Work-in-Progress about dynamicity as a foundation for AMI, a mobile intelligent and adaptive learning system.

Richard Hotte[1], Anis Masmoudi[1], Aymen Jaballah[2], Omar Masmoudi[2], and Alhoudourou Almaimoune Maïga[3]

[1] Institut de recherche LICEF, Université TÉLUQ, Montréal (Qc), Canada
[2] ESPRIT, 1, 2 rue André Ampère - 2083 - Pôle Technologique - El Ghazala, Tunisie
[3] Université Alioune Diop de Bambey (UADB), Bambey, Sénégal
richard.hotte@teluq.ca
anis.masmoudi@teluq.ca
aymen.jaballah@esprit.tn
omar.masmoudi@esprit.tn
alhoudouroumali@gmail.com

Abstract. If school, in its traditional form, cannot be accessible to all the children of the world, we believe that school can become accessible to them in the form of a smart learning system (smart system and smart learning), adaptative/personalized, and mobile. AMI, an intelligence-based learning system, could be a solution for children who are out of school.

AMI aims to enable learner self-learning. To do this, it must be dynamic. Its dynamicity stems from a close and sustained interaction between the learner and the system, which infers its adaptability. The system is then alive and, therefore, in constant reaction to the learner's activity. The continuous integration of new data from this learner/system interaction modifies the learner's profile and/or the learning path in progress. Therefore, how to provide the system with dynamic and sustainable self-learning capabilities, based on the learner's behaviors throughout his interaction with the system? More precisely, how to represent and interpret random events as messages to which the system can react to produce actions in continuous mode?

This paper presents a Work-in Progress on the implementation of two of the four intelligent components of the AMI system aiming at allowing a maximum adaptability of a personalized learning offer.

Keywords: Dynamicity, Adaptive Learning System, Learner Profile.

Introduction

The problem of education access for millions of children around the world is far from new. Despite efforts to date, it is still challenging to catch children who start with the traditional classroom approach with a teacher present. The idea that school could be accessible to these children if it came to them involves notions of intelligence (smart system and smart learning), adaptability and personalization, and mobility.

In a context of mobility, the school is perceived not as a classroom, but as a mobile educational system, accessible everywhere and at all times: at home, in the family, on the street, in the bush, and on the river, accessible to all, anytime and anywhere, adapted to local contexts and local traditional cultures, oriented towards the development of the child without any form of discrimination and finally safe, free from conflict. This type of learning system uses innovative mobile pedagogies.

Purpose or Goal

The Intelligence Mediated Learning (AMI in French) project asserts itself as a solution to the lack of education access. Modeling an intelligent adaptative/personalized mobile learning system as such is far from new (Brusilowsky et al. 2004; Chin 2001; Chen 2008; Limongelli et al. 2008; Kearney et al. 2012; Kim 2009; Yin, 2010; Kim et al. 2013; Xie et al. 2019)., However, it is necessary to describe how the system can have dynamic and sustainable self-learning capabilities based on the learner's behaviors throughout the learner's interaction with the system. More precisely, we need to represent and interpret the messages of random events so that the system can react to produce actions in a synchronous and continuous mode. To be optimal, such adaptability must be dynamic, i.e., it must continuously take into account the progressive evolution of the learner's cognitive abilities and constantly update the proposed learning content according to this evolution.

This paper aims to present a Work-in-Progress on implementing two out of four intelligent micro-service-oriented components of the AMI system, aiming to allow maximum adaptability of a personalized learning offer. These components will allow, on the one hand, the intelligent selection of one or more types of learning paths and, on the other hand, the adaptation of these types of approaches to the evolution, interests, and needs of a learner throughout his interaction with the system and according to the evolution of the learner's profile. This paper is organized as follows. Section 2 gives some core concepts of intelligent, adaptative/personalized, and mobile learning systems. Section 3 introduces the notion of dynamicity related to the AMI system. Section 4 presents the practicality and relevance of a model-driven methodological approach for the development of the solution. Finally, Section 5 presents conclusions and further works.

Conceptual background

Analysis of a set of journal articles related to trends and developments in personalized adaptative technologies published between 2007 and 2017 led Xie, H., Chu, H.-C., Hwang, G.-J., Wang, C.-C. (2019) to conclude that "adaptative personalized learning presents a significant number of opportunities of applications on smart devices such as wearable devices, smartphones, tablet computers, and computers with the rapid development of artificial intelligence, virtual reality, cloud computing, and wearable computing." Furthermore, "Adaptative/personalized learning has become possible by implementing intelligent learning systems, integrating learners' preferences, analyzing individual learning data, and so on" (Xie et al., 2019). For the latter, adaptative/personalized learning is informed by students' preferences and learning outcomes. According to Peng, H., Ma, S., Spector, J.-M. (2019), "Personalized adaptative learning is formed by the combination of personalized learning and adaptative learning".

Smart Learning and Smart Learning Environment

When we talk about an intelligent learning environment, we are dealing with two realities simultaneously: smart learning and a smart learning environment.

Smart learning relies on smart devices: telephones, watches, tablets, etc., and smart technologies, i.e., technologies that use the Internet and advanced levels of automatization to operate effectively. In a literature review by (Zhu et al. 2016), it is indicated that Kim et al. (2013) considered that smart learning, which combines the advantages of social learning and ubiquitous learning, is a learner-centric and service-oriented educational paradigm, rather than one just focused on utilizing devices.

Moreover, the fact that smart learning is based on personal and smart technologies makes learners engage in their learning and increase their independence in more open, connected, and augmented ways through personally richer contexts. Thus, the challenge of intelligent learning is to feedback the control of learning to the learner, regardless of the context in which he or she is learning, with all other resources contributing to this autonomy, and to empower a system to respond dynamically, and thus vividly, to this challenge.

A smart learning environment aims to support effective, efficient, and meaningful learning for learners. "Smart learning environments supported by technologies should not only enable learners to digital resources and interact with the learning systems in any place and at any time, but also actively provides them with the necessary learning guidance, supportive tools. or learning suggestions in the right place, at the right time, and in the right form (Hwang 2014: 2)" (Zhu et al. 2016).

There are many different types of technologies used to support and enhance learning, including hardware and software. Hardware includes those tangible objects such as interactive whiteboard, smart table, e-bag, mobile phone, wearable device, smart device, sensors, which use ubiquitous computing, cloud computing, ambient intelligence, IoT technology, etc. Software includes learning systems, learning tools, online resources, educational games that use social networking, learning analytics, visualization, virtual reality, etc.

Dynamicity, the core of the AMI learning system

A review of the literature by Elghibari et al. (2015) leads to the observation that the limitation of the proposed systems lies in the fact that they present content adapted to the initial parameters of the learner's profile (preferences, learning style, score, etc...), without taking into account the evolution of his/her cognitive abilities. There is, therefore, the need for dynamic content that follows the transformations of the learner profile (cognitive abilities, preferences, learning style) during the use of the system by the user himself. According to the latter (2015), in order to understand the learners' behavior and current content tailored to their needs, adaptation must take into account the changes in the learner's profile during the learning process.

The Importance of Learner Profile

Learner profiles play an important role in the adaptation of the online learning environment. They are the key elements of system modeling and consist of a set of data and metadata based on one or more learners that influence the system's behavior (Herder, 2016). By implementing intelligent systems, integrating learners' preferences, analysis of individual learning data, and adaptative/personalized learning have become possible (Xie, H., Chu, H.-C., Hwang, G.-J., Wang, C-C. (2019). Everything hinges on the degree of dynamicity of such educational systems, i.e., their ability to act dynamically and synchronously with the learner's activity in progress. According to (Baldiris, S., Graf, S., and Fabregat, R., 2011), "The concept of dynamic user characteristics has evolved to describe certain user characteristics that change continuously during the user's use of the system. The use of such characteristics in constructing user models defines the second type of user models, the dynamic user mode (DUM)." In the words of Elghibari et al. (2015), "There must be a continuous adjustment between the instructional resources and the learner's profile, producing a dynamic and flexible instructional process."

A Learner Master of his Choices

The primary function of intelligent selection is to make the learning system proactive by offering the learner-user a choice of courses, new courses or paths, aligned to his/her learning objective(s) as prescribed in the initial learner-user model. In this model, the learner profile is continuously modified throughout the completion of the selected typical course or par-course. The primary function of the course modification is to ensure the evolution of selected specific courses under the learner-user's action with the system in order to adapt to his/her real learning needs, thus to take the form of a course or a path adapted to both his/her learner profile (user model) and, also, to his/her cognitive style throughout his/her learning activity

The modeling of the AMI solution in the form of a domain model has made it possible to position, among other things, the processes of 1) intelligent selection of typical courses or pathways, predefined according to typical learner user models and their evolution, and 2) modification of these typical pathways into a real pathway, i.e., a flexible and dynamic pathway (Elghibari et al. 2015), which follows the evolution of the user's learning, thus the learner throughout his/her interaction with the system.

AMI, a Model-Driven Software Solution

It seems very difficult to create a flexible learning environment without modeling learner profiles. Modeling typical learner profiles is the key to an adaptative learning system. As said by Peter Brusilovsky and Eva Millán (2007: 3): "*The user model is a representation of information about an individual user that is essential for an adaptive system to provide the adaptation effect, i.e., to behave differently for different users*".

A field study in a community in the Gao region of northern Mali provided the data needed to develop a user profile, the basis for modeling the AMI system as a solution to the problem of access to school for children in Gao. The personas method was used to collect information about a typical potential AMI user profile. According to Bornet and Brangier (2013), the persona is an instrument for stimulating prospective activity, making it possible to define a model adapted to a future user or learner because for them, Vygotski(1985)'s work emphasizes that effective learning should anticipate the development of the person and its advances. The results show that the profile of the randomly selected learner within a family that includes several characteristics related to the living environment and the local context is plural and is defined by taking into account his/her siblings, parents, and entourage.

The Domain Model

The domain model is derived from the organic architecture of the AMI system. Initially, this declarative model represents the initial state of the proposed solution to the problem of education access for GAO children. It makes that solution explicit. This model has three goals: 1) to create a learner-centered learning system that is accessible to anyone, anywhere, at any time, 2) to integrate this personalized system into the learner's environment, and 3) to adapt this learning system to the learner's family, social, economic, and cultural reality.

This solution is based on the following three assumptions: 1) the solution is built around a set of existing components or tools that are independent of each other and can be integrated into an ecosystem, 2) the collaboration, course management, instant communication, and learning content management components are proposed based on existing tools, and 3) the course management, learner profile management, learning path tracking and learning assistance components are redesigned around adaptive learning based on four types of intelligence that provide intelligent assistance to 1) the learner, his/her tutor or any other adult in charge of the child, 2) adapting the learning path to the learner's reality, 3) completing the path of the learner in difficulty and 4) injecting new data at the end of the learning path to update the learner's profile and, also, to enrich and diversify the path offer.

In addition, the solution must take into account two major constraints. The first is the enrichment of the learner profile adopted by the learner's family, cultural, economic, and social aspects. The second is the accessibility and logging of all the data on the learner's activities related to his or her learning path and interactions with the actors with whom he or she is in a support relationship in order to adapt the profile and path.

Towards the Dynamicity of AMI

AMI introduces dynamicity into both the learner's profile and the evolution of the learner's learning path by maintaining a sustained interrelationship between two components in a flexible and intelligent environment. This is in line with what is expressed by (Peng et al. 2019: 9) when they write, on the one hand, that "learner profile-based progression assesses learner progress by continuously measuring the individual performance of the learner's learning goals" and, on the other hand, that the flexible and intelligent learning environment can provide functional support for the adaptive adjustment of teaching strategies.

Figure 1 illustrates the dynamicity of the AMI system through a fictitious use case, that of the learner Sam Petros. It consists of nine steps. Step 0 is a preliminary step that reports the learner's profile which" aims to portray the individual characteristics of each learner's strengths, preferences, motivations, etc." (Peng et al. 2019).

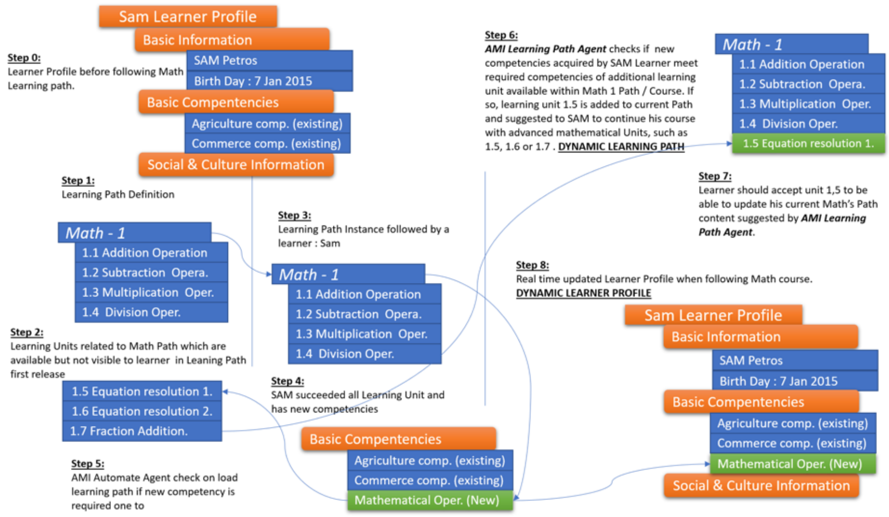

Fig. 1. Business Use Case

Then follow eight steps: 1) the knowledge model of the path, 2) its structure in learning units, 3) the instantiation of the learning path based on the enriched learner profile Sam, 4) Sam's success on the whole path, which allowed him to acquire new skills, 5) the AMI system's automaton agent checks if the learning path load requires new skills, 6) a DYNAMIC LEARNING PATH, where the path's automaton agent checks if the new skills acquired by the Sam learner match the skills required for the additional learning unit available in the Math 1 path/course. If so, learning unit 1.5 is added to the current pathway, and Sam is invited to continue with advanced math units, such as 1.5, 1.6, or 1.7, 7) the learner must accept unit 1.5 in order to update the content of his/her current math pathway suggested by the AMI Learning Pathway Agent, 8) a DYNAMIC LEARNER PROFILE, where the learner's profile is updated in real-time as his/she completes a math course.

The flow of information indicates that the dynamicity occurs at two points: when a learning unit is added to the initial course to match the learner's learning (step 6) and when the learner profile is updated in real-time as new skills are acquired (step 8). According to the SAM basic profile, steps 1 to 3 indicate a transition from a typical chosen path (step 1) to an instantiated path (step 3). Step 4 corresponds to an enrichment of SAM's skills, allowing him to enrich his learning path with units of his choice.

Figure 2 presents a diagram illustrating the implementation of use case as a schematic of the deployment of various AMI software components in different application servers.

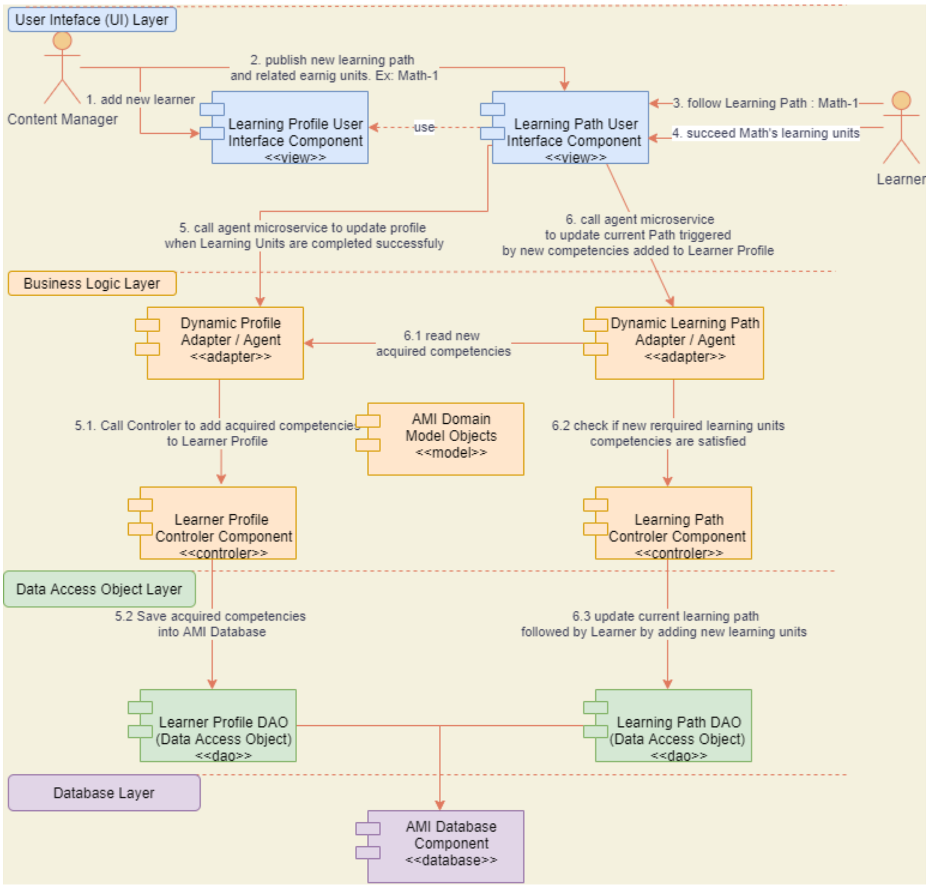

Fig. 2. Implementation of use case

Figure 2 shows how AMI uses the Model-View-Controller (MVC) software architecture through the various software components. AMI is deployed on three application servers: user interface (UI), learning path, and learner profile. The integration layer uses a microservices-oriented architecture. The UI layer shows that the UI component calls microservices provided by the learner profile and learning path adapters. The overall taxonomy of AMI is defined by four sub-domains of activity: Learning Path Selection, Learner Profile Management, Learning Path Management, and Learner Support. Each subdomain publishes a set of microservices that provide the necessary information to the other consumer components such as Learning Path, User Profile, and Learning Path Selection. Figure 2 shows all of the microservices of the above subdomains except those of the Learner Support subdomain. It is important to specify that the Learning Path Selection component uses two search sub-components corresponding to the two types of criteria: the existing path and the correlated learner profile. An existing path is a path completed by a learner, which enriches the bank of existing and available paths. A correlated learner profile results from an intelligent selection, i.e., a selection by keywords enriched by the correlation between the learner's existing profile and similar corresponding profiles. Each profile is weighted and validated. Some of these profiles will appear during the search for matching profiles. An aggregate component will integrate the search results of the two sub-components and assign weights to them. The user interface components (sequence calls 5, 6, and 8) call different components that manage the learner profile, the learning path, and the learning path's selection. Our goal is to reuse our adapters and controllers in order to be able to integrate different e-learning systems that will allow the reuse of their learning object metadata (LOM) or learning units.

Conclusions

Literature reviews and benchmarking analyses confirm that advances in artificial intelligence can help enrich mobile adaptive learning systems by adapting learning to learner profiles. The degree of dynamicity of these systems, i.e., their capacity to act dynamically according to the learner's behavior, will directly impact the evolution of the user's profile characteristics.

We believe that the system must continuously adapt to the learner's progress to ensure its vitality. Hence the need for a dynamic, learner-centered pedagogy that adapts to changes in the learner's profile when the learner is using the system. This dynamicity must be embodied in an intelligent selection of one or more typical learning paths and the modification of these paths according to the learner's needs and learning achievements.

The development of the two intelligent microservice-oriented components, i.e., the dynamic path selection and the dynamic profile adaptation, is nearing completion. We will prepare one or more test scenarios. In a first step, we will validate the components in the form of prototypes with the field researcher. In a second step, we will validate them with a sample of the targeted population in the GAO region in the north of Mali.

Acknowledgments. We would like to express our gratitude to the Canadian Commission for UNESCO and the Fonds de recherche du Québec for their support and funding to the UNESCO Chair in GSDL, to the MRIF - Québec for its financial support from the Québec-Sénégal bilateral cooperation program, and to the Fonds d'aide à la recherche de l'Université TÉLUQ. Finally, we would like to thank the team of students who contribute to the advancement of the research through their investment in internships and theses.

References

1. Baldiris, S., Graf S., and Fabregat R. Dynamic user modeling and adaptation based on learning styles for supporting semi-automatic generation of IMS learning design. In *11th International Conference on Advanced Learning Technologies*, pp. 218-220. *IEEE,* Athens, GA, USA. (2011)
2. Bornet, C. and Brangier, É. La méthode des personas : principes, intérêts et limites. *Bulletin de Psychologie*, 524(2), pp. 115-134 (2013).
3. Brusilovsky P., and Nejdl W. Adaptive Hypermedia and Adaptive Web. Practical Handbook of Internet Computing, Chapman & Hall / CRC Press LLC (2004).
4. Brusilovsky, P., and E. Millán, User models for adaptive hypermedia and adaptive educational systems, In Brusilovsky, P., Kobsa, A., and Nejdl, W (eds). *The Adaptive Web*, Vol. 4321, pp. 3-53, Springer (2007).
5. Chen, C.-M. Intelligent web-based learning system with personalized learning path guidance, *Computer & Education*, 51(2), pp. 787-814 (2008).
6. Chin, D.N Empirical Evaluation of User Models and User-Adapted Systems. *User Modeling and User-Adapted Interaction* 11**,** pp. 181–194**,** SpringerLink (2001).
7. Elghibari, F., Elouahbi, R., Elkhoukhi, F., Chehbi, S., and Kamsa, I. Intelligent e-learning system model for maintenance of updates courses. In *International Conference on Information Technology Based Higher Education and Training (ITHET),* pp. 1-3. IEEE*Xplor*e, Lisbon (2015).
8. Herder, Eelco. User modeling and personalization. 3: User modeling – Techniques. In *Web Science – Investigating the future of Information and Communication*. 55 slices (2016).
9. Hwang, G.-J. Definition, framework and research issues of smart learning environments - a context-aware ubiquitous learning perspective Smart Learning environment – a context-aware ubiquitous learning perspective. *Smart Learning Environments*, 1, 14 p. SpringerOpen (2014).
10. Kearney, M., Schuck, S., Burden, K., and Aubusson, P. Viewing mobile learning from a pedagogical perspective. *Research in Learning Technology*, 20(1), 17 p. (2012).
11. Kim, P.H. Action research approach on mobile learning design for the underserved. *Educational Technology Research and Development*, 57(3), pp. 415-435 (2009).
12. Kim, T., Cho, J.Y., Lee, B.G. Evolution to Smart Learning in public education: a case study of Korean public education. In Tobias, L., Mikko, R., Mart, L., Arthur, T (eds). *Open and Social Technologies for Networked Learning*, pp. 70–178, SpringerLink, Berlin Heidelberg (2013).
13. Limongelli, C., Sciarrone, F., Vaste, G. LS-plan: An effective combination of dynamic courseware generation and learning styles in web-based education. *Adaptive Hypermedia and Adaptive Web-Based Systems*, pp. 133–142 (2008).

14. Peng H, Ma S., and Spector J M. Personalized adaptative learning: an emerging pedagogical approach enabled by a smart learning environment. *Smart Learning Environments* 6(9), 14p., SpringerOpen (2019)
15. Xie, H., Chu, H.-C., Hwang, G.-J., Wang, C-C. Trends and development in technology-enhanced adaptive, personalized learning: A systematic review of journal publications from 2007 to 2017. *Computer & Education*, 140,16p., SpringerOpen (2019).
16. Yin, C. Samcco. Un système d'apprentissage mobile contextuel et collaboratif dans des situations professionnelles. (Thèse) Sciences de l'ingénieur, ÉcoleCentrale de Lyon. 225p (2010).
17. Zhu, Z.-T., Yu, M.-H., Riezebos, P. A research framework of smart education. In *Smart Learning Environments*, 3(1), 17 p., SpringerOpen (2016)