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Design of an Intelligent Tutor System for the Personalization of Learning Activities Using Case-Based Reasoning and Multi-Agent System

Anoir Lamya[1], Chelliq Ikram[1], Khaldi Maha[2] and Khaldi Mohamed[1]

[1]*Research team in Computer Science and University Pedagogical Engineering, Higher Normal School, Abdelmalek Essaadi University, Tetouan, Morocco*
[2]*Rabat Business School, Rabat International University, Rabat, Morocco*

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Abstract: The impact of Artificial Intelligence (AI) has significantly remodelled the educational environment, with tutoring systems emerging as essential tools for adapting personalized learning tracks. This article explores the significant benefits achieved through the smooth integration of Intelligent Tutoring Systems (ITS) and Multi-Agent Systems (MAS) with Case-Based Reasoning (CBR). Intelligent tutoring systems, which operate as an interactive platform, exploit the strength of educational data mining to construct meticulously personalized learner profiles. In tandem, multi-agent systems facilitate dynamic collaboration between a whole range of agents, including profile agents, recommendation agents, assessment agents and adaptation agents. This collaborative effort aims to orchestrate personalized learning activities that are finely adjusted to respond to the specific needs of each learner. The introduction of case-based reasoning elevates the sophistication of personalized learning by exploiting the depth of prior knowledge and experience. By systematically exploring a specific knowledge base of similar cases, the system provides recommendations and proven solutions. This ensures a learning experience that not only works with each learner's unique profile but also guarantees relevance and effectiveness. This article embarks on a comprehensive exploration of personalized learning activities by integrating ITS, MAS and CBR transparently. The main objective is to optimize learning engagement and effectiveness by proactively adapting educational content to the individual needs of each learner. This exploration is part of the continued focus on improving the educational experience through the advancement of AI and educational technologies.

Keywords: Personalization, Artificial intelligence, Intelligent tutoring systems, Multi-agent systems, Case-based reasoning, Learning activity

1. INTRODUCTION

The integration of innovative technologies has led to the advancement of personalized or adaptive learning. In the early 1970s, researchers utilized an Artificial Intelligence (AI) approach to address the issue of designing learning environments [1]. Personalized and interactive learning depends on adapting learning models to the learner's knowledge, emotions, and actions. AI has played a major impact in enhancing tutoring systems. Educational data mining is essential for comprehending the learning process and learner behaviour, which enhances research on the effectiveness of personalized systems [2]. In addition, to the importance of the content being suggested, AI can also personalize and adapt the content courses based on the identified skill level and speed of the learner. These intelligent systems will engage with the learner like an online personal tutor, thus known as Intelligent Tutoring Systems (ITS) that utilize AI methods for adaptive teaching. Education is currently moving toward personalized learning methods to meet learners' different requirements and preferences. ITS uses technology and data to create personalized learning experiences. Integrating CBR and MAS in ITS can improve personalized learning. ITS are computer-based learning environments resulting from Computer-Assisted Instruction (CAI) and are designed to adapt to individual learner's needs through personalized AI systems. This innovation addresses the restrictions of CAI by offering more adaptable and engaging platforms that evaluate and address each learner's challenges to offer suitable support [3]. ITS is mainly utilized as a platform for solving problems or practicing exercises. They facilitate learning within a particular subject area by directing and supporting the learner [4]. Personalizing learning with ITS allows for unique learning paths to be created for each learner based on their needs, interests, and skill level. These systems use learner data, such as assessment results,

E-mail address: lamya.anoir@uae.ac.ma, ikram.chelliq@etu.uae.ac.ma maha.khaldi@etu.uae.ac.ma, m.khaldi1@uae.ac.ma

learning preferences, and interactions with content, to adapt content and learning activities in real-time. This allows for a more effective and engaging learning experience for learners, as they receive content that matches their skill level and assists them in achieving their learning objectives. CBR utilizes previous knowledge for problem-solving while MAS involves multiple independent agents collaborating to achieve a common objective [5]. The merging of CBR and MAS provides synergistic potential for the adaptation and personalization of learning activities, enabling ITS to dynamically adapt to learners' unique profiles, preferences, and performance.

In the following sections, we explore this fusion, revealing the potential that it offers for educators, learners and the educational ecosystem at large. By converging technological innovation and educational pedagogy, we aim to present a holistic perspective on the trans-formative power of personalized learning in the age of AI.

This article thoroughly examines how combining CBR and MAS can improve the personalization of learning activities in ITS. We explore the theoretical background of CBR and MAS, highlighting their respective strengths and capabilities in the context of personalized learning. Building on existing research on CBR and MAS, we offer an innovative framework that takes advantage of the interaction between these two approaches to produce a comprehensive and adaptable learning environment. This article has two main objectives: firstly, to clarify the theoretical basis of CBR and MAS, emphasizing their importance in personalized learning within ITS. secondly, to present a conceptual architecture that illustrates the transparent integration of CBR and MAS to optimize the personalization of learning activities, enabling a sophisticated and personalized learning experience to be offered to different learner profiles throughout the learning process through CBR and MAS, to offer personalized recommendations and learning activities adapted to individual learners' needs, ultimately boosting their engagement, motivation, and success in learning.

2. BACKGROUND THEORY AND METHODOLOGY

Several recent studies have explored the development of ITS aimed at personalizing learning activities. These systems have presented a positive impact on personalized learning, contributing to improving learner performance and better time management. For instance, Duque Méndez et al. (2018) designed a personal intelligent assistant to help users select educational materials from repositories of learning objects. They implemented a recommendation system based on the artificial intelligence technique known as CBR, which leverages past outcomes of similar learners to enhance the relevance of materials for each individual [6].

Similarly, Mamcenk et al. (2019) examined the use of CBR to provide relevant recommendations in online learning contexts. They explored educational data and utilized case-based reasoning to profile learners and design a personalized intelligent learning system, aiming to assist learners in creating learning units that suit them [7].

In 2020, Yasar Akyuz evaluated the effectiveness of intelligent tutoring systems in facilitating personalized learning, covering various aspects such as architecture, future role, methodology, and the importance of ITS [8].

In parallel, Ciloglugil et al. (2021) proposed a multiple-agent-based adaptive online learning system that supports customization based on learning styles. With the rise of distance learning, particularly due to the COVID-19 pandemic, the goal is to provide an adaptive online learning system solution that offers more effective learning experiences by considering individual differences in learning processes. The Felder and Silverman learning style model was used to represent these differences [9].

These studies have established the basis for an integrated approach to personalized learning activities, in which intelligent tutoring systems make use of both prior knowledge. In this approach, we have combined all the key points for our working methodology to propose adaptive and personalized solutions. This paragraph emphasizes the critical significance of personalized pedagogical activities in learning systems. Adapting educational content and resources to learners' individual preferences and abilities is crucial for enhancing motivation, improving learning efficiency, and creating a more engaging educational experience. Additionally, understanding learners' preferences and learning styles is essential for successful personalized learning in e-learning environments, requiring knowledge of their unique learning needs and information assimilation methods. This paragraph highlights a particular approach in the article, involving cognitive tutoring and personalized system design through MAS and ITS, with an emphasis on the CBR paradigm. By analyzing past cases in its knowledge base, the system can create adapted learning scenarios to meet each learner's specific needs effectively. The methodology adopted in this article is based on a systematic approach aimed at effectively integrating cognitive tutoring and personalized system design in e-learning. We have centered our approach on the joint use of MAS, ITS and CBR to exploit the richness of educational data and promote dynamic collaboration among various agents, including the profile agent, the recommendation agent, the evaluation agent and the adaptation agent.

A. Multi-Agent Systems (MAS)

The idea of an intelligent agent is derived from the field of AI. AI focuses on developing autonomous objects capable of intelligent behaviour. As per a widely accepted definition, an agent should be able to sense its surroundings, plan how to achieve its objectives, and communicate with other agents[10], which is presented in Fig. 1:

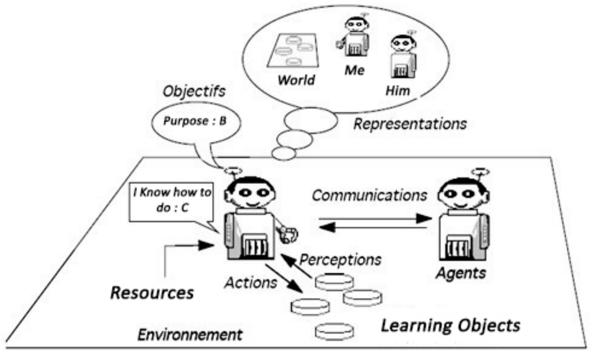

Figure 1. An multi-agent universe

In Fig. 1, According to Ferber (1995), an agent is a computing entity situated in an environment, which can be real or virtual, and engages with other agents to create a social structure that is the basis of their social organization [11]. The MAS are a unique type of distributed system, with autonomous and self-interested components that pursue their own goals. Additionally, MAS is distinguished for being an open system without centralized design [12]. MAS has attracted considerable interest. due to their role as a technology that supports intricate applications needing distributed and parallel data processing, functioning independently in complex and adapted environments. The MAS, have potential advantages in solving problems related to open, distributed and complex systems. Indeed, it is reasonable to deal with them through modular and functional decomposition, so that "agents" are specialized in solving specific parts of the problem to create cohesive multi-agent systems [13], [14]. The MAS can play a major part in personalizing learning by allowing learners to interact with personalized agents that provide adaptive content adapted to their individual needs. The agents' purpose is to monitor learners' performance, gather information about their learning preferences, and propose personalized content that is adapted to their specific needs. They can also serve as virtual tutors, providing personalized instructional support while assisting learners in solving educational problems and challenges, as well as providing real-time feedback on learners' performance, allowing learners to track their progress and make continuous progress, thus boosting their engagement and success in the learning process.

B. Intelligent Tutor Systems (ITS)

ITS have been developed since the 80's. Researchers tried to produce systems that could simulate a human teacher, adding to the system some solving capabilities (hence the adjective intelligent), allowing it to advise the learner when the latter made a mistake in solving an exercise (hence the adjective tutorial). Therefore, as indicated by [15], ITS can be defined as a teaching system whose pedagogical objective is to transmit knowledge and especially expertise [16]. ITS are composed of four models Fig. 2:

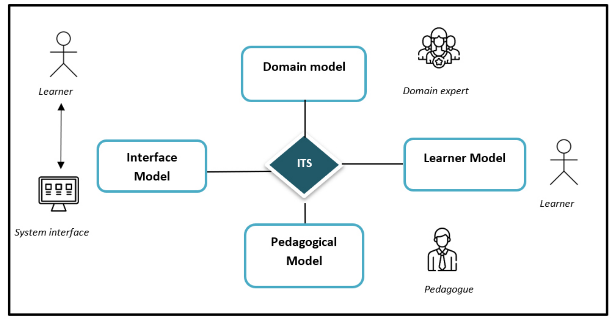

Figure 2. The 4 models of an ITS

To further explain the behaviour of ITS, we must examine their design. The traditional structure of an ITS includes four models (Fig. 2).

- Domain model: represents the expertise of a domain expert.
- Learner model: determines the learner's knowledge level.
- Pedagogical model: allows for instruction modification based on learner behaviour.
- Interface model: facilitates information exchange between system and user.

Certainly, ITS are tools that support the learner in their learning process through AI methods, which personalize learning tasks, scenarios, and feedback according to individual requirements. When combined, ITS and personalized learning enable a more immersive and efficient educational experience and engagement for learners [17]. AI recommendation algorithms in ITS suggest learning activities adapted to individuals based on their interests and skills, using various AI algorithms like language processing, image processing, structured data processing, and automatic reasoning. Intelligent dialogue agents are used to personalize learning and track learners' progress. ITS are considered necessary and important for personalizing learning for several reasons:

- ITS can personalize instructions and activities by identifying each learner's needs and preferences through learning data, adapting to their profile.
- Enhanced engagement and motivation are achieved by using natural dialogue methods to interact with learners more naturally and address their inquiries, potentially boosting engagement and motivation levels.
- Increased engagement and motivation are obtained through the use of natural dialogue techniques when interacting with learners in a more authentic way to

answer their questions, potentially enhancing engagement and motivation levels.

- To promote participation in education, consider the various types of learners, including their unique requirements, preferences, and learning styles.

In summary, ITS can provide significant benefits in personalizing learning by adapting instruction and learning activities to meet individual learner needs, improving learner engagement and motivation, increasing learning efficiency, and accommodating learner diversity. Although MAS and ITS have similar educational objectives, their approach is different. MAS focus on agent interaction to provide personalized educational support, while ITS uses tutoring algorithms to adapt educational content and activities to individual learner needs. Ultimately, both approaches can provide personalized educational support to learners based on their individual needs.

C. Case-Based Reasoning (CBR)

Case-Based Reasoning (CBR) is an AI paradigm that involves using past knowledge to solve new and similar problems, as it relies on the concept that similar issues tend to have comparable solutions that can be reapplied [18]. The CBR stores various cases in memory. When faced with a new problem, it searches for the most comparable situation in its memory and adjusts it to discover a resolution [19]. When a similar situation is found, the solution used to resolve it can be modified to fit the new problem by considering any differences between the situations. This adjustment can be made through analogy or by adjusting the previous solution based on updated information [20]. CBR is applied in various sectors like healthcare, project management, manufacturing scheduling, and engineering to effectively address intricate issues using previously gained knowledge. The CBR cycle, as introduced by Aamodt and Plaza in 1994, is presented in the following process (Fig. 3):

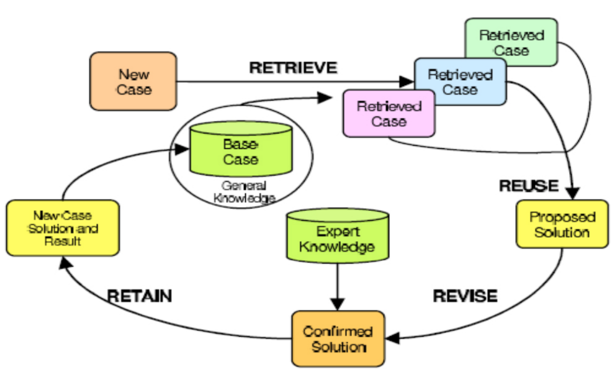

Figure 3. Cycle of CBR Adapted from [18].

This figure clearly depicts the essential processes in the process of a case-based reasoning system. These steps emerge:

- Recover previously experienced cases related to the current problem.
- Reuse these cases in some way.
- Revise the solution by reusing the previous cases.
- Maintain the new solution (as a new case) by adding it to the existing case database. Then a CBR system will progressively expand and become a valuable resource.

CBR in adaptive e-learning assists learners in problem-solving and question-answering by finding solutions from comparable cases. Through personalization, e-learning tailored to individual preferences enhances efficiency and reduces time and effort in addressing learner challenges. Personalization is a topic that is gaining more attention, with its time and motivation benefits being well proven [21], [22]. Personalizing educational activities primarily implies knowing learners' needs; numerous AI approaches have been employed to model learners to personalize online educational materials and provide pedagogic instruments, such as planning, case-based reasoning, etc [23].
Using our theoretical framework, our primary goal is to create an intelligent system that personalizes learning experiences for individual learners by personalizing scenarios that align with their needs. This personalized approach is grounded in pedagogy, to enhance learning motivation, and consequently improve the overall quality and efficiency of the learning process. For a specific learner, a high-quality scenario entails a methodical sequence of learning components that have the highest suitability indices.
In this theoretical background, we combine MAS, ITS and CBR to provide a promising approach for designing our advanced and personalized AI systems, using prior knowledge and interacting autonomously with other agents.

3. RESULTS

The study's findings underscore the efficiency and importance of personalizing CBR and MAS for developing a personalized ITS. By merging these methods, ITS presents outstanding proficiency in offering personalized recommendations and interventions tailored to the specific needs of each learner.
Integrating CBR techniques can be a valuable resource for personalizing and adapting each learner's learning experience. By using CBR to analyze performance, identify knowledge gaps and provide personalized learner feedback and recommendations, using CBR will accelerate the learner profiling procedure, since classes for recognized learners will be pre-established using this data, and learners with profiles will be grouped according to similarities with other profiled learners. MAS prioritize agent interaction for personalized educational support, while ITS focuses on tutoring algorithms to create a personalized learning system that tailors activities and scenarios to individual learner needs and preferences (Fig. 4):

Figure 4. CBR adaptation process for personalizing an ITS

Fig. 4 presents the CBR adaptation process for personalizing an ITS in the following steps:

- ***Learner profile analysis, data collection and analysis:*** Agents can help assess the learner's characteristics such as their preferred learning style, skills, and preferences, while other agents collect in real-time data on the learners' activities and interactions for analysis. The information collected may consist of the learner's achievements, performance, knowledge, skills, preferences, etc.

- ***Using CBR to adapt learning activities:*** The gathered data can form a case repository, utilized by the CBR system to adapt learning activities to individual learners by matching each activity with an appropriate scenario according to their needs and preferences. For instance, when a learner struggles with grasping a specific concept, the CBR system can suggest an alternative scenario for that particular learning activity to assist in overcoming the difficulty.

- ***Using ITS***: The ITS can offer personalized learning support adapted to the individual knowledge and skill levels of each learner. For instance, it can deliver in-depth explanations, examples, questions, and feedback, enabling learners to advance at their own speed.

- ***Personalized activity recommendation****:* Agents can recommend personalized learning activities based on the individual learner's past performance and preferences. For example, if a learner has demonstrated a strong interest in practical activities, the MAS system can recommend practical activities to maintain their engagement.

- ***Interaction and collaboration with other learners:*** Agents can also be used to facilitate interaction and collaboration between learners, where they can be grouped according to preferences and performance, to work together on collaborative learning projects.

CBR and ITS are implemented by representing learner profiles as cases. This method has the benefit of making it simple to visualize an issue in terms of agents and then implement it as a CBR system. The system monitors track of its case base to adjust to changes in the learning activity, suggesting the most suitable scenario for each activity based on the learner's profile each time. The suggested framework consists of an integrated collection of distributed components, categorized into segments known as agents. CBR techniques and agents can be advantageously combined to solve ITS design problems where no single technique can provide a satisfactory solution. To this observation, we propose our system based on three levels :
- Determining the learner's profile from the learning style.
- Case base of scenarios for multi-agent learning activities.
- Personalization and adaptation of the ITS.

A. Determining the learner's profile from the learning style:

Learner profiles demonstrate how learners engage with content, including their behaviour and interaction patterns, as well as their preferred learning styles, which center on individual learner traits. When considering learning scenarios, they are delineated based on the information to be learned and the materials presented, all from the learner's perspective [24], [25]. The learning style is defined by a variety of attributes of the learner in connection to several aspects, each of which influences unique variations in the learning environment. Each component operates separately but cooperates to form a unified functional whole [26]. We determine a learner's preferred learning style in our context by referring to Kolb's experiential learning model, which emphasizes the impact of learning on personal development and the individualized nature of learning processes [27].
Kolb has developed a learning cycle theory, emphasizing four unique learning styles:

- **The "Concrete and experiential" learning style:** This learning style entails a fondness for tangible experiences and active participation. Individuals with this style prefer hands-on learning and enjoy experimenting with new experiences.

- **The Reflective and observant:** This learning style is defined by a liking for watching and contemplating. Learners who have this learning preference like to carefully observe and analyze before they take action.

- **The Abstract and theoretical:** This learning style is presented by a preference for conceptualization and theorizing. Learners with this learning style prefer to work on abstract concepts and ideas rather than on concrete situations.

- **The Pragmatic and Purposeful:** This learning style is defined by a preference for the practical application of theory. Learners with this learning style prefer to solve concrete problems and apply learned concepts to real-life situations.

Therefore, to assess a learner's learning profile with Kolb's

theory, a questionnaire known as "Learning Style Inventory" (LSI) is utilized, consisting of 80 items to help and identify the learning styles of each [28], identifying their preferences for specific activities, abstract concepts, observing, reflecting, and solving problems will help determine the learner's learning style and create the corresponding learner profile [29].
When applying CBR, problem-solving cases resembling those the learner will face in learning can be utilized after identifying their style with Kolb. For example, suppose a learner has a "pragmatic and purposeful" learning style. To determine his or her learner profile, we use the CBR approach to search for similar cases of practical problem-solving, which have been successfully solved by other learners with a similar learning style. Once similar cases are found, the information obtained can be utilized to adapt learning tasks for the individual learner. In cases where practical problem-solving methods were used, providing learners with similar practical activities could help with their learning.
Similarly, when a learner exhibits a "concrete and experimental" learning style, the CBR method can be employed to pinpoint analogous instances of hands-on problem-solving that have been effectively tackled by other learners sharing a similar learning approach. Then, the knowledge extracted from these cases can be used to propose practical learning activities that help the learner implement the concepts and theories learned. After identifying the learner profile, we will personalize the learning activities to fit the learner's engagement, likes, and educational requirements. This approach allows for the adjustment of learning activities to enhance both efficiency and effectiveness in learning (Fig. 5) :

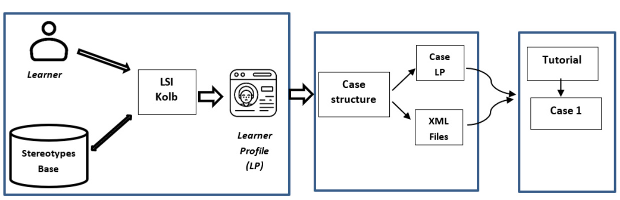

Figure 5. Learner profile simulation process through CBR

Fig. 5 describes the process of identifying a learner's profile to imitate their knowledge by analyzing data such as question responses, task time, errors, learning preferences, prerequisites, and assessments, based on Kolb's learning style model to analyze collected data for determining skill level, areas of confusion, and preferences, etc. Upon identifying his style, it is archived within a case to personalize activities according to his preferred approach.

B. Case base of scenarios for multi-agent learning activities:

The base of scenario cases can support personalized learning activities in MAS and ITS by offering personalized and adapted educational support to learners (Fig. 6) :

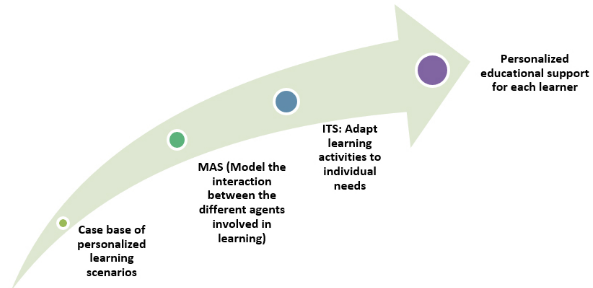

Figure 6. Learner profile simulation process through CBR

In Fig. 6, the personalized learning scenario case base maintains information about learners, including factors like learning style, skill level, and interests, the MAS simulates how different agents like teachers, tutors, and peers interact during learning, using data from the case repository to personalize learning tasks for each learner. Similarly, the ITS adjusts learning activities to respond to the specific needs of individual learners through tutoring algorithms and uses information stored in the case repository to personalize learning tasks according to each learner's distinct needs. In conclusion, developing a case base that includes learner styles ensures diverse learning scenarios adapted to each learner, enhancing the efficiency and effectiveness of educational support.

C. Personalization and adaptation of the ITS:

The ITS uses algorithms to personalize learning based on learners' individual needs and preferences. This can involve using machine learning models to create adaptive algorithms for choosing the most appropriate content, suggesting additional learning activities through recommendation algorithms, and evaluating learner progress with classification algorithms. Intelligent tutorial systems also use feedback mechanisms to adjust learning strategies in real-time [30]. Example of an algorithm to provide the adaptation of personalized pedagogical activities to the MAS and ITS area.

- **Learning data collection:** The system records data on the learner's performance, such as question responses, task time, errors, learning preferences, etc.
- **Learning data analysis:** The collected learning data is analyzed to evaluate the learner's skill level, gaps in understanding, learning preferences, etc.
- **Learning activity generation:** The system uses the learning data to generate a personalized pedagogical activity for the learner. The activity can be a quiz, a practical exercise, a simulation, etc.
- **Transfer the personalized pedagogical activity:** The system sends the personalized pedagogical activity to the learner, who completes it.

- **Collecting the results of the activity:** The system collects the personalized pedagogical activity results, such as correct and incorrect answers, time spent on the task, etc.

- **Analysis of activity results:** The results of the personalized pedagogical activity are analyzed to determine the learner's skill level, gaps in understanding, learning preferences, etc.

- **Adaptation of the following pedagogical activity:** The system employs the results of the adapted educational activity to personalize the next pedagogical activity to the learner's needs.

- **Interaction with agents:** MAS agents interact with the learner to provide personalized instructional support throughout the process.

Following is an illustration of how this algorithm is implemented in Python (Fig. 7) :

```python
# Collection of learning data
performance = collection_of_learning_Data()

# Analysis of learning data
skill_level = analysis_skill_level(performance)
gaps_comprehension = analysis_gaps_comprehension(performance)
preferences_learning = analysis_preferences_learning(performance)

# Generation of the personalized learning activity
activity = generate_activity_perso(skill_level, gaps_comprehension, preferences_learning)

# Sending the personalized learning activity to the learner
send_activity(activity)

# Collection of activity results
results = collecte_results_activity()

# Analysis of the results of the activity
skill_level = analysis_skill_level(results)
gaps_comprehension = analysis_gaps_comprehension(results)
preferences_learning = analysis_preferences_learning(results)

# Adaptation of the following pedagogical activity
activity = generate_activity_perso(skill_level, gaps_comprehension, preferences_learning)

# Interaction with agents
agents.interact()
```

Figure 7. Examples of personalized pedagogical activities adaptation algorithm through ITS and MAS

By combining MAS and ITS, this algorithm (Fig. 7) allows the tailoring of pedagogical activities depending on each learner's requirements and preferences, while also offering interactive and personalized support throughout the learning process.
The ITS include an adequate knowledge domain, and its objective is to give this knowledge to learners through a personalized iterative process, similar to how a human tutor guides the learner through the learning process.
In this article, we conceptualize a case-based (agent-based) distributed learner modelling ITS architecture to support self-paced, highly interactive learner-centered learning.

Fig. 8 presents our proposed system architecture.

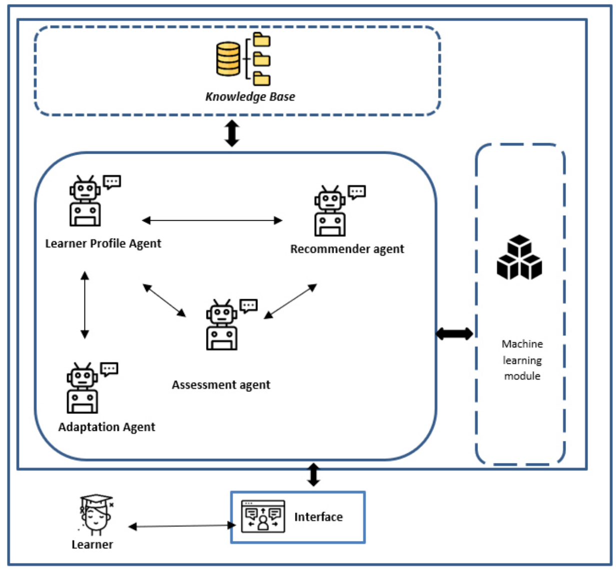

Figure 8. System architecture based on MAS, ITS and CBR

Fig. 8, demonstrates our system architecture based on a MAS and ITS, which uses CBR to personalize pedagogical activities based on the learner's profile.
In a MAS and ITS that incorporates reasoning from CBR situations, the various agents collaborate to personalize educational tasks according to the individual learner's characteristics. The following is a description of the principal agents involved:

- **Knowledge Base:** This database contains information about pedagogical activities, learner profiles and similar cases used by the recommender to personalize recommendations. The knowledge base is updated regularly to incorporate new data and improve the accuracy of recommendations.

- **Learner Profile Agent:** This agent is in charge of obtaining information about the learner, including past knowledge, learning preferences, learning style, and performance experience. It uses this data to build a complete profile of the learner. It uses this data to build and update the learner's profile.

- **Recommender agent:** This agent employs a case-based approach to offer personalized pedagogical tasks to the learner. It examines the learner's profile and searches for similar examples in a knowledge base that includes instructional activities and associated learner profiles. Based on similar examples, the recommendation agent suggests activities adapted to the learner's requirements.

- **Assessment agent:** This agent continually monitors the learner's performance. It records information on the learner's answers, progress, and issues. This data is utilized to update the learner's profile, evaluate performance, and personalize pedagogical activity recommendations.

- **Adaptation Agent:** This agent tracks the learner's interactions with the ITS in real-time. It can change the elements of the learning environment, such as task difficulty, response time, and information presentation, based on the learner's responses and performance. The adaptation agent ensures that the learner is engaged and stimulated by the recommended activities.

- **Machine learning module:** This module uses machine learning algorithms to enhance the system's performance over time. It can be used to adjust recommendation models, optimize adaption parameters, and increase evaluation accuracy.

- **Learner Interface:** This is the interface through which the learner connects with the ITS. It can be accessible through a computer, tablet, or smartphone. The user interface allows the learner to receive activity recommendations, complete learning tasks, and track their progress.

- **Learner**: The learner is the individual who connects and interacts with the system through the interface and the activities available.

In this architecture, agents collaborate to provide all learners with a personalized learning experience. The learner profile agent accumulates information about the learner, the recommendation agent uses CBR to offer personalized pedagogical activities, the evaluation agent monitors the learner's performance, and the agent responsible for adaptation adjusts the learning environment according to the learner's needs. The interaction of these agents allows instructional activities to be personalized based on the learner's profile, resulting in recommendations adapted to his knowledge, preferences, and progress.

4. DISCUSSION

Learning personalization refers to how AI applications contribute to providing personalized learning programs to boost learner engagement and respond to learner needs. For example, AI is employed for profiling, prediction, evaluation, and review [31]. In other words, learner profiles are identified through AI, and these profiles are then utilized to predict which learners will drop or even fail a course. When learners become confused or stuck in their work, this can be used to provide feedback and guidance during the learning process through the use of suggestions. Personalizing learning activities in ITS with CBR and MAS is a good technique for reacting to learners' particular requirements (Fig. 4). This topic focuses on the significance and benefits of adapting learning activities, as well as the unique contributions of CBR and MAS to this personalization. One of the primary benefits of personalized learning activities is that they allow learners to develop at their own accelerate and based on their unique needs. Each learner has different knowledge, skills, and learning preferences, and personalizing activities can help adapt resources and instructional strategies to respond to these individual differences (Fig. 5, Fig. 6). This can promote learner engagement, motivation, and success. CBR is a relevant approach to personalized learning activities because it uses previous experience to solve new problems [7]. By using similar cases, CBR can recommend learning activities that have been effective for learners with similar profiles (Fig. 7). For example, if a learner has difficulty with a particular concept, CBR can discover similar examples where other learners have solved those issues and offer specific exercises that have been advantageous in such cases [32]. The MAS provide a framework for personalized learning activities by allowing dynamic interaction between the different agents involved. Agents can collaborate to collect information about the learner's profile, assess their performance, recommend personalized activities and adapt to the learning environment. This collaboration between agents enables the integration of numerous sources of knowledge and expertise, which provides a more efficient and comprehensive adapted learning experience (Fig. 8). The combination of CBR and MAS to improve personalized learning in ITS has several advantages that result in a more effective personalized educational experience:

- **Enhanced Personalization:** By combining CBR and MAS, the solution offers a dynamic and context-aware approach to personalizing learning activities. Learners receive adapted recommendations and interventions based on their individual learning preferences, progress, and performance.

- **Using the experiences:** CBR exploits past learning experiences and examples of successful problem-solving to provide relevant and effective recommendations. Learners can take advantage of the experience acquired from previous cases, improving their understanding and mastery of the subject.

- **Collaborative Learning Environment:** The collaborative nature of MAS encourages interactions between autonomous agents, promoting a highly enriching and engaging learning environment. Agents work together to optimize learning activities, creating a holistic and comprehensive educational experience.

- **Adaptive Learning Pathways:** The integrated solution adapts in real-time to learners' evolving needs and progress. Learners receive adaptive learning paths that dynamically adjust to their evolving skill levels, ensuring constant challenge without causing frustration.

- **Efficient Knowledge Transfer:** CBR facilitates effective knowledge transfer by re-using successful strategies and solutions. Learners can benefit from the collective expertise stored in the case base, which accelerates their understanding and acquisition of skills.

- **Personalized Learning Pace:** Learners can progress at their own pace, with the solution offering personalized content and challenges in line with their current skills. What's more, learners can take part in the training at their own pace, with the solution offering personalized content and challenges in line with their current skills.
- **Individualized Feedback:** MAS enables agents to provide personalized, timely, and constructive feedback to learners. This feedback loop supports a deeper understanding of concepts, helps correct misconceptions, and encourages reflective learning.
- **Adaptation to Learning Styles:** CBR and MAS can account for diverse learning styles, catering to visual, auditory, kinesthetic, or other preferences. This ensures that instructional materials align with learners' unique ways of absorbing information.
- **Continuous Improvement:** The system's ability to learn from learner interactions and adapt its recommendations over time enhances its effectiveness. As learners engage more, the system becomes more attuned to their needs, providing increasingly relevant suggestions.
- **Comprehensive Learning Insights:** The combined system offers instructors and administrators essential insights into learners' development and achievement. This data-driven approach allows for more informed decisions on instructional design and intervention approaches.

The integration of CBR and MAS allows for the benefits of each approach. CBR provides a method of reasoning based on previous experiences, while MAS provides a framework for collaboration and coordination between agents for dynamic personalization [33]. For example, profile and recommendation agents can work together to identify relevant similar cases and propose personalized activities using these cases.

The limitations and challenges of our study relate mainly to several aspects: The effectiveness of adaptation and personalized learning depends largely on available data and learner profiles. The availability and quality of such data can be a limitation, limiting the generalization of results to other contexts or learner populations. While adaptation and recommendation algorithms are essential, optimizing them to ensure relevant and effective recommendations can be a challenge. Ongoing adjustments and regular evaluations are required to improve the accuracy and relevance of recommendations. Measuring the real impact of personalized learning on learner engagement, knowledge retention and overall performance can be complex. Robust methodologies and adapted evaluation tools are needed to reliably assess the effectiveness of personalized systems.

By focusing on these limitations, we need to identify the key challenges for improving the design and effectiveness of personalized learning systems, thus setting the way for future research and innovation in this field.

5. CONCLUSION

This article presents our proposal for integrating CBR and MAS to design a personalized ITS, thus providing an innovative and powerful approach to enhancing personalized learning. The results achieve demonstrate that the joint exploitation of these techniques overcomes the traditional challenges associated with personalizing learning activities. The adaptation of CBR and MAS has resulted in the development of an ITS able to determine a learner's profile based on his or her learning style. This technique results in recommendations and interventions that are more appropriate to each learner's specific requirements and preferences. This extensive personalizing has increased learner engagement, increased intrinsic motivation, and enhanced learning results. In addition, ITS's dynamic personalization and adaptation process demonstrates its ability to offer flexible and evolving learning paths. By exploiting collaboration between MAS agents, the system responded to learners' progress and changes, ensuring a highly adaptable and effective educational experience. In conclusion, personalizing learning activities through ITS and MAS with CBR holds exciting prospects for improving personalized learning. Exploiting the advantages of each approach. In this context, we are currently focusing on integrating our intelligent, personalized system in future productions.

6. FUTURE PERSPECTIVES

The perspectives of this work open promising gates towards the concrete development of the system we have conceptualized. The next research phase will focus on developing this concept into a functional, personalized, adaptive and intelligent system. In developing the system, we plan to implement the key elements identified in our approach, by operationally integrating MAS, ITS and CBR. This development phase will involve the actual creation of the various agents, the implementation of communication between them, the exploitation of educational data, and the implementation of CBR for personalized learning scenarios. In addition to developing the system, our future work will focus on the continuous improvement of the approach, exploring new avenues for more personalized learning, taking into consideration technological and pedagogical developments. We also plan to extend our research to other educational contexts and different disciplines, to generalize the applicability of our approach. In short, our commitment to this perspective of continuous development aims to make a significant contribution to the advancement of personalized and intelligent learning systems.

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Anoir Lamya PhD Student in Computer sciences, and member of Research Team in Computer Science and University Pedagogical Engineering Higher Normal School, Abdelmalek Essaadi University, Tetouan, Morocco. She has a Master degree in Instructional design Multimedia engineering at Higher Normal School of Martil, Morocco in 2019. The current research focuses on: Personnalized E-learning, Adaptive Hypermedia Systems, Artificial Intelligence. She can be contacted at email: lamya.anoir@uae.ac.ma.

Chelliq Ikram PhD student in Computer sciences, and member of the Research team in Computer Science and University Pedagogical Engineering Higher Normal School, Abdelmalek Essaadi University, Tetouan, Morocco. She has a Master's degree in Instructional Design Multimedia Engineering at Higher Normal School of Martil, Morocco in 2020. She has published different articles related to Pedagogical Objects, Adaptive Hypermedia Systems, Personalization, Artificial Intelligence and E-learning.

Khaldi Maha holds a Ph.D. in computer science specializing in eLearning, and a master's degree in Pedagogical Engineering and Multimedia from Abdelmalek Essaadi University Tetouan. Actually She is professor/ Lecturer in Rabat Business School-Rabat International University, Rabat, Morocco. With a deep interest in research, Dr. Khaldi actively explores eLearning and pedagogical scenarios in online classes.

Khaldi Mohamed Professor at Higher Normal School of Tetouan, and member of the Research team in Computer Science and University Pedagogical Engineering Higher Normal School, Abdelmalek Essaadi University, Tetouan, Morocco. He is the (co)author or (co)editor of 31 academic books and (co)author of over 200 articles and book chapters at international journals and conferences. Authored an international textbook of "Springer", "Bentham Science Publishers" and IGI Global Publicaton along with Patents and Copyright to his credit. His areas of interest include Artificial Intelligence, Pedagogical approach, Assessment methods, Adaptive Hypermedia Systems, Bayesian Networks, and E-learning. He gives training to undergraduate, postgraduate students and guides research scholars in these areas.