LEARNING STYLES AS A TOOL FOR PERSONALIZATION IN ONLINE LEARNING

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Abstract
In the paper an idea of personalization in online education based on learning styles and Howard Gardner's multiple intelligences theory (1983) is presented. It gives the results of research carried out by the author aimed at recognizing individual profiles of online learners. The analysis of data collected by KS-TIW questionnaire built for that purpose shows important regularities and gives useful indications about how to build a model of personalized online learning that helps to prepare more individualized and more effective courses.

Introduction

In the last decades of the twentieth century it was a commonly held belief that introduction of computers into everyday school practice would change not only the way the knowledge is delivered to the students but also the way they absorbed and retained it. It was expected that students would become more active and more creative participants of educational process and, in consequence, this process will become more efficient. Those unfulfilled expectations were transferred to e-learning, which seemed to give the learners more independence by allowing them to work on their own path according to their individual arrangements (at least with regard to time and place of learning). It looks as if it was about time to formulate a question concerning the influence of those teaching forms and techniques, which e-learning "brings to school" on the efficiency of educational efforts both on the students and on the teachers' side. Do they really change the contemporary school? Do they change the way we learn? And, finally, do they help learning and teaching become more efficient?

The extent to which e-learning is involved in educational systems varies significantly from one country to another and therefore it is quite difficult to give one simple answer to such a set of questions, but there are some common factors which do not depend actually on the legal regulations, financial conditions or even the access to computer labs and Internet in particular schools and countries. Those factors refer to pedagogical backgrounds of online education and therefore may be applied across the country borders and school levels. One of such factors is personalization. The first section of this paper contains the information on how it is and could be understood and implemented in the context of e-learning. In the next section the scope and the aim of research carried out by the author will be presented, followed by the description of a tool which can be used for gathering the personal data describing the participants of the learning process. That section will also contain the information on how this data can be interpreted for educational purposes and, finally, some useful indications on how to build a model of personalized online course will be defined.

Different Faces of Personalization in e-Learning

There is a tendency to claim that personalization is an immanent feature of e-learning. The content placed on the platform, easily accessible from any place at any time, seems to fulfil individual needs of the learners. While it is true, it is also true that easy access does not ensure better results of teaching and learning. This is probably one of the reasons why, despite quite common expectations, e-learning did not bring significant change in efficiency of educational processes. At least such claims can be quite often heard at conferences aimed at online education like for instance annual EDEN (European Distance and E-learning Network) conferences. Also the results of a survey (Dabrowski & Zajac, 2006) carried out at Warsaw School of Economics, where every semester up to 2000 of students attend online lectures, have shown that there are no significant differences between the grades that student get in e-learning courses and in traditional on campus classes.

One of the possible explanations is that accessibility of learning resources only makes the “learning conditions” more friendly and suitable, but the way of presenting learning material and performing learning activities remains the same for all the learners, whereas in fact everyone has his or her own individual learning preferences (Felder, 1998). In the traditional classroom a good teacher can monitor the behaviour of his or her students and change the teaching methods, sometimes even on the spot, in order to get the best possible results of the work. In a virtual learning environment (VLE) such adaptations are usually impossible.

Another commonly used means of personalization takes into account different levels of advancement of the users (like in ALATUS LCMS, 2003). There are two possible ways of fulfilling such requirement. In first approach learning content offered to all the learners remains the same but users are allowed to skip freely some parts of a course if they are already familiar with those pieces of information. The other approach requires preparing the learning content in such a way that various learning paths (corresponding to different levels of advancement) are possible and the learners can modify their own path along the course by switching to more advanced topics or — just the opposite — trying to find some basic explanations if necessary. Usually, both of these ways involve automatically assessed tests, results of which establish further steps. According to them the learner can be unable to proceed to the next steps of a course and is “forced” to go back and revise some already passed parts of it. On the other hand, it may be suggested to go to the upper level if the results of tests show that the current level is too simple for that particular learner.

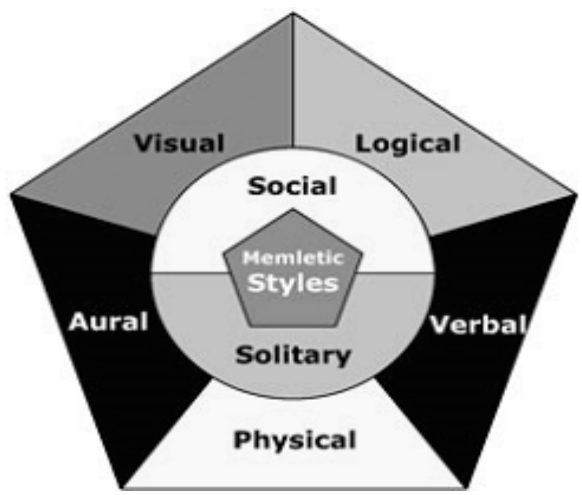
Quite interesting and a little bit more sophisticated solution of that type of personalization was elaborated by IBM research team, that proposed the idea of Dynamic Assembly Engine (Farell, Liburd, & Thomas 2003), which built into e-learning platform allows the learner to decide on their own whether they want to change the mode of further learning. More precisely, it gives the learners the opportunity to absorb only these pieces of information they actually need. Moreover, they can choose the form those pieces are presented in. One can say, there is no better way to personalize learning than to give the free choice to the learner. It may seem plausible, but the pilot study led by IBM research team has shown that some learners had spent too much time on making up their minds. In other words, they had not been able to decide which form was most suitable for them. The reason is that in fact we rarely think about the way we obtain knowledge. We just do it. It means that although the learning process itself could have been optimized by better adjustment of learning content in general the process of learning had not been more efficient because of wasting time on making appropriate decisions.

Psychological Backgrounds of Personalization

As mentioned above, in classroom teaching a good teacher is able to differentiate and adapt learning methods he or she uses to the current needs of the students. One of the possible ways of doing that is to recognize individual learning styles of the learners. This recognition can come from the teacher’s own experience, but it can also be supported by various inventories aimed at measuring learning styles according to the theory applied for establishing them. For instance, Richard Felder (1998) describes that when the background for classification is Carl Jung’s theory of personality types (extroverts, sensory, thinkers and judgers) 16 different learning styles are usually named and measured. Meyers-Briggs Type Indicator (MBTI — http://www.personalitypathways.com/MBTI_intro.html) and Paragon Learning Style Inventory (http://www.oswego.edu/plsi/) are the well known examples of inventories used for that purpose. Alternatively Hermann Brain Dominance Instrument (HBDI) (http://www.hbdi.com/) classifies learners’ preferences for thinking in four different modes based on the task-specialized functioning of the physical brain (left brain, cerebral, left brain, limbic, right brain, cerebral, right brain, limbic). Another well known type of learning styles indicator was elaborated by David Kolb (initialized in 1975 and continuously developed). The questionnaire allows one to distinguish four learning styles: diverging, assimilating, converging and accommodating. Those styles have been derived according to Kolb's four stage cycle (Kolb & Fry 1975) of experiential learning that includes the following processes: concrete experience, reflective observation, abstract conceptualization and last but not least — active experimentation.

Slightly different approach is presented in Memletic Learning Styles Inventory elaborated by Sean Whiteley (http://www.accelerated-learning-online.com/styles/default.asp). Seven different learning styles are recognized by this inventory in accordance with seven types of intelligence indicated by Gardner in 1983 (see Figure 1). It is a verbal (linguistic) learning style, visual, aural, logical and a physical and with regard to our relations with others participants of learning there are also solitary and social learning styles.

Figure 1: Memletic learning styles



(Source: http://www.learning-styles-online.com/overview/)

There is a significant difference between all the other previously mentioned definitions and the last one. While the outcome of a typical learning styles inventory is normally one dominating learning style (or, in some cases, two of them) Memletic LSI gives the information about the extent to what each of seven learning styles taken into account is used by a particular learner. Such indications are particularly important to e-learning as the learning content must be, in the major part, prepared in advance and it is difficult to adapt it "on the spot" according to learners' needs. Provided that the initial recognition of one's learning style was not precise (there can be many reasons for that) the whole learning throughout the course will be affected by those misleading indications. Approach based on recognition of various learning styles helps to "soften" consequences of such incorrect "diagnosis".

The only problem that remains then is to prepare the appropriate content in a way that corresponds with indications of learning preferences described by the learning styles. This can really be an obstacle because of the amount of work and time taken by the preparation of such content. Nevertheless it is the problem worth the effort put in solving it. This aspect will be described more precisely later on — the only thing that should be mentioned here is the idea of RLO (Reusable Learning Objects), which helps to reduce this work at least a bit.

Research Aims and Scope

The purpose of the research project described in this paper was to investigate the possibility of implementing personalization tools in a Virtual Learning Environment (VLE). As it was already mentioned, the concept of personalization was based on Howard Gardner's Multiple Intelligence Theory. Three separate steps/phases of the project can be distinguished. The first one — already completed — was aimed at elaborating a tool for gathering the data about the learners' individual preferences. In this phase some statistical analysis was also made, supplied by the use of data mining techniques.

The main goal of step two is to define the structure of a knowledge base (learning content repository) which could be used for personalization purposes. There are three main requirements such database should fulfil:

- the content must be divided into little "portions" called Learning Objects, which can be joined together in order to create a new online course;
- the same content should be stored in various forms (e.g., text, audio or video recording, graphic representation (table, flowchart);
- the way of combining different LOs must be defined.

The third step of research is aimed at implementation of an "intelligent" steering algorithm in chosen LMS. Its "intelligence" comes not only from the use of AI techniques but first of all from its ability to "learn" and to generate the set of indications describing the needs of a particular learner with regard to learning content, which should be prepared for them. The role of such algorithm is to enable the system to interpret information concerning learner's preferences and to create a tailored online course corresponding with those preferences. In pilot phase of research the algorithm will be implemented in a system used by Warsaw School of Economics (www.e-sgh.pl), but it is planned that the solution will also be tested in conjunction with other e-learning platforms, like Moodle for instance.

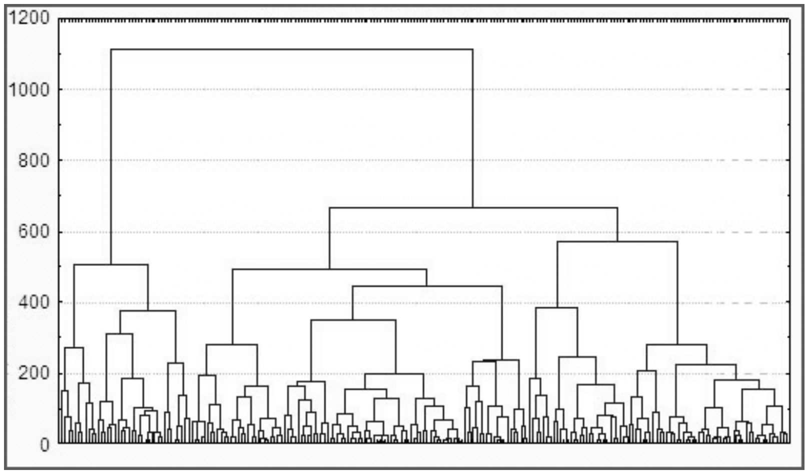
Collected Data and its Interpretation

During the research study the questionnaire data filled in by 220 students were collected. There were two major groups of respondents: 160 people were university students, whereas 60 others were upper secondary school students. The structure of the first group was composed in a way that it should represent various subjects of study and it covered such faculties as: mathematics, informatics, Polish literature and linguistics, German language studies, political and social sciences as well as psychology and pedagogy. The students were mostly in the 6th term, some of them in the 4th. The secondary school group was more homogenous — all the students went to the same school. The purpose of including this group was to compare how the learning styles change with age and educational level. The diversity of the first group was planned in order to check the dependence of learning styles on the subject.

Not surprisingly, despite many visible similarities among the students belonging to the same group (school or university class) every single set of data derived from a questionnaire was different from the others. This is obviously a natural consequence of the fact that every one of us has his or her unique personality. But, when we intend to reflect a reality in an artificial system we have to make some simplifications as such “infinite” diversity cannot be practically implemented. That is why the analysis of colleted data was aimed at distinguishing a group of sample learners’ profiles that would, possibly well, represent various individuals. For such a group the initial version of the steering algorithm can be prepared and tested. As there are no simple rules that would enable finding the subsets of learners represented by the same profile it was decided to use some artificial intelligence techniques. Actually a two step approach was undertaken. During the first phase cluster analysis was used in order to divide the population of 220 learners into several clusters. Each cluster would represent a different learning profile. As the number of possible clusters was unknown the agglomeration method was used. Various types of linkage and different possible metrics were tested. Figure 2 shows a sample cluster dendrogram illustrating clustering results by complete linkage and Euclidean metric (some other metrics like exponent metric, i.e., generalized Euclidean distance and Manhattan, have also been tested).

X axis in the Figure 2 illustrates the objects, in this context — respondents to the questionnaire. As can be seen in the figure it is possible to distinguish some clusters of those objects. Their number depends on the level of clustering we choose, i.e. on the accuracy we allow while deciding whether two objects can be concerned as being similar or not. The measure of similarity in this context is a “distance” between the values describing two objects being compared. The smaller the distance the bigger is the number of groups (clusters). These clusters refer to various profiles of learners we try to distinguish and define in order to make the task finite. In this step of research the most important task however was to prepare a tool that would enable collecting the data about the learners and this tool will be described in the following section.

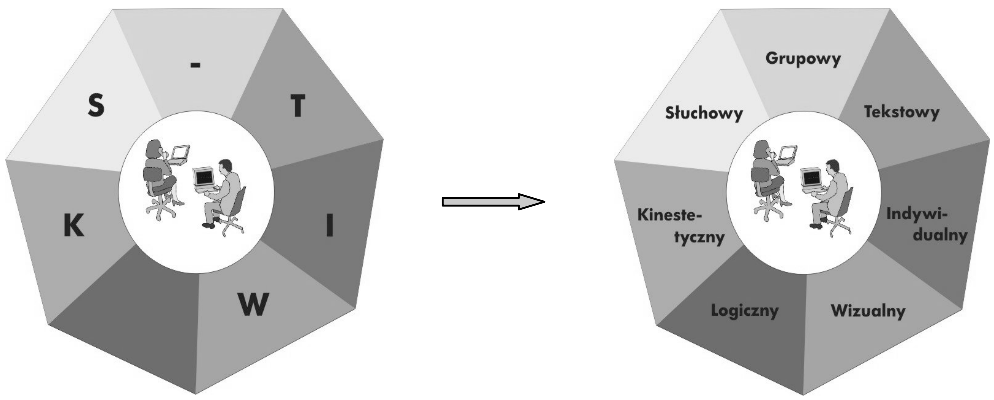
Figure 2: Cluster analysis of collected data — Euclidean metrics



KS-TIW Questionnaire

As already mentioned most commonly used means of collecting data concerning user's profile is a questionnaire. There are lots of such tools prepared in electronic version which can be quite easily included within the e-learning platform. For the purpose of research described in this paper a questionnaire based on Howard Gardner's Multiple Intelligence theory and Memletics Learning Styles Inventory has been elaborated. It must be clearly underlined that it is not simply a translation from the English version, but a model built on the same backgrounds. Learning styles are strongly dependent on cultural and educational context, which means that the questions must correspond with one's educational experience and the conditions he or she was grown up in and therefore cannot be directly transferred from the other environment. The questionnaire has the acronym KS-TIW from its Polish name, which can be translated into English as Learning Styles Questionnaire based on Multiple Intelligences Theory.

Figure 3: Learning styles recognized by KS-TIW questionnaire

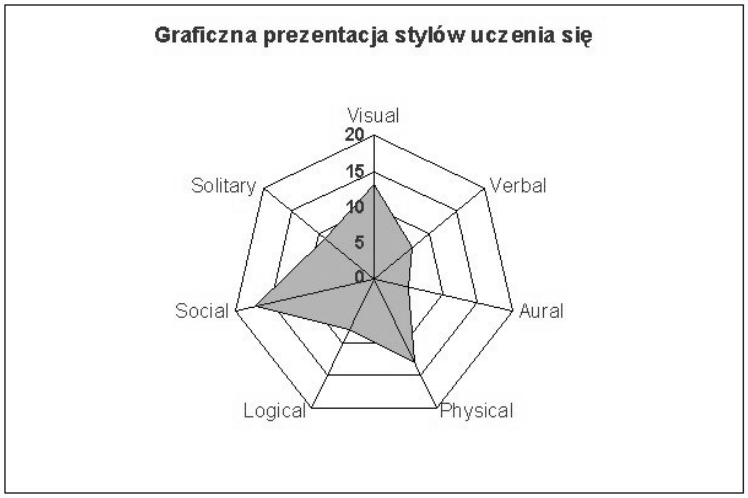


The questionnaire consists of 70 questions divided into 7 groups related to 7 learning styles being recognized. Its role in the system is to bring the information about possible learning styles of the potential learners. Each person is represented by the set of 7 values from the range 0–20, which illustrate the "involvement" of every recognized learning style in one's learning process. The results can also be presented in a graphic form.

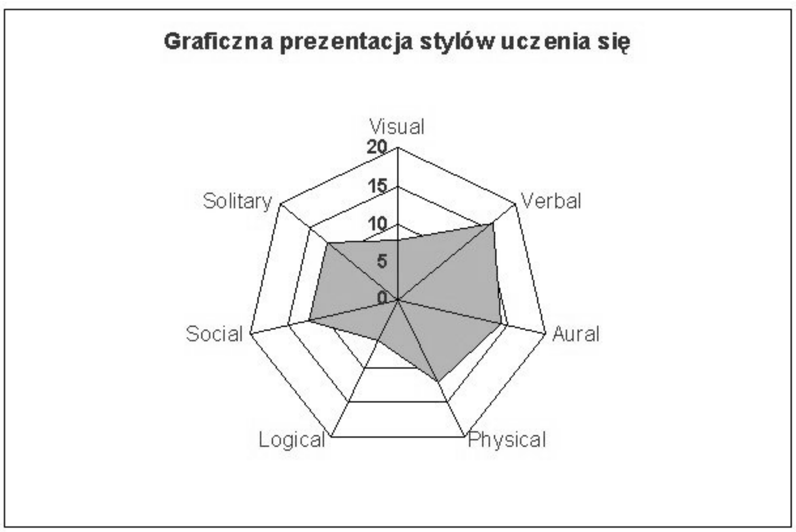
Figure 4 shows chosen graphs based on KS-TIW data. In Figure 4a we can spot the dominance of physical learning style, which means that this person prefers "learning by doing". As the social dimension for this learner has also high value probably the group work will be more appropriate then individual studying. Figure 4b shows slightly different preferences – we can presume that although still "learning by doing" is also effective for this person verbal delivery of knowledge (e.g., descriptions and explanations) both in written and in aural form are even more important. Such information can be really helpful in construction of personalized courses.

Figure 4: Graphical visualization of learning styles

(a) dominance of social and physical learning styles



(b) dominance of verbal, aural and physical learning styles



These graphs show significant differences in learning styles of those two people. Both of them were upper secondary school students. The difference between them was quite high. We can assume that their learning styles originate mostly in their individual interests and personalities and have not been strongly influenced by the particular way of studying. The situation looks quite differently when we try to analyze the graphs illustrating the learning styles of university students. Almost all the respondents who study political sciences, for instance, prefer verbal forms of knowledge delivery (both aural and written). Taking into account that studying political sciences requires getting familiar with lots of texts, essays or legal documents, such preferences are not surprising, In comparison to secondary school students it is quite visible that such abilities are worked out during the study period at the university.

Implications for Online Learning

With regard to online courses learning styles can bring the information on the form in which the learning content should be presented. Visual learning style implies the use of graphs, tables, illustrations and photos appropriately to the subject being taught. Video recordings will also be advisable in that case. The dominance of verbal style indicates that the main means of presenting the information should be text — both written and as an audio recording. The logical style can be successfully supported by various tasks and problems to be solved. With regard to physical style in online learning context, it may refer to simulations, again — to solving problems and to some sort of educational games. All these indications must be combined with appropriate social inclinations. In other words combination of logical and social styles may lead to the use of group work like case studies or project work, while logical and solitary style may indicate that logical puzzles and crosswords are more advisable for that particular learner. These are only a few examples of possible combinations of content and activities linked together in an online course in order to make it better adjusted to one's individual needs. Needless to say, such approach requires high variety in preparing the learning content. More precise analysis of the possible structure of online courses in the context of personalization will be the subject of further research.

Technical Aspects of Preparing the Content of the Repository

As it was indicated while presenting the scope of research, repository of learning content that will be used by a personalised LMS should be prepared according to the strictly defined rules. Most important among them is the requirement of the appropriate structure of data stored in the repository. It refers not only to the type, size and form of individual learning objects but also to the way the learning material is divided into little "bricks". Actually both parts of this task may not be trivial and cannot be done automatically. Much more difficult, however, is a precise description of sequence in which the individual objects appear in a course — which of them can be combined or linked together and which of them imply the necessity of the others.

From a technical point of view some specifications already existing can be applied in that context. For instance, the IEEE Learning Object Metadata (LOM) standard offers some commonly used items for description of typical learning objects grouped into several categories. Moreover, the IMS learning design specification allows adding to this description some pieces of necessary information concerning pedagogical aspects and learning objectives of the objects. And last but not least, the idea of RDF (Resource Description Framework) graphs proposed by W3C's Semantic Web working group seems to be really useful. It is based on a model of entities and properties. Entities in this context are learning objects and the properties are their characteristics, attributes, aspects or relations to other entities.

An appropriate set of metadata built in accordance to the already mentioned standards must describe all the learning objects stored in a repository that will be used as a knowledge base for the online learning system.

Conclusions

The problem of personalization in online learning remains the focus of attention of many researchers nowadays. There have been various attempts undertaken but only some of the solutions are used for teaching real courses. Sophisticated web-based Adaptive Hypermedia systems as well as Intelligent Tutorial systems are often oriented on one type of tasks, like quizzes or assessments for instance, and therefore cannot be used for other purposes (Brusilovsky, 2003). Moreover, their content is not shareable and that is also a real obstacle, which blocks their popularization.

In this paper another approach has been presented. The author and her colleagues from The Pedagogical University Krakow, Poland started to carry out research that would allow implementing some personalization tools directly in LMS (Learning Management System) already used at the university. Personalization is in this case based on learning styles theory and an appropriate questionnaire has been adapted to the virtual environment. Its role was to collect the data necessary to define the possible profiles of the learners. This phase of work has been already described in the paper and it was actually the first part of the whole project. The other parts will be aimed at distinguishing possible elements of online courses with regard to their usefulness for personalization purposes and the last one should allow us to define the structure of Reusable Learning Objects and metadata that will describe them in order to enable their proper linking adequately to the structure of personalized e-learning course. Provided all these steps are achieved another project oriented on implementing an "intelligent" steering algorithm in an LMS can be launched.

References

Alatus Ltd. (2003). Alatus LCMS — Official system documentation. Warszawa.

Brusilovsky, P. (2003). A distributed architecture for adaptive and intelligent learning management systems. In R. Calvo, & M. Grandbastien (Eds.), *Intelligent Management Systems Workshop, Supplementary Proceedings of Artificial Intelligence in Education* (pp. 106–114).

Dabrowski, M., & Zajac, M. (2006). 1000 opinii o e-dukacji. *e-mentor, 1*(13), 50–52

Farell, R., Liburd, S. D., & Thomas J. C. (2003). Dynamic assembly of learning objects. In *Proceedings of the 13th international World Wide Web conference on Alternate track papers & posters*, New York, USA. Retrieved April 4, 2008, from: http://www.research.ibm.com/XML/farrell-Dynamic-Assembly-of-Learning-Objects-2004May.pdf

Felder R. (1998). *Matters of style.* Retrieved April 15, 2008, from http://www4.ncsu.edu/unity/lockers/users/f/felder/public/Papers/LS-Prism.htm

Kolb, D. *Experiential Learning and Learning Style Inventory.* Retrieved May 25, 2008, from http://www.learningfromexperience.com/assessment-tools/#LSI

Memletic Learning Styles Inventory. Retrieved April 14, 2008, from http://www.learning-styles-online.com

Myers, I. B., McCaulley, M. H., Quenk, N. L., & Hammer, A. L. (1998). *MBTI Manual: A guide to the development and use of the Myers-Briggs Type Indicator* (3rd ed.). Palo Alto, CA: Consulting Psychologists Press.

Paragon Learning Style Inventory. Retrieved May 25, 2008, from http://www.oswego.edu/plsi/