

INTELLIGENT DIGITAL PLATFORM FOR CREATING AN ADAPTIVE EDUCATIONAL ENVIRONMENT



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Abstract. *The problem of organizing the educational process in a higher education institution and its existing solutions are analyzed. A comprehensive solution for organizing the adaptive e-learning process is proposed, which can be used as a supplement to the organization of the classical educational process. Key tasks are identified, in the solution of which artificial intelligence technologies can be used. A description of the developed software solutions for solving the tasks is provided.*

Keywords: *educational process, adaptive learning, machine learning, data mining, artificial intelligence in education.*

Introduction. Currently, the most promising and rapidly developing format of organizing training is e-learning. This format of organizing training in modern realities is very flexible and universal: it can be used both in traditional forms of obtaining education and in distance learning. Its relevance and development are due to both external factors in relation to the education system (for example, the Covid-19 pandemic) and internal ones (digitalization of the educational process, the need to increase the export of educational services, etc.). As separate factors in the development

of the e-learning format, we can highlight its advantages in comparison with traditional formats: the possibility of introducing and using virtual and augmented realities in the educational process [1, 2], an increase in the degree of inclusiveness of the educational process [3], higher economic efficiency [4], the use of innovative information and communication technologies in education [5, 6], the implementation of a game approach in learning [7], increasing competition in the educational services market [8], etc.

In turn, the development of e-learning has created a need for the development of modern intelligent learning systems (platforms) and their learning content. Intelligent learning platforms implement the concept of managing the learner's knowledge and his learning trajectory.

The most promising, within the framework of this concept, are adaptive learning systems, which allow achieving maximum learning efficiency with minimal expenditure of resources of participants in the educational process. Thus, it is possible to individualize the post-industrial learning model [9] and replace it with a more effective adaptive learning model [10].

Proposed solution. An analysis of the subject area and capabilities of existing adaptive electronic learning tools showed that these solutions implement an adaptive learning model by constructing individual learning trajectories based on individual learner models. This approach allows the learning process to be adapted to the current level of learners' knowledge only during the learning process (and not from the very beginning of learning), and the educational content remains static and has no mechanisms for identifying the need for its adaptation to learners.

Considering the identified shortcomings, to solve the identified problems, the authors proposed a comprehensive solution that includes an interconnected mechanism for constructing models of learners, models of adaptation and information-subject area (ISA) and their software and algorithmic implementation using artificial intelligence. The general functional diagram of the intelligent digital platform (IDP) is presented in Figure 1.

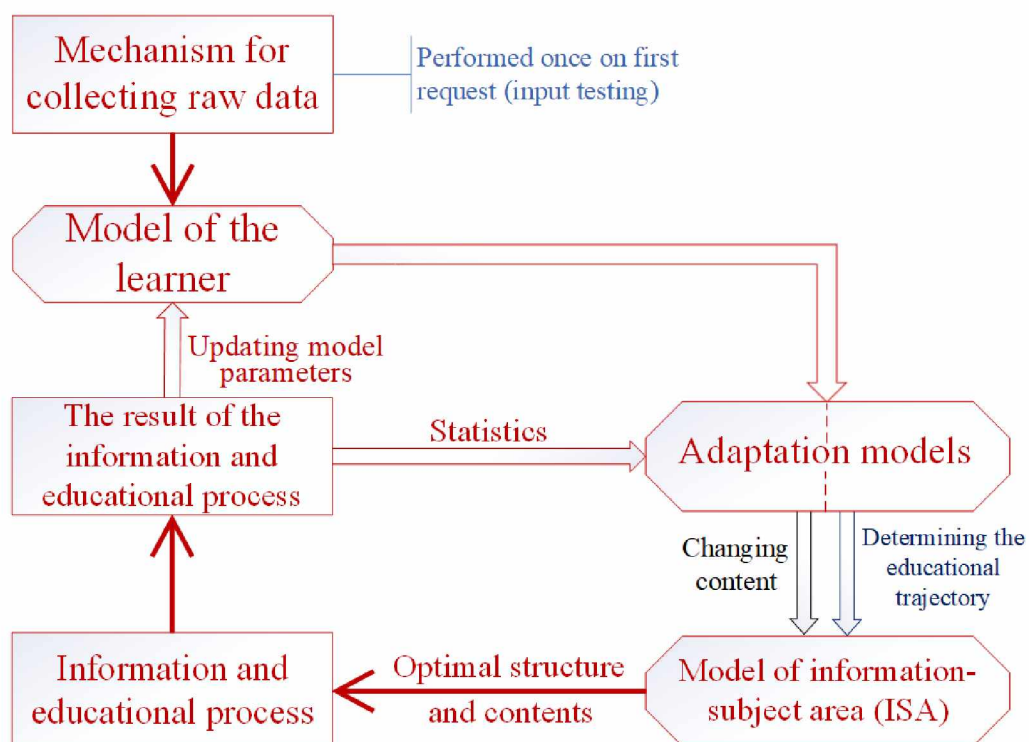


Fig. 1. General functional diagram of the IDP

To solve the problem of building an effective educational trajectory even before the start of training, the digital platform provides a mechanism for obtaining initial data (entry testing and questionnaires), which determine the initial threshold of knowledge and various individual characteristics of students. Much of this data cannot be established during the normal learning process. The information obtained constitutes an individual model of the student, which is subsequently supplemented as a result of the learning process.

The IDP has its own ISA designer (the disciplines studied, their content, and trial and control testing of students' knowledge). The designer provides for a three-level organization of educational content, corresponding to the modern education system: 1 – discipline; 2 – module (section or topic of the discipline); 3 – block (practical/laboratory/calculation work, etc.). Trial (for self-testing of knowledge by students) and control testing are provided at any of the levels. The graph model of the IDP with control testing at the module level is shown in Figure 2.

The ISA model is a weighted multigraph, where the set of students S is the number of all students; the set of all studied disciplines D is the number of all disciplines; $m_1–m_3$ are modules of discipline d_1 .

Edges incident to nodes s_i and m_k have weights $TIME$ and $SCORE$. Weight $TIME$ is the time it takes to pass the control test module m_k . Weight $SCORE$ is the assessment of the control test module m_k obtained by a specific student. The edges incident to nodes s_i and d_j have the weights equals the average grade of specific students in specific disciplines (in Figure 2, it's designated as “average score”). The weight of the edge's incident to the nodes m_k and d_j is the average grade of passing the control test for the module of all students studying this module.

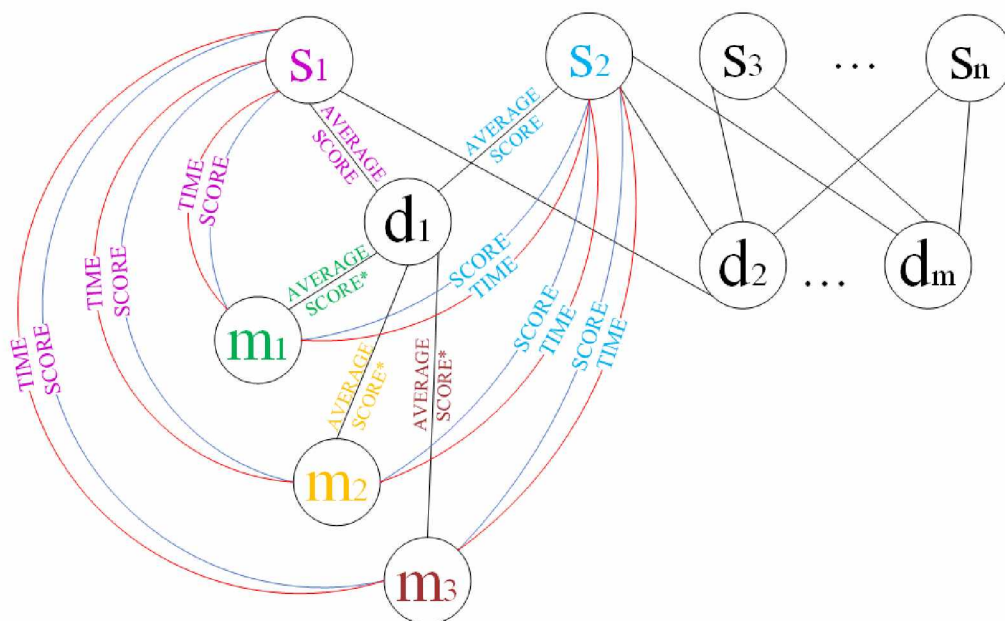


Fig. 2. Example of a graph model of ISA

A distinctive feature of the constructor is the connection of separate parts of educational content with specific questions of control testing. It's necessary to the intelligent analysis of educational content for the possibility of its adaptation. This connection is carried out by means of identifiers (labels) of content's parts (paragraph, file, video recording timing, etc.).

Model of connections is present on Figure 3.

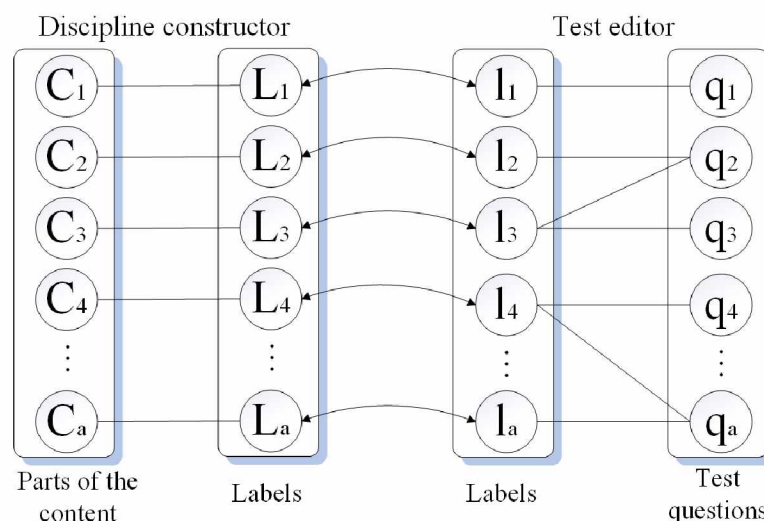


Fig. 3. Graph model of the connection between separate parts of the educational content and the control test questions

One of the adaptation models is designed to build an effective educational trajectory for each student based on their student model. For this purpose, a mechanism for preparing and organizing IDP data has been developed that implements machine learning (ML). The initial construction of the educational trajectory occurs through the implementation of an adaptive search for objects and criteria contained in the learner's model. From this point of view, the data organization model must "learn" and also accumulate data that is absent from the IDP, but is necessary to obtain a relevant result.

To implement this mechanism, it is of primary importance to prepare the data contained in all IDP models. Since the input data for constructing an individual educational trajectory are search objects and a list of criteria for their search for the learner's model, they must be as specific as possible so that it is easier for the ML-algorithm (formation of generalizations of search criteria) to identify the necessary generalizations and classes to which these criteria relate.

The output data of training should be the search criteria themselves and a list of generalizations to which these criteria relate. At the first stage of ML, each input criterion is supplemented with some definition or characteristic in natural language. At the second stage, the natural language description obtained from a third-party data source (for example, an electronic encyclopedia) is broken down into separate parts and key lexemes are selected (tokenized).

The process of forming generalizations and training the database is automated and is not tied to a specific type or scheme of the data source for forming generalizations, and, using ML technologies, independently selects significant properties from the natural language description, forms connections from them and saves them in a graph database.

To obtain tokens (key lexemes) from a description of search criteria in natural language and associated with each search criterion, the following sequence of actions must be performed:

- step 1. The incoming description is divided into noun groups (phrases). Phrases are selected in which the noun is the top, i.e. the main word defining the characteristic of the entire component;
- step 2. Perform a cycle through all the resulting noun groups and divide each of them into words;
- step 3. Exclude all “stop words” and all punctuation marks from the resulting words;

– step 4. At the final step, a purified noun group is formed, which will be included in the database as one of the generalizations.

The resulting database is multilayered due to the formation of layers of generalizations of the criteria for searching for an effective learning trajectory, specified in natural language both during the entrance testing and questionnaire, and in the process of learning in the ICP (data of individual models of learners). An example of this database in the one search object's context is present in Figure 4.

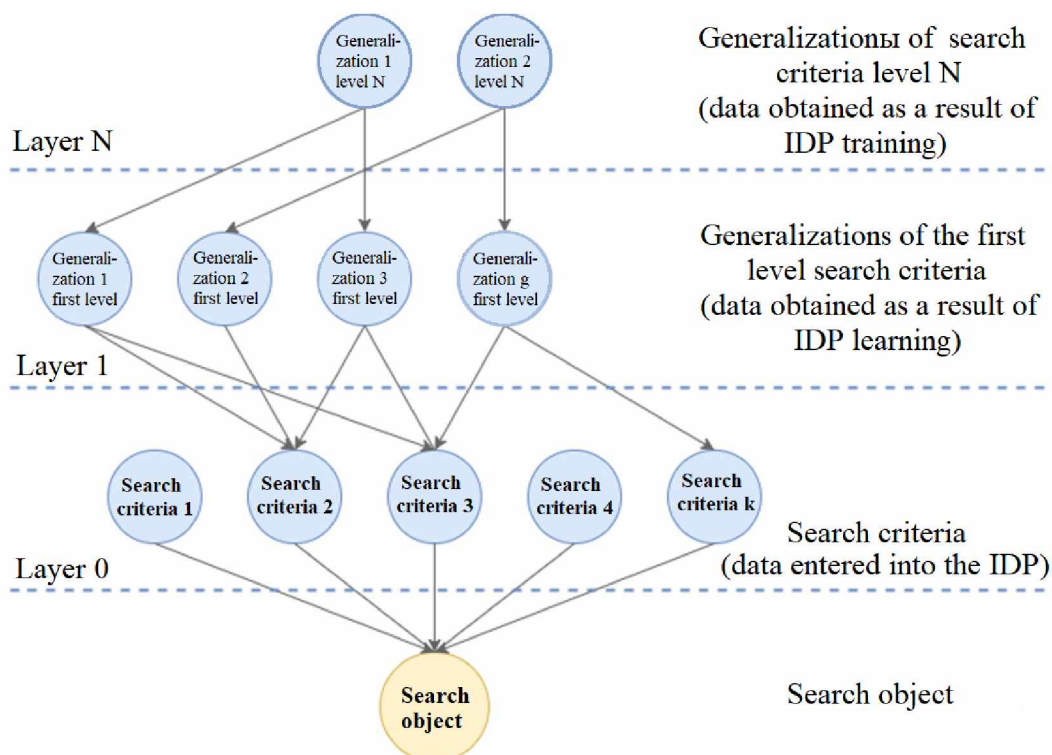


Fig. 4. Example of a database in the search object context

The second adaptation model is designed to identify and improve educational content materials that objectively cause difficulties for students when studying disciplines, and is an intelligent data analysis. As a rule, students cope with the study of academic subjects differently. This may be due to different basic training and individual characteristics. However, if most students have difficulty answering one or the same questions of the control test, this may indicate shortcomings in the teaching methodology, presentation of the material and the quality of the educational content. Therefore, there is a need to improve a certain part of the educational content. The initial data for identifying such cause-and-effect relationships can be statistics on the students' performance in the studied disciplines (modules or blocks). The intelligent analysis algorithm processes such data as the time spent on passing the control test, the students' progress in other modules of the discipline, the progress in other disciplines and the successes of a specific student in a time frame.

At the first stage, the algorithm compares the absolute performance of all students in a module block with the current value of the mathematical expectation of performance in this block. If the absolute performance is less than the rational, this indicates that students are doing worse than expected in this module block and the algorithm moves on to the second stage. If, on the contrary, the absolute performance is higher than the rational, this means that the value of the

rational performance may be underestimated and needs to be adjusted. To do this, the current value of the absolute performance is compared with the maximum value of the rational performance during the module's operation. If the former is higher, then it will be suggested to increase the value of the current rational performance. Otherwise, no changes will be required. Next, data such as the time spent on passing the control test, the students' performance in other modules of the discipline, and the performance in the time frame are analyzed. Thus, data from students whose performance characteristics are low for internal reasons and are not related to the quality of the educational content are excluded from the overall sample. At the third stage, the results of the algorithm execution are output. If a dependence of low student performance on the quality of the educational content has been established, the corresponding message is sent to the expert (teacher) to make a decision on the need to improve part of the educational content. The generalized functional diagram of the intelligent analysis is presented in Figure 5.

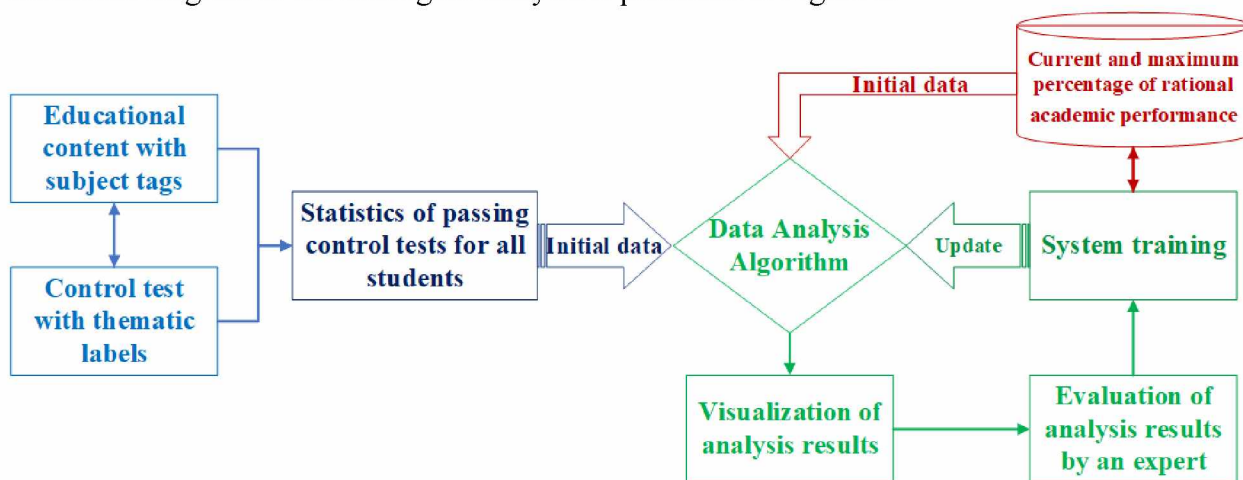


Fig. 5. Generalized functional diagram of intellectual analysis

Conclusion. The proposed models and their algorithms are implemented in the form of the adaptive learning management system "SCORINA", which is the core of the intelligent digital platform. Thus, comprehensive support for the organization of the adaptive e-learning process has been developed, which eliminates a few shortcomings of existing solutions identified during the analysis of organizing the educational process problems.

Reference

1. Савенко, А. Г. Преимущества и перспективы использования виртуальной и дополненной реальности в дистанционном образовательном процессе / А. Г. Савенко // Дистанционное обучение – образовательная среда XXI века : материалы X Междунар. науч.-метод. конф., Минск, 7–8 дек. 2017 г. – Минск : БГУИР, 2017. – С. 119 (in Russian).
2. Савенко, А. Г. Виртуальная реальность как способ получения и доставки учебного контента / А. Г. Савенко, Н. А. Кукалев, А. Г. Савенко // Высшее техническое образование: проблемы и пути развития : материалы IX Междунар. науч.-метод. конф. – Минск : БГУИР, 2018. – С. 394–397 (in Russian).
3. Савенко, А. Г. Преимущества и реализация дистанционного образовательного процесса для лиц с особыми потребностями / А. Г. Савенко // Непрерывное профессиональное образование лиц с особыми потребностями : сб. ст. Междунар. науч.-практ. конф., Минск, 14–15 дек. 2017 г. – Минск : БГУИР, 2017. – С. 106–108 (in Russian).

4. Карпекин, И. А. Преимущества и эффективность внедрения дистанционной формы образования в образовательный процесс учреждений образования любого типа / И. А. Карпекин, А. Г. Савенко // Дистанционное обучение – образовательная среда XXI века : материалы XI Междунар. науч.-метод. конф., Минск, 12–13 дек. 2019 г. – Минск : БГУИР, 2019. – С. 136–137 (in Russian).

5. Парамонов, А. И. Проблемы дистанционного образования и их прикладные решения в образовательных технологиях / Парамонов А. И. // Высшее техническое образование : проблемы и пути развития = Engineering education: challenges and developments : материалы X Междунар. науч.-метод. конф., Минск, 26 ноября 2020 г. / Министерство образования Республики Беларусь, Белорусский государственный университет информатики и радиоэлектроники. – Минск : БГУИР, 2020. – С. 182–187 (in Russian).

6. Суский, А. А. Преимущества и перспективы внедрения нейронных сетей в образовательный процесс как инструмент повышения качества подготовки специалистов / А. А. Суский, А. Г. Савенко // Высшее техническое образование: проблемы и пути развития : материалы IX Междунар. науч.-метод. конф., Минск, 1–2 нояб. 2018 г. – Минск : БГУИР, 2018. – С. 454–456 (in Russian).

7. Савенко, А. Г. Игровой подход в обучении программированию детей и подростков / А. Г. Савенко // Информационные технологии в технических, политических и социально-экономических системах : материалы Междунар. науч.-техн. конф. / Белорусский национальный технический университет. – Минск : БНТУ, 2018. – С. 30 (in Russian).

8. Fitzgerald M. Toward a model of a distributed learning: [An interview] // Educom review. – L. , 1999. – Vol. 34, n 6. : pp. 38–50.

9. Brusilovsky P., Eklund J., Schwarz E. Web-based education for all: a tool for development adaptive courseware. Computer networks and ISDN systems. 1998. – 30(1-7) : pp. 291-300. DOI:10.1016/S0169-7552(98)00082-8.

10. Weber G. Adaptive Learning Systems in the World Wide Web. UM99 User Modeling. CISM International Centre for Mechanical Sciences. Proceedings of the seventh international conference on User modeling. Vienna: Springer; 1999 : pp. 371–377. DOI:10.1007/978-3-7091-2490-1_49.