GENERATIVE AI SUPPORTED PERSONAL LIFE LEARNING ENVIRONMENT

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ABSTRACT

With the emergence of IT technologies, educational institutions have diversified their logistics in order to improve students' performance and learning quality. They invest in the implementation of learning management systems offering personalization to learners. Such personalization depends most of the time on institutions constraints. Considering this limit, the personal learning environments (PLE) represent an interesting solution for learners to develop their own learning environment. This concept fits perfectly with the lifelong learning context, which is one of the recommendations of the sustainable development goals (SDGs). However, such an environment is not necessary based on pedagogical foundations, then, we are faced with uncomfortable situations: learning not aligned with prerequisites, training layout not aligned with content and learner expectations. We developed an approach to build a PLE allowing learner to define his/her learning objectives, to build an appropriate curriculum and to follow his/her. However, the approach implementation in real context is very complex, so its generalization is essential. To overcome this, we provide an updated version of our approach using Machine-Learning algorithms and Generative AI.

KEYWORDS

Lifelong Learning, Personal Learning Environment (PLE), Generative Artificial Intelligence (GAI), Machine Learning Algorithms (MLA), Recommendations System, Standard 8.

INTRODUCTION

Nowadays, learners use different learning platforms, tools, resources to improve their skills, to acquire knowledge and to evolve in their careers. However, choosing, using and managing those heterogeneous learning artifacts can lead to an inefficient learning experience.
Regarding this situation, we have developed a PLE approach to assist learner to have a best learning experience. Our previous CDIO-contribution (Guettat et al., 2024a) introduces a method to support learners in constructing their own curriculum without the need for prior pedagogical expertise, allowing them to take independent control of their learning within a Personal Learning Environment (PLE). This approach emphasizes lifelong learning and aligns with the Sustainable Development Goals (SDGs). However, our approach is still complex to be implemented in the real world with its full potential. Therefore, we come up with an updated version, precisely an AI-enhanced version to overcome this limitation.

This paper is organized in six sections. After the introduction, we present the PLE and the lifelong learning concepts. Next, we summarize the main elements of our approach to build an efficiency PLE, the experiment results and the limitations of our approach. The next section is dedicated to our new PLE architecture based on Large Language Models (LLMs) (part of Generative Artificial Intelligence) which is an improvement of the old architecture using innovative AI technologies. The fifth section presents a prototype of our system based on this new architecture. In the last section, we conclude by summarizing our main contribution and describing our ongoing work.

PLE & LIFELONG LEARNING CONCEPTS

PLE Context

Personal Learning Environment (PLE) refers to the use of learning technologies that prioritize learner autonomy in managing tools and resources. Key questions explored include: How does the learner utilize technology to manage their own learning? What are the unique features of a personal learning environment? A PLE can be viewed as a complex activity system in coherence with the activity theory (AT) (Bal, et al., 2023; Buchem, et al., 2011).

PLE Definition, Characteristics And Objectives

“A PLE is a learner-centered approach, based on web technologies and allowing support, control and appropriation of learning independently of technical and institutional constraints” (Guettat, et al., 2024a; Guettat et al., 2024b; Guettat & Farhat, 2017).

Based on the views of (Guettat, et al. 2024a; Chatti, et al., 2021; Yen, et al., 2021; Göksel & Mutlu, 2021; Martindale, et al., 2019; Guettat & Farhat, 2017; Göksel, et al., 2016; Chatti, et al., 2011; Drachsler, et al., 2008; Jafari, et al., 2006; Johnson, et al., 2006; Lubensky, 2008), PLEs should have the following characteristics:

- PLEs are open systems controlled by learners independently of the educational establishment.
- PLEs are customizable by learners.
- PLEs concentrate all the tools useful for the learner in a single environment.
- PLEs promote informal learning and lifelong learning.

As a result, it becomes clear that PLEs represent a turning point, from a model where learners simply consume information to one where learners become autonomous and create connections with a variety of resources that they select and curate themselves.

Although some of the fundamental needs of users of PLEs have not yet been clearly defined, two major objectives have nonetheless emerged in the literature: a PLE must be centered on learner and should enable lifelong learning (Attwell, 2023; Bal, et al., 2023; Buchem, et al., 2011). These two goals align with the Sustainable Development Goals (SDGs).

Activity Theory (AT) As An Integrated Framework

The PLE concept emphasizes the appropriation of tools and resources by learners. The view of learning as a mediation tool or collective activity is the basic principle of activity theory (Bal, et al., 2023; Kuhn, 2017; Sharples et al., 2005; Scanlon & Issroff, 2005). Activity Theory (AT) has been used as a framework for exploring pedagogical innovations and as a conceptual framework for analyzing and designing support systems for collaborative learning (Kuhn, 2017; Couros, 2010; Holton, 2007), for mobile learning (Kuhn, 2017; Sharples, et al., 2005) and for learning technologies evaluation (Kuhn, 2017; Albero, 2001).

The study conducted by Buchem on a wide range of PLE publications, supports the idea that a PLE can be considered as a complex system of activities and can be analyzed using the framework of activity theory in order to describe its main components (Attwell, 2023; Bal, et al., 2023; Buchem, et al., 2011; Holton, 2007).

Lifelong Learning Context

Faced with the new landscape of educational technologies, learners continually face challenges in their learning. The speed of change as well as the growth of needs emphasizes the value of lifelong learning and learners' motivation. PLEs can be the appropriate solutions to these situations. These environments give learners the freedom to learn beyond course boundaries and institutional constraints, and customize their own learning environments before and during training. Additionally, e-Portfolios used by learners as a tool to trace their learning provide future employers an overview of the individual's learning history and results, skills and achievements. With PLEs, they allow learners to demonstrate their professional abilities in a continuous learning framework (Pan & Chen, 2023; Bal, et al., 2011; Chen, 2003).

Lifelong Learning Vision

The lifelong learning is the "Ongoing, voluntary, and self-motivated pursuit of knowledge for either personal or professional reasons. Therefore, it not only enhances social inclusion, active citizenship, and personal development, but also competitiveness and employability" (Leone, 2019; 2013), (Downes, 2019; 2018; 2010), (Guettat et al. 2024b; Guettat & Farhat, 2013). The diffusing of the lifelong learning vision, signal the need for more personal, social and participatory approaches that support learners in becoming an active users and co-producers of his/her learning resources (Leone, 2019; 2013; European Commission, 2008). The emphasis on the shift from formal to informal e-Learning through knowledge management and sharing has been placed, with particular attention to the PLE as learner-centered space. Nevertheless, the investigations are motivated by the many educational theories, implications and challenges that PLE concept has posed (Zhou, et al., 2020; Mcloughlin & Lee, 2010).

Learner Centered Learning

In a landscape marked by the evolution and emergence of educational technologies, and innovation in learning modes, models and methods, the learner must assume his/her tool choices to use and contributions intended to make in learning. Therefore, we need a learner-centered learning model, which is adaptable, flexible and specific, depending on the context, such that the learner will be able to control his/her individual choices in terms of the technologies to use by aligning them with his/her personal needs, interests, learning style, preferences and context. In this way, learner will know how to build and manage a personal and self-reflective learning environment rather than operating an environment constructed, managed and imposed by the teacher and/or institution (Attwell, 2023; 2007).

PLEs Roles In the Lifelong Learning

The PLEs give students the freedom to learn beyond course boundaries, and to personalize their own learning environment. They allow learners to learn anytime and anywhere. Learners in many education institutions currently use E-portfolios as a tool to document and to reflect on their learning. They provide future employers with a snapshot of the learner's learning history, learning achievements, and reflective practice. (Drajati, 2020; Renon, 2012).

Our Critical Analysis

Today's learning systems should break away from traditional learning methods because they can no longer satisfy everyone, especially with the perpetual evolution of technology. Other measures should be found to motivate learners to learn not only when they are in academic training, but also when they are independent. In our context, we are interested in lifelong engineering learners whose appropriation of learning can constitute a challenge for them. The solution that seems to be most appropriate is PLE. However, putting up personal learning environments requires solving a number of problems: How can the learner build his own personal curriculum? How will the learner profile be maintained?

OUR ASSISTANCE APPROACH

Overview

As part of our research in the field of PLE started in 2008, we have developed an innovative approach (Guettat, et al. 2024a; 2024b; Guettat & Farhat, 2017; Guettat, et al., 2013b) allowing learners to build their personal learning environment, by building their own curriculums and choosing their appropriate learning activities. Such an approach will promote lifelong learning. To do this, we defined an architecture with three components: The "Learning objective formulation assistance", the "Curriculum generator" and the "Learning resources recommender" (Figure 1). The first component, allows the learner to define his/her learning objective without having any pedagogical experience. It's use as input the learning profile, the Bloom Taxonomy (Bloom, Krathwohl, & Masia, 1984) and the Concepts ontology, and applies to learner a dynamic questionnaire.

The second component, use the defined learning objective in the first component, and search in our curriculums repository, those matching of the learner-learning objective. We met different situations to obtain the right curriculums. From the curriculums found, we apply the Ascending Hierarchical Classification Machine Learning algorithm to recommend the best curriculum. Finally, the third component uses the recommended curriculum and using the

learner preferences and activities repository, and applies the same algorithm in the second component to recommend the best activities.

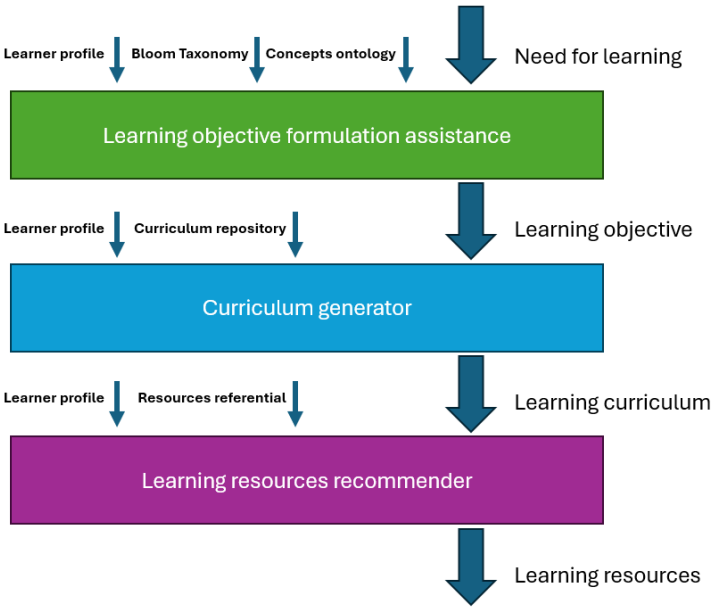

Figure 1. Overview of our Approach

Experiment and Critics

In order to verify the feasibility and the efficiency of our approach we have developed a PLE system, which allows any learner to use services offered without any technical or institutional constraints. The learner has to install a web browser extension as a frontend in order to communicate with the backend. Nearly, a hundred learners enrolled in the first year of IT engineering took part in the experiment. At the first, they passed a pre-test to divide them in two similar groups (control and experimental) according to their level. After that, the two groups invited in the same day for a test (2 hours). We asked the learners to solve the same exercise by creating their own PLE. Each learner in the control group must rely on himself to learn the concept by looking for available resource on the web and then pass the test. However, learners in the experimental group have access to our assistance system installed in their web browser. To evaluate the effectiveness of our approach, we measured the time, and scores obtained by the both groups. We observed firstly the time of realization for the same activity to the two groups (Control and Experimental) (Table 1).

Table 1. Average of time activity

	Group	Number of Participants	Average (mn)	Standard deviation
Time	Control	50	~ 92	8,9122
	Experimental	50	~ 21	2,1441

The results confirm what we observed on the premises: the learner in the control group wasted a lot of time to find the appropriate resources to carry out the activity. We conclude that with an assisted PLE there is a gain in required learning time. On the other hand, we obtained the scores obtained by the two groups (Table 2).

Table 2. Average of score activity

	Group	Number of Participants	Average /20	Standard deviation
Score	Control	50	8,34	5,12086
	Experimental	50	15,48	1,23485

We find that the mean of the control group is 8.34 with a standard deviation of 5.1. On the other hand, the results obtained in the experimental group are much better. Indeed, the average score is 15.5 with a small standard deviation compared to that observed in the control group. This clearly shows that the use of an assisted PLE improves the learners 'performance.

However, this experimentation shows that such a system needs a lot of development, and a huge effort to collect and manage learner profiles, curriculums repository and educational resources referential. In addition, this is even for experimentation with a limited number of participants and a very precise learning objective. An extension or even a generalization of our system is then necessary.

OUR NEW PLE ARCHITECTURE

Motivation

With the release of the ChatGPT in 2022 and then the emergence of a wide range of LLM (Large Language Model) based tools, new opportunities emerge. In addition, advances in Machine Learning open new horizons to improve existing PLE architectures. In this context, we propose an update of our PLE architecture, which benefits from new approaches and tools available today.

Related Works

The intersection of Artificial Intelligence (AI) and Personal Learning Environments (PLEs) has been the focus of various studies, highlighting their significance in promoting personalized learning experiences. (Buchem & Hamel, 2016) discuss the vital role of PLEs in cultivating essential 21st-century skills, emphasizing that personalized learning environments are instrumental in developing competencies that are crucial for modern learners. Similarly, (Almenara et al., 2024) provide a systematic review of AI applications in education, highlighting how adaptive learning environments can enhance personalization and improve educational outcomes. Furthermore, Santos & De Souza (2021) analyze the synergy between AI and PLEs, presenting frameworks and implementations that leverage intelligent systems to enrich personalized learning experiences. (Baker & Inventado, 2014; Yap et al, 2022), who detail how these technologies contribute to the creation of intelligent tutoring systems that tailor learning pathways to individual needs, also underscore the importance of educational data mining and learning analytics. In addition, (Drachsler & Greller, 2016) highlight the significance of learning analytics in deciphering learner behavior and preferences, which is essential for the development of effective AI-driven PLEs. Collectively, these works illustrate the potential of AI to transform PLEs into dynamic, learner-centric environments that support personalized and adaptive learning.

New PLE Architecture

Our new version of PLE architecture still has three components. However, they are enhanced throw the use of new AI based components (Figure 2). The first component, which is dedicated to identifying the personal learning objective, will be based on LLM (in this paper ChatGpt). Since existing LLM solutions provide configurable Rest API, it is then possible to tailor the LLM chatbot to play the role of a pedagogical expert. Then throw the learner/system chat interaction it will be possible to identify the personal learning objective.

The second component of our architecture is the curriculum generator. Gathering curriculum from the web can be done with web scraping technics. However, this will produce a huge amount of data. For this reason, we propose a decision tree model allowing curriculum matching with the fixed learning objective. Compared to our original architecture, there are at least two advantages: The first is that the curriculum does no longer needs to be described in a specific format based on a specific domain ontology and on the Bloom taxonomy; the second is related to the first one, since with no specific format constraint and with the web scrapping, the curriculum repository will be richer.

The third component is the resources recommender. Analyzing content and align it with the personal curriculum path and the learner preferences can be implemented with content-based model in machine learning like TF-IDF (Term Frequency-Inverse Document Frequency). Moreover, since in our approach we just recommend resources sorted from the most to the less relevant, it is possible to generate a summary of each content to help the learner to take the decision (Guettat et al., 2024c).

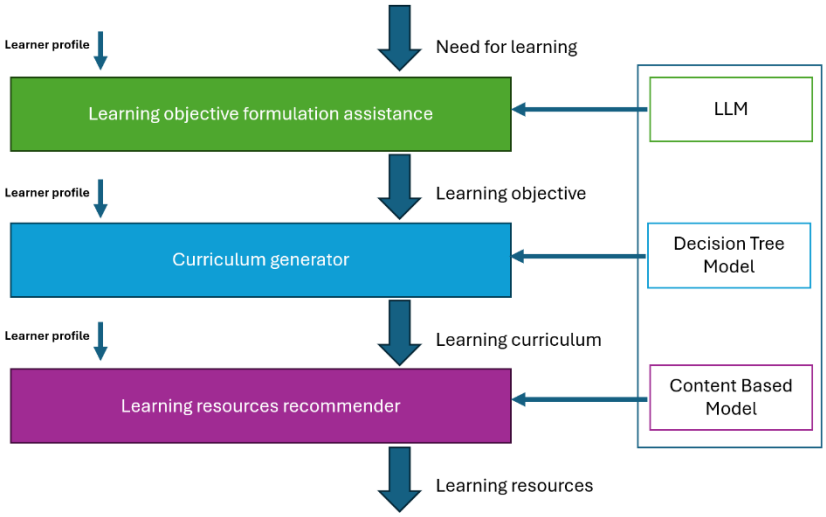

Figure 2. AI-enhanced PLE architecture

OUR NEW PROTOTYPE

ChatGpt Contributions

Our prototype is developed in close collaboration with ChatGpt 4. In advance, it was necessary to understand its philosophy and its API to make it ready to interoperate with the PLE and lifelong learning domains. Thus, we programmed its prompt by first indicating its role in our system (expert in pedagogy, mastering learning technologies), then the context (detailed specifications) and finally, we must tell it in detail the tasks it must do.

In the following, we will show in detail how we have configured this prompt, so that it can take into consideration the learner's needs in terms of defining the learning objective, generating the appropriate curriculum and recommending learning resources related to the curriculum.

ChatGpt Role

We indicate to ChatGpt, that it's an expert in pedagogy, with a long career in teaching; and master emerging technologies (AI and LLMs) as well as the related tools to assist learner in order to improve learning efficiency as well as learner performance. ChatGpt is invited to set up an assistance and recommendation system to allow a learner who is not necessarily knowledgeable in pedagogy, to build his own training curriculum after defining his learning objective; this curriculum should also contain all the appropriate learning activities to be carried out according to the learner's profile.

ChatGpt Context

As part of lifelong learning, we want to enable learner to create their own training curriculum without being an expert in pedagogy and without considering institutional constraints. Once the curriculum constructed, he/she can carry out the learning activities included in the curriculum.

To achieve all this, you are asked to assist the learner in defining their learning objective, which is made up of a concept and a taxonomic level (Bloom's taxonomy must be used), recommend the associated curriculum and finally recommend the learning activities to be carried out which align perfectly with the learning objective. Obviously, the learner's profile must be updated as the various components of the support system are implemented.

We inform you that each learner has a portfolio, initially empty, which will contain all completed, ongoing, and planned future training. Therefore, you must consider this constraint, in order to avoid the redundancy of certain activities: e.g. redoing an activity already completed and validated.

ChatGpt Process

To meet the learner's requirements, you must follow a process based on the following steps:

Step 1: Learning Objective

You must guide the learner in introducing the concept to be learned (e.g., Big Data). Based on their profile and portfolio, you should be able to recommend the appropriate Bloom's taxonomy level. The learning objective will be the pair O(c, n), where O denotes the objective, c denotes the concept, and n denotes the taxonomy level. Once the learner has validated this objective, their profile should be systematically updated.

Step 2: Recommended Curriculum

Based on the validated objective, you will need to search the internet for all learning curricula that perfectly match this objective. You must consider three situations: The first is the learning objective and the curriculum objective found coincide exactly (perfect match), the second is the learning objective does not coincide with that of the curriculum, but is part of the curriculum as a sub-objective, finally, the third situation occurs when the learning objective is not found in any curriculum; but by aggregating the fragments of several curricula, the objective in question can be retrieved.

By searching for curriculums matching the learning objective, you can find several curriculums. There, it must be able to classify them and recommend the best one. To do this, we must provide it the features and indicate which machine-learning algorithm it should use; in our case, we opted for ascending hierarchical classification.

Step 3 : Recommended Learning Activities

Starting from the recommended curriculum, you now need to recommend appropriate learning activities to the learner, taking into account the features we have defined, on the one hand, and the learner's preferences. To decide between the activities, you also need to apply a machine-learning algorithm, that of ascending hierarchical classification.

ChatGpt Tasks

The implementation of these steps can only be done by explaining clearly the tasks that ChatGpt must perform:

- Task 1: Management of the learner profile – initial training, background, possibly disabilities (myopia, deaf, blind, etc.), preferences (colors, resources, type of rapid training or not, etc.). If they have already achieved certain learning objectives, you must be able to highlight them and store them in the profile.
- Task 2: Assistance in defining the Learning Objective – You must provide the learner with the opportunity to grasp the concept they wish to learn. Once validated, the system must recommend the Bloom's taxonomy level to adopt, based on their profile. The pair O(c, n) with O: Objective, c: Concept, and n: Taxonomy level, constitutes the learning objective sought by the learner.
- Task 3: Generation of curriculums and recommendation the best that is perfectly aligned with the objective defined in the second task.
- Task 4: Generation of the appropriate learning activities that perfectly match the selected curriculum.
- Task 5: Generation of the detailed curriculum including the objective, sub-objectives, content elements of each sub-objective, activities to be carried out, recommended resources and detailed duration per activity/sub-objective and objective.
- Task 6: Update the learner profile – Everything the learner is going to do must be injected into his/her profile; the goal is to avoid repeating activities already done.

Technical implementation
The Learning Objective Component

The first thing the learner must do is define his learning objective that consists of a concept, and a taxonomic level. No more question of using a domain ontology, which must be previously designed and constantly updated. It is up to the LLM to take care of it. The concept being chosen, the learner will no longer go through the dynamic questionnaire to fix the taxonomic level he must follow. The LLM according to the profile of the learner and his preferences will systematically recommend the taxonomic level that the learner should follow. Suddenly, the learning objective (concept, taxonomic level) is well defined (Figure 3, Figure 4)

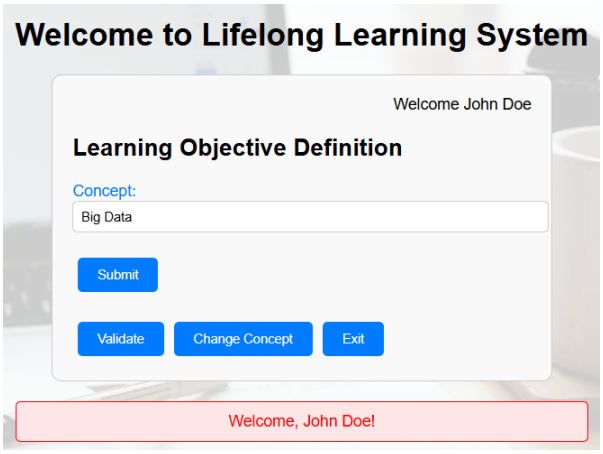

Figure 3. Concept Submitted & Validated Recommended

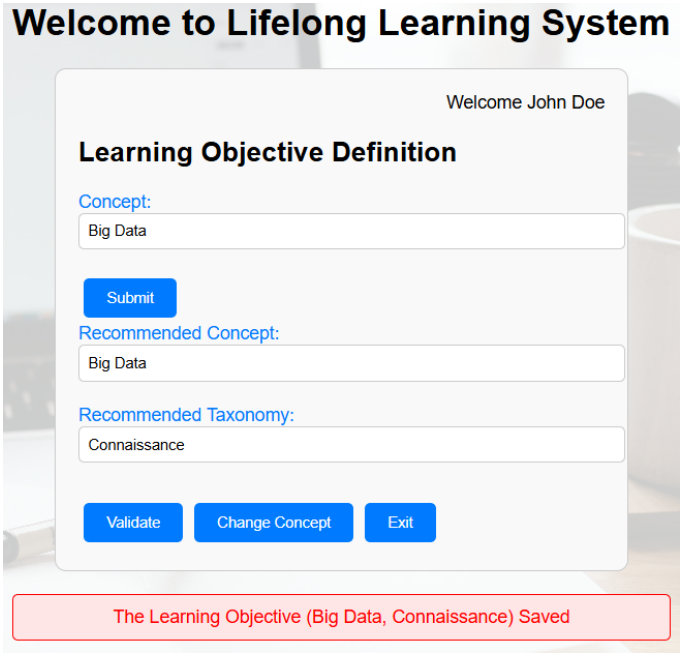

Figure 4. Taxonomy

The Recommended Learning Curriculum Component

Starting from the learning objective that the learner has just defined, and taking in consideration the learner preferences (Language, Training-type, etc.) (Figure 5), our LLM will scan on the net through search engines and using scraping techniques, to find the curriculums that match perfectly with this objective of learning. As deliverable, we have a list of recommended curriculums. Based on this list and applying an algorithm of machine learning (in our case that of the ascending hierarchical classification), the system will recommend to the learner the best curriculum (Figure 6). This classification is based on the same criteria that we have used in our previous assistance approach.

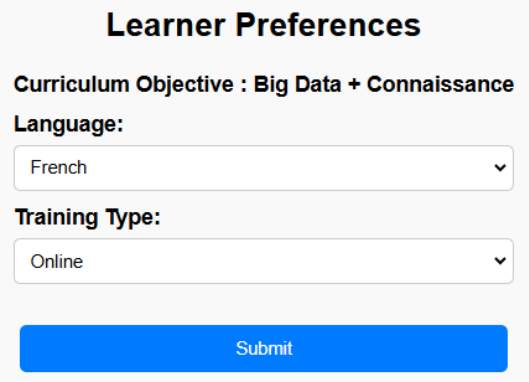

Figure 6. Learner Preferences

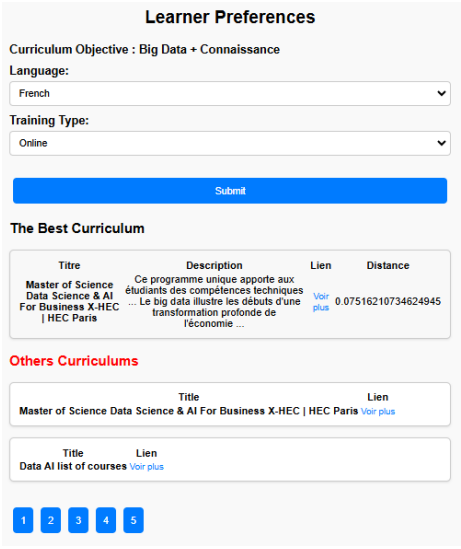

Figure 7. Recommended Curriculums

The Recommended Learning Activities Component

The curriculum being chosen, the learner must start his learning. To do this, it must carry out activities, which must comply with the objective defined and compatible with the curriculum in question. According to his profile and especially according to his preferences, and relying on the recommended curriculum, the LLM will proceed in the same way as when searching for curriculums, and will recommend the appropriate activities that the learner must carry out to achieve his goal learning. Classification criteria that are not the same compared to those used in the classification of curriculums are applied to recommend the best activities. The results obtained following the achievement of these activities will be injected into his/her portfolio and update his/her performance in his/her profile accordingly. Technically, this component is in progress.

Prototype Implementation Environment

Our LLM was powerful in the implementation of our architecture and saved us a lot of time in development. However, for better efficiency, good configuration is required to achieve good satisfaction of the developed product. Today, it is one of the most requested professions (prompt engineering). To do this, we have clearly defined and in detail the role, context and tasks of our LLM. Consequently, we have obtained a system based on backend server (Nodejs server) and a Frontend server (React Server). This system was tested locally on the practical level and the results are very encouraging: we have obtained what the deliverables we expected from it.

COMPARISON OF THE TWO APPROACHES

The table below describes a synthetized comparison between our two proposed approaches:

	The Old Version	**The New Version with LLM & AI**
System Architecture	Backend & Frontend	Backend & Frontend
Development	Lot of Effort	Low of Effort
Data Management	Relational Databases	JSON Files
Development Environ.	Heavy Environment	Light Environment
Learning Objective Definition	Bloom's Taxonomy Programming	LLM takes care of Bloom's taxonomic level recommendation.
Curriculums Recommendation	Huge effort to manage the curriculums repository.	No effort, LLM ensures the search and recommendation of the curriculums.
Activities Recommendation	Huge effort to manage and update the learning activities and resources repository.	No effort, LLM ensures the search and recommendation of the appropriate activities.

CONCLUSION AND ONGOING WORK

Nowadays, the use of Internet and especially the web is a part of our everyday activities. Web resources and tools are frequently used for learning. The learner can look for the appropriate resources by asking peers in social medias or by using search engines for examples. The resources and tools chosen by the learner to learn can be considered as a PLE. We have provided an approach to build assisted PLE for learner with promising experimental results especially on terms of efficiency.

With the advancements in the field of AI, we have investigated in this paper how we can take advantages from those advancements to enhance our approach. We began by explaining the concept of PLE and its specificities. The question that subsequently arose is how to find a method that will allow the learner to create his or her own PLE. To answer this question, we have defined and implemented an approach to help learners to build their PLE. An overview of our approach, of the architecture and of the experimental results are provided.

With the advancement in the field of AI, we proposed an updated version of our approach with the integration of modern AI models. We have explained how those models can improve our approach.

We are currently working on the final implementation of a prototype as a proof of concept. The next step is to make experimentation to verify if the results will be as good as those obtained with the original system architecture. In addition, we need to evaluate the quality of the interaction between the learner and the new system. The TAM (Technology Acceptance Model) (Venkatesh & Davis, 2000) can be used for this purpose.

As perspective, we must discuss the possible shortcomings of LLM, e.g. hallucinations and compare the quality of its output to expert output.

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Belhassen Guettat is a Doctor, Engineer and Aggregate in computer ccience. He is a senior researcher in the LaTice laboratory (University of Tunis – ENSIT: National Higher School of Engineers of Tunis) and works on human learning environments (personal learning, personalized learning, lifelong learning), and Learning Analytics.
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Ramzi Farhat is a Doctor, Engineer in computer science, and senior researcher at the LaTice laboratory of the National School of Engineers of Tunis (ENSIT); he has supervised several master's and thesis students. He leads the laboratory's e-Learning team and has produced several scientific publications in international journals and conferences in the areas of e-Learning, Smart Learning Environments, Learning Analytics and AI in education. He has been working at this school since 2008, as a Master-Assistant and has been an expert with ALECSO since 2010. Ramzi Farhat is a certified professional trainer in Oracle Java SE 11 developer, Andela React, IBM Data Science, etc.

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