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MODELLING SUPPORT SYSTEMS FOR SELECTING PROFESSIONS FOR APPLICANTS IN THE CONTENT OF PERSONALIZATION OF EDUCATION

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Abstract

Various methods are currently being used in examining the initial "START" knowledge of applicants and their placement for specialties. Studies show that applicants are placed on the decreasing principle in terms of their overall scores at universities. In this case, applicants with a high level of knowledge are placed in the prestigious specialties as medicine and law as they require high results. Though, while applying for other professions, the applicants do not perform enough results on the key disciplines for the profession, they are placed in those professions when the general results enable it. This causes them to face a number of problems while working both in education process and in the industry.

To avoid this problem and to place applicants in a specialty that is more relevant to their level of knowledge, the introduction of an individual approach to the evaluation of initial level of knowledge may be more promising.

This article presents a modeling of the "evaluation – placement" support system for the individual approach to assessing applicants' knowledge and positioning them in relevant specialties. The main goal of the system is to give each applicant the opportunity to choose and study the specialty that is more relevant to their knowledge and skills, as well as to analyze the results for each discipline along with the overall results. The system is implemented using fuzzy logic based artificial neural networks.

The network consists of 100 neurons in the input layer, two hidden layers and one output layer. The number of neurons at the output is the same as the number of specialties taught at university.

Keywords: artificial neural network, intellectual system, fuzzy sets, personalization of education, fuzzy logic.

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1. Introduction

Universities have been performing the sacred objective to satisfy the scientific needs of society since its inception. Affected by this factor, the society is already experiencing the transition to the knowledge economy. At the time of globalization, the intellectual capital invested by universities and research institutions has become the main production factor [1]. The use of new technologies in all three areas of psychosocial activity to increase the interest in different disciplines can lead to significant results [2]. This factor is only possible in the e-university environment.

Currently there are many e-university models in the world such as on-off campus, tele-university, consortium [3]. However, despite so much development, applicants in almost all countries of the world are tested and placed based on their general knowledge, without taking into account the knowledge and skills in particular subjects required for specific specialties. This often makes applicants to be placed in the specialties where their knowledge and skills are incompatible.

In this case, the individual approach to entrants emerges during their admission to universities, which has many advantages. The personalization of education has already become one of the requirements for the transition to the virtual world [4]. Personalization in education is a key trend in e-learning. In [5], the authors use fuzzy logic in testing computer skills of students.

The introduction of intellectual systems in the learning environment contributes to the development of maximum interaction and interconnection between educational resources and learners [6]. New opportunities for facilitating academic tasks, developing smart content, personal and global education as well as enhancing educational effectiveness can be estimated as the changes in the artificial intelligence sector [7]. The main requirement for modern educational resources used in knowledge management systems includes the ability to adapt the education to specific educational tasks, competence levels, personality traits. Moreover, the neural networks can be applied as

one of the most promising technologies in assessing students' competence [8]. Intelligent analysis in the educational environment is based on decision making, statistics, pattern recognition, cluster analysis, classification, regression and factor analysis, fuzzy logic, artificial neural networks and other methods [9–15]. The personalization of education or the determination of individual learning trajectories for each student is also possible through the use of artificial intelligence in the learning process. One of the characteristics of learners is their learning style [16].

The trajectory of the personal education is a three-stage process that involves evaluating the basic knowledge and directing to occupations, from the initial assessment to the beginning of education and the stages of the educational process [17].

There are many articles in the scientific literature on the use of intellectual systems at different stages of the educational process. A creation concept has been specified for a learning management system of new generation that allows forming individual learning trajectories based on analysis of student's achievements, wishes and peculiarities. Forming individual learning trajectories based on student's achievements and functional state analysis provides the possibility to build educational process automatically that will be suitable for a specific student and satisfy the requirements of the educational program [18].Guzman-Ramirez and Enrique propose the education system modeling based on the Gate matrix using multiple preceptors [11]. In the article [19], the authors use Data Mining technology to explore students' interests and their successes in these areas. The article [9] sets out the criteria for the international assessment of IT knowledge using artificial intelligence in education. [20] proposes the use of artificial intelligence based adaptive learning hypermedia systems in e-learning.

Projecting the "educational process" phase of the personal education trajectory using fuzzy set theory helps students become more promising graduates [12].

Obviously successful use of genetic algorithms, neural networks, and matrices in addressing the teacher-learner relationship and their interaction issues in the virtual learning environment [21, 23]. [23] shows an example of the use of software such as CATIA V5 and Fluidsim CAD systems in the teaching technique of laboratory and technical subjects. Intellectual learning systems (ITL) are developed as part of a blended/hybrid design initiative to support learning processes. At present, there is a growing interest in the intellectual analysis of data in educational systems [24]. The results obtained from the model developed with the method of artificial neural networks were verified and compared through classification (quota) tables, Chi-square test, simple linear regression analysis and correlation analysis methods. According to these results, the estimated success measures and the observed success measures and the success/failure classification formed by these measures were significantly similar [25]. [13] presents an analysis of the average performance indicators of graduates in the SPSS package. In [14], the authors use the Mamdani algorithm to solve the problem of predicting student success rates with fuzzy logic. Wai Yan Min implements a MATLAB system that can analyze successes for each semester by analyzing the results of each student using neural networks [26]. Certain results are obtained using the data mining technologies in the educational outcomes [27]. In addition, the authors in [28] propose the use of artificial intelligence in assessing the performance of the academic personnel (teachers, professors, etc.).

Recognizing all these successful solutions, it should be noted that the problem of assessment of initial knowledge and skills and relating it with the choice of the profession, which is most appropriate for the achieved results, has not been explored well enough. Therefore, in the context of the personalization of education, the modeling of a support system for applicants in the choice of profession can be relevant. The essence of this issue includes the need for the use of intellectual technologies in its solution.

The aim of research is to develop a method for evaluating the primary knowledge of the students and directing them to the relevant specialties. The results of the knowledge evaluation of the students through the proposed method are compared to the requirements specified for the specialties, and consequently, students are enabled to study the most relevant specialty. The students selecting the specialties through this method are assumed to be more promising cadres after the graduation.

To achieve the aim, the following 3 objectives are set and resolved:

1. Analysis of the results on the main disciplines covered by the specialties chosen by the applicants during the admission exams in the country.

2. Comparison of the results of the students of any university on the disciplines covered by the specialties they are admitted with the results of the disciplines taught at the university on the basis of those disciplines.

3. Grouping the answers of first-year students of any university on the subjects covered by the basic disciplines of the specialties they are admitted to, and entering these results as input data to the proposed model to determine the most suitable specialty offered by the model.

2. Materials and methods

In the process of modeling an applicant support system, the results of various surveys conducted by the State Examination Center of the Republic of Azerbaijan, the results of various surveys conducted among students and citizens, matrices and artificial neural networks are used the research materials.

3. Experiments

3. 1. Exploring the results of entrance examinations

At the first stage of the survey, the survey is conducted based on the statistical data for the years 2013–2017 provided by the State Examination Center of the Republic of Azerbaijan. It is found that in some cases, although applicants perform low results on the basic disciplines of the chosen specialties, due to the high overall results, they can be placed in the chosen specialties [29].

In the second study, the results of the students admitted to Nakhchivan State University during the entrance exams are mutually compared with the results on the disciplines they studied at the university (**Fig. 1**).

It is revealed that the results on the subjects remain almost unchanged during the course of study, and the student can't achieve even higher scores in the university disciplines which play a key role.

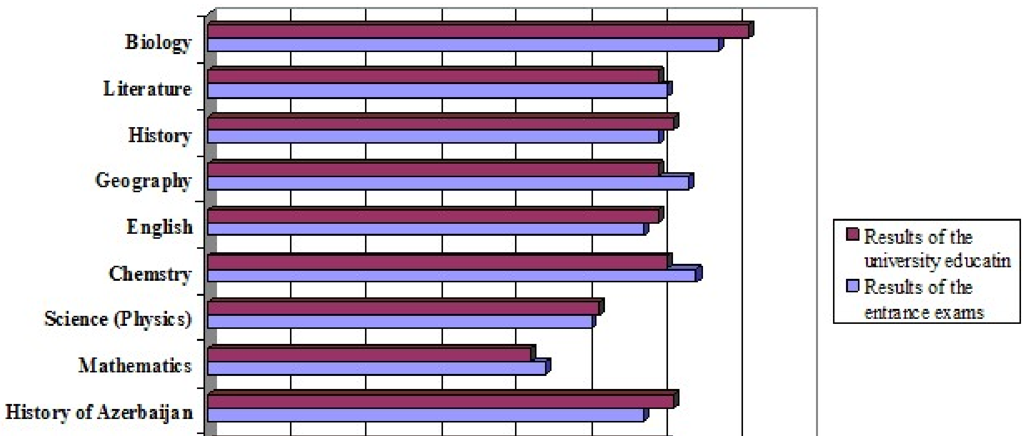

Fig. 1. Average score of applicants on disciplines in 2013–2017

A survey is conducted among the students to find out how this problem is solved by the students (**Fig. 2**).

35 % of the surveyed students said they would like to go to additional training courses, 48 % – to study in distant form, 3 % – to study again, and 14 % – to change their specialization. The results of the analysis once again prove that modelling the intellectual decision support system is necessary for the placement of applicants in specialties.

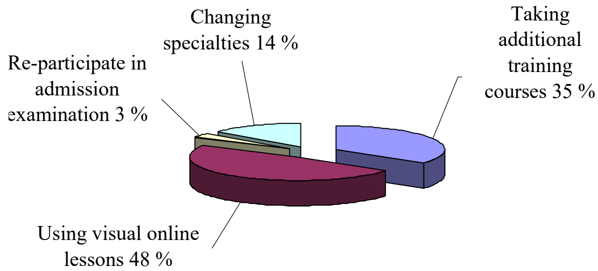

Fig. 2. The ways used by students to improve their capacity in basic disciplines

In the third stage of the study, the questions presented to the students in the entrance exam are grouped according to the disciplines and subjects they are referred to. These results are included as input data to the proposed model. As a result of the analysis of 981 results introduced to the system through the proposed model, it becomes clear that the knowledge of 231 students is more appropriate for other specialties rather than for chosen ones. In the end, the reasons for this are clarified. **Table 1** presents the results of 10 students by the selection method, the specialties they have chosen and the specialties that the system considers appropriate according to their knowledge.

Table 1

Results of 10 students by the selection method

Students	Total results	Currently studying specialty	Specialty considered appropriate by the proposed model according to the knowledge level	Note
Student 1	340	Physics teaching	Mathematics teaching	8 questions on physics and 22 questions on mathematics answered
Student 2	432	Electrical engineering	Water management engineering	Questions on electricity not answered
Student 3	452	Information systems	Water management engineering	Questions on electricity, magnetism and impulses not answered
Student 4	253	Water management engineering	Architecture	Only geometric questions on mathematics answered
Student 5	382	Pharmacology	Biology	25 questions on biology, 3 on chemistry and 5 on physics answered
Student 6	341	Biology	Veterinary	Only questions on zoology answered
Student 7	258	Veterinary	Ecology	Questions on zoology not answered, only questions on botany answered
Student 8	262	Veterinary	Chemistry	25 questions on 3 on biology and 4 questions on chemistry answered
Student 9	401	Chemistry teaching	Biology teaching	Only 5 questions on chemistry answered
Student 10	374	Biology teaching	Veterinary	Only questions related to zoology answered

3. 2. Assessment-guiding method architecture

Through the proposed method, the occupations are grouped in order to more easily identify the level of knowledge of a learner. These groups are conventionally referred to as I, II, III, IV, V groups which respectively include the specialties in the following disciplines:

– group I – Mathematics, (Science) Physics, Engineering, Architecture, Agrarian studies;

– group II – Economics, Management, International Relations, Regional Studies, Sociology and Geography;

– group III – Humanitarian and Pedagogical;

– group IV – Medicine, Chemistry, Biology, Psychology, Agriculture;

– group V – Art, Music, and Sports.

The main disciplines in the first specialty group are physics and mathematics, in the second specialty group – mathematics and geography, in the third specialty group – native language and history, and in the fourth specialty group – chemistry and biology.

Testing of "start" knowledge through the assessment-guiding method is mainly performed in two specialties, which can reveal the applicant's knowledge through test questions and is carried out in two stages. The structural scheme of the model is presented in **Fig. 3**.

At the first stage, the student is presented 10 questions in each of the 10 disciplines that cover the specialty groups. At the end of this phase, the general knowledge level of the learner is determined for compliance with the requirements. If the student's scientific potential provides the requirements, it is checked for his/her specialty. The level of general and specialty groups is determined by the academic management team of the e-university.

In the second round, the learner is presented 25 questions on each of the two core subjects that cover the specialty group. These questions mainly concern the specialties taught at the university. At the end of this phase, the most appropriate specialty(ies) is assigned to the learner. If there are more than one related specialty, the learner will be given the chance to choose.

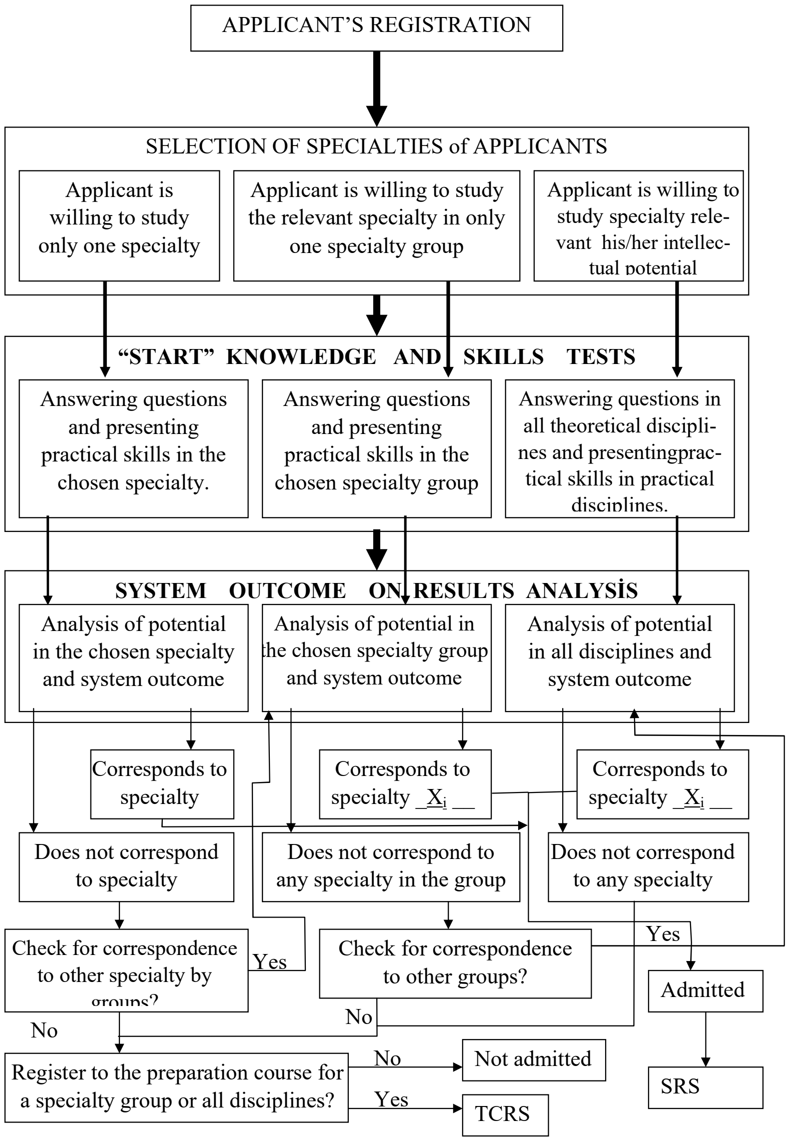

Fig. 3. Testing "start" knowledge of applicants and specialization system

Through this system, the knowledge of the learner on the specific group or the specialty rather than the general knowledge is assessed. Thus, the questions are presented on the specialty group in this case, and in the second case, the questions are presented on the specialties with the requirements set out in the second phase. Once the results of the system are "analyzed", the system

presents the outcome as "does not correspond" to the specialty, "__X_i___ fully corresponds to the specialty" and "__X_j__" corresponds to the training course.

3. 3. Characteristics of the elements of applicants and questions sets and the relationship between them

Obviously, each discipline is made up of different subjects, and the subjects are made up of topics. Proper answers to the questions that are relevant to the future specialty of learners are more important in his/her right placement in specific specialty.

Assume that the e-university requires the learner to perform 85 % results in physics for the specialties "electro-energy engineering" and "melioration and water economy building engineering". According to the current rules, the learner can apply to both specialties performing 85 % results without responding to the questions that involve the subject "electrics". However, the proposed assessment method does not allow the admission of that learner to the specialty "electro-energy engineering", but allows the admission to the specialties as "melioration and water economy building engineering" or other "electrics" subjects which is less important.

Let's assume that applicants (applying to be learners) willing to enter the e-university is presented as a set mentioned below:

$$O = \{O_h\}, \; h = \overline{1, z}.$$

$s = \{S_a\}, (a = \overline{1, p})$ is a set of questions prepared to test the applicants knowledge by specialty groups and occupations.

However, such a compilation of the set "S" is of no importance to the proposed method. In this case, it remains unknown which subject the presented question refers to.

To address this problem, along with the current number, discipline, content, answer options, correct answer or answers (for open-ended questions) and difficulty rate settings, it is also suggested to define the subjects and topics parameters for each question, which is a prerequisite for the proposed method to be sustainable and flexible (**Fig. 4**). Thus, the set "S" includes the sets of disciplines "*F*", each of which includes the sets of subjects "*B*", and the sets of subjects in turn include subsets of topics "*M*".

Obviously, the number of subjects per discipline and the number of topics per subject differ. The number of questions per topic is finite, and the number of elements in the set "S" varies depending on the subsets *F*, *B*, and *M*, and is generally fuzzy.

In this case, the following relationships can be written.

Assume that $F = \{F_i\}, i = \overline{1, k}$ is the set of disciplines in which the applicant's knowledge is tested, $B = \{B_j\}, \; j = \overline{1, n}$ is the set of subjects, and $M = \{M_y\}, \;\; y = \overline{1, t}$ is the set of topics.

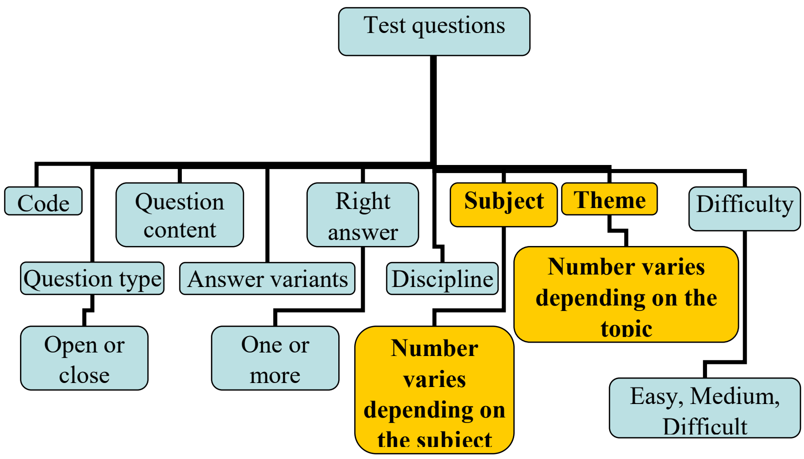

Fig. 4. Structure of the test questions table

In this case, each question can be described as $S_y^{(a)} \in M_y$ since it is referred to a particular topic.

Obviously, the number of questions on the topics differs. Each of the topics is related to a particular subject, and their numbers vary depending on the subjects. Hence, each of the sets of subjects consists of the combinations of unequal subsets $M(j)_y$ (1)–(3).

$$M_{j1} \cap M_{j2} \cap \ldots \cap M_{jt} = \varnothing, \tag{1}$$

$$B(j) = M_{(j)1} \vee M_{(j)2} \vee \ldots \vee M_{(j)y}, \tag{2}$$

$$M(j)_y \subseteq B(j). \tag{3}$$

In this case, description of the question that generates set of questions is as $S_{jy}^{(a)} \in M_{jy} \in B_j$.

The subjects, in turn, are the unequal subsets of the sets of disciplines, and their separate combinations generate the sets of disciplines (4)–(6).

$$B_{i1} \cap B_{i2} \cap \ldots \cap B_{ij} = \varnothing, \tag{4}$$

$$F(i) = B_{(i)1} \vee B_{(i)2} \vee \ldots \vee B_{(i)j}, \tag{5}$$

$$B(i)_j \subseteq F(i). \tag{6}$$

Thus, each element of the set of questions is represented as $S_{ijy}^{(a)} \in M_{jy} \in B_{ij} \in F_i$.

All sets of disciplines are also assembled to generate the set of general questions "S" (7)–(9).

$$F_1 \cap F_2 \cap \ldots \cap F_k = \varnothing, \tag{7}$$

$$S = F_1 \vee F_2 \vee \ldots \vee F_k, \tag{8}$$

$$F_k \subseteq S. \tag{9}$$

Finally, each element of the set of questions is represented as (9), which meets the requirements of the proposed method for fully identifying the applicant's knowledge.

$$S_{ijy}^{(a)} \in M_{jy} \in B_{ij} \in F_i \in S;$$

$$S_a (a = \overline{1, p})$$

$$p \to \infty. \tag{10}$$

Here P is the maximum number of questions that can be included into the question bank. The question number or code come from a combination of these parameters. For example, the selected question $S_{157}^{(587)}$ is generally the 587th element of the subject and refers to the seventh subject of the fifth topic of the first discipline. Set of questions is described in the Euler-Venn diagram in **Fig. 5**.

The questions are entered to the question bank according to the specified rules with the algorithm presented in **Fig. 6**.

Here *ss* is the serial number of questions on a specific topic, *t* is the type of question, *s* is the text of question, *c* is the correct answer to the question, *M* is the topic the question refers to, *B* is the subject the topic refers to, and *F* is the discipline the subject refers to. The code variable is the unique number of the question in the database generated from the combination of variables *F*, *B*, and *M*.

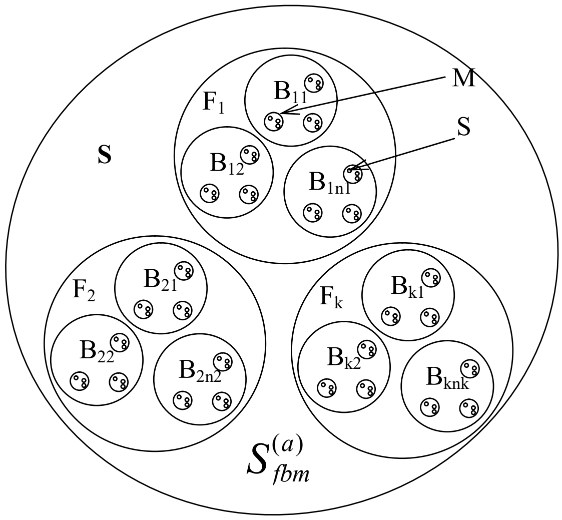

Fig. 5. Descriptions of the set of questions in the Euler-Venn diagram

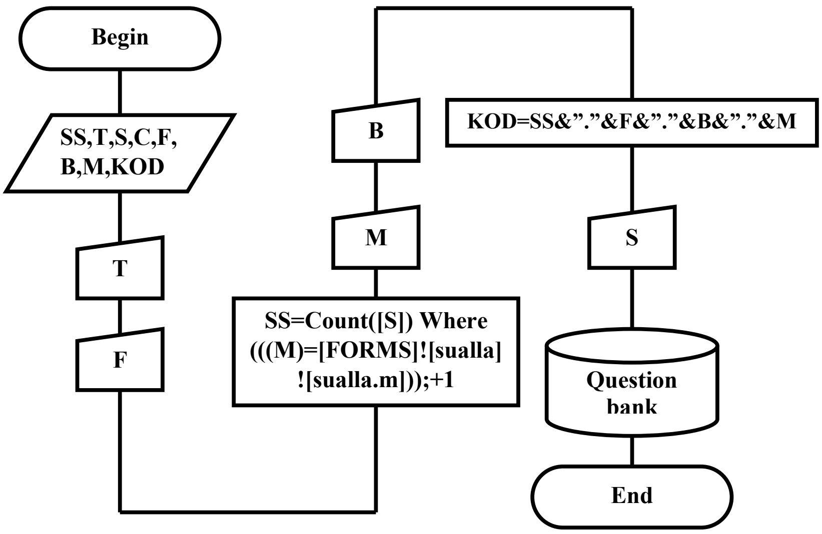

Fig. 6. Algorithm for inclusion of test questions into the database

The VB relational principle is used to implement the algorithm.

As seen from the block diagram description and the structural diagram of the algorithm, once the question is entered the dataset, each question enters only the subset it refers to, which prevents the unnecessary question to be presented to the applicant.

After specifying the characteristics of the elements of applicants and question sets, the requirement model A=(S) for the questions presented to the applicant can be represented by the matrix. Each line of O_h here describes the candidate who is supposed to be a learner, and the column S_{zp} describes the questions to be selected to test the candidate's knowledge in accordance with his/her claim.

The membership function, which indicates the degree of response to the questions s_{ha} to be presented to the applicant $O_h\left(h=\overline{1,z}\right)$ is determined by a fuzzy set.

The block diagram of the algorithm providing these conditions is presented in **Fig. 7**.

As seen from the algorithm, each applicant will be asked specific questions, covering each discipline, subject, and topic in accordance with his/her choice. The questions are distributed among the applicants in an ambiguous sequence.

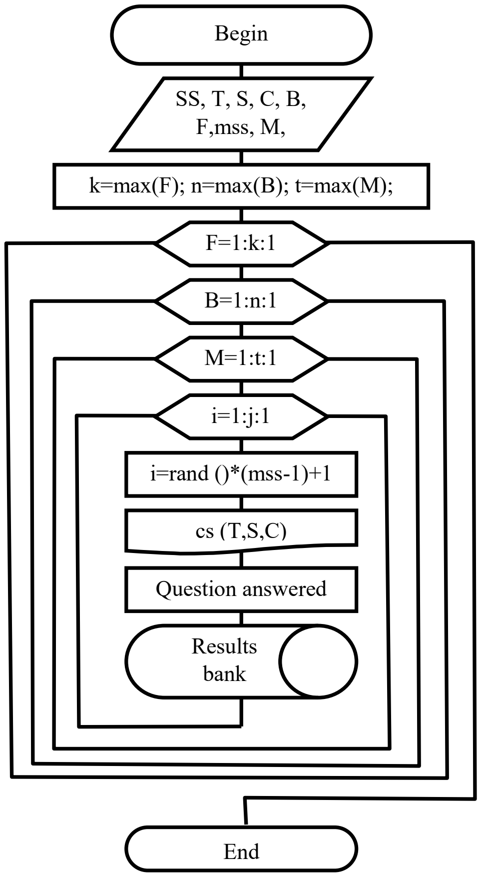

Fig. 7. Algorithm for presenting the test questions

3. 3. Developing relationship function among elements of specialties' set, requirements and results matrices

The next step to ensure the sustainable operation of the proposed method is the development of a conventional set of "specialties" "I", which includes university-specific specialties.

A number of specialties can be generally described as $\dot{I} = \{\dot{I}_v\}$, $v = \overline{1, z}$. However, the proposed method at the first stage, performs a guiding function for the specialty groups rather than the specialties. Therefore, let's compile a set of specialty groups IQ to perform the first phase of knowledge assessment with the proposed method.

The learner's knowledge on different specialties is examined in different disciplines.

The relationships between the demand for each specialty group and the disciplines it includes and the real knowledge of the learner on different disciplines can be illustrated by fuzzy demand and supply models [30–32].

Then requirements to the level of knowledge for the specialty groups can be described as the matrix $T_{ig}(r)$ (11).

$$T_{iq}(r) = (f_w); w = \overline{1, W}. \tag{11}$$

Here, W is the number of disciplines included into the r-th specialty group.

The demand model $IQ=(T_{ig})$ for different disciplines of separate specialty groups can be compiled with two-dimensional matrix $IQ_{Tiq} = \|Tiq_{rw}\|_{4W}$. Here, each line of $\dot{I}Q_{Tiq}$ characterizes the individual requirements for the specialty groups. Each column Tiq_{4W} characterizes the disciplines required for the specialty group and their membership to the groups.

Thus, the degree of correspondence of knowledge to the disciplines of the specialty groups is determined by a membership function fuzzy set as follows (12).

$$\mu_{t_f}(IQ_w): IQ \times T \to [0,1]. \quad (12)$$

The results performed by each learner whose initial knowledge is tested can also be similarly described as a matrix (13).

$$N_{iq}(O) = (f_g); g = \overline{1,G}. \quad (13)$$

Here, O is an element of a set of learners and represents a learner whose knowledge is tested. f_g denotes the result of the learner on a specific discipline, and G is the total number of disciplines the learner responds to.

The demand model for the individual learners' knowledge in different disciplines can be designed with a two-dimensional matrix $O=(N_{ig})$. $O_{Niq} = \|Niq_{hg}\|_{zG}$. Each of the lines of O_{Niq} here describes the individual learners whose start knowledge is tested. Each Niq_{zG} column describes the learner's performance in various disciplines. In this case, the degree of provision of performance matrix by the set of learners is expressed by the fuzzy membership function $\mu_{N_f}(O_h): O \times N \to [0,1]$.

The general requirement for knowledge by specialty groups is described as a total of requirements set for various disciplines (14).

$$UT_{iq} = \mathrm{MAX}(T_f). \quad (14)$$

Moreover, the overall performance indicators of the learner can also be summarized in separate disciplines (15).

$$UN_{iq} = \mathrm{MAX}(N_f). \quad (15)$$

The correspondence of each learner's knowledge to the disciplines is assessed by the difference between the numerical value of the requirements set for the disciplines and the numerical value of the performance of the learner (16).

$$U = |UT_{iq} - UN_{iq}|. \quad (16)$$

Guiding the learner for the specialty group is based on the condition $U \to \min$. That is, the smallest value of U is a discipline or disciplines on which the learner has high knowledge. U=0 is considered to be most appropriate. The mutual fuzzy inclusion of the requirements of specialty groups for disciplines and the learners' performance on the disciplines can be stated as follows (17).

$$\theta(\tilde{O}_h, I\tilde{Q}_w) = \min\left|\mu_{Tf}(IQ) - \mu_{Nf}(O)\right|. \quad (17)$$

In the second phase of the proposed method, the relationship between the set of specialties and the requirements matrix must provide other conditions. In this case, the requirements matrix is two-dimensional and follows from the appropriate combination of disciplines and subjects. Each line of the matrix characterizes the disciplines for which the result will be taken into account for the specialty, and the columns refer to the subjects by the disciplines (**Fig. 8**).

Let's assume that $\dot{I} = \{\dot{I}_v\}, v = \overline{1,z}$ is a set of specialties taught at university. Then, the requirements for disciplines and subjects by the specialty can be described as $T = |t_{fb}|,\ f = \overline{1,k},\ b = \overline{1,n}.$ Here, f specifies the disciplines covered by the specialty, and b denotes the subjects covered by the disciplines.

Thus, the demand model of the set of specialties versus the demand matrix is as $I=(T)$ and is represented as a three-dimensional matrix: $I_T = \|t_{vfb}\|_{zkn}$. Here, each line of I_v corresponds to a two-dimensional matrix of T_{fb}. Here, the requirements on the specialties include the total questions to be answered on relevant disciplines, and the requirements on the disciplines include the total questions to be answered on relevant subjects, and the requirements for the subjects $T_f = \sum T_b$;

$T_i = \sum T_f$. Thus, the degree of membership of the requirement matrix to the set of specialties is expressed as follows (18).

$$\mu_{T_{vfb}}(\dot{I}_v) : \dot{I} \times T \to [0,1]. \quad (18)$$

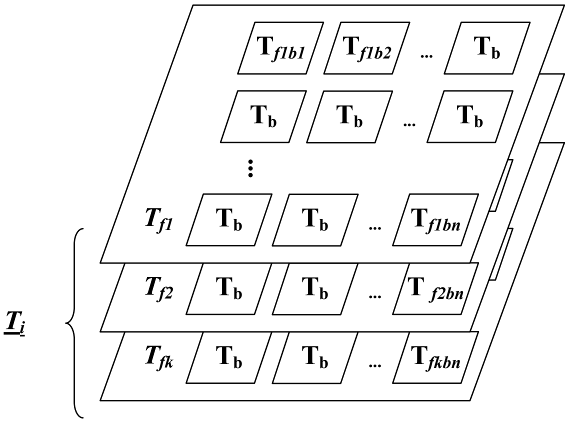

Fig. 8. Requirements for disciplines on specialties

In the second phase, the results of the study can also be described on disciplines and subjects as a two-dimensional matrix (19).

$$N = \left| N_{fb} \right|, \; f = \overline{1,k}, \; b = \overline{1,n}. \quad (19)$$

The lines here are the general result of the learner on the discipline, and the columns are the results of answers to the questions covering the subjects related to the relevant disciplines (20)–(22).

$$N_b = \sum N_{ms}, \quad (20)$$

$$N_f = \sum N_b, \quad (21)$$

$$N_i = \sum N_f. \quad (22)$$

N_i, N_f, N_b respectively represent the examination results of the learner on subject, discipline, and specalty. N_b and N_f are calculated using the formulas (23) and (24).

$$N_b = \frac{BDC}{FSS}; \quad (23)$$

$$N_f = \frac{FDC}{FSS}. \quad (24)$$

Here, BDC is the number of correct answers on the subject, FDC is the number of correct answers on the discipline, and FSS is the number of total questions on the discipline.

Thus, the demand model of the set of learners against the results matrix is described as a three-dimensional matrix: $O_N = \left\| N_{hfb} \right\|_{zkn}$. Here, each line of O_h corresponds to a two-dimensional matrix of N_{fb}.

In this case, in the set of learners of the results matrix, the membership function of is as follows (25).

$$\mu_{N_{hfb}}(O_h) : O \times N \to [0,1]. \quad (25)$$

The optimal situation in the second phase, as in the first phase, is that all the values of the correspondence matrix "U" are minimum, which is resulting from the difference of the requirement and result matrices.

$$U = |T - N|. \tag{26}$$

$$F(u) = \min(u). \tag{27}$$

The degree of reciprocal inclusion of the learners' results on the disciplines and the requirements for the specialties for the second phase can be summarized as follows (28).

$$\theta(\tilde{O}_h, \tilde{I}_v) = \min\left|\mu_{T_{vfb}}(I) - \mu_{N_{hfb}}(O)\right|. \tag{28}$$

Using these methods, the level of knowledge of the learner is achieved through an instrumental tool created through the database management system. Correctly answered questions are denoted as 1, and the incorrectly answered questions or unanswered questions are denoted as 0. As a result, these values are summarized on separate disciplines. If the result is considered quantitatively sufficient, the results are then transmitted to the neural network and processed as input data.

3. 5. Assessment of "Start" knowledge using neural networks

Assessment of knowledge on specialty groups is implemented through a fully-connected neural network.

Obviously, neural networks are a mathematical model inspired from the biological neural networks. Artificial neural networks are computer programs that simulate the connected neural cells (neurons) in the human brain. Neural networks enable computers to recognize templates by self-training. As the human brain, the neural networks produce only approximate results; however, no other types of computer programs can do this work effectively.

3 types of neural networks are generally distinguished:

1) fully connected networks;

2) multiple neural networks;

3) poorly connected networks.

The main principle in fully connected neuron networks is that each neuron in the network is connected to other neurons [12].

The input signal matrix of the presented model consists of 10 lines and 10 columns (**Fig. 9**).

Matrix is conventionally referred to as S since it contains the answered questions.

$$S = \left(s_{fm}\right)\left(f = \overline{1,10}; m = \overline{1,10}\right), \tag{29}$$

where f denotes the discipline, and m – the topic.

The output matrix consists of 1 column and 4 lines. The matrix is conventionally called I (specialty group).

$$\dot{I} = [i_{4,1}]. \tag{30}$$

The elements of the input and output matrices get the values 0 or 1.

The network consists of input and output layers and 1 hidden layer. There are 100 neurons in the input layer, 10 – in the hidden layer, and 4 – in the output layer. The signals from each of the following 10 neurons in the input layer are concentrated in the following j-th layer of the hidden layer. As a result, the intellectual potential of learner on each discipline is determined. These results are transmitted to each layer of the output layer. According to the

potential of the learner, the corresponding element of matrix I gets the value 1, while the other elements get the value 0.

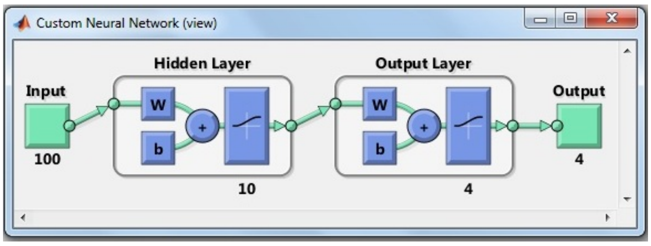

Fig. 9. Description of the neural network at the first phase of the assessment of the start knowledge of learner

The network activation function is a sigmoid function [10].

The Sigmoid function is the most common form of activation function, and its mathematical expression is as follows:

$$\sigma(x) = \frac{1}{(1+\exp(-tx))}. \tag{31}$$

When the total input approaches –∞, the activation level approaches zero, and at very high values of the overall input, the activation level almost equals to "1".

At the second phase, namely, guiding the learner to the relevant specialty, the given neural network consists of input and output layers and two hidden layers (**Fig. 10**).

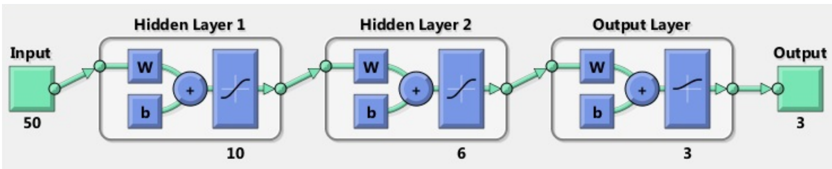

Fig. 10. Description of the neural network at the second phase of the assessment of the start knowledge of learner

The first hidden layer defines the subjects, in which the learner has more potential, while the second hidden layer identifies more promising specialties on the disciplines. In the output layer, the specialty(ies), in which the learner has more potential on both disciplines, are identified.

4. Discussions

There are 5 subjects for both disciplines in the presented network. It is accepted that 3 specialties are taught in this specialty group at the e-university. As a result of the experiments, the results obtained during the admission examinations of newly enrolled volunteer students in a group of universities were uploaded into the system as the input values, and the specialties, in which the knowledge of the learners was more relevant, were identified.

Some of these students voluntarily take part in the final exams at the end of the academic year together with the students of the specialties whose knowledge are considered appropriate by the model proposed. Their overall results in these specialties are higher than the overall results in the specialties they are currently studying, **Table 2**.

As the table shows, the indicators of the membership function are higher in the specialties considered appropriate by the proposed model.

The presented theoretical explanations and the survey examples give grounds to say once again that the introduction of the proposed model to the choice of specialization of applicants can lead to the development of better-quality personnel in the future.

Table 2

Overall results for the professions currently being studied

Students	OASR (overall average success rate) in the currently studying specialty	OASR in the specialty considered appropriate by the proposed model according to the knowledge level
Student 1	Physics teaching (67 – d)	Mathematics teaching (78 – c)
Student 2	Electrical Engineering (58 – e)	Water management engineering (71 – c)
Student 3	Information systems (61 – d)	Water management engineering (79 – c)
Student 4	Water management engineering (71 – c)	Architecture (80 – c)
Student 5	Pharmacology (70 – d)	Biology (81 – b)
Student 6	Biology (58 – e)	Veterinary (71 – c)
Student 7	Veterinary (57 – e)	Ecology (68 – d)
Student 8	Veterinary (61 – d)	Chemistry (73 – c)
Student 9	Chemistry teaching (61 – d)	Biology teaching (72 – c)
Student 10	Biology teaching (53 – e)	Veterinary (73 – c)

5. Conclusion

At the initial phase of the study, the applicants' results during the admission examinations were studied, and the architecture and the working principle of the assessment and guiding method were presented. At the next phase, the characteristics of the elements of the sets of applicants and questions and the relationships between them were identified. The specialties, requirements to disciplines and subjects were clarified, and the requirements and the results of applicants were presented as a matrix and the relationship function between them is designed.

At the last phase, the application of a neural network for knowledge assessment was proposed, the network was established and "trained", and the sample values were entered and tested.

As the researches and practical results showed, the assessment of the applicants' knowledge through the proposed method might ensure the correct guidance of the knowledge level of the society. Taking this into consideration, it was concluded that the introduction of the model and the relevant system were appropriate.

References

[1] Varghese, N. V. (2013). Globalization and higher education: Changing trends in cross border education. Analytical reports in international education, 5 (1), 7–20.

[2] Reber, R., Canning, E. A., Harackiewicz, J. M. (2018). Personalized Education to Increase Interest. Current Directions in Psychological Science, 27 (6), 449–454. doi: http://doi.org/10.1177/0963721418793140

[3] Mammadova, M., Gasimov, H. (2017). E-UNIVERSITY: CONCEPTUAL, TECHNOLOGICAL AND ARCHITECTURAL APPROACHES. Problems of Information Technology, 8 (2), 51–62. doi: http://doi.org/10.25045/jpit.v08.i2.06

[4] Özcan, B., Güler, E., Yerlikaya, Z. (2017). Kocaeli Mühendislik Fakültesi Mezunlarının Akademik Başarılarının İncelenmesi. Kocaeli Üniversitesi Sosyal Bilimler Dergisi, 34, 143–168. Available at: https://dergipark.org.tr/en/pub/kosbed/issue/43233/524969

[5] Meenakshi, N., Pankaj, N. (2015). Application of Fuzzy Logic for Evaluation of Academic Performance of Students of Computer Application Course. IJRASET 2015, 3 (X).

[6] Apatova, N. V., Gaponov, A. I., Mayorova, A. N. (2017). Forecasting students well doing based on fuzzy logic. Advanced scientific technology, 4, 7–11.

[7] Johnson, A. (2019). 5 Ways AI Is Changing The Education Industry. ELearning Industry. Available at: https://elearningindustry.com/ai-is-changing-the-education-industry-5-ways

[8] Lomakin, N. I., Plaksunova, T. A., Loginova, E. V., Lukyanov, G. I., Kozlova, E. A., Skobora, E. A. et. al. (2017). Neural network for evaluating the competence of students. EDCRUNCH Ural: new educational technology at uiversity–2017. Ekaterenburg, 307–319.

[9] Abuzagia, K. M. (2017). International intentions in the field of information technology (Artificial intelligence systems and their importance in the fields of education). 2017 Joint International Conference on Information and Communication Technologies for Education and Training and International Conference on Computing in Arabic (ICCA-TICET). doi: http://doi.org/10.1109/icca-ticet.2017.8095300

[10] Hahm, N.-W., Hong, B.-I. (2009). A simultaneous neural network approximation with the squashing function. Honam Mathematical Journal, 31 (2), 147–156. doi: http://doi.org/10.5831/hmj.2009.31.2.147
[11] Guzmán-Ramírez, E., Garcia, I., García-Juárez, M. (2019). A "learning by design" application for modeling, implementing, and evaluating hardware architectures for artificial neural networks at undergraduate level. Computer Applications in Engineering Education, 27 (5), 1236–1252. doi: http://doi.org/10.1002/cae.22148
[12] Gasimov, H. (2018). Fuzzy sets method to adhere to the student's intellectual potential to choose the path of education. DILET2018 The 2nd International Conference on Distance Learning and Innovative Educational Technologies. Ankara, 240
[13] Mammadova, M. H., Jabrayilova, Z. (2012). Multi-criteria model of decision-making support in the personnel management problems. Problems of information technology, 2, 37–46.
[14] Min, W. Y. (2017). Neural Network Application to Control and Prediction of Educational Process Results in the University. Economic and social-humanitarian research, 4, 130–132.
[15] Arora, N., Saini, J. R. (2014). Predicting student academic performance using fuzzy artmap network. International Journal of Advances in Engineering Science and Technology, 3 (3), 187–192.
[16] Drachsler, H., Kirschner, P. A. (2012). Learner Characteristics. Encyclopedia of the Sciences of Learning, 1743–1745. doi: http://doi.org/10.1007/978-1-4419-1428-6_347
[17] Qasımov, H. (2018). Yapay sinir ağları kullanarak öğrencinin bilgi düzeyine daha uygun üniversite meslek seçimine yönlendirilmesi metödünün yapılandırılması. DILET 2018 – 2. Uluslararası Uzaktan Öğrenme ve Yenilikçi Eğitim Teknolojileri Konferansı. Ankara, 239.
[18] Lyamin, A. V. (2018). Creation of individual learning trajectories based on student's achievements and functional state analysis. Scientific and Technical Journal of Information Technologies, Mechanics and Optics, 115 (3), 543–553. doi: http://doi.org/10.17586/2226-1494-2018-18-3-543-553
[19] Ktona, A., Xhaja, D., Ninka, I. (2014, May). Extracting Relationships between Students' Academic Performance and Their Area of Interest Using Data Mining Techniques. 2014 Sixth International Conference on Computational Intelligence, Communication Systems and Networks, 6–11. doi: http://doi.org/10.1109/cicsyn.2014.18
[20] Alsobhi, A. Y., Alyoubi, K. H. (2019). Adaptation algorithms for selecting personalised learning experience based on learning style and dyslexia type. Data Technologies and Applications, 53 (2), 189–200. doi: http://doi.org/10.1108/dta-10-2018-0092
[21] Oancea, B., Dragoescu, R., Ciucu, S. (2013). Predicting students' results in higher education using a neural network. International Conference on Applied Information and Communication Technologies (AICT2013), 190–193.
[22] Gasymov, G. A. ogly. (2018). Development of the mechanism of intellectual management of "student-lecturer" relations in the space of virtual education with the use of neural networks. Open Education, 22 (5), 94–103. doi: http://doi.org/10.21686/1818-4243-2018-5-94-103
[23] Matúšová, M., Hrušková, E. (2019). Applying the Computer Aided Systems in Education Process. Management Systems in Production Engineering, 27 (1), 46–50. doi: http://doi.org/10.1515/mspe-2019-0008
[24] Kotova, E. E. (2017). Intellectual data analysis in the educational process. 2017 XX IEEE International Conference on Soft Computing and Measurements (SCM), 757–759. doi: http://doi.org/10.1109/scm.2017.7970714
[25] Aydoğan, İ., Zirhlioğlu, G. (2018). Öğrenci Başarılarının Yapay Sinir Ağları ile Kestirilmesi. Yuzunci Yil Universitesi Egitim Fakultesi Dergisi, 15 (1), 577–610. doi: http://doi.org/10.23891/efdyyu.2018.80
[26] Domenech, D., Sherman, M., Brown, J. L. (2016). Personalizing 21st century education: A framework for student success. John Wiley & Sons, 144.
[27] Ray, S., Saeed, M. (2018). Applications of Educational Data Mining and Learning Analytics Tools in Handling Big Data in Higher Education. Applications of Big Data Analytics. Cham: Springer, 135–160. doi: http://doi.org/10.1007/978-3-319-76472-6_7
[28] Jyothi, G., Parvathi, C., Srinivas, P., Althaf, S. (2014). Fuzzy expert model for evaluation of faculty performance in Technical educational Institutions. International Journal of Engineering Research and Applications, 4 (5), 41–50.
[29] State Examination Centre of the Republic of Azerbaijan (2014–2017). Available at: http://dim.gov.az/en/center/
[30] Mammadova, M. (2019). Methods for fuzzy demand assessment for it specialties. EUREKA: Physics and Engineering, 4, 23–33. doi: http://doi.org/10.21303/2461-4262.2019.00939
[31] Mammadova, M. H., Jabrayilova, Z. G., Mammadzada, F. R. (2015). Managing the IT labor market in conditions of fuzzy information. Automatic Control and Computer Sciences, 49 (2), 88–93. doi: http://doi.org/10.3103/s0146411615020030
[32] Grosan, C., Abraham, A. (2011) Artificial Neural Networks. Intelligent Systems Reference Library. Berlin, Heidelberg: Springer, 281–323. doi: http://doi.org/10.1007/978-3-642-21004-4_12

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