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Gracja Niesler
Wroclaw University of Economics and Business
e-mail: gracja.niesler@ue.wroc.pl
ORCID: 0000-0003-3309-7219

Andrzej Niesler
Wroclaw University of Economics and Business
e-mail: andrzej.niesler@ue.wroc.pl
ORCID: 0000-0003-1249-3239

METHODOLOGICAL APPARATUS AND INSTRUMENTS FOR PERSONALIZATION IN ADAPTIVE TUTORING SYSTEMS

ADAPTACYJNY SYSTEM WSPOMAGANIA NAUCZANIA: APARAT METODOLOGICZNY ORAZ NARZĘDZIA PERSONALIZACJI

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Summary: Most learning difficulties are rooted in the individual learner's perspective. As a common practice, modern educational systems are formed on the basis of a set of standardized didactic methods, which are then used repeatedly in the teaching of the whole population. However, every learning group consists of individuals with different cognitive model and individual learning process. The key to provide effective knowledge absorption is to adapt the set of teaching methods and use it in such a way that the individual characteristics of the learner are taken into account to the highest, reasonable extent. This paper addresses the problem of defining the personalization and adaptability of the learning process in the context of tutoring systems. The authors propose a methodological apparatus for identifying and acquiring the user's individual characteristics and transforming it into a set of tools and instruments that can provide adaptability in tutoring systems.

Keywords: adaptability, personalization, intelligent tutoring systems, learning process.

Streszczenie: Większość problemów związanych z nauczaniem odnosi się do perspektywy uczącego się. Obecne systemy edukacyjne stanowią zbiory ustandaryzowanych metod dydaktycznych, które następnie stosowane są w powielarny sposób w nauczaniu całych zbiorowości. Grupy składają się jednak z indywidualności, a każda z nich reprezentuje odmienny model kognitywny oraz indywidualny proces uczenia się. Kluczem do efektywnego uczenia się jest takie dostosowywanie zestawu metod dydaktycznych, aby uwzględniały indywidualne cechy uczącego się oraz były w stanie adaptować się z czasem do poziomu osiąganych postępów i zmieniających się potrzeb. W artykule podjęto problem adaptacyjności w inteligentnych systemach wspomagających nauczanie. Autorzy proponują instrumentarium do identyfikacji indywidualnej charakterystyki użytkownika, a następnie transformacji i wykorzystania jej w tworzeniu mechanizmów umożliwiających uzyskanie procesu uczenia dostosowanego do aktualnych, indywidualnych potrzeb użytkowników systemu.

Słowa kluczowe: adaptacyjność, personalizacja, inteligentne systemy wspomagania nauczania, proces uczenia się.

1. Introduction

The present educational system has been perceived from a holistic point of view through the years. The main concern was not the individual student, but the group of students, the year, the class, or the whole population. The focus was not on individual successes, failures, or problems, but on trends, rankings, and statistical indicators.

In the past when access to knowledge was limited, the relationship between master and pupil was based on a highly individualized path and tutoring methods. The pupil had often a real chance to become a master in the given professional field at the end of that path. However, the ubiquitous access to education has significantly decreased the student-teacher ratio, which, subsequently, has resulted in a reduction of the effectiveness of the applied teaching methods.

The mass availability of education undoubtedly requires standardized procedures and methods of teaching. It depends more on the validity of educational system, rather than on the individual potential of the student. Despite the broad and extensive curricula, the main concern is still to find a single, universal way of dealing with parallel aspects of the teaching-learning process. While many efforts have been made and actions taken, especially on the basis of emerging quality measurements in education, the main problem remains. Figure 1 illustrates the concept of the collective elements leading to the student's learning process (Mayer, Mullens, Moore, & Ralph, 2000).

One can notice that apart from the remote influencers like 'goals' and 'community', the direct indicators of students' learning are: 'skills of the teacher', 'course content', 'pedagogy', 'technology', and 'class size'. Assuming that the teacher is highly skilled and professional, all of them are completely dependent on the teaching time that the teacher can devote to each and every student in the classroom, and that is definitely determined by the last indicator, 'class size', which according to the common international indicators, should not be higher than 16. In any case, the tutor is not able to spend enough time with every student to adjust the teaching program to their individual needs and requirements.

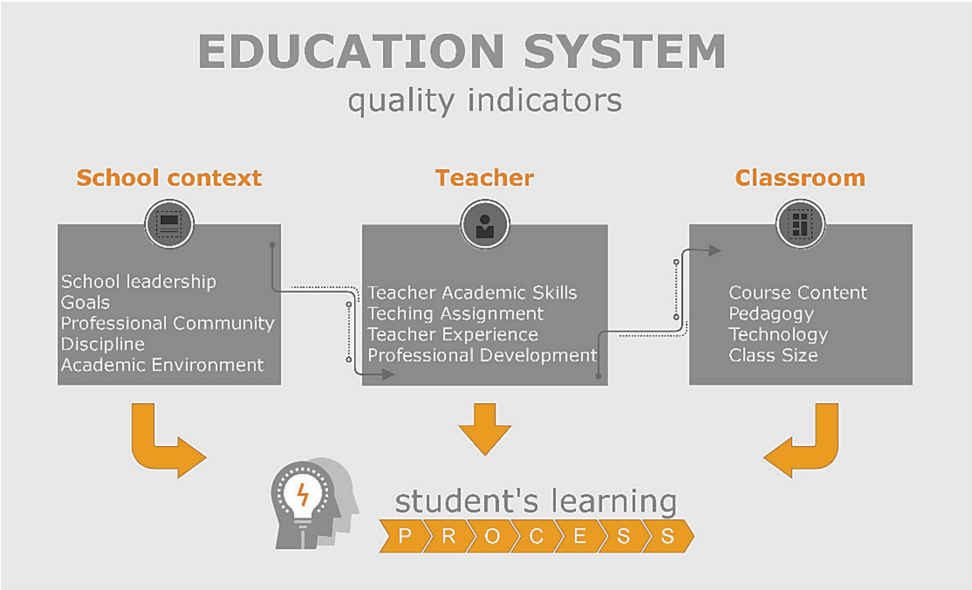

Fig. 1. Education system quality indicators affecting a student's learning process

Source: own study.

Most likely the main problem in education is to teach students **how to learn**, because even if all people started with the same level of opportunities, the learning process would still be carried out differently due to individual differences in mental and cognitive abilities. This then brings in an additional aspect: the **meta-learning process modelling**. Regardless of the approach taken, **learning is always an individual experience** and ought to be perceived as such. Therefore, it implies the necessity of adjusting the teaching process to the learner's needs in order to achieve the optimal effects. Therefore, the following questions need to be answered:

- What are the learner's characteristics, allowing to learn, that could help in adapting the tutoring process to their optimal learning process?
- Which methodology should be used to personalize the tutoring system?

The aim of this paper is to propose a set of methods and instruments for personalization that could be used to provide adaptability of the teaching-learning process in the tutoring systems. The presented concept is based on the results of research and experiments on the influence of a personalized approach on the level of learning, problem solving, and decision-making effectiveness.

The structure of this paper is as follows. Section 2 provides some background and analyzes related work to define the core concepts used throughout the research. Section 3 provides the foundations for understanding the individual approach to teaching and learning. Section 4 presents the instruments for creating the adaptive tutoring content, and Section 5 introduces the personalization process that can be used to achieve adaptability as a feature of a tutoring system. Section 6 discusses the findings and observations. Finally, Section 7 provides the final conclusion and addresses the scenarios for future work.

2. Background and related work

In this section the authors discuss the core concepts and their definitions in this research, with the goal to provide a general background for teaching, learning, tutoring, the education systems themselves and their supporting tools, methods, and instruments.

One of the central concepts in this research is **Intelligent Tutoring System** (ITS). This class of information systems is used primarily in education and offers a comprehensive support in the execution and control of the learning process. An ITS creates a complete learning environment. It allows teachers to enter and structure learning materials into the system, define learning goals and teaching strategies, and monitor the progress. Students can interact with the system and participate in the learning process on an individual or group basis. The intelligence of an ITS is based on the user model, representing information gathered on every individual student, and recommendation mechanisms featuring various modes of enhancing the standard linear learning path.

Since the system monitors actions of all the learners and has access to all their data, an important part of that intelligence of ITS comes from possible **context-awareness** (Bicans, 2015). The system can use historical or real-time data to adjust its behavior in order to offer the best known recommendations, tailored to the current situation of a particular learner. This may involve the propagation of the best practices, matching students working on the same activities or experiencing similar difficulties, and then facilitating collaboration between them in order to overcome them. In some situations the system may even introduce benchmarking functionality or even some ways of direct competition, if that learning strategy is desired. The real advantage of an ITS can be experienced when the user model delivers data for personalization and the system is capable of making use of it in order to adapt to the individual learner's needs.

There are different approaches to achieve **adaptability** in the area of developing ITS. The first factor to consider is the specificity of the learning material. In cases of a well-defined domain, the most effective learning path may be well established and relatively constant. In such an environment the system should rather offer the possibility to personalize the content of every knowledge unit separately, e.g. its form or the way it is presented, than allow the student to experiment with altering the initial learning path. On the other hand, in ill-defined domains it is possible for the system to discover and adapt the best path using the records of learning interactions and outcomes of the students that have already finished using the system. An example of implementing such an architecture featuring the usage of educational data mining techniques was presented in (Jugo, Kovačić, & Slavuj, 2016).

Adaptability is a broad topic and can be executed on many different levels, especially in the context of the broad functionality of an ITS. However, the real challenge remains to propose an approach that would include the individual adjustment of the learning process with a recognition of the learner's advances and needs on the meta-learning level, i.e. addressing the lifelong relevant task of learning how to learn. The concept of meta-learning appeared in the 1970s, and it differs significantly from the interpretation that derives from the area of artificial intelligence in machine learning. This paper focuses on the primary definition addressing the problem from the pedagogical and cognitive points of view. This is mainly because of the fact that the subject of the research concerns the learners themselves, and not just an ITS alone.

According to Maudsley, **meta-learning** is "*the process by which learners become aware of and are increasingly in control of habits of perception, inquiry, learning, and growth that they have internalized*" (Maudsley, 1979). The best personalization of educational process can be achieved by teaching the learners 'how to learn'. Hence one should focus particularly on meta-learning, because this will allow to identify those elements that make the analysis legitimate. The combination of a process approach and a meta-learning perspective is the answer to the use of data science for the benefit of the learner. The other definition of the concept, defined by Biggs, is describing the state of "*being aware of and taking control of one's own learning*", including epistemological beliefs and learning processes and skills (Biggs, 1985).

The idea of a self-aware learning process has been further expanded by other researchers with 'metacognition', as the 'growth mind-set' letting the learner know their own capacities to learn (Dweck, 2016; Fadel, Trilling, & Bialik, 2015). Some solutions to the problem featuring metacognition, involve dedicated training (Bacon & Mackinnon, 2014), extending the individual learning process or, in fact, introducing a concurrent track to the standard curriculum.

3. The basis for individual approach to teaching and learning

Irrespective of taking part in individual or standardized and mass teaching, students are now being assessed by the same outcomes – learning effects, which, according to the European Qualifications Framework, are described as knowledge, skills, and competences (European Comission, 2012). The students' skills in the meta-learning process, however, are incomparable and tacit. How to measure this factor then, while only the effects are being estimated as the final result of the learning process?

One ought to start from the basis, i.e. the learning process itself. From the cognitive point of view, everyone differs in perceiving reality and requires different teaching methods. The Nobel prize winner Gerald M. Edelman proved that there are no two identical brains, even among twins (Edelman, 1999), which may imply that this individuality requires a variant approach. Therefore, one should focus on what learning process determinants are, and what premise for adaptive teaching approach emerge from that.

All the teaching/learning resources corresponding with the way of information processing consist in:

- **data** – singular values, elemental components of didactic content,
- **information** – data aggregates, linked with each other according to the predefined relations (logical, semantic, etc.) that allow to create complex messages,
- **context** – indicates the means and possibilities for data and information usage in practice (information adhibition).

Meanwhile the learning process itself, which corresponds with the area of human cognition, is determined by the following three elements:

- **memory** – remembering, which allows to record singular and collective data, data sets in the form of information, and the appliance of their context,
- **understanding** – required to combine the data into information, and to comprehend the message stemming from the information,
- **content association** – which requires the context appliance for the practical (situational) usage of the information delivered.

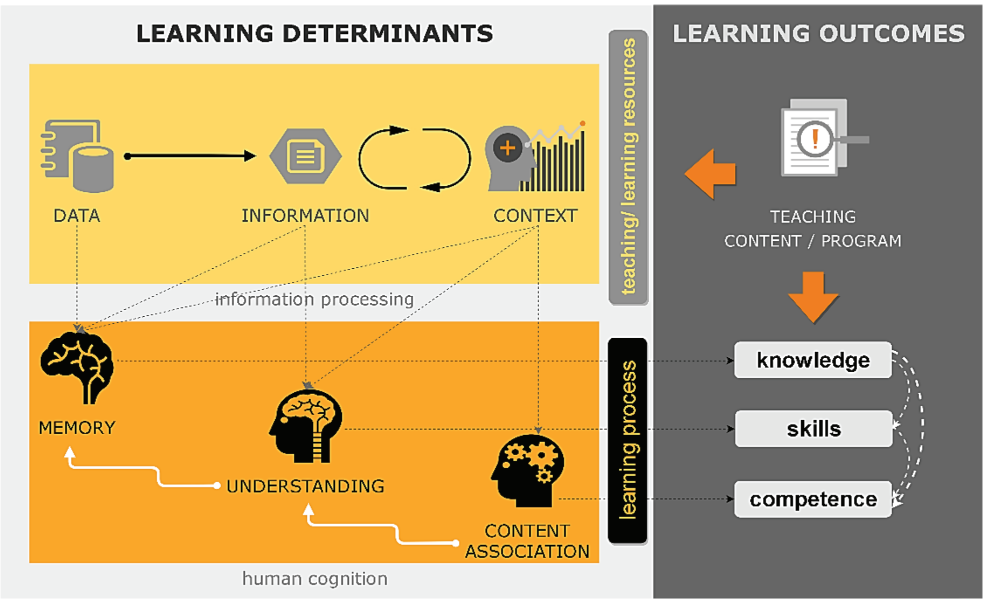

Fig. 2. Learning determinants vs. learning outcomes model

Source: own study.

The elements comprising the content to be learned and the elements of a learning process constitute the learning determinants (Figure 2). Between the information and the context there is a constant feedback that allows to complement the usage of context with new information. The context itself can enhance the stored information with an additional one for understanding and memorizing. Content association derives from the context and requires understanding. The information needs to be comprehended and subsequently memorized, as is the case with the elemental data.

Learning outcomes are connected to the didactic program and consist of:

- **knowledge** – which, according to the teaching/learning resources, is the comprehension gained individually by a student, based on the memorized data, information, their associations, and the practical usage context – it should be described in the teaching course goals,
- **skills** – proficiencies that result from the understanding of the delivered information and their practical appliance,
- **competences** – the authority gained from the cognizance of practical use of contextual associations of acquired knowledge and its extrapolation to other areas.

Since both the learning process elements and the outcomes have been defined, there is a need to explore what instruments can be used to define the learner's profile and help to personalize the teaching-learning process. The learner's profile is determined by their mental model and specific abilities to learn. The identification of individual needs derived from predispositions for learning indicates also the methods for creating adequate tutoring content.

4. Instruments for creating adaptive tutoring content

On the basis of the learning determinants, specific instruments can be proposed that influence particular elements of the learning process, with regard to the natural learning predispositions (Niesler & Wydmuch, 2008). For the 'memory' learning element one can distinguish 'frequency' (*high* and *low repetition*) and 'time unit' (*short, intensive training* and *long, extensive training*). For the 'understanding' one has 'analytics' (*deduction*) and 'synthetics' (*induction*) as the learning instruments. For the 'content association' one focuses on the 'intelligence types' for IQ measurement as the natural brain predispositions for solving the specific type of tasks. One distinguishes 'perceptiveness' (responsible for *visualization*), 'language' (*keywords and semantic relations*), 'logic' (*causal-result relationship*) and 'numbers' (*formula representation*).

Furthermore, the learning determinants can appear in different combinations, which gives the 32 different tutoring methods dependent on the individual learning predispositions. Figure 3 presents the matrix of the predisposition-based instruments, that illustrates the methods based on understanding, memory, and content association.

The variety of methods ought to be extended by the learning outcomes, such as expected knowledge, skills, and competences. To measure them one can use the same instruments as for exploring the learning predispositions, and receive both, the tools and methods for tutoring content presentation, and the verification of learning outcomes.

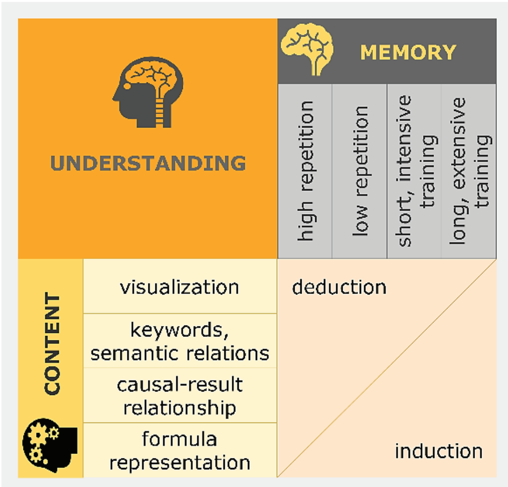

Fig. 3. Matrix of the predisposition-based instruments for tutoring programs

Source: own study.

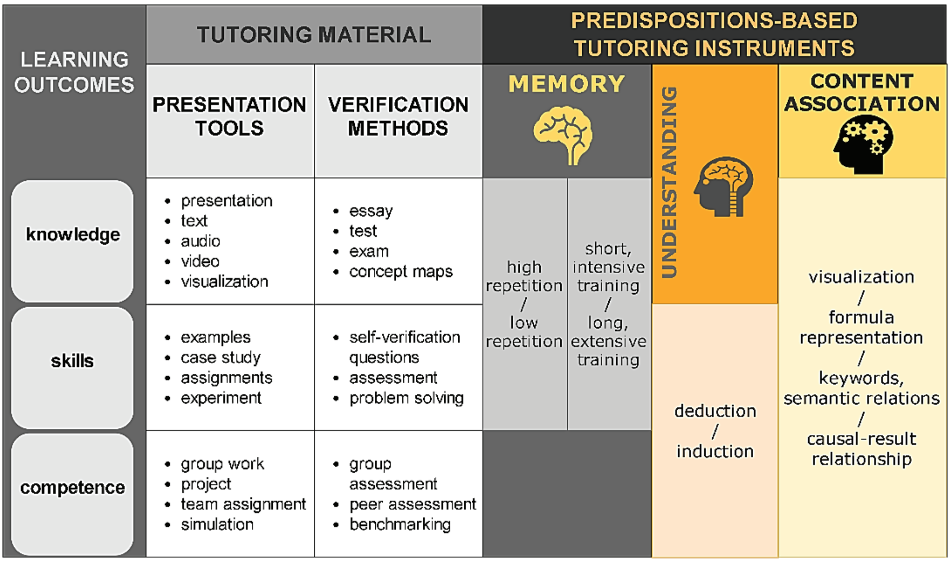

Fig. 4. Tutoring content delivery tools and verification methods according to the learning effects and predisposition-based instruments

Source: own study.

Figure 4 presents the aforementioned tools for didactic methods in the tutoring system, according to the learning predispositions and teaching outcomes. The memory predispositions-based instruments apply to all of the learning effects. The didactic unit resulting with gaining knowledge can be delivered in different forms, e.g. presentation, text, audio, video, and other kinds of visualization (pictures, graphs, diagrams, storyboarding) and be verified through essays, tests, exams, and concept maps. Both delivery and verification can be conducted in high or low repetition ratio and be organized in short, intensive or long, extensive training. The same memory instruments apply to 'skills'. The instruments of understanding (deduction and/or induction) can be used for delivery and verification of skills and competences, which also involves the content association tutoring methods.

These tools and methods apply in the 'local' context, i.e. how to represent and present the tutoring content and verify the result of teaching-learning process. To provide the adaptability of the system, one has to look for methods for the delivery of tutoring process.

5. Personalization process for tutoring system's adaptability

The predispositions alone cannot give the whole picture on individual learning determinants, despite the fact that their contribution to the learning process is crucial. Beside the guidelines for creating the content and based on individual types of 'intelligence' and the ways of reality perceiving, it is important how the tutoring content is delivered. It is associated with the personality types and the ensuing preferences for learning, problem solving, and decision-making.

For enhancing the scope with the personality types one can use the MBTI (Myers-Briggs Type Indicator), originally based on Jung's model of the temperament's influence on individual behaviour (Niesler & Wydmuch, 2009). According to MBTI the combination of the opposing preferences (**E**xtraversion – **I**ntroversion, **S**ensing – i**N**tuition, **T**hinking – **F**eeling and **J**udging – **P**erception) based on four mental functions, represented by the attitude towards the outer world, processing information, making decisions and life, gives 16 different personality types.

However, in practice a single preference is not unequivocal, even among the same type. Hence the more specific criteria ought to be delivered. Figure 5 presents the preference-oriented tutoring methods, which is an extension to the instruments based on predispositions. It has been divided into *orientation* and *processing mental functions*. *Orientation* indicates the methods used for **tutoring organization** and the *processing* for **content presentation**. One can note that the methods used for obtaining tutoring organization support competences (as the learning objectives) and the content presentation brings the skills (T-F) and knowledge (S-N) acquiring.

While analyzing the preference matrix one has to confer that, unlike the original MBTI analysis, the preferences can be fuzzy and to determinate not only 16 types, but $2^{14,}$ which equals **16 384** of methods' combinations. Using the specific methods set for a course unit, based both on preferences and predispositions can be an apparatus for tutoring adaptation to the individual needs of the learner. Figure 6 presents the taxonomy of apparatus' methods that can be used for providing the

TUTORING ORGANIZATION / CONTENT PRESENTATION		(S-N) Sensing-Intuition	(T-F) Thinking-Feeling
(E-I) Extravert-Introvert	empirical-reasoning varied-thorough group-individual	facts-ideas	logic-principles
		practical-imaginative	solution-attitude
(J-P) Judging-Perceiving	scheduled-adaptive result-method decision-analysis	detailed-general	prescriptive-descriptive
		step by step-creative	calculation-contribution

Fig. 5. Matrix of preference-oriented tutoring delivery

Source: own study.

adaptability of tutoring system. Those methods indicate elements of **personalization process**, including tutoring organization, content presentation and content acquiring.

Within the stage of **TUTORING ORGANIZATION** one can denote the alternative methods concerning **concentration and attention** (cognitive mode, precision, cooperation), and **managing and conducting** (planning, outcome focus, aiming). The alternative methods are used only when they are applicable to the specific tutoring program. The specific, elementary methods are the exclusive alternative, so one can choose only that parameter which corresponds with learner's preferences. The methods for the stage of **CONTENT PRESENTATION** correspond also with learner's preferences and include alternatively the way of **processing** (reliability, appliance, complexity, sequence) and **dealing with task and problem solving** (engagement, focus, standardization, orientation). The methods for the stage of **CONTENT ACQUIRING** represent the lowest abstraction level of tutoring system adaptability, because it corresponds with the learner's mental model and their predispositions to learn.

The methods connected to **memorizing** require using in conjunction the recurrence (exclusively alternative high or low repetition or the tutoring unit) and intensity (short, intensive or long, extensive learning). The methods for adaptation on the level of **understanding** and **representation** are dependent on the specific tutoring material and are applicable alternatively (all of them or selected).

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teaching-learning instruments AND
/___ tutoring organization OR
        {___ concentration and attention OR
                {___ cognitive mode XOR
                        |___ empirical
                        |___ reasoning
                {___ precision XOR
                        |___ varied
                        |___ thorough
                {___ cooperation XOR
                        |___ group
                        |___ individual
        {___ managing and conducting OR
                {___ planning XOR
                        |___ scheduled
                        |___ reasoning
                {___ outcome focus XOR
                        |___ result
                        |___ method
                {___ aiming XOR
                        |___ decision
                        |___ analysis
/___ content presentation OR
        {___ processing OR
                {___ reliability XOR
                        |___ facts
                        |___ ideas
                {___ appliance XOR
                        |___ practical
                        |___ imaginative
                {___ complexity XOR
                        |___ detailed
                        |___ general
                {___ sequence XOR
                        |___ step-by-step
                        |___ creative
        {___ dealing with tasks, problem solving OR
                {___ engagement XOR
                        |___ logic
                        |___ principles
                {___ focus XOR
                        |___ solution
                        |___ attitude
                {___ standardization XOR
                        |___ prescriptive
                        |___ descriptive
                {___ orientation XOR
                        |___ calculation
                        |___ contribution
/___ content acquiring OR
        {___ memorizing AND
                /___ recurrence XOR
                        |___ high repetition
                        |___ low repetition
                /___ intensity XOR
                        |___ short, intensive
                        |___ long, extensive
        {___ understanding OR
                {___ analytics (deduction)
                {___ synthetics (induction)
        {___ representation OR
                {___ visualization
                {___ text, keywords, semantics
                {___ causal-result relationship
                {___ formulas
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Fig. 6. Tutoring methods' taxonomic tree

Source: own study.

Each student may prefer particular ways of content delivery; this cannot be done by the teacher or the student themselves. It needs the analytics, which would help with the decision as to what methods are suitable for each learner. Individual learning preferences and predispositions analysis deliver numerous data, continuously changing in time, because the orientation mental function tends to evolve. It is impossible to analyze that amount of data without advanced analytics. Nevertheless, the present opportunities, available through computer-aided and data-analysis-aided tools and technologies, can bring the golden mean between aligning to the formal standards and simultaneously finding the best individual path for fulfilling them. The application of intelligent technologies and data analytics can transpose the best practices of teaching to the individual context of the learner.

The individual approach is based on the granulation of the teaching content and the application of the adaptive tutoring mechanisms, then replacing the static, uniform educational program which is unsuitable to the individual's needs. Meta-learning process modeling is the solution that can give the answer to the question of how to teach/learn to achieve the best results with the most suitable tutoring methods. While using the intelligent solution of the tutoring systems one can observe the phenomenon of pseudo meta-learning due to the fact that the learner is not fully aware of the learning process control flow and conditions. The part of 'knowing how to learn' is conducted by the tutoring system. Therefore, there is a need for developing and designing further methods and modules for non-invasive learner's preferences and predispositions testing. The adjustment of the system should be based on the historical data of the learner's interactions with the system and the tutoring content.

6. Discussion

The study of learning outcomes' indicators leads to an observation of the gradation process of knowledge, skills, and competences. Indicating different levels of learning objectives for measurement would help to evaluate the level of delivered tutoring content. Apart from analyzing the learning predispositions and preferences one should address the learner's proficiencies as well, expressed by different levels of knowledge, skills, and competences. Sometimes the lack of proficiency on the particular level prevents from acquiring the knowledge and skills which are required on the specific level in the educational process. For example, the learner is not able to fulfil the autonomic tasks or absorb the knowledge using critical understanding.

The analysis of the educational program can benefit with receiving the answers to the selection of teaching methods, creation of conceptual didactic material, the way of conducting courses, identification of learners' needs, and also monitoring teaching results and adjusting the suitable tools and methods, as well as attempts to comprehend the learning phenomena.

The learning process approach from the learner's perspective can also be considered on different planes:

- **educational path** – expressed in educational levels, according to the International Standard Classification of Education (ISCED) elaborated by the UNESCO Institute for Statistics (UNESCO, 2012),
- **e-learning/tutoring course** – as the set of activities usually conducted in computer-aided learning,
- **mental model** – based on Cartesian division of reality and epistemological states of human mind, as perceptive and reflective modes allowing identification and encoding the information for further processing and usage.

The combination of these perspectives gives the holistic spectrum of analytical data source for further adaptation. Moreover, the learning process based on educational path is expressed in levels which differ in how the instructions are organized (regarding the characteristics of teaching-learning process and the applied assessment methods).

7. Conclusion

The problem of adaptability in learning and teaching is very extensive. The quest for solutions involves interdisciplinarity in such fields as psychology, cognitive science, and advanced information and communication technologies. In this paper the authors addressed the aspects of individual predispositions and preferences for learning, and the context of meta-learning, and presented the theoretical foundation for understanding personalization with regard to the learning process and discussed its applicability in achieving adaptability in intelligent tutoring systems. The methodological apparatus for the identification and acquisition of the user's individual characteristics were proposed and can be used as a starting point in the development of tools and instruments supporting the realization of the discussed concepts in practice.

Future work shall focus on further analysis of the learning process adaptability and the introduction of the support tools that could leverage AI algorithms and learning data analytics to design fully automated mechanisms for the adaptation of tutoring material to the individual characteristics of the learner.

It is worth noting the fact that tutoring system adjustment can be a motivational factor. The facilities on the level of content and organization adaptation can influence the sense of comfort, increase of dopamine level, which is connected with a sense of achievement resulting from the task fulfilled, and finally an incentive for achieving higher levels in learning. Further research could examine the validity of this relationship in more detail.

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