Towards Intelligent Personalization In Learning Systems

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Abstract. Personalizing learning has become a crucial issue in modern educational environments, aiming to meet learners' individual needs and maximize their potential. This paper presents the process of designing and implementing an innovative intelligent system combining intelligent tutor systems (ITS) and multi-agent systems (MAS) to deliver personalized learning. The proposed system uses learner profiles and domain models to dynamically adapt learning paths according to learners' performance and preferences. Evaluation of the system through case studies demonstrated a significant improvement in learner satisfaction and pedagogical effectiveness. The results show that the integration of ITS and MAS makes it possible to create an adaptive and responsive learning environment, capable of adjusting in real time to learners' needs.
This article makes important contributions to educational technology research, proposing a robust solution for personalizing learning. The implications for the future of education are promising, leading the way for future developments and further research to perfect and extend the use of such intelligent systems in various educational contexts.

Keywords: personalization, design, intelligent system, intelligent tutor system, multi-agent system

1 Introduction

In the current educational context, personalized learning has become an essential priority to meet the diverse needs of learners. Traditional teaching methods, often uniform, struggle to adapt to the rhythms, learning styles, and individual interests of learners. This mismatch can lead to a decrease in motivation and limited pedagogical effectiveness. The advent of digital technologies offers unprecedented opportunities to overcome these challenges, particularly through the development of Intelligent tutor Systems (ITS) and Multi-Agent Systems (MAS) [1].

ITS are artificial intelligence-assisted teaching tools [2], designed to mimic human interaction in an educational context [3]. They are capable of analyzing learners' performance in real time, diagnosing their needs and providing personalized feedback. MAS, on the other hand, represent a distributed approach to artificial intelligence, where several autonomous agents cooperate to solve complex problems. The integra-

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tion of these two technologies promises to create adaptive and responsive learning environments, capable of dynamically and continuously personalizing educational pathways [4].

The aim of this article is to describe the foundations of the design and implementation of our intelligent system based on the combination of ITS and MAS to offer genuinely personalized learning. We present detailed modeling of learners and knowledge domains, as well as a system architecture incorporating sophisticated adaptation mechanisms. The development of the prototype and the technical challenges encountered are also discussed.

Finally, we evaluate the effectiveness of the system through practical case studies. The results show a significant improvement in learner engagement and performance, confirming the potential benefits of this innovative approach. This work thus contributes to educational technology research by proposing a robust solution for personalizing learning, opening up new perspectives for the future of education.

2 Scientific and methodological background

2.1 Scientific background

Personalization of learning is based on the idea that each learner has unique needs, preferences and learning rhythms [5], [6]. This personalization is facilitated by the use of advanced technologies such as ITS and MAS.

A. Intelligent Tutor Systems (ITS):

ITS are artificial intelligence applications designed to provide personalized teaching. They use cognitive models to understand and anticipate learners' needs, adjusting pedagogical content and feedback in real time. The effectiveness of ITSs lies in their ability to simulate pedagogical interactions similar to those of a human tutor [7].

B. Multi-Agent Systems (MAS)

MAS consist of a collection of autonomous agents that interact to accomplish complex tasks. Each agent has specific capabilities and can cooperate or coordinate with other agents to achieve common goals [8]. In the field of education, MAS allow efficient distribution of educational tasks and large-scale personalization [9], [10], [11].

The integration of ITS and MAS into a single intelligent system offers considerable potential for personalizing learning. ITS can provide personalized pedagogical recommendations, while MAS can manage the coordination and distribution of these recommendations.

2.2 Methodology

The methodology of this study can be decomposed into several key steps, from modeling learners and knowledge domains to designing and evaluating the prototype system:

- **Learner modeling**

The first step is to develop detailed learner profiles, including information on their academic performance, learning styles, and personal preferences. These profiles are used to inform pedagogical adaptation decisions [12], [13].

- **Knowledge Domain Modeling**

Knowledge Domain Modeling involves structuring educational content into logical, interconnected units. Each unit is associated with specific learning objectives and assessment criteria, enabling fine-tuning of educational content.

- **System design**

The system architecture combines ITS and MAS functionalities. ITS provides pedagogical recommendations based on learner profiles, while MAS coordinates and executes these recommendations. Machine learning algorithms are used to continuously improve the personalization model.

By combining ITS and MAS in a coherent architecture and using rigorous modeling methods, this study aims to demonstrate the feasibility and effectiveness of personalized learning on a massive scale. The results obtained will validate the proposed approach and provide recommendations for future research in this promising field.

3 Results and Discussion

To evaluate the effectiveness of the intelligent system based on ITS and MAS, we conducted several practical case studies. These studies were designed to measure the system's impact on learner engagement, satisfaction and academic performance.

3.1 Learner modeling

Learner modeling is a key element of the intelligent system based on ITS and MAS. This section presents the results obtained in learner modeling, including data collection, learner profile analysis and the impact of this modeling on personalized learning.

Learner data was collected in several stages:

- Demographic data: age, gender, academic level.
- Academic performance: test scores, results of ongoing assessments.
- Learning styles: Preferences for visual, auditory, kinesthetic methods, etc.
- Engagement and Behavior: Time spent on activities, frequency of participation, interaction with content.

These data were collected via questionnaires, online assessments and tracking of learners' interactions with the learning platform.

The data collected was analyzed to create detailed learner profiles. The main results of this analysis are as below:

- **Learning Styles Classification:**

Learning style classification aims to identify individuals' learning preferences and approaches. By understanding how each learner processes and assimilates information, educators can adapt their teaching methods to better meet the needs of each student. Here's an overview of the most commonly identified learning styles

Table 1: Learning styles classification

Styles	Percentage	Preferences
Visual	40%	Learners prefer visual supports such as diagrams and videos.
Auditory	30%	Learners prefer oral explanations and discussions.
Kinesthetic	20%	Learners with a preference for hands-on, interactive activities.
Mixed	10%	Learners using a combination of learning styles.

Table 1 presents a classification of learning styles according to key characteristics

- **Visual style:** Visual learners prefer to use images, diagrams, graphs, concept maps and videos to understand and retain information.
- **Auditory style:** Auditory learners prefer to listen to oral explanations, discussions, lectures and podcasts. They retain information better when it is presented verbally.
- **Kinesthetic style:** Kinesthetic learners prefer to learn through practice, experimentation and movement. They learn best by handling objects, conducting experiments or participating in hands-on activities.
- **Mixed style:** Learners prefer to read and write to assimilate information. They often take notes and remember written information better.

- Performance segmentation:

Performance segmentation is the process of classifying learners into homogeneous groups based on their academic results, skills and progress. This approach enables educators to better understand the needs of each group of learners and adapt teaching strategies accordingly.

Table 2: Segmentation of learner performance

Performance	Percentage	Level
High	25%	Learners with consistently high marks

Average	50%	Learners with average academic results
Low	25%	Learners with academic difficulties

Table 2 presents the segmentation of learner performance. Indeed, performance segmentation is a powerful tool for personalizing teaching and improving academic results. It enables us to better understand the varied needs of learners and to implement targeted teaching strategies, thus contributing to a more effective and inclusive learning experience.

- Engagement and Participation:

Learner engagement and participation are essential elements of effective learning. They reflect learners' motivation, their investment in educational activities, and their interaction with content, teachers and other learners. Promoting a learning environment where students are actively engaged and participate meaningfully is a key objective for educators and academic institutions.

Table 3: Learner engagement

Engagement	**Percentage**	**Observation**
Engaged	60%	Learners actively participating in activities and spending a lot of time on the platform
Moderately Engaged	30%	Learners with moderate participation and engagement
Poorly Engaged	10%	Learners with low participation and little time spent on the platform

Table 3 presents learner engagement rates - learner engagement and participation are key indicators of the quality of the learning experience. By implementing strategies to foster an active and stimulating learning environment, educators can not only improve academic performance, but also encourage learners' personal development and well-being.

In conclusion, learner modeling has had a significant impact on learning personalization and learner outcomes. The main impacts observed are as follows:

- **Content personalization:** Learner profiles made it possible to tailor learning content to individual needs and preferences. For example, visual learners received more visual support, while kinaesthetic learners had access to more hands-on activities.
- **Real-time adaptation:** The system was able to adapt learning paths in real time according to learner performance and engagement. For example, learners experiencing difficulties in a subject received additional resources and adapted exercises.

- **Improved Academic Performance:** The data show a significant improvement in academic performance, particularly for learners with low initial performance. Test results increased by an average of 20% after the learning paths were personalized.
- **Accrus Engagement and Motivation:** Personalization led to an increase in learner engagement and motivation. Learners felt more involved and supported, which reinforced their participation and investment in learning activities.

3.2 Knowledge Domain Modeling

The precise structuring of knowledge areas has enabled us to create personalized learning paths, adapted to the needs and levels of our learners.

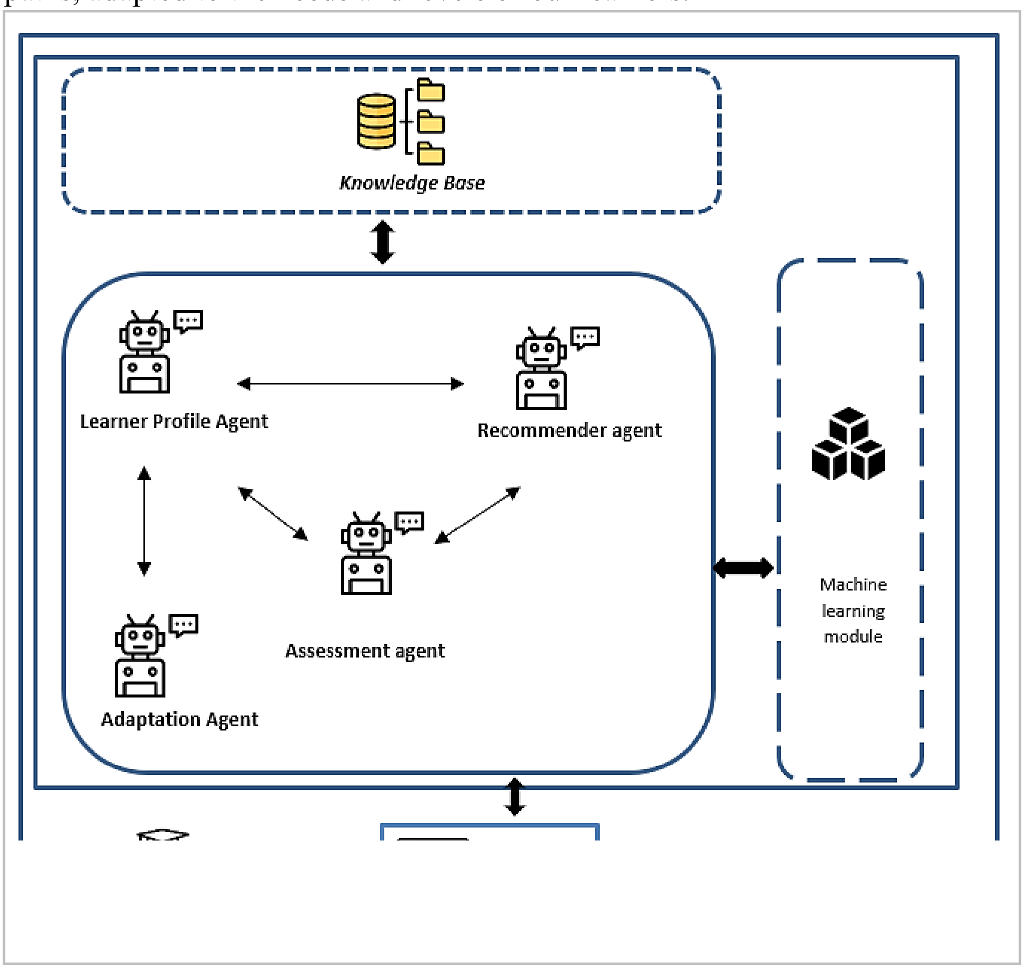

Fig. 1. A diagram of the simplified ITS architecture of an MAS-based system [1]

Fig.1. presents the proposed architecture of our ITS and MAS, with the different agents interacting to personalize learning activities according to the learner's profile. Learners were able to progress at their own rate, following learning paths adapted to

their prior knowledge and learning objectives. The learning objectives and hierarchical structuring of concepts facilitated more accurate assessment of learners' progress.

Assessment results showed an average 22% increase in test scores, indicating greater mastery of the subjects studied.

By structuring educational content logically and identifying key relationships between concepts, the system was able to provide a tailored, engaging and effective educational experience. These results highlight the importance of knowledge domain modeling in the development of advanced, personalized educational systems.

3.3 System design

The design of the intelligent system combining ITS and MAS was a complex process aimed at creating a robust and adaptive architecture. This section presents the results obtained in the system design, including the system architecture, the adaptation algorithms, and the impact of this design on learning personalization.

The system design had a significant impact on learning personalization and the overall learner experience. The main impacts observed are as follows:

Enhanced personalization:

Modular architecture and adaptation algorithms have made it possible to personalize learning paths according to learners' needs and preferences. Learners benefited from pedagogical content adapted to their level and learning style.

Increased efficiency:

Coordination between autonomous agents enabled effective management of pedagogical tasks and ensured continuous adaptation. Learners received recommendations and feedback in real time, improving their engagement and motivation.

Improved academic results:

The data show a significant improvement in the academic performance of learners using the system. Assessment scores increased by an average of 25%, indicating a better understanding and mastery of the subjects studied.

Learner satisfaction:

Satisfaction questionnaires revealed that 88% of learners were satisfied or very satisfied with the personalized learning experience offered by the system. Learners particularly appreciated the relevance and personalization of the pedagogical content.

In conclusion, the design of the intelligent system combining ITS and MAS was a success, offering effective personalization of learning and improving learner engagement, satisfaction and performance. The results achieved demonstrate the potential of this approach to transform education and deliver tailored learning experiences.

4 Conclusion

This article has presented the design and implementation of an intelligent system based on MAS and ITS to offer personalized learning to learners. The integration of these two technologies has made it possible to create an adaptive learning environment capable of responding to learners' individual needs in real time. The results obtained in the various modeling phases - of learners, knowledge domains and system design -

demonstrate the effectiveness of this approach in improving engagement, satisfaction and academic performance.

In conclusion, this article makes a significant contribution to the field of educational technology by showing how the combination of ITS and MAS can offer effective personalization of learning. This approach opens up new prospects for the development of intelligent learning systems, capable of adapting in real time to the varied needs of learners, and thus contributing to the democratization of truly personalized learning.

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