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Diagnostics of the Student's Learning Style With the Use of Modern Information Technologies

Abstract

The paper deals with learning styles and their initial diagnostics in the process of the student's learning. It is focused on a method of learning styles recognition with the support of modern information technologies. The paper analyses different methods of the learning styles diagnostics, incorporating this issue into the scientific field of artificial intelligence and presents an idea on how to diagnose a learning style by using an unconventional fuzzy logic linguistic expert system. The expert system was designed to diagnose learning styles of university students in adaptive computer aided learning systems. A significant benefit is continuous numerical evaluation of the student's degree of affiliation to all learning categories (types of student) with a possibility of simple determination of dominant and subdominant types, the use of a linguistic rule-based decision-making model, which is completely transparent and open, and the use of a decision-making procedure corresponding to the process of human consideration. The paper is an example of an application of modern information technologies in education.

Key words: *learning, learning style, diagnostics of learning styles, adaptive learning systems, model learning style model, methods of diagnostics of a learning style, typology of learning styles, artificial intelligence, expert systems, linguistic fuzzy model, fuzzy set, fuzzy logic, degree of affiliation.*

Introduction

Learning is a part of our lives. It is a lifelong, active, and creative process with an aim of shaping the individual. According to Čáp (Čáp, 1993), in the most general terms, we can understand learning as a process of acquiring individual experiences. In a narrower sense, learning is associated with school and school education and is understood as acquisition of knowledge, skills, habits, and attitudes, as well as a change in mental processes and a state of mental qualities. We understand learning in a narrower sense – as the student's activity leading to the acquisition of new knowledge, skills and attitudes. While learning, each student processes a lot of information and approaches it in different ways; everyone has his own unique style. As a learning style we understand learning processes that an individual uses during a certain period of life in most situations related to study. To a certain extent, they do not depend on study content. They appear at the congenital basis (cognitive style) and develop by an influence of both internal and external factors (Průcha, Walterová, Mareš, 2009). The student usually does not realize his learning style, does not analyse it systematically and does not improve it deliberately. A learning style seems to be an obvious, common, habitual and satisfactory approach (Mareš, 1998). But the learning process, i.e. its progress and efficiency, is influenced by the way (style) each student learns (Nakonečný, 1998). Therefore, knowing one's own learning style before studying is useful for the student, so he can target and individualise interventions in the course of learning in order to streamline this process.

Although there are specialised computer programs for dealing with the diagnostics of learning styles, they are usually designed for off-line decision-making support by the teacher; the final decision must be made by the teacher himself. However, if such programs are a part of on-line systems, their conclusions must be sophisticated and reliable enough. There are tools from the scientific field of Artificial Intelligence for the creation of such systems. Among them there is a fuzzy-logic expert system designed to determine the student's individual learning style before he starts studying. Users of the system can be both teachers and university students, especially part-time students.

Diagnostics of learning styles

Understanding learning styles is difficult. A learning style is a hidden and latent variable which can be measured only indirectly, because it is mediated by other variables; we can indicate its quality using the available indicators (Marton, 1988). There are many specific methods used for the learning styles diagnostics worldwide. They can be classified according to various criteria. For our purposes, the important aspect is the method of acquiring information. This aspect classifies methods to rather direct and rather indirect ones (Mareš, 1998).

Direct methods include observation of the student's learning progress and computer-aided learning. Procedures which use computers for studying particular material were described by V. Kulič (Kulič, 1992). He talks about the so-called procedural diagnostics of the student's learning in which continuous characteristics of the student's performance and the process of learning should be recorded and evaluated. These procedures have been further elaborated in intelligent mentoring systems, which are computer-aided systems with programs that teach students how to resolve a defined problematic situation correctly and effectively (Kulič, 1992, cited according to Mareš, 1998).

Intelligent mentoring systems are related to adaptive learning systems which try to adapt the learning process to individual characteristics and needs of students. For more than 20 years, Peter Brusilovsky has been dealing with the issue of adaptive systems. He published numerous papers on adaptive hypermedia and an adaptive web, and also focused on the issue of hypermedia systems which attempt to adapt to the student's learning style (Brusilovsky, 2001, 2003). Adaptive learning is more or less close to AHA System – the adaptive hypermedia learning system (Bureš & Jelínek, 2004, Paramythis & Loidl-Reisinger, 2004), which is based on the idea of an adaptive web. The web is adjusted to the needs of the student based on his behaviour while working with a hypermedia system. However, AHA ignores the psychological-pedagogical features of the student. The introduction of adaptation based on learning styles is described by Liu, who stresses the importance of learning styles for education (Liu, 2010).

Indirect methods are used very often for the diagnostics of learning styles, even though they anticipate that students have developed skills of introspection and self-reflection. Questionnaires that fulfil diagnostic or self-diagnostic functions are particularly popular. Mareš (Mareš, 1998) provides an overview of main questionnaire methods which detect learning styles. However, authors define learning styles differently. Therefore, many learning styles models have appeared which exhibit similar approaches even though they were developed in various R&D institutions, independently of one another and are described with the use of different terminology. For instance, Briggs and Myers' model understands the learning style as a part of a relatively permanent personality type, which is visible from the outside (Coffield, 2004). A questionnaire for learning style determination of The Myers-Briggs Type Indicator- MBTI firstly sets the personality type of the learner, from which it derives his reactions to the outside world. According to Kolb, Felder, and Silverman, learning styles are not a permanent, unchanging personality trait; they are defined as a prefered learning method which varies according to a particular situation. Kolb's learning styles questionnaire (Learning Style Inventory, LSI) comes from the theory of acquiring knowledge based on the transformation of experience (Kolb, 1984).

Felder and Silverman created a typology of learning styles based on four dimensions taken from the Kolb and Myers-Briggs models (Kaliská, 2012). Particular dimensions are independent of each other; they consist of two poles (categories) which determine a particular type of the student. The different types of students can be briefly described as following:

1. Sensing and Intuitive Type of Student

Students tend to perceive the world either by their senses or intuition. The perception of the senses includes observation and gathering data through the senses. Intuitive perception involves indirect, unconscious perception through considerations, imagination and feelings.

2. Visual and Verbal Type of Student

Visual learners perceive and remember best what they see- pictures, diagrams, charts, tables, maps, etc. Verbal students are oriented on information presented by words. They put emphasis on text input and output- reading and writing in all its forms.

3. Active and Reflective Type of Student

Felder and Silverman state that complex mental processes, which transform the perceived information into knowledge, consist of two categories- active experimentation and reflective observation. Active types of students prefer to learn in situations that allow group work and active experimentation. Reflective types of students require a situation that gives them an opportunity to think about the presented information. They prefer theoretical deduction and study themselves or with one more person (Felder, Silverman, 1998).

4. Sequential and Global Type of Student

Sequential types of students are satisfied with dealing with materials presented in a coherent order. They learn by small steps and it is most convenient for them when their teacher presents material in the final form in which they need to know it. It takes global students quite a long time to learn, sometimes up to several weeks, with numerous interruptions and new starts, without the need to solve a basic problem, but then suddenly everything makes sense to them. They try to look at the problem holistically (Felder, Silverman, 1998).

According to Felder and Spurlin (Felder, Spurlin, 2005), each student has his learning style defined by one of the categories of each of the four dimensions. The decision which dimension the student should be classified in is based on a mathematical interval method. Transitions between the intervals are sharp; the transition to the next category (pole) of each dimension at the endpoint of the interval is conditioned only by the change of evaluation by one distinguishing degree (point). This solution does not provide a possibility for continuous transition between categories.

However, Kaliská (Kaliská, 2012) notes that although each student always tends to one specific pole (category) of each dimension, we cannot say that this category is the only one typical of the student, because his learning style is a combination of all his individual learning preferences. Therefore, determination of the student's learning style involves particular uncertainty, which can be well described by modern methods of artificial intelligence (Mařík, 1997).

That is why there is a fuzzy-logic expert system presented in the paper, which uses the learning styles typology according to Felder and Silverman to diagnose learning styles, but also allows for numerical determination of the degree of affiliation to each category. Such a system, which formalises mental models of experts and uses artificial intelligence methods, is described in the following part.

Unconventional methods of learning styles diagnostics

Computer-aided decision-making processes require the creation of abstract (computer) models of decision-making situations. If we consider the decision-making process in complex real-life situations, creating quality and adequate computer models tends to be very difficult. To deal with this problem, let us consider the fact that real-life decision-making processes may be resolved by a person, especially an expert in his area, using his brain, mental, and intellectual cogitative processes. The scientific field called Artificial Intelligence is engaged in computer formalisation of such processes. It uses new unconventional approaches which flow from the analysis of human cogitation. Cogitation involves mostly words and sentences of the natural language, which represents the basis for creating non-numerical linguistic models of the resolved situations. These so-called mental models are created by an expert on the basis of information, knowledge and experience.

The basic feature of human knowledge formalised verbally is its vagueness. This feature contrasts with mathematical and numerical formulations, which are precise and sharp. Analyses have shown that it is the ability of the human brain to utilise vagueness effectively which makes the significant condition for the quality of one's cogitation. The first condition of creating computer-aided linguistic models is resolving the problem of formalising the vagueness as obscurity of verbal expression. One of the most widely spread methods is the method of fuzzy set mathematics. The next problem, which is the creation of logical inference algorithms which are capable of applying linguistic vagueness for an output recommendation, is resolved using the approaches of unconventional multi-value linguistic fuzzy logic.

A sophisticated decision on the learning style of a particular student requires the determination of his dominant style as well as a considerable degree of influence of other subdominant styles (Kaliská, 2012). Within the artificial intelligence, this problem is resolved introducing so-called fuzzy sets (fuzzy meaning blurry, without clear boundaries, vague) that, apart from absolute affiliation (1) and absolute non-affiliation (0), introduce the very important term of partial affiliation expressed by a real number from the interval (0,1) (Novák, 2000, Pokorný, 2012). The final classification is not expressed by affiliation into a sharp numerical interval, but continuous evaluation of all classification classes in the range from 0 (absolutely no) to 1 (absolutely yes) with a continuous expression of the degree of partial affiliation (0 to 1). Such an output allows for effective and natural expression and evaluation of the degree of the student's affiliation into individual categories and their combinations. The student's learning style may then be determined by the dominant style (such as degree 0.75), as well as other subdominant styles (e.g., affiliation degrees 0.24 and 0.30). The form of such a decision fully corresponds to the outcome of the teacher 's decision-making process.

The evaluation of particular types of student using the degrees of the student's affiliation is the issue of constructing a linguistic model "Character of student → Type of student". Our aim is to formalise the mental model of the teacher using a computer and to apply the methods of linguistic modelling, which greatly resemble the mental model. In this paper, we will use the widely applied rule-based linguistic model where the dependencies between inputs and outputs are described by the relation IF THEN.

The linguistic model comprises the so-called knowledge base – the base of the expert system. Its other relevant part is the so-called inference mechanism (algorithm) which evaluates the linguistic values of the output quantity after inputting particular variables. The inference algorithm applies the laws of fuzzy multi-value linguistic logic and general (fuzzy) principle Modus Ponens (Pokorný, 2012; Novák, 2000). The aim of the inference algorithm is an evaluation of linguistic values of the output quantity which an expert teacher would achieve if he dealt with the same case. The structure of the knowledge base of a linguistic model and a simulation of its function are described in the following part of the paper.

After studying the typology of learning styles according to Felder and Silverman (Felder, Silverman, 1998), the typical features which influence a learning style were determined for each category (type) of the student (see above). Such qualities of the student also represent the input variables of the expert system. These are the following seven qualities:

1. *Social aspect* – qualifies the way of involvement in the social environment preferred by the student while studying (if he prefers being alone or in a group),
2. *Way of information processing* – determines whether the student prefers theoretical inference or practical experiments,
3. *Sensual perception* – describes which sense the student uses mostly to perceive, in what way he grasps the information and remembers it
4. *Way of learning* – describes the depth of learning the material,
5. *Methods* (applied while learning) – it is the way of the fastest acquisition of the required knowledge,
6. *Systematic learning* (or the order of information processing) – describes whether the student prefers an exactly given system or method or whether he prefers his own way of learning,
7. *Learning process* – determines how extensive the information the student can process at once is.

The particular values of the student's qualities are achieved by evaluating the questionnaire resulting from the ILS (Index of Learning Styles). The ILS questionnaire was compiled by Richard Felder and Barbara Solomon. It contains 44 questions the aim of which is to place students' preferences of learning styles in one category in each of the four dimensions (Felder, Soloman, 2004). We selected this questionnaire as its electronic use was proved to be suitable, e.g. by research (Carver, 1999) or studies (Felder, Spurlin, 2005; Kaliská, 2012). The results of the studies prove that the ILS questionnaire is adequately reliable.

The rule-based fuzzy model has seven input linguistic variables and four output linguistic variables which correspond to the dimensions according to the typology of learning styles according to Felder and Silverman (Felder, Silverman, 1998). The linguistic variables, their linguistic values, identifiers, and extent of universes (as required by the method of creation of a linguistic model) are listed below.

A. Input linguistic variable	Universe	Linguistic values
SOCIAL ASPECT (SA)	[0, 100]	INDIVIDUAL (INV), GROUP (GRO)
METHOD OF KNOWLEDGE ACQUISITION (MKA)	[0, 100]	THEORETICIAN (THE), PRACTICIAN (PRA)
SENSUAL PERCEPTION (SP)	[0, 100]	GRAPHIC (GRA), VERBAL (VER)
LEARNING STYLE (LS)	[0, 100]	SHALLOW (SHA), INDEPTH (IND)
WORK METHODS (WM)	[0, 100]	KNOWN (KNO), INNOVATIVE (INN)
SYSTEMIC LEARNING (SL)	[0, 100]	FREEDOM (FRE), ORDER (ORD)
LEARNING PROCESS (LP)	[0, 100]	HOLIST (HOL), DETAIL-ORIENTED (DET)

B. Output linguistic variable	Linguistic values
REFLECTIVE/ACTIVE TYPE (REF/ACT)	REFLECTIVE (REF), ACTIVE (ACT), REFLECTVE-ACTIVE (RA)
VISUAL/VERBAL TYPE (VIS/VER)	VISUAL (VIS), VERBAL (VER)
SENSING/INTUITIVE TYPE (SEN/INT)	SENSING (SEN), INTUITIVE (INT), SENSING-INTUITIVE (SI)
GLOBAL/SEQUENTIAL TYPE (GLO/SEQ)	GLOBAL (GLO), SEQUENTIAL (SEQ), GLOBAL-SEQUENTIAL (GS)

The rule-based fuzzy model formalising the expert mental model of determining the student's learning style has 128 rules, the condition parts of which represent all combinations of linguistic values of input variables. Particular combinations were evaluated by an expert by matching the respective linguistic values of output variables. The first five rules of the fuzzy model (IF – THEN in the common English notation) are listed in Table 1.

Table 1. Fragment of fuzzy model rules

No.		Antecedent								Consequent			
		SA	MKA	SP	LS	WM	SL	LP		REF/ ACT	VIS/ VER	SEN/ INT	GLO/ SEQ
1	IF	INV	THE	GRA	IND	KNO	FRE	HOL	THEN	REF	VIS	SEN	GLO
2		INV	THE	GRA	IND	KNO	FRE	DET		REF	VIS	SEN	GS
3		INV	THE	GRA	IND	KNO	ORD	HOL		REF	VIS	SEN	GS
4		INV	THE	GRA	IND	KNO	ORD	DET		REF	VIS	SEN	SEQ
5		INV	THE	GRA	IND	INV	FRE	HOL		REF	VIS	SI	GLO

Rule R1 in the form:

R1: IF (SA is INV) and (MKA is THE) and (SP is GRA) and (LS is I>TD) and (WM is KNO) and (SL is FR.E) and (LP is HOL) THEN (REF/ACT is REF) and (VIS/VER is VIS) and (SEN/INT is SEN) and (GLO/SEQ is GLO)

formalises the following knowledge:

If a student prefers learning individually, prefers theoretical inference, remembers better what he sees, strives to understand the sense of the studied information in depth, resolves problems by common (known) methods, but likes applying his own processes of solution and prefers large chunks of information, then he is a reflective, visual, sensing and global student.

The linguistic fuzzy model is open; it can be extended by new preferential or otherwise modified rules. In this case, the fuzzy model is implemented and tuned in the program environment Linguistic Model Processing System (LWMS), which further contains the inference algorithm as well as other processes for entering input data, displaying results and information that a user needs for good orientation (Pokorný, 2012). Now the system is prepared for simulation verification.

Verification of the expert system function

Simulation calculations are performed as follows: the input values of the model are set as the values of seven input variables and the expert system then infers the degree of the student's affiliation into particular linguistic values of all four output variables (dimensions). The output values are numeric, obtained by evaluation of the questionnaire based on ILS. For our simulation, the input values presented in Table 2 were used; Table 3 shows the output values. Simulation 1 is shown in Figure 1 to Figure 4 as the output screens of the expert system, both simulations are then interpreted verbally.

Table 2. Values of the input variables for inferring a learning style

Simulation	SA	MKA	SP	LS	WM	SL	LP
1	89	70	25	5	20	95	90
2	30	20	70	85	90	20	17

Table 3. Degree of the student's affiliation into particular learning styles

Simulation	Output variables										
	REF/ACT			VIS/VER		SEN/INT			GLO/SEQ		
	REF	ACT	RA	VIS	VER	SEN	INT	SI	GLO	SEQ	GS
1	0.11	0.73	0.30	0.75	0.25	0.74	0.05	0.20	0.05	0.71	0.10
2	0.71	0.20	0.30	0.30	0.70	0.10	0.70	0.15	0.72	0.17	0.20

Simulation 1 shows a situation when the student indicates that he prefers working in a group using the trial and error method. He remembers better what he sees. He uses proven and standard methods of learning with the aim to reach a deep understanding of the studied material. He prefers learning based on a guide or methodology and he processes information in smaller units. The system drew a conclusion (Table 3) that such the student is rather active (0.73), visual (0.75), sensing (0.74) and sequential (0.71). The degrees of his affiliation into other types are neglectable (graphic presentations of the outputs are presented in Figure 1 to Figure 4).

Simulation 2 represents the student who prefers learning alone and considers everything thoroughly. He remembers better what he hears or reads. He often processes the studied material by his own innovative methods and ways of solution aiming at learning the material with the least effort, passively, without any effort towards a deep understanding the topic and its context. The system concluded (Table 3) that such a student is rather reflective (0.70), verbal (0.70), intuitive (0.70) and global (0.72). The degrees of his affiliation into other types are neglectable.

A well-arranged overview of the results is graphically represented in columns (Simulation 1, Figure 1 to Figure 4). The student is affiliated into particular types according to the column height within the interval <0.1>. The higher the yellow column is, the higher his affiliation into the type is.

Figure 1. Simulation 1 – Evaluation of the type Reflective/Active

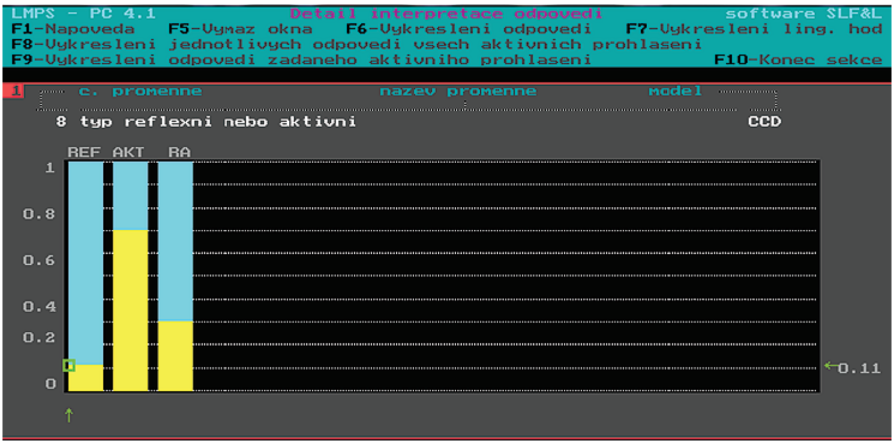


Figure 2. Simulation 1 – Evaluation of the type Visual/Verbal

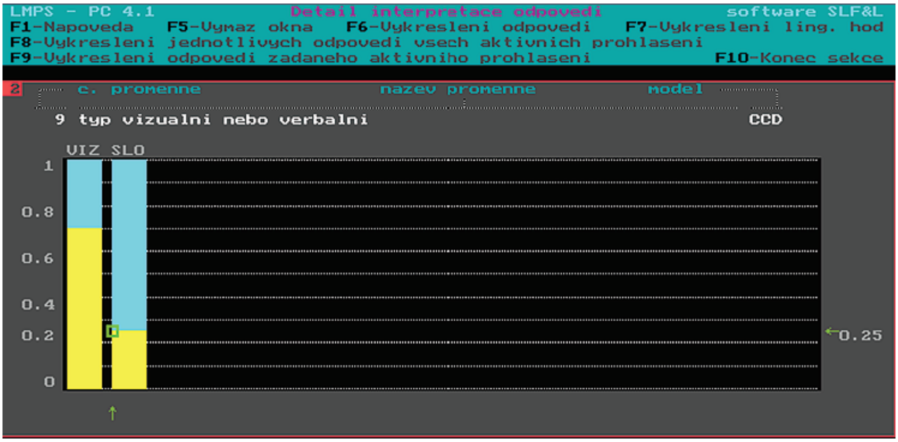


Figure 3. Simulation 1 – Evaluation of the type Sensing/Intuitive

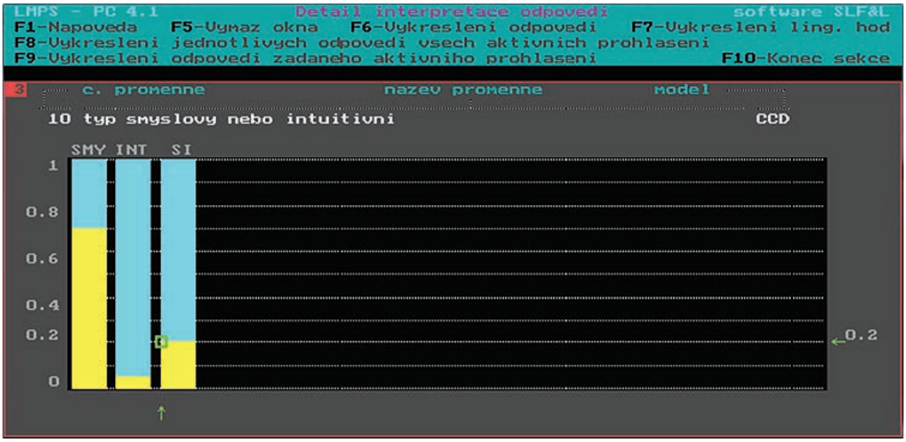
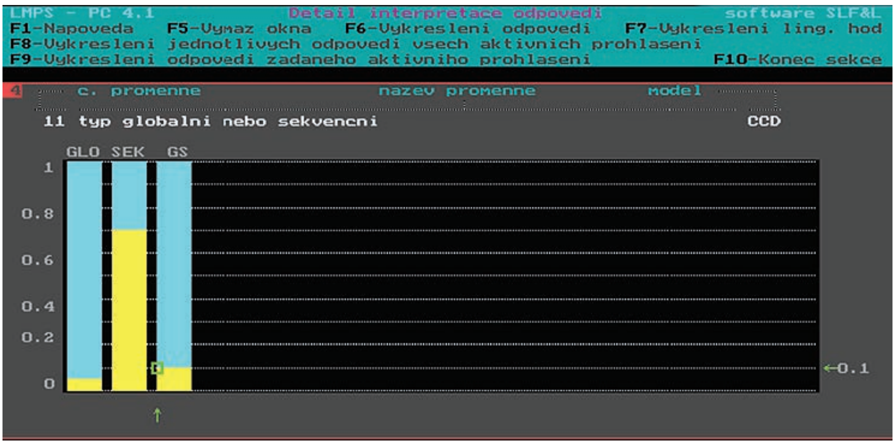


Figure 4. Simulation 1 – Evaluation of the type Global/Sequential



As an experienced teacher may assess as well, the results of learning style diagnostics in both simulations correspond to expectations.

Conclusion

A learning style means the learning techniques and methods which an individual uses in a certain period of his life in most situations related to study. They are to a certain extent independent of the content of learning. They appear at the congenital basis and develop by influence of both internal and external factors.

Every student has his individual learning style which the teacher should respect and thus support his effective learning processes. Correct recognition of the student's learning style is a skill of a good teacher. Even though there are specialized computer programs for solving decision-making tasks, they are usually designed for off-line decision-making support by the teacher – the final decision must be made by the teacher himself. However, if such programs are a part of on-line systems, their conclusions must be sophisticated and reliable enough.

Commonly used decision-making about a learning style by applying the method of mathematical numerical intervals does not correspond to the way of human thinking. For instance, close to the endpoints of the interval, the increase of the testing criterion (number of acquired points) by one distinguishing point results in the shift to the neighbouring learning style. However, human thinking corresponds to continuous transition, allowing, in a certain range of values, for the student's affiliation into two learning styles.

Modern IT methods allow for applying these approaches and tools in the scientific field called Artificial Intelligence. One of them is also the linguistic fuzzy-logic expert system presented in the paper, which was designed to determine the individual learning style of the student before he starts learning. This solution is distinguished by continuous evaluation of all categories of students by the degree from 0 to 1 with the possibility to simply determine both dominant and subdominant types, with the use of a linguistic rule-based decision-making model which is completely transparent and open, and with the use of a decision-making procedure corresponding to the process of human consideration (Fuzzy Modus Ponens).

Efficiency of the expert system was proved by numerical simulations. The expert system represents an autonomous module which will be incorporated as a component procedure into the automated teaching and learning system. Users of the automated expert system can be both teachers and university students, especially in the part-time study. The expert system is an example of the application of modern information technologies in education.

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