interests, marking a significant departure from conventional educational methods. By focusing on personalization, the AIPRS algorithm enhances the overall learning experience, offering tailored learning programs that align with students' unique preferences. This system not only supports teachers and students in achieving educational goals but also improves the accessibility and effectiveness of learning resources through the integration of diverse data sources, including learning styles, academic performance, behavioral insights, and Internet of Things data.

While the proposed system presents numerous advantages, it also faces challenges in implementation, such as privacy concerns, bias and fairness issues, and the risk of overreliance on quantitative data. Addressing these challenges requires careful attention to transparency and fairness in decision-making processes. By navigating these complexities, the AIPRS can provide a more equitable and supportive learning environment for all students.

In establishing this foundational algorithm, we acknowledge that further exploration and refinement are necessary to realize its full potential. Future work will focus on developing detailed logic and data processing methods for the actual implementation of the intelligent system. It is important to note that the current research primarily addresses foundational aspects, with the rigorous application of machine learning methods for testing, remaining an open question for subsequent studies.

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