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A fully personalization strategy of E-learning scenarios

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ABSTRACT

The personalization in E-learning systems has been the subject of many recent research efforts. While a large number of systems have been implemented, many of these systems allow the application of very few if not just one predefined personalization strategy. This is a constraint for providing effective E-learning experience and for rationalizing the personalization needs of the pedagogues, the professors and the learners. In this paper, we propose a new approach for personalization of learning scenarios based on two levels: The first level allows the personalization of learning scenarios according to a predefined personalization strategy. The second level allows teachers to select personalization parameters and combine them flexibly to define different personalization strategies according to the specifics of courses. The proposed solution is a step to federate the research efforts on the E-learning personalization by integrating and combining the personalization parameters. Concerning the technological aspect, Web service technology constitutes an operational solution for implementing our approach and for the interoperability with other E-learning personalization systems. Beside the implementation of an interoperable solution, we also aim to enable teachers to provide proper personalized learning scenarios.

1. Introduction

The issue of personalization in E-learning has become an important topic of research in recent years. With the emergence of Web-based learning systems, it has become possible to provide access to content to wider learner community, and hence open up learning opportunities for those who typically are not able to avail formal education. However, such wider access has raised challenging issues with respect to providing adequate learning experiences to different learners, since Web-based learning systems generally did not adapt content to suit individual learner needs. Research on personalization stemmed from the need to circumvent this situation and looked for ways in which the learners' needs could be identified and the content could be adapted to suit those needs.

In this paper, we address the personalization in the E-learning domain and define an approach for the personalization of learning scenarios according to often used personalization parameters. A personalization parameter defines some divergent characteristics and needs of learners such as learners' prior knowledge, their motivation and learning styles. The divergent characteristics are useful for delivering personalized learning scenarios. The combination of a set of personalization parameters for the personalization of learning scenarios is called personalization strategy. The main objective of this work is to allow teachers to choose and apply the personalization strategy which matches the learners' characteristics and the specifics of the courses. In order to achieve this objective, we propose an approach based on two complementary personalization levels: the E-Learning Personalization level 1 (ELP1), and the E-Learning Personalization level 2 (ELP2). ELP1 allows the personalization of learning contents and structure of the course according to a given (specified within ELP2) personalization strategy. ELP2 allows defining the personalization strategy flexibly. This level of personalization enables teachers to select the learning scenario and to specify the personalization strategy (to be applied on the selected learning scenario) by choosing a subset of personalization parameters. Given that ELP1 depends strongly on ELP2, the acquisition of the learner profiles at the time the learners enroll for learning one of the specified concepts is based only on the personalization parameters included in the personalization strategy specified for that particular learning scenario. This ensures that each learner will receive the learning material according to his/her profile. This approach allows the application of the declared personalization strategies without developing a personalization system for each possible personalization strategy. In fact, the personalization parameters can be reused and combined in different ways for defining different personalization strategies. Each subset of personalization parameters can serve for defining a

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personalization strategy and different personalization parameters can be integrated in different personalization strategies.

This paper is structured as follows: Section 2 discusses personalization parameters and how adaptation can be provided in E-learning systems. Section 3 gives an overview of the current adaptive E-learning systems and discusses the applied personalization strategies. In Section 4, the motivation of our work is presented by pointing out the large number of possible personalization strategies, and the new approach is introduced, which is composed of two personalization levels (ELP1 and ELP2) for exploiting these personalization strategies according to the learning scenarios. Section 5 introduces the architecture of ELP1 + ELP2. This architecture is based on Web services technologies, which constitute an emergent solution for integrating applications on the Web. Section 6 presents the evaluation of ELP1 + ELP2. Section 7 discusses the different alternatives of the personalization level 2. The paper finally concludes with a summary of the research and future directions.

2. Personalization parameters

The personalization parameters constitute the source for personalization of E-learning scenarios. In this section, 16 personalization parameters that are most commonly used in the E-learning domain are explained. Then for each personalization parameter, an example of a set of values used for providing personalization is presented.

- *Information seeking task* (Höök et al., 1996) is used to facilitate information searching from a vast amount of information. In particular, the information is delivered according to a set of stereotypical tasks defined in (Höök et al., 1996) for a specific domain: a method for development of large telecommunications software systems, SDP-TA (System Development Process for Telecommunications Applications).
- *Learner's level of knowledge* is used for taking into account the learner background when communicating learning materials to the learner.
- *Learning goals* are used to plan the learning and to communicate the learning materials which satisfy the learner goals.
- *Media preference* enables the learner to be provided with the form of learning materials he/she prefers most (e.g., text, graphic, video, audio).
- *Language preference* allows the presentation of learning material in the learner's preferred language (e.g., English, French, Arabic, German, etc.).
- *Kolb learning cycle.* Kolb (1984) defined the Experiential Learning Model composed of four-stages (Concrete Experience, Reflective Observation, Abstract Conceptualization, and Active Experimentation). The personalization can be performed according to the learning styles which are derived from this learning cycle.
- *Honey–Mumford* learning style. Honey and Mumford (1986) identified four styles of learning (Activist, Reflector, Theorist, and Pragmatist), which had much in common with Kolb's work and had strong correlations with the learning cycle.
- *Felder–Silverman* learning style. Felder and Silverman (1988) proposed four dimensions of learning styles (Sensing/Intuiting, Visual/Verbal, Active/Reflective, and Sequential/Global) pertaining to the ways learners receive and process information.
- *La Garanderie learning style.* Based on psychological studies, La Garanderie (1993) defined six learning styles (competitive, cooperative, access on the avoidance, participative, dependant, and independent).
- *Participation balance* (Constantino-González, Suthers, & Santos, 2003) enables monitoring of group dynamics concerning the balance in learners' participation.
- *Progress on task* (Constantino-González et al., 2003) encourages students to devote adequate time to the task of constructing the shared solution.
- *Waiting for feedback* (Constantino-González et al., 2003) allows the system to make decisions when certain period of time has passed and the student has not pressed any opinion button (e.g., "OK," "not OK," or "unsure"), or when certain period of time has passed and the student has not received any feedback.
- *Motivation level.* Keller (1983) cited in Small (1997) defined the ARCS model which identifies four essential components for motivating instruction (Attention, Relevance, Confidence, and Satisfaction).
- *Navigation preference* allows the navigation in the learning material in the learner's preferred order (in breadth-first or depth-first).
- *Cognitive traits.* Kinshuk and Lin (2004) defined the Cognitive Trait Model (CTM) that offers the role of 'learning companion', which can be consulted by and interacted with different learning environments about a particular learner. Current implementation of CTM is composed of four cognitive traits (working memory capacity, inductive reasoning ability, information processing speed, associative learning skills).
- *Pedagogical approach.* Essalmi, Jemni Ben Ayed, and Jemni (2007) introduced the pedagogical approach as a personalization parameter and identified three pedagogical approaches (objectivist approach, competency based approach, collaborative approach).

The personalization according to a personalization parameter is based on the divergent characteristics and needs of learners to be represented by the values of the parameter. Table 1 presents examples of a set of values for each personalization parameter which are used by the teachers to make decisions concerning the personalization of learning scenarios. The perceptions/decisions of teachers can be solicited via an interface, which is then used for automatically providing personalized learning scenarios. In particular, a teacher decides which learning material will be provided for a specific value of a personalization parameter.

By considering the column "set of values" of Table 1, we observe that each of the personalization parameter constitutes a linguistic variable. For example, the set of values used to explain the personalization parameter *learner's level of knowledge* is {beginner, intermediate, advanced} and the set of values used in the literature for the personalization parameter *Honey–Mumford learning style* is {activist, reflector, theorist, pragmatist}. The personalization parameters *Felder–Silverman learning style* and *cognitive traits* are particular cases of linguistic variables. *Felder–Silverman learning style* is composed of four dimensions; each of them is a linguistic variable. As an example, a learner can be sensing, visual, active and sequential at the same time. The Felder–Silverman learning style model is considered as the Cartesian product of the linguistic variable presenting its four dimensions. Similarly, the personalization parameter *cognitive traits* is composed of four dimensions; each of them is a linguistic variable. For example, a learner can simultaneously have low working memory capacity, high inductive reasoning ability, high information processing speed and high associative learning skills. The personalization parameter *cognitive traits* is considered as the Cartesian product of the linguistic variable presenting its four dimensions.

The use of words or sentences for the enumeration of values of personalization parameters in the literature is not a new idea. Indeed, this way of enumeration of values is relevant for teachers when they make decisions concerning the learning material which fits each value. For example, considering that "a learning object fits a high motivation level" is more relevant and easier to understand for teachers than considering that "a learning object fits a motiva-

Table 1
Examples of values for the personalization parameters.

Personalization parameter	Set of values
Information seeking task	{learning the structure of SDP-TA, project planning, reverse engineering, following an activity} (Höök et al., 1996)
Learner's level of knowledge	{beginner, intermediate, advanced} (Chorfi & Jemni, 2004)
Learning goals	{knowledge, comprehension, application} (Melis et al., 2001)
Media preference	{video, sound, simulation, text/image} (Chorfi & Jemni, 2004)
Language preference	{English, German} (Weber & Brusilovsky, 2001)
Kolb learning cycle	{Converger, Diverger, Assimilator, Accommodator} (Milosevic et al., 2006)
Honey–Mumford learning style	{activist, reflector, theorist, pragmatist} (Honey & Mumford, 1986)
Felder–Silverman learning style	{sensing, intuiting} × {visual, verbal} × {active, reflective} × {sequential, global} (Felder & Silverman, 1988)
La Garanderie learning style	{competitive, cooperative, access on the avoidance, participative, dependant, independent} (La Garanderie, 1993)
Participation balance	{tooMuch, notEnough, acceptable} (Constantino-González et al., 2003)
Progress on task	{small, large} (Constantino-González et al., 2003)
Waiting for feedback	{significant, medium, low} (Constantino-González et al., 2003)
Motivation level	{low, moderate, high} (Milosevic et al., 2006)
Navigation Preference	{breadth-first, depth-first} (Stash et al., 2006)
Cognitive traits	{low working memory capacity, high working memory capacity} × {low inductive reasoning ability, high inductive reasoning ability} × {low information processing speed, high information processing speed} × {low associative learning skills, high associative learning skills.} (Kinshuk & Graf, 2007)
Pedagogical approach	{objectivist, competencies based, collaborative} (Essalmi et al., 2007)

tion level = 5". As another example, let us assume that a teacher has to decide which learning material is appropriate for each learner's level of knowledge. Considering a list of linguistics values such as beginner, intermediate, and advanced would be more relevant and easier to associate with appropriate learning material than numeric values. In fact, each of the above mentioned linguistic values summarize common characteristics for learners. In contrast, it is very hard if not impossible to consider separately the values in the set $\{0, 1, 2, \ldots, 20\}$ or in the interval $[0 \ldots 20]$ and associate specific learning material for each value in the interval. In this context, linguistic values have the promise of representing learner characteristics with relevant and flexible granularity.

3. Literature survey

Several systems have been reported in the literature for the personalization of E-learning. Table 2 provides a representative review of such systems and enumerates for each system the applied personalization parameters. Each of these systems uses, at the most, three personalization parameters. Most of them use the personalization parameter: *learner's level of knowledge*. Many of them give importance to the learner's *media preference*. For example, NetCoach has been designed to enable authors to develop adaptive learning courses without requiring any programming knowledge (Weber, Kuhl, & Weibelzahl, 2001). ActiveMath has been developed to generate interactive mathematical courses adapted to the *learner's level of knowledge*, *learning goals*, and *media preference* (Melis et al., 2001). ELM-ART supports learning of programming in LISP and provides the learning material online in the form of an adaptive interactive textbook (Weber & Brusilovsky, 2001). PERSO uses CBR (Case Based Reasoning) approach to determine which course to propose to the students based on their *levels of knowledge*, and their *media preferences* (Chorfi & Jemni, 2004). SIMBAD focuses on building personalized courses by the assembly of

Table 2
Example of personalization systems classified according to personalization parameters.

Personalized E-learning system	Personalization parameters
POP (Höök et al., 1996)	Information, seeking task
Interbook (Brusilovsky et al., 1996)	Learner's level of knowledge
The Intelligent Helpdesk (Greer et al., 1998)	Learner's level of knowledge, learning goals
ECSAI (Grandbastien, 1999)	Learner's level of knowledge, learning goals
KBS-hyperbook (Henze & Nejdl, 1999)	Learner's level of knowledge, learning goals
VC prolog tutor (Peylo, Thelen, Rollinger, & Gust, 2000)	Learner's level of knowledge, learning goals
NetCoach (Weber et al., 2001)	Learner's level of knowledge, learning goals, media preferences
German Tutor (Heift & Nicholson, 2001)	Learner's level of knowledge
ActiveMath (Melis et al., 2001)	Learner's level of knowledge, learning goals, media preference
ELM-ART (Weber & Brusilovsky, 2001)	Learner's level of knowledge, media preferences, language preference (English or German)
KOD (Sampson, Karagiannidis, & Cardinali, 2002)	Learner's level of knowledge, language preference, learning goals
SIMBAD (Bouzeghoub et al., 2003)	Learner's level of knowledge, learning goals, media preferences
MetaLinks (Murray, 2003)	Learner's level of knowledge, learning goals, media preferences
INSPIRE (Papanikolaou et al., 2003)	Learner's level of knowledge, learning goals, learning style (of Honey and Mumford)
MLTutor (Smith & Blandford, 2003)	Learning goals (based on user's browsing history)
COLER (Constantino-González et al., 2003)	Participation balance, progress on task, waiting for feedback
SQL-Tutor (Mitrovic, 2003)	Learner's level of knowledge
EPSILON (Soller, 2004)	Learner's level of knowledge
SIETTE (Conejo et al. (2004))	Learner's level of knowledge
PERSO (Chorfi & Jemni, 2004)	Learner's level of knowledge, media preference
ELENA (Dolog, Henze, Nejdl, & Sintek, 2005)	Learner's level of knowledge, language preference, learning goals
AHA! (Stash et al., 2006)	Felder–Silverman learning style, media preference, navigation preference
(Milosevic et al., 2006)	Kolb learning cycle, motivation level

components (Bouzeghoub, Carpentier, Defude, & Duitama, 2003). MetaLinks, an authoring tool and web server for adaptive hyperbooks, has been used to build a geology hyperbook (Murray, 2003). Other works have attempted the integration of *learning styles* as a parameter for the personalization of learning scenarios. For example, INSPIRE adopts the learning style model of Honey and Mumford as the basis for determining the presentation of the educational material on each of the performance levels (Papanikolaou, Grigoriadou, Kornilakis, & Magoulas, 2003). Milosevic, Brkovic, and Bjekic (2006) used Kolb's learning cycle for tailoring lessons. Their work also incorporated the *learner motivation* as a personalization parameter, which is used to determine the complexity and the semantic quantity of learning objects.

The column "personalization parameters" of Table 2 contains 11 different subsets of personalization parameters. Each of these subsets reflects personalization needs, and the strategies used to respond to these needs depend strongly on the selected subset of personalization parameters. Furthermore, the above introduced 16 personalization parameters have been used widely in the literature: information seeking task (e.g., Höök et al., 1996), learner's level of knowledge (e.g., Brusilovsky, Schwarz, & Weber, 1996), learning goals (e.g., Greer et al., 1998), media preference (e.g., Weber et al., 2001), language preference (e.g., Weber & Brusilovsky, 2001), learning style model of Honey–Mumford (e.g., Papanikolaou et al., 2003), learning style model of Felder–Silverman (e.g., Kinshuk & Graf, 2007), learning style model of "la Garanderie" (e.g., Essalmi et al., 2007), learning style model of Kolb (e.g., Milosevic et al., 2006), participation balance (e.g., Constantino-González et al., 2003), progress on task (e.g., Constantino-González et al., 2003), waiting for feedback (e.g., Constantino-González et al., 2003), motivation level (e.g., Milosevic et al., 2006), navigation preference (e.g., Stash, Cristea, & de Bra, 2006), cognitive traits (e.g., Kinshuk & Graf, 2007), and pedagogical approach (e.g., Essalmi et al., 2007). Each of the systems presented in Table 2 combines, at the most, three predefined personalization parameters in order to activate a predefined personalization strategy. In addition, further needs of specific personalization strategies continue to appear in the literature. For example, Kinshuk and Graf (2007) emphasize on the combination of cognitive traits and the learning style model of Felder–Silverman for providing a more holistic adaptivity. Furthermore, Essalmi et al. (2007) point out the need for combining several personalization parameters and introduce the pedagogical approach as a personalization parameter. Other personalization needs could continue to appear in the future given that several combinations of personalization parameters have not been tested.

4. Specification and application of personalization strategies

There are many personalization strategies used for adapting learning scenarios to the learner profiles, and most of the available personalization systems allow the application of very few if not just one predefined personalization strategies. Furthermore, pedagogues and researchers can identify other needs for implementing new personalization strategies. In fact, even if we consider only personalization strategies with maximum 10 personalization parameters from the 16 personalization parameters listed in Table 1, the number of possible personalization strategies can reach up to $\sum_{i=1}^{10} C_i^{16} = 58650$ where C_i^{16} denotes that a subset of i personalization parameters are selected from the 16 personalization parameters.[1]

In order to facilitate the specification/definition and the application of different personalization strategies according to the personalization needs, we take into account two levels of personalization: the first one, ELP1, allows the application of the defined personalization strategies, and the second one, ELP2, allows the specification of the personalization strategies according to the personalization needs. In this section, we present the two E-learning personalization levels, with the help of an illustrative example for each level. Since ELP1 depends strongly on ELP2, the level 2 of personalization (ELP2) is described first.

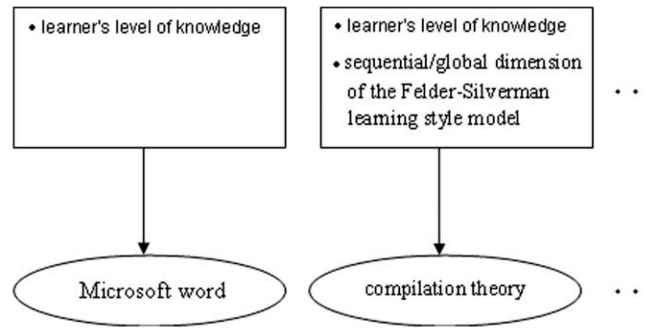

Fig. 1. Examples of personalization strategies.

4.1. The E-learning personalization level 2

Let us assume that there are different personalization strategies proposed by the teachers according to the learning scenarios. As an example, one of these proposed strategies consists of personalizing the learning scenario for learning to use Microsoft Word according to the *learner's level of knowledge*. Another proposed strategy consists of personalizing the compilation theory course according to the *learner's level of knowledge* and the sequential/global dimension of the *Felder–Silverman learning style model* (see Fig. 1).

ELP2 allows teachers to specify the personalization strategy in two steps. First, the teacher selects a subset of personalization parameters for given courses. Then, the teacher combines the selected personalization parameters and decides how the learning material will be composed with respect to each possible value of the personalization parameters. The combination defined by the teacher will be used by ELP1 to provide personalized courses.

4.2. The E-Learning personalization level 1

The main function of ELP1 is the application of the personalization strategies specified with ELP2. For example, the personalization strategy declared in ELP2 for the personalization of the Microsoft Word course includes the personalization parameter *learner's level of knowledge*. The left part of Fig. 2 depicts some personalized learning scenarios by taking into account the specified parameter. This part shows that, if two learners have different level of knowledge, one being beginner and the other one having already prior knowledge, they will receive different presentation of learning scenarios. In this case, for the learner who is beginner, more detailed content will be presented than for the advanced learner. In particular, teachers can consider that the two sections *Introduction* and *Update Text* are relevant (recommended) for a learner who is beginner whereas only the section *Update Text* is relevant for the learner who is advanced. As a second example, the personalization strategy declared in ELP2 for the personalization of the compilation theory course includes the personalization parameters *learner's level of knowledge* and the sequential/global dimension of the *Felder–Silverman learning style model*. The right part of Fig. 2 depicts some personalized learning scenarios by taking into account the specified parameters.

[1] $C_i^{16} = \frac{16!}{i!(16-i)!}$.

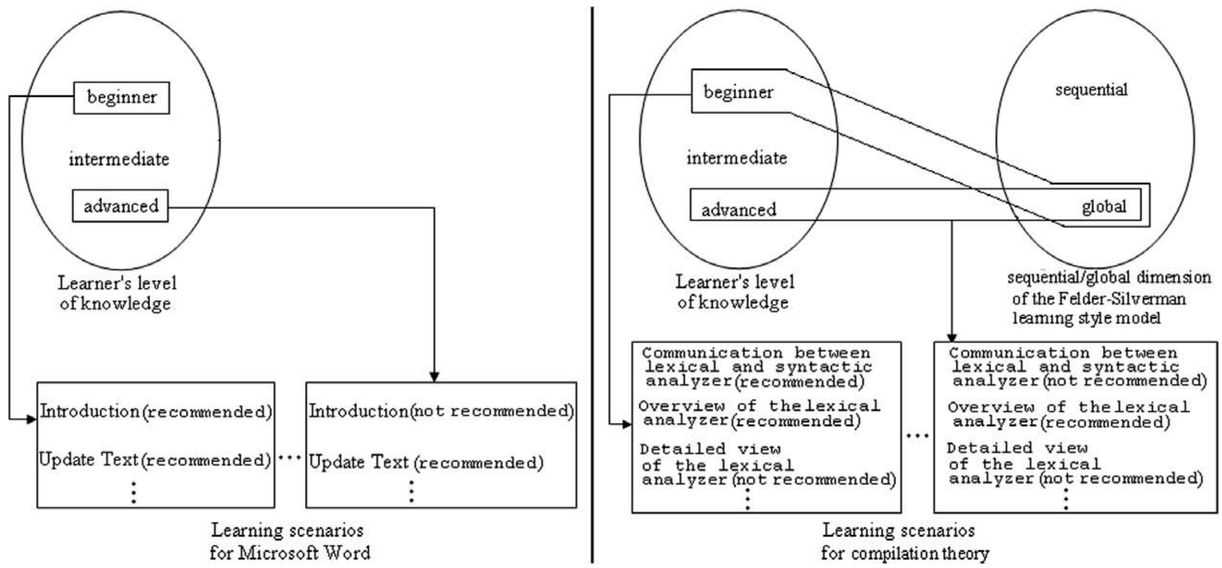

Fig. 2. Examples of personalization of learning scenarios.

The main idea of ELP1 + ELP2 is the specification and the application of personalization strategies in a flexible way. For a given learning scenario, a subset of personalization parameters can be selected for the specification of the personalization strategy to be applied. When the subset contains more than one personalization parameters, these parameters have to be combined. A personalization parameter can be seen as a set of values. For example, the personalization parameter *learner's level of knowledge* can be represented by the set {beginner, intermediate, advanced}. This signifies that a given learner has a level of knowledge either at beginner, intermediate or advanced level. Mathematical functions can be defined for combining the personalization parameters based on their specification as linguistic variables. The specification of a personalization strategy starts by the selection of personalization parameters (SPP) to be used for personalizing Learning Scenarios (LS) and the Combination of the selected Personalization Parameters (CPP). SPP and CPP constitute the bases for ELP2.

The SPP (see Fig. 3) can be considered as a function which associates an LS from the Set of Learning Scenarios (SLS) with a subset of personalization parameters (SubSP). SubSP belongs to the set of partition of Personalization Parameters (PP).

$$SPP : SLS \rightarrow P(PP)$$

where P denotes the set of partitions.

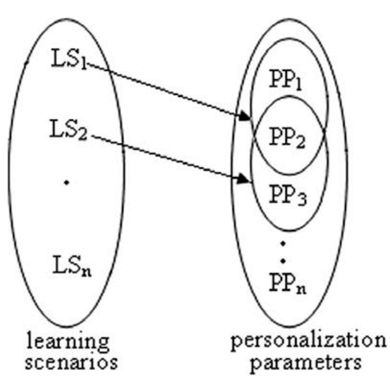

Fig. 3. Selection of personalization parameters.

Let us assume that an LS is a tree[2] of Learning Objects (LO), the CPP (see Fig. 4) can be considered as a function which combines each LO in LS with the values V_{jk} of the selected personalization parameters PP_j and associates the resulted combination with a set of adaptation decision (A). Formally, A is a set of linguistic values used to determine whether the LO is adapted or not with some values of the selected personalization parameters (SubSP). If there is no available information for the adaptation decision for some LOs, the adaptation is considered as neutral for these LOs.

$$\mathrm{CPP} : \mathrm{LS} \times \prod_{\mathrm{Pi} \in \mathrm{SubSP}} \mathrm{Pi} \rightarrow A$$

The functions SPP and CPP constitute as the theoretical foundation for our approach. In particular, these functions play a major role for the combination of the personalization parameters.

5. The architecture of ELP1 + ELP2

To build ELP1 + ELP2, components which focus on the personalization level 1 (ELP1) and the personalization level 2 (ELP2) are integrated. Furthermore, ELP1 must apply the personalization strategy specified by the teacher in ELP2. ELP1 + ELP2 is a new vision of personalization that offers a solution to some fundamental limitations of E-learning personalization systems. The main advantages of ELP1 + ELP2 include the ability of teachers to select the most suitable personalization parameters for their learning scenarios and the possibility of applying more than one personalization parameter according to the specifics of the learning scenarios.

Each of the personalization systems developed in the literature offers important functionalities for determining the learner characteristics according to a predefined subset of the personalization parameters. The federation of these functionalities and their combination allows generating other personalization strategies. However, the personalization systems are developed with different programming languages and tested/used in different contexts. This makes the combination of the function offered by these systems difficult. In this context, the Web services technology offers a

[2] A learning scenario can be represented by a tree of learning object where chapters (or sections) constitute the components (child) of the learning scenarios; each chapter can be composed of subchapters (subsection); and each subchapter can be composed of more specific learning objects like definition and pedagogical activities.

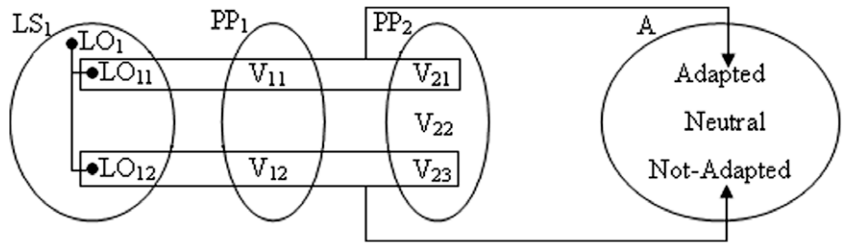

Fig. 4. Combination of personalization parameters.

powerful solution for the interoperability between multiple applications. In fact, a service can be considered as a distant function which is executed when it is called. In this way, when using services, developers are not interested in the implementation (algorithm, structure, programming language) and the platform of the service. Developers want to only call the service when they need it. Therefore, Web service is an emergent solution for integration of applications. Besides, the personalization systems are tested on different Web servers. This also advocates use of Web services technology for the integration of these personalization systems.

Web services technology also offers a major solution for federation of the functionality of personalization systems. In this context, an important step for concretizing proposed approach consists of utilizing Web services technology when developing ELP1 + ELP2. Fig. 5 depicts the resulting architecture of ELP1 + ELP2.

The mechanism of ELP2 is based on the Service for Specifying Personalization Strategies (SSPS). SSPS is needed to concretize the new idea of allowing the pedagogues and teachers to specify the personalization strategy adapted for the learning scenario. This service allows the selection of personalization parameters (SPP), and the combination of personalization parameters (CPP). For the given courses, the selected personalization parameters and their list of values are stored in a relational database.

ELP1 includes:

- *Service for Specifying and Reusing Learning Scenarios (SSRLS)*

The SSRLS allows the designer of learning scenarios to define a structure of a learning scenario and to determine the content to be communicated to the learners for each component of the defined structure. As an alternative, a learning scenario can be represented in the form of a tree of chapters, subchapters, pedagogical activities, and so on.

- *Services for Determining Learners' Characteristics (SDLC)*

The aim of SDLC is to federate the set of services for determining the learners' characteristics where each of them is associated with a personalization parameter.

- *Service for Applying Personalization Strategies (SAPS)*

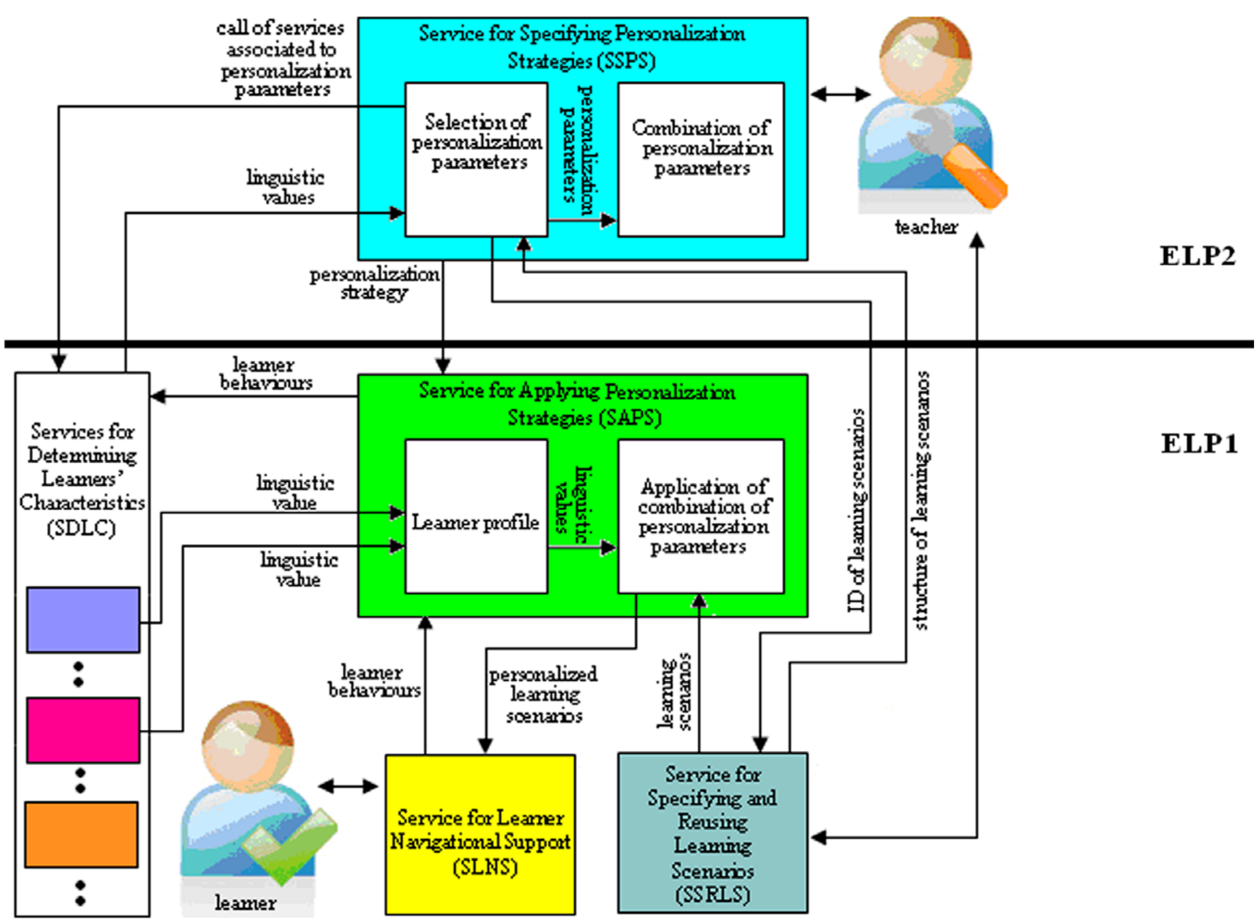

Fig. 5. Architecture of ELP1 + ELP2.

Table 3
Structure of the matrix.

		Parameter 1			...	Parameter m	
		Characteristic 1·1	...	Characteristic 1·i		Characteristic m·1	Characteristic m·j
Courses 1	Concept 1.1						
	Concept 1.k						
...							
Courses n	Concept n.1						
	Concept n.p						

SAPS allows the application of the personalization strategy specified in SSPS by combining the learner profile with the learning scenarios. This application refers to the function CPP presented in section 5. Besides, the SAPS is responsible for building the learner profile by gathering the output of the selected services for approximating the required learner characteristics.

- *Service for Learner Navigational Support (SLNS)*

SLNS allows the illustration of the learning content in the form of adaptive navigational support.

6. Experiment

Experimentations were conducted to test ELP1 + ELP2 and to measure its acceptance by users. A total of 150 students used the system during the academic year 2008–2009. The value of ELP1 + ELP2 is in its capability to specify different personalization strategies and to apply them. For that reason, three experimentations were conducted to test this capability. One of them (experimentation 2, during January–February 2009) focused on the specification of personalization strategies. In this experimentation, 19 students used the system for personalizing three courses (programming language C, data base, and Microsoft Excel). These users also visualized the impact of the specified strategies on the learner interface. The two other experimentations focused more on the application of different personalization strategies. 36 learners (experimentation 1, during November–December 2008) followed a course on C2I (Certificat Informatique et Internet) personalized according to the *learner's level of knowledge* and 95 learners (experimentation 3, during February–April 2009) followed a course on compilation theory personalized according to the *learner's level of knowledge* and the sequential/global dimension of the *Felder–Silverman learning style model.*

6.1. Procedure

The experimentations were conducted in a tertiary education institution in Tunisia. The participants in the experimentation 1 were first year students (computer science, and physics). This experimentation was started by a presentation of ELP1 + ELP2 interfaces for students. Then, the students used personal computers for connecting to ELP1 + ELP2 which was deployed on a server available through the local network of the institution. The students followed the course C2I in a personalized way according to their level of knowledge, as calculated by ELP1 + ELP2.

In experimentation 2, the participants were third year students (computer science). Students were given explanation of the principles of ELP1 + ELP2 by a teacher, who also clarified the final objective of the students' projects: development of a system which allows for determination of the most significant personalization parameters for a given course and the generation of learning scenarios to be added in ELP1 + ELP2 (the output of the system will be an input for ELP1 + ELP2). Then, the teacher introduced the personalization parameters already integrated in ELP1 + ELP2 and presented to the students a method which allows for determination of the most significant personalization parameters for each course and the generation of learning scenarios. This method starts by the construction of a matrix (structured like Table 3) which contains the personalization parameters and their divergent characteristics in the columns. The rows of the matrix contain the courses and the concepts included in them. Each cell contains the learning objects presenting a specific concept according to a specific characteristic. Students have also the possibility to specify beside the learning object, the percentage of its appropriateness to the specific characteristic. A cell which does not contain any learning object means that the concept specified in that row is not appropriate for the specific characteristic specified in that column.

After that, the teacher asked the students to individually do the following steps:

- Manually updating the cells of the matrix for three delivered courses (programming language C, database, and Microsoft Excel). Columns and rows of the matrix were given to the students.
- Manually determining the most significant personalization parameters for each course according to the number of learning objects and their average appropriateness to the characteristics included in the personalization parameters.
- Manually generating learning scenarios adapted for each combination of the characteristics in the significant personalization parameters.
- Using ELP1 + ELP2 for the specification of three personalization strategies (associating each course with the appropriate personalization parameters and combination of concepts and characteristics).
- Implementing the system which allowed the updating of the matrix (step 1), putting in order the personalization parameters (step 2), and generating learning scenarios (step 3). 5 students succeeded to implement the systems which allowed the execution of the 3 steps; 10 students implemented systems that allow only the execution of steps 1 and 2, and 2 students did not succeed in implementing the system at all.
- Testing and updating the realized parts of the developed system until the eliminations of the technical bugs. In addition, 2 students tested their systems by introducing the manually constructed matrix. Then they executed steps 2 and 3 automatically. As the outcome, their systems generated the same results as those that were produced manually (for each course, their systems generated the same order of personalization parameters and the same learning scenarios as were produced manually).

The participants in the experimentation 3 were third year students (computer science). This experimentation was started by a pre-

Table 4
Description of the questionnaires.

	Questionnaire 1	Questionnaire 2	Questionnaire 3
Context	Inspired from ISO/IEC definition of usability. Prepared for learners.	Inspired from ISO/IEC definition of usability and validated questionnaire from the literature. Prepared for teachers.	Inspired from ISO/IEC definition of usability and validated questionnaire from the literature. Prepared for learners.
Items	Three items for EOU, two items for AD, two items for L, and one item for S.	Four items for U, four items for EOU, four items for ATT and three items for INT.	Four items for U, four items for EOU, four items for ATT, three items for INT and four items for AD.

Note. EOU = ease of use, AD = adaptability, L = overall look, S = overall satisfaction, U = usefulness, ATT = attitude towards using the system, and INT = behavioural intention to use the system.

sentation of ELP1 + ELP2 interfaces for students. Then the students used personal computers for connecting to ELP1 + ELP2 which was deployed on a server available from the local network of the institution. The students followed the course on compilation theory that was personalized according to their *level of knowledge* and the sequential/global dimension of the *Felder–Silverman learning style model*.

6.2. Construct

The questionnaire used in the experimentation 1 was created based on the ISO/IEC definition of usability (2000) which defines usability as the capability of the software product to be understood, learned, used and be attractive to the user, when used under specified conditions. Concerning the questionnaires used in the experimentations 2 and 3, validated items from the literature were exploited in addition to the ISO/IEC definition of usability. For perceived Usefulness (U) and Ease Of Use (EOU), the items presented in (Davis, Bagozzi, & Warshaw, 1989) were used. In the questionnaire for learners, system adaptability (AD) items were composed of items derived from (Tobing, Hamzah, Sura, & Amin, 2008). Four items for attitude toward using the system (ATT) and three items for behavioural intention to use the system (INT) proposed in (Masrom, 2007) were also used. These items have been exploited in the research on Technology Acceptance Model (TAM) which offers a validation method for use of information systems by the users. Table 4 describes the origins of questionnaires prepared for the three experimentations.

The three questionnaires were validated for their internal consistency (see Section 6.5 for more details). These questionnaires were then used to calculate the satisfaction rates (see Section 6.6 for more details). In addition, Questionnaire 1 served in the earlier experimentation to collect information useful to enhance the system. In particular, this questionnaire provided rich information based on the open response (comments) of the students. These comments are described in the Section 6.3. In the second and third experimentations, literature was referred for validated and reliable items of questionnaires. Concerning the scale values, each item of the questionnaire 1 contained 5 values on Likert scale ranging from 1 for the total disagreement to 5 representing the total agreement. In the questionnaires 2 and 3, the scale was composed of 7 values on Likert scale with 1 representing the total agreement and 7 representing the total disagreement.

6.3. Students comments

Student comments served for enhancing ELP1 + ELP2 in the earlier period of the experimentation 1. For example, one student commented, "*The connection to the platform is low sometimes.*" The described problem was triggered when there were several simultaneous connections to the server. To resolve this problem, the number of possible simultaneous connections to the used application server "glassfish-v2.1" was checked. As a result, this was not found to be the source of the problem. Second, the thread count allowed for the request processing of the HTTP Service was checked and the respective parameter was found to be configured by default to 5 which was an insufficient count. By reconfiguring this parameter to 100, the problem was resolved. Another student commented, "*I like that the courses will include more exercises.*" This comment was considered in the experimentation 3 by including many exercises in the course compilation theory. Another comment was, "*I like that the platform interface will be in French.*" By considering this comment, two versions of ELP1 + ELP2 interfaces (in English and in French languages) were then made available. Many positive comments were also received, such as "*Overall, the presentation of courses with ELP1 + ELP2 is good.*", "*The images and the animations are very useful and explain well the tools Microsoft Word and Microsoft Excel.*", "*The understanding of information is very easy.*", "*The course is clear.*", and "*It is suitable to add other courses in ELP1 + ELP2 like programming languages C, C++, JAVA, and JavaScript.*".

6.4. Selected personalization strategies

In experimentation 2, each student selected the two most significant personalization parameters for each course. Table 5 shows the total number of times that each personalization parameter appeared as one of the most significant for each course.

According to the column Total, the personalization parameter *learner's level of knowledge* is the most used personalization parameter (33 times). This shows that the personalization parameter *learner's level of knowledge* is easy and significant to use for personalizing courses. In fact, most courses do have prerequisites and are composed of concepts which are related by the prerequisite rela-

Table 5
Number of times that personalization parameter appeared as one of the most significant.

Personalization parameter	Courses			Total
	Programming Language C	Data base	Microsoft Excel	
Active/reflective dimension of the Felder–Silverman learning style model	17	10	3	30
Sensing/intuiting dimension of the Felder–Silverman learning style model		4	2	6
Visual/verbal dimension of the Felder–Silverman learning style model	2		7	9
Sequential/global dimension of the Felder–Silverman learning style model			3	3
Honey–Mumford learning style		3	2	5
Learner's level of knowledge	13	15	5	33
Media preference	8	2	11	21

Table 6
Measure of internal consistencies.

Variable	Experimentation 1				Experimentation 2				Experimentation 3				
	EOU	AD	Look	S	U	EOU	ATT	INT	U	EOU	ATT	INT	AD
α	0.72	0.82	0.76		0.80	0.75	0.43	0.75	0.87	0.74	0.73	0.77	0.75

tions. These prerequisites of courses and/or concepts add significance for the personalization parameter *learner's level of knowledge*. This result coincides with the result presented in Table 2 which shows that the personalization parameter *learner's level of knowledge* is the most used parameter on the studied personalization systems.

For a given course, there exists a subset of personalization parameters that is more significant than the other subsets of personalization parameters. In the same column, the numbers of selection of the personalization parameters have wide variance. For example, the number of selection of the Active/Reflective dimension of the personalization parameter *Felder–Silverman learning style model* is 17 from 20 students for the course programming language C, and the number of selection of the Sensing/Intuiting dimension of the personalization parameter *Felder–Silverman learning style model* is 0 for the same course.

For a given course, the professors can see different subsets of personalization parameters. In fact, if we assume that the professors have selected the same subset of personalization parameters, each column of Table 5 would show only two cells containing a number (the two common most significant personalization parameters). This assumption is not valid and this shows the difference in teachers' decisions which depend on the teachers' background or the teachers' idiosyncrasy.

6.5. Internal consistency

The internal consistency of the construct was calculated by using the Cronbach's α[3] which has been commonly used in the literature, and its output expresses good internal consistency when the α value is near 1. Hair, Anderson, Tatham, and Black (1998) recommended that Cronbach's α values from 0.6 to 0.7 were deemed as the lower limit of acceptability. An alpha of more than 0.7 would indicate that the items are homogeneous and measuring the same constant. By measuring Cronbach's α, an acceptable rate of construct reliability was found for U, EOU and INT. Table 6 presents the internal consistencies calculated during the three experimentations.

The internal consistency is significant for the majority of variables in the experimentation 2, and it is significant for all investigated variables in the experimentation 1 and 3. For the variable S, the internal consistency was not calculated because there was only one item for this variable.

6.6. Satisfaction rates

In order to estimate the satisfaction of users, the averages[4] and medians[5] of the variables used in the three experimentations were calculated.

According to the 5-item Likert scale used in the experimentation 1, an average value greater than 3 indicates that on average users were satisfied with respect to the respective variable (e.g., found the system easy to use). In addition, a median value like 4 indicates that 50% of users were very satisfied with respect to the respective variable. In the experimentations 2 and 3, a 7-item Likert scale was used. An average value smaller than 4 indicates that on average users were satisfied with respect to the respective variable. Furthermore, a median value like 2 indicates that 50% of users were very satisfied with respect to the respective variable. Table 7 presents the calculated averages and medians. These estimates show good rates for each variable, indicating high users' satisfaction for all variables and very high satisfaction of 50% of users for most variables.

7. Discussion

When several personalization parameters are used in the literature, the question is: what personalization parameters are to be used for personalizing each course? The alternatives (propositions) *A1*, *A2*, *A3*, and *A4* are discussed.

- *A1: Using all the personalization parameters for each course.*

This alternative aims to apply a large number of personalization parameters for the personalization of each course. Consequently the generated learning scenarios will fit all the characteristics of the learners. However, there are two major constraints for the application of this alternative. The first one is the huge task that learners would need to undertake to respond to many explicit questionnaires for the calculation of their level of knowledge, motivation, cognitive traits, learning styles, and so on. The second constraint is the high cost for the development of learning scenarios personalized according to all the personalization parameters. In fact, each learning scenario will have to contain all learning material which fits all the learners' characteristics.

- *A2: Using the subset of personalization parameters which includes divergent characteristics of learners.*

After the measurement of learners' characteristics according to a large number of personalization parameters, the learning scenarios will be personalized according to the personalization parameters which do not have the same values for all the learners. This solution can eliminate some personalization parameters, and consequently the effort of development of personalized learning scenarios is economised. However, by applying this alternative, the learners may need to undertake huge task of responding to many explicit questionnaires for the calculation of their profile. In fact, the elimination of some personalization parameters can be achieved only after the measurement of the learners' characteristics. Furthermore, there is another constraint for developing the personalized courses after the elimination of some personalization parameters and the measurement of the learners' characteristics. When the personalization parameters are selected based on the individual learners' characteristics, the course might not contain the types of learning objects which would suit to the learners' characteristics included in the selected parameters. If the course does not contain the needed types of learning objects, the professor

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[3] $\alpha = N/N - 1)\left(1 - \left(\frac{\sum_{i=1}^{N}\sigma^2_{Y_i}}{\sigma^2_X}\right)\right)$, where σ^2_X is the variance of the total item for the variable, $\sigma^2_{Y_i}$ is the variance of item i in the variable, and N is the number of items in the variable.

[4] The average is calculated according to the following formula:

$$average = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} value_{ij}}{n * m},$$

where n is the number of participants, and m is the number of items in the variable.

[5] The median represents the value, which indicates that 50% of values are higher than or equal to it.

Table 7
Satisfaction rates.

Variable	Experimentation 1				Experimentation 2				Experimentation 3				
	EOU	AD	Look	S	U	EOU	ATT	INT	U	EOU	ATT	INT	AD
Average	3.59	3.62	3.97	3.08	2.76	2.44	2.24	2.24	3.08	2.17	2.53	2.75	2.73
Median	4	4	4	3	2	2	2	3	3	2	2	3	2

responsible of the course may have to redesign the course to satisfy the included learners' characteristics. This may take some time and may delay the learning process. This constraint may be a serious problem if the learning process has already started at the time the learners responded to the explicit questionnaires. In this case, the learning process may have to be stopped until the redesign of the learning scenarios is completed.

- *A3: Using the subset of personalization parameters to include only the most significant ones for each course.*

This alternative can be applied after the building of the matrix (Table 3) by the addition of the information (lines of the matrix): for each concept of the courses, the learning objects appropriate to each characteristic (or the learning objects and their degrees of appropriateness to the characteristics) of learners. After that, the columns of the matrix have to be analyzed, which describe the most satisfied characteristics (the columns which include the largest numbers of non empty cells). Given that a personalization parameter is composed of a set of divergent characteristics, the most significant parameters are those composed of the most satisfied characteristics.

- *A4: Using the subset of personalization parameters recommended by the professor responsible for the course.*

This alternative is based on the assumption that the professor responsible for the course is the expert in that subject and is the best familiar person regarding the context related to the particular offering of that course (such as the qualification to be awarded to the learners at the end of the study, and general information on the learners). He/she can select the personalization parameters which constitute an operational personalization strategy. In particular, he/she can eliminate some personalization parameters according to some general assumption, for example, in the context of learning a human language, the personalization of learning scenarios according to the personalization parameter *language preference* is not relevant. Furthermore, the professor responsible of the course takes advantage from his/her expertise in teaching and authoring courses while deciding the personalization parameters adapted to his/her course.

8. Conclusion and perspectives

There is no single personalization strategy that exists for the personalization of learning scenarios, and each personalization strategy depends strongly on the used personalization parameters. When there are different personalization needs determined by the pedagogues, the professors, and the learners, an approach has to be defined dealing with the personalization of learning scenarios according to the personalization strategies proposed by the person responsible for personalization. In this context, ELP1 + ELP2 addresses the personalization of learning scenarios at two levels. The first level (ELP1) allows the application of a personalization strategy, and the second level (ELP2) allows the specification of the personalization strategies. For a given personalization strategy, ELP1 supports the development of personalizable learning scenarios, and their personalization. When combined with ELP1, ELP2 supports the personalization not only by adapting the course to the learners by applying a personalization strategy, but also by allowing the person responsible for personalization to define the personalization strategy which matches the personalization need. This new vision of personalization has the promise of eliminating an important limitation of E-learning personalization systems by allowing teachers to select the personalization parameters which fit their courses. In addition to the axiom (1) "there is no one size that fits all learners", ELP1 + ELP2 considers two other axioms: (2) there is no one size that fits all courses, and (3) there is no one size that fits all teachers. Axiom (1) is explained by the individual differences of learners. Axiom (2) is due to the differences in the ways of course presentations, and axiom (3) is explained by the individual differences of teachers.

In the next step, the methods which allow the guidance of the person responsible for personalization in the selection of the personalization strategy will be studied. This means that the system will be able to propose a personalization strategy for a given course. Last but not the least, the ELP*n* as the general form of the E-learning personalization will be studied where ELP0 represents the E-learning systems which do not support the personalization, ELP1 symbolizes the E-learning systems which support the personalization according to one predefined strategy, ELP2 denotes the E-learning systems which support the personalization according to the personalization needs formulated as a personalization strategy, and so on.

This work can serve researchers in the E-learning personalization domain for understanding the most used personalization parameters which represent the learners' characteristics and needs. Furthermore, this work shows the feasibility of generating different personalization strategies according to the learning scenarios. Besides, ELP1 + ELP2 aims at federating the research effort for personalization and the exploitation of different personalization strategies according to the specifics of learning scenarios. In addition, ELP1 + ELP2 can be exploited as a general framework for the research in the E-learning personalization domain by the experimentation of different personalization strategies and concluding remarks on their suitability for the personalization of learning scenarios. Typical remark can be in the form: the use of the set of personalization parameters {P1, P2 , ... P*n*} is recommended for the personalization of the learning scenarios LS. Another typical interpretation can be in more synthetic form such as: the use of the set of personalization parameters {P1, P2 , ... P*n*} is recommended for the personalization of learning scenarios in the computer sciences domain, or on the domain of physics, and so on.

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References

Bouzeghoub, A., Carpentier, C., Defude, B., & Duitama, F. (2003). A model of reusable educational components for the generation of adaptive courses. In *The first international workshop on semantic web for Web-based learning in conjunction with CAISE'03 conference, Klagenfurt, Autriche*.

Brusilovsky, P., Schwarz, E., & Weber, G. (1996). A tool for developing adaptive electronic textbooks on WWW. In *WebNet 96 conference proceedings*.

Chorfi, H., & Jemni, M. (2004). PERSO: Towards an adaptive e-learning system. *Journal of Interactive Learning Research, 15*, 433–447.

Conejo, R., Guzmán, E., Millán, E., Trella, M., Pérez-De-La-Cruz, L., & Ríos, A. (2004). SIETTE: A web-based tool for adaptive testing. *International Journal of Artificial Intelligence in Education, 14*, 1–33.

Constantino-González, M., Suthers, D., & Santos, J. (2003). Coaching web-based collaborative learning based on problem solution differences and participation. *International Journal of Artificial Intelligence in Education, 13*, 261–297.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). *User acceptance of computer technology: A comparison of two theoretical models* (pp. 982–1003). The Institute of Management Sciences.

Dolog, P., Henze, N., Nejdl, W., & Sintek, M. (2005). Personalization in distributed e-learning environments. *ACM*, 170–179.

Essalmi, F., Jemni Ben Ayed, L., & Jemni, M. (2007). A multi-parameters personalization approach of learning scenarios. In *The 7th IEEE international conference on advanced learning technologies, Niigata, Japan* (pp. 90–91).

Felder, R. M., & Silverman, L. K. (1988). Learning and teaching styles in engineering education. *Engineering Education, 78*(7), 674–681.

Grandbastien, M. (1999). Teaching expertise is at the core of ITS research. *International Journal of Artificial Intelligence in Education, 335*, 349.

Greer, J., McCalla, G., Cooke, J., Collins, J., Kumar, V., Bishop, A., et al. (1998). The intelligent helpdesk: Supporting peer-help in a university course. In *4th international conference on intelligent tutoring systems* (pp. 494–503). New York: Springer.

Hair, J. E., Anderson, R. E., Tatham, R. L., & Black, W. C. (1998). *Multivariate data analysis 5*. NJ: Prentice-Hall.

Heift, T., & Nicholson, D. (2001). Web delivery of adaptive and interactive language tutoring. *International Journal of Artificial Intelligence in Education, 12*, 310–324.

Henze, N., & Nejdl, W. (1999). Adaptivity in the KBS Hyperbook System. In *Second workshop on adaptive systems and user modeling on the WWW Toronto, Canada* (pp. 67–74).

Honey, P., & Mumford, A. (1986). A manual of learning styles. In Peter Honey & Maidenhead (Eds.), *Learning styles*. Engineering Subject Centre.

Höök, K., Karlgren, J., Waern, A., Dahlbäck, N., Jansson, C.-G., Karlgren, K., et al. (1996). A glass box approach to adaptive hypermedia. *User Modeling and User-Adapted Interaction, 6*(2–3), 157–184.

ISO/IEC 9126-1 (2000). Software engineering – Product quality – Part 1: Quality model, 2000. In Hema Banati, Punam Bedi, Grover P. S. (2006). Evaluating Web Usability from the User's Perspective. *Journal of Computer Science, 2*(4), 314–317.

Keller, J. M. (1983). Motivational design of instruction. In C. M. Reigeluth (Ed.), *Instructional design theories and models: An overview of their current status*. Hillsdale, NJ: Erlbaum.

Kinshuk, & Graf, S. (2007). Considering cognitive traits and learning styles to open web-based learning to a larger student community. In *The first International Conference on ICT & Accessibility, Hammamet, Tunisia* (pp. 21–26).

Kinshuk & Lin, T. (2004). Cognitive profiling towards formal adaptive technologies in web-based learning communities. *International journal of WWW-based communities, 1*, 103–108.

Kolb, D. A. (1984). Experiential learning: Experience as the source of learning and development. NJ: Prentice-Hall. In David A. Kolb, Richard E. Boyatzis, Charalampos Mainemelis (Eds.), *Experiential learning theory: Previous research and new directions*. R. J. Sternberg, L. F. Zhang (Eds.), *Perspectives on cognitive, learning, and thinking styles*. NJ: Lawrence Erlbaum (2000). Available from http://www.learningfromexperience.com/images/uploads/experiential-learning-theory.pdf.

La Garanderie, A. (1993). Les profils pédagogiques. Paris, Bayard, Tunis, Publications de l'ATURED. In A. Chabchoub (Ed.), *Enseigner à l'Université de la théorie à la pratique, 2006*.

Masrom, M. (2007). Technology acceptance model and E-learning. In *12th International conference on education.* sultan Hassanal Bolkiah Institute of Education, Universiti Brunei Darussalam.

Melis, E., Andrès, E., Büdenbender, J., Frischauf, A., Goguadze, G., Libbrecht, P., et al. (2001). ActiveMath: A generic and adaptive web-based learning environment. *International Journal of Artificial Intelligence in Education, 12*(4), 385–407.

Milosevic, D., Brkovic, M., Bjekic, D. (2006). Designing lesson content in adaptive learning environments. *International Journal of Emerging Technologies in Learning, 1*, 2.

Mitrovic, A. (2003). An intelligent SQL tutor on the Web. *International Journal of Artificial Intelligence in Education, 13*, 171–195.

Murray, T. (2003). MetaLinks: Authoring and affordances for conceptual and narrative flow in adaptive hyperbooks. *International Journal of Artificial Intelligence in Education, 13*, 199–233.

Papanikolaou, K. A., Grigoriadou, M., Kornilakis, H., & Magoulas, G. (2003). *Personalizing the interaction in a Web-based educational hypermedia system: The case of INSPIRE. User modeling and user-adapted interaction* (pp 213–267). Kluwer Academic Publishers.

Peylo, C., Thelen, T., Rollinger, C., & Gust, H. (2000). A Web-based intelligent educational system for PROLOG. In *Proceedings of workshop on adaptive and intelligent webbased education systems at 5th international conference on intelligent tutoring systems, Montreal, Canada* (pp. 70–81).

Sampson, D., Karagiannidis, C., & Cardinali, F. (2002). An architecture for Web-based e-learning promoting re-usable adaptive educational e-content. *Journal of Educational Technology & Society, 5*, 27–37.

Small, R. V. (1997). *Motivation in instructional design*. NY: ERIC Clearinghouse on Information and Technology Syracuse. Available from http://www.ericdigests.org/1998-1/motivation.htm.

Smith, A. S. G., & Blandford, A. (2003). MLTutor: An application of machine learning algorithms for an adaptive web-based information system. *International Journal of Artificial Intelligence in Education, 13*, 235–261.

Soller, A. (2004). Computational modeling and analysis of knowledge sharing in collaborative distance learning. *User Modeling and User-Adapted Interaction: The Journal of Personalization Research, 14*, 351–381.

Stash, N., Cristea, A., & de Bra, P. (2006). Adaptation to Learning Styles in ELearning: Approach evaluation. In T. Reeves & S. Yamashita (Eds.), *Proceedings of world conference on e-learning in Corporate, Government, Healthcare, and Higher Education* (pp. 284–291). AACE: Chesapeake, VA.

Tobing, V., Hamzah, M., Sura, S., & Amin, H. (2008). Assessing the acceptability of adaptive E-learning system. In *Fifth international conference on elearning for knowledge-based society, Bangkok, Thailand*.

Weber, G., & Brusilovsky, P. (2001). ELM-ART: An adaptive versatile system for Web-based instruction. *International Journal of Artificial Intelligence in Education, 12*, 351–384.

Weber, G., Kuhl, H.-C., & Weibelzahl, S. (2001). Developing Adaptive Internet Based Courses with the Authoring System NetCoach. In *Proceedings of the third workshop on adaptive hypermedia*, LNCS, 2266 (pp. 226–238).