European Journal of Contemporary Education
E-ISSN 2305-6746
2024. 13(3): 589-597
DOI: 10.13187/ejced.2024.3.589
https://ejce.cherkasgu.press

Possibilities of Application of Adaptive Knowledge Testing Using Artificial Neural Networks in Training Economics Students

Irina Polozhentseva [a, *], Irina Vaslavskaya [b], Vitalii Vasyukov [c], Natalya Nesova [d]

[a] K.G. Razumovsky Moscow State University of Technologies and Management (the First Cossack University), Moscow, Russian Federation
[b] Kazan Federal University, Kazan, Russian Federation
[c] Moscow State Institute of International Relations (University), Moscow, Russian Federation
[d] Peoples' Friendship University of Russia (RUDN University), Moscow, Russian Federation

Abstract

In line with the advancement of information technology, we are witnessing the development of adaptive knowledge testing, which presents a computerized system for evidence-based testing and assessment of learning outcomes. This system is distinguished by high efficiency owing to the optimization of generation procedures and the presentation and assessment of the results of adaptive tests. The study aims to evaluate the application of adaptive knowledge testing through artificial neural networks on the improvement of the level of training in economics students. A pedagogical experiment was conducted during the second semester of the 2022–2023 academic year at three universities on 288 3rd-year students. The authors developed assessment materials for adaptive knowledge testing with the use of artificial neural networks and developed and carried out the procedure of adaptive knowledge testing. Based on the dynamics of students' success indicators, conclusions were drawn about the efficiency of adaptive testing using artificial neural networks. The results of the pedagogical experiment support the hypothesis that the quality of economics students' training is significantly improved as a result of implementing adaptive knowledge testing using artificial neural networks.

Keywords: artificial neural network, adaptive testing, knowledge quality control, students, teachers, learning success.

1. Introduction

The test method using the test material is one of the most effective and objective methods of knowledge control (Kurgansky, 2022). The test method using the test material is one of the most

* Corresponding author
E-mail addresses: i.v.polozhentseva@mail.ru (I. Polozhentseva)

effective and objective methods of knowledge control. However, studies have shown that despite the diversity of pedagogical tests in different scientific disciplines, all of them have some shortcomings, including skewing of the weights between test tasks, the quantity of test assignments is not optimal or its co-similarity, interconnectedness of consecutive test assignments (Belenkova et al., 2022; Voskresensky et al., 2023).

Therefore, there is a problem related to the selection of test assignments depending on their level of complexity for the most objective assessment of students' knowledge. The increase in the number of tests used in universities with a fixed number of tasks, as well as their insufficient quality, leads to the inability to adequately determine the level of students' knowledge (Gorlova et al., 2023). According to the researchers, this deficiency is compensated by using tests that can match the students' level of knowledge, change the complexity and number of test assignments according to the answers received (correct/incorrect).

The process of adapting tests to the individual knowledge level of each student offers several advantages. It allows for more accurate and reliable assessment outcomes, reduces the overall time required for testing, and fosters increased student motivation by tailoring the difficulty of tasks to their current abilities. This method, known as adaptive testing, ensures that students are neither overwhelmed by excessively difficult questions nor under-challenged by overly simplistic ones (Isaeva et al., 2023).

In computer-based adaptive testing, each test is customized for the individual examinee, based on their performance in preceding tasks. The content, structure, and sequencing of the questions are dynamically adjusted to fit the student's proficiency level. Such a tailored approach not only yields a more precise evaluation of the student's knowledge, abilities, and skills but also helps in identifying gaps or misconceptions in their understanding. By doing so, it creates a clear roadmap for their continued learning and development, offering a path for targeted remediation or further skill enhancement (Uteuliyev et al., 2023). Moreover, this method enhances engagement and reduces testing fatigue by continuously adjusting the difficulty in response to the student’s progress.

Analyzing the subject matter, we arrive at several conclusions:

1. The objective of developing and implementing tests as pedagogical assessment tools is topical and should be considered in conjunction with other objectives in improving the level of students' training and optimizing the learning process (Tretyakova et al., 2023);

2. There currently is a great variety of mathematical models and methods for testing and processing results (Gagarin, 2023);

3. The considered methods of test result processing, including classical statistical methods and methods under the contemporary orientation of testing, allow analyzing the results of testing but are unable to provide recommendations on optimizing the learning process and adapting the content of tests, the complexity of tasks, and the allocation of time for different topics (Lykova et al., 2023);

4. Adaptive computer testing methods are the most commonly used to adapt the procedure of presenting test items (Nikolaeva et al., 2023);

5. There is not enough attention in modern studies to the adaptation of training courses according to test results, although some tools (for example, artificial neural networks – ANN) provide the possibility of its implementation (Chumakova et al., 2022).

The article aims to evaluate the effectiveness of adaptive testing application using ANN in the training of students-economists.

Research objectives:

1. Definition of the characteristics of the work of ANN and their possibilities of application in the design of educational tests with variable complexity of tasks;

2. Development of test assignments for adaptive testing on economic discipline;

3. Improvement of test tasks through ANN;

4. Development of a methodology for the use of research results.

The hypothesis of the study states that the quality of training significantly improves as a result of the application of adaptive knowledge testing with the use of ANN.

2. Theoretical background

One of the methods to increase the efficiency of computer tests is the development and utilization of adaptive testing methods. The term "adaptive testing" is regularly used to refer to computer systems of evidence-based verification and evaluation of test results that have high efficiency due to the opportunity to optimize the procedures of generation, presentation, and evaluation of adaptive test results (Frey et al., 2016).

You may find a lot more questions with intermediate answers or no options at all, with an open question, where the answer is evaluated on a scale (for example, from 1 to 5). For example, the Partial Credft Model (PCM) is a model that takes into account the increasing sequence of correct answers (Ang et al., 2022).

An undeniable advantage of the modern item response theory models is the opportunity to obtain well-grounded statistical assessments of specific tasks in addition to the assessment of students' competencies, which can serve as a basis for improving the educational programs of higher education institutions. The assessment of the level of knowledge of the entire list of tasks, and the skipping of individual tasks is not considered critical (Gorshkova et al., 2021).

It should be emphasized that in this case the test tasks must carry out an assessment of one specific competence. The main means of improving the objectivity of the results of the knowledge assessment is to take into account not the final examination but the intermediate assessments, which are used for various tasks. This will require a review and increase of the number of test assignments for all subjects, with each assignment being dedicated to the diagnosis of a specific competence. It is also necessary to provide for the recording and storage of the received estimates in the information system of the university (Pominov et al., 2020).

As argued by D. Denisova et al. (Denisova et al., 2023), this model is advisable when:

– Grading partially correct responses (e.g., multiple-choice tasks);

– The task implies a sequence of steps to complete it (e.g., solving a math problem), while the difficulty of different steps may vary.

Adaptive testing raises the efficiency of pedagogical measurements, reduces the number of items in the test, lowers the time and monetary costs of testing, and enhances its precision (Zhang et al., 2019).

Implementing the technology of adaptive testing requires the following steps (Sergeeva et al., 2022):

– Determining the goals of implementation of adaptive testing (Why is adaptation needed in the given test?);

– Determining the factors to be considered as input information in making decisions on adaptation (What is the test being adapted to?);

– Identifying the aspects to be evaluated in the process of adaptation (What will be adapted?);

– Deciding on which adaptation mechanisms will be deployed and how they will be implemented (How will the adaptation be achieved?).

As a rule, adaptive testing relies on the procedure of optimizing the difficulty of tasks based on the projected level of students' training. In its simplest form, the procedure is as follows. The student receives the first test task based on initial projections. If it is completed successfully, the difficulty of the next task increases. Otherwise, the next task has a lower difficulty. The process of testing can be aborted, for example, if the student fails three tasks in a row. In the general case, more complex procedures for stopping the test can be employed (Tolmachev et al., 2022).

Thus, even in its simplest form, adaptive testing allows dynamically changing the number and difficulty of test tasks for each student (Gabidullina et al., 2023). More complex adaptive testing algorithms can account not only for the difficulty of tasks but also for their association with specific topics in the discipline, the form of their presentation, and other factors when selecting the next tasks. This procedure ultimately generates a unique test for each student. Different students are presented with tests that vary in difficulty and the composition of tasks, passing through the test space along different trajectories (Babina et al., 2022; Efremova et al., 2022).

Adaptive testing algorithms may also differ by the strategy of testing. Specifically, there are two-step and multi-step strategies. Under the two-step strategy, all students receive the same tests at the first step. Based on the results of this test, students are distributed along the axis of the variable under measurement. At the second step, the adaptive mode is enabled, and final adaptive testing is performed. Multi-step strategies are distinguished into fixed-branching and variable-branching (Astuti et al., 2023; Musah et al., 2022). Fixed-branching strategies use the same set of tasks with a fixed position on the difficulty scale for all students, but the path of each student is unique. Usually, all tasks are spaced equally on this scale, or the step decreases with higher difficulty. This allows changing the speed of testing to account for students' tiredness. In variable-branching tests, the tasks are chosen from the bank through specific algorithms that predict the optimal difficulty of the next task. These individual tasks make up the adaptive test. This strategy thus realizes a step-by-step reevaluation of the student's level of knowledge, which is repeated after each task is completed.

3. Methods

To accomplish the research objectives, this study utilized both a review of relevant scientific and methodological literature as well as a pedagogical experiment. The main research method involved conducting a pedagogical experiment, which took place during the second semester of the 2022–2023 academic year across three universities. From each university, one experimental group (EG) and one control group (CG) were chosen for participation. In total, the experiment covered 288 students in their 3rd year of study. The EG and CG were formed based on pre-existing academic groups. To ensure comparability between the CG and EG, both groups were assessed for homogeneity before the experiment. The groups were found to be similar in terms of initial academic performance based on grades from the previous semester.

The participants included 3rd-year economics students enrolled in the "Information Support for Professional Activities" course at the selected universities. The inclusion criteria for participation were as follows:

1. Students must be in their 3rd year of study in the economics program.
2. Students must be enrolled in the required course and regularly attending classes.
3. Consent to participate in the study was required from all participants.

Exclusion criteria were:

1. Students who had previously participated in similar adaptive knowledge testing experiments.
2. Students who were unable to attend the full sequence of testing sessions due to illness or other valid reasons.

The experiment proceeded in several stages (Table 1).

Table 1. Stages of the pedagogical experiment

Stage	Content
Preparatory	Determination of the relevance, goal, objective, object, and subject of the experiment
Organizational	Development of test materials, selection of participants
Practical	Carrying out the procedure of adaptive knowledge testing
Summarization	Assessment of results (determining the dynamics of students' success indicators)

To measure students' knowledge with high quality and reliability, the following procedure was followed:

– select the educational content by examining the curriculum of the chosen (required) course;

– Develop a system of tests on the chosen discipline (create a knowledge base);

– Develop the software necessary for testing;

– Build a testing algorithm for the ANN and train it on the results of previous tests;

– Conduct testing and perform the processing and interpretation of the acquired results.

Per this procedure, at the organizational stage of the study, we chose the "Information support for professional activities" course taught to economics students, which consisted of 11 topics. The total volume of the base of testing results included 288 since each student was taking the test. This amount is sufficient for our study. The training and testing of students were carried out using the Moodle system.

The total volume of the test base included 30 tasks. For testing, all tasks first underwent preliminary processing – assessment of difficulty.

The difficulty of tasks was determined by expert assessment. The role of the expert was performed by a teacher, which is justified by the relatively small number of tasks.

The proposed procedure of adaptive testing employed a multi-step strategy. In this testing strategy, the next task was chosen from the bank based on the results of the previous two tasks accounting for their difficulty.

The tasks in the adaptive test were close-ended questions with a choice of one of four options. At each stage of testing, the student was presented with two tasks of each difficulty level, based on which the difficulty of further tasks was determined. This number of questions (two) ensured a more accurate assessment of knowledge than just one task, while also keeping the number of combinations of answer choices not too high, in contrast to three or more tasks.

The algorithm operates as follows: The test contains *m* levels of task difficulty (in this study, there were three levels). A coefficient, Ki = 100/m, is then calculated. In the subsequent stage, the student's current knowledge level is represented by *t*, with t_n indicating the minimum knowledge level and *tv* representing the maximum. Knowledge levels are assigned values ranging from 0 (no knowledge) to 100 (complete knowledge).

First, we assume the student to have an average level of training. Thus, we set t=50, t_n=0, and t_v=100. The current difficulty level is calculated as *tt=t/Ki*.

At the next stage, the student is presented with two tasks at the difficulty level of *tt,* and the number of correct answers k_{pr} is monitored.

The level of knowledge is recalculated based on responses to the first two tasks:

If k_{pr}=2, then $t_n=t$; $t_v=t_v+0.5t$. If $t_v>100$, then t_v=100.

If k_{pr}=1, then $t_n=t_n/4$; $t_v=t_v+0.1t$. If $t_v>100$, then t_v=v100.

If k_{pr}=0, then $t_n=t_n/2$; $t_v=t$.

Calculating $t_v=(t_n+t_v)/2$.

If $|t–t_v|>0$, then $t=t_1$.

If the critical level of the number of tasks or points for a task is reached, the level of knowledge equals t_j. End.

Otherwise, proceed to the second step.

Learning success was determined by the following formula: number of "excellent" grades + number of "good" grades x 0.64 + number of "satisfactory" grades x 0.36 + number of "passing" grades x 0.16 + number of "not passing" grades x 0.08 x 100%/total number of students.

The results of the pedagogical experiment were subsequently analyzed using mathematical and statistical methods. Specifically, Pearson's χ^2 test was applied to detect differences in the distribution of learning success between two empirical groups. The data was categorized into two groups: "successful" and "not successful," resulting in one degree of freedom (v=1).

The null hypothesis H0: there was no significant difference in learning success between the control group (CG) and the experimental group (EG).

Alternative hypothesis H1: a significant difference did exist between the control group (CG) and the experimental group (EG).

4. Results

The test results were presented in binary form in a table. The table data served as input information for the second step of adaptation – estimation of test questions difficulty (Table 2).

Table 2. Results of ANN operation

Difficulty rating	Question number														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1		+		+										+	
0	+		+		+	+	+	+	+	+	+	+	+		+
-1															
	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1					+										
0	+	+	+	+		+	+	+	+		+	+	+	+	+
-1										+					

The system deems it necessary to raise the difficulty of items 2, 4, 14, and 20 and decrease the difficulty of task 25. The remaining test tasks do not need alterations.

This information was reviewed by the expert (teacher) for analysis and further decisions.

The next stage of processing the test results was to provide recommendations on changing the number of academic hours for individual topics in the discipline.

Let us consider the results of the student success assessment.

Before the implementation of adaptive testing using ANN, the success rate of EG and CG students in the previous semester was analyzed. The groups were found to be close in initial success rates (76 and 73 %, respectively). After the adaptive testing was completed, the overall knowledge quality level in the EG and CG in the considered discipline amounted to 89 and 75 %, respectively (Table 3).

Table 3. Comparative analysis of learning success in the EG and CG

No.	Group	Number of students	Learning success, %	
			Last semester	Current semester
1	CG	141	73 %	75 %
2	EG	147	76 %	89 %

Table 3 shows that the pedagogical impact amounted to an 11 % improvement in the EG compared to a 2 % improvement in the CG, supporting the effectiveness of adaptive testing using ANN.

From the table of values of $\chi 2$ for the significance level of $\alpha=0.05$ and $v=1$ degrees of freedom, we find that the critical value of $\chi 2_{crit}=3.841$. Since before the pedagogical experiment the calculated value $\chi 2<\chi 2_{crit}$ (0.104<3.841), i.e., does not fall in the critical range. This indicates that at the beginning of the experiment, there was no significant difference in learning success between the CG and EG.

Analyzing Pearson's $\chi 2$ for the CG and EG after the pedagogical experiment, we find that $\chi 2>\chi 2_{crit}$ (5.724>3.841). This leads to the rejection of the null hypothesis (H_0) and acceptance of the alternative hypothesis (H_1), confirming statistically significant differences between the two groups.

Since the EG students participated in adaptive testing using ANN, it can be concluded that this was the primary factor contributing to their higher learning success. Thus, the experimental hypothesis is supported by the results.

5. Discussion

As a result of adaptive testing, ANN provided the developers of educational materials with information on the initial difficulty level of each task and recommendations on adjusting it (increase, leave unchanged, or lower).

Indeed, if adaptive testing reveals students' general lack of understanding of a course topic, the teacher needs to spend more time and pay greater attention to covering this topic in future training. The practical implementation of systems that adjust educational content and teaching methods based on students' knowledge, as measured through adaptive testing, encounters significant challenges. Chief among these is the need to process and analyze vast amounts of data in real time, as the system must continuously adjust to individual learning needs. Handling these large information flows efficiently is a complex task, but it can be effectively managed through the use of artificial neural networks (ANN), which have the capacity to process and analyze large datasets with high accuracy and speed (Chumakova et al., 2022). ANN offers a scalable solution to the complexities of adaptive testing, allowing for dynamic adjustments that personalize the learning experience for each student.

Initial assessments to feed into the adaptive testing process can be derived from several sources. These may include results from preliminary tests, data gathered from tests administered over a defined period, or even a learning model of the subject matter, if such a model is integrated into the system (Gorshkova et al., 2021). By utilizing these varied data points, the system can build an accurate profile of a student's current understanding, enabling more precise and personalized testing from the outset. This preparatory data gathering helps to ensure that the adaptive test is appropriately challenging and effectively targets areas where the student requires further learning or reinforcement.

In addition to improving the precision of testing, such systems also offer the potential to revolutionize instructional methodologies by providing real-time feedback on student performance, allowing educators to modify instructional strategies and content delivery based on the individual needs of learners. This continuous feedback loop enhances the learning process, making it more responsive and efficient.

Importantly, the proper operation of ANN depends on the appropriateness of the chosen ANN model and training algorithm. If the algorithm is chosen improperly, the ANN will not be able to learn from test results correctly (Syzdykova et al., 2022; Uralbaeva et al., 2023), therefore, no improvement of the adaptive test will be achieved (Chirkov et al., 2022; Goyushova, Kapustina, 2022).

One limitation of the study is the use of pre-existing academic groups to assign participants to the control and experimental groups, which may have introduced selection bias. Without full randomization, the comparability between groups may be affected, potentially influencing the generalizability of the results. Additionally, this convenience sampling method may limit the ability to rule out other variables impacting students' performance.

A prospect for further research is the analysis of prospective uses of adaptive knowledge testing utilizing ANN.

6. Conclusion

The idea of adaptive testing based on a block of questions is directly connected with one of the most common multi-stage testing formats, in which the learning subject passes through a sequence of tests, proceeding to more difficult questions if they answer correctly or to simpler ones if the answers are wrong. The transition to the next question is subject to certain rules. The automation in the practice of testing enables statistical assessment of knowledge at each step in the test.

Different levels of difficulty of the basic and additional questions and the proposed connection between the main questions and the branches of additional questions allow minimizing the number of answers needed to determine the student's level of knowledge and significantly improve the adaptive properties of testing.

Statistical methods addressing additional indicators in tests can also be used to process test results and to account for additional factors affecting these results. Among such useful indicators are the percentage of correct and wrong answers, relative success of students in one topic compared to other topics in the course, distribution of students' knowledge across all topics, average level of training in the group, etc.

References

Ang et al., 2022 – *Ang, K.M., Lim, W.H., Tiang, S.S., Ang, C.K., Natarajan, E., Ahamed Khan, M.K.A.* (2022). Optimal training of feedforward neural networks using teaching-learning-based optimization with modified learning phases. In Lecture notes in electrical engineering. Vol. 770. *Proceedings of the 12th National Technical Seminar on Unmanned System Technology 2020* (pp. 867-887). Singapore: Springer. DOI: 10.1007/978-981-16-2406-3_65

Astuti et al., 2023 – *Astuti, I.A.D., Bhakti, Y.B., Prasetya, R., Zulherman, Z.* (2023). Android-based 4-tier physics test app to identify student misconception profiles. *International Journal of Evaluation and Research in Education*. 12(3): 1356-1363. DOI: 10.11591/ijere.v12i3.25536

Babina et al., 2022 – *Babina, A., Berezuev, E., Artamonova, M., Utusikov, S.* (2022). Socio-psychological adaptation of students when choosing the direction of general physical training in the educational and training process. *Nuances: Estudos Sobre Educação*. 33(00): e022025. DOI: 10.32930/nuances.v33i00.9747

Belenkova et al., 2022 – *Belenkova, L.Y., Skudnyakova, Y.V., Bosov, D.V.* (2022). La pedagogía digital en el sistema de educación superior inclusiva [Digital pedagogy in the system of inclusive higher education]. *Interacción y Perspectiva*. 12(1): 27-42. [in Spanish]

Chirkov et al., 2022 – *Chirkov, D., Plohih, G., Kapustina, D., Vasyukov, V.* (2022). Opportunities for using dugutal data in evidence for criminal cases. *Revista Juridica*. 4(71): 364-380.

Chumakova et al., 2022 – *Chumakova, E.V., Korneev, D.G., Gasparian, M.S.* (2022). Razrabotka metoda adaptivnogo testirovaniia na osnove neirotekhnologii [Development of adaptive testing method based on neurotechnologies]. *Open Education*. 26(2): 4-13. DOI: 10.21686/1818-4243-2022-2-4-13 [in Russian]

Denisova et al., 2023 – *Denisova, D., Strandstrem, E., Akhmetshin, E., Nikolenko, D.* (2023). Efficiency of various forms of simulation training in the training of medical professionals. *European Journal of Contemporary Education*. 12(3): 788-796. DOI: 10.13187/ejced.2023.3.788

Efremova et al., 2022 – *Efremova, P., Romanova, I., Belkin, V., Vasilyeva, L.* (2022). Indicators for assessment of the development of a university's innovative activity as a factor in its competitiveness in the national and international markets. *Nuances: Estudos Sobre Educação*. 33(00): e022022. DOI: 10.32930/nuances.v33i00.9623

Frey et al., 2016 – *Frey, A., Seitz, N.-N., Brandt, S.* (2016). Testlet-based multidimensional adaptive testing. *Frontiers in Psychology*. 7: 1758. DOI: 10.3389/fpsyg.2016.01758

Gabidullina et al., 2023 – *Gabidullina, F., Nikiforova, N., Afanasyeva, I., Zharov, A.* (2023). Improvement of the learning process: The experience of introducing a cumulative system in assessing student learning success in distance learning. *European Journal of Contemporary Education*. 12(4): 1223-1230. DOI: 10.13187/ejced.2023.4.1223

Gagarin, 2023 – *Gagarin, A.P.* (2023). Monitoring and control of the program comprehension teaching in a computer class environment. *Perspectives of Science and Education*. 61(1): 482-504. DOI: 10.32744/pse.2023.1.29

Gorlova et al., 2023 – *Gorlova, O., Laamarti, Y., Butyrin, A.* (2023). Impact of educational games in the learning process on the development of students' professional and economic competence. *Revista Conrado*. 19(S1): 166-170.

Gorshkova et al., 2021 – *Gorshkova, K., Tugashova, L., Zueva, V., Kuznetsova, M.* (2021). Optimizing deep learning methods in neural network architectures. *International Review of Automatic Control*. 14(2): 93-101. DOI: 10.15866/ireaco.v14i2.20591

Goyushova, Kapustina, 2022 – *Goyushova, L., Kapustina, D.* (2022). Adaptation problems during the transition to distance foreign language learning of technical university students. *AIP Conference Proceedings*. 2647: 040025. DOI: 10.1063/5.0104288

Isaeva et al., 2023 – *Isaeva, G., Omuralieva, A., Bekboeva, R., Asan Uulu, T., Kalmatov, R.* (2023). Strategies for the development of Higher Education in the Kyrgyz Republic: Digitalization and integration of science and education. *Revista Conrado*. 19(94): 95-100.

Kurgansky, 2022 – *Kurgansky, S.I., Kovalenko, E.V., Sokolova, O.A.* (2022). Cooperación de sujetos en formación como base metodológica para enriquecer la experiencia de la interacción social en los jóvenes estudiantes [Cooperation of training individuals as a methodological basis for enriching the experience of social interaction in young students]. *Interacción y Perspectiva*. 13(1): 39-49.

Lykova et al., 2023 – *Lykova, I., Mayer, A., Shestakova, O., Voinova, A.* (2023). Desenvolvimento de um complexo diagnóstico para o estudo das tradições de educação familiar [Developing a diagnostic complex for the study of family upbringing traditions]. *Revista on line de Política e Gestão Educacional*. 27(00): e023068. DOI: 10.22633/rpge.v27i00.18802

Musah et al., 2022 – *Musah, M.B., Tahir, L.M., Al-Hudawi, S.H., Issah, M., Hussein, A.R., Ibrahim, M.* (2022). Testing content validity of teacher-made test: Profiling teacher perceptions and demographic variables. *International Journal of Evaluation and Research in Education*. 11(2): 878-887. DOI: 10.11591/ijere.v11i2.21992

Nikolaeva et al., 2023 – *Nikolaeva, E., Kotliar, P., Nikolaev, M.* (2023). Revisiting traditional educational practices in the age of digitalization. *Revista on Line Política e Gestão Educacional*. 27(00): e023057. DOI: 10.22633/rpge.v27i00.18527

Pominov et al., 2020 – *Pominov, D.A., Kuravsky, L.S., Dumin, P.N., Yuriev, G.A.* (2020). Adaptive trainer for preparing students for mathematical exams. *International Journal of Advanced Research in Engineering and Technology*. 11(11): 260-268.

Sergeeva et al., 2022 – *Sergeeva, M.G., Yakovleva, E.V., Nikashina, N.V., Blinova, S.A.* (2022). Preparação de futuros gestores de educação para atividades profissionais [Preparation of future education managers for professional activities]. *Revista on line de Política e Gestão Educacional*. 26(esp.2): e022068. DOI: 10.22633/rpge.v26iesp.2.16566

Syzdykova et al., 2022 – *Syzdykova, M.B., Bimakhanov, T.D., Fursova, V.V., Makhambetova, M.A., Abikenov, Z.O.* (2022). Position of higher education system graduates in the labor market: Search for new opportunities. *Academic Journal of Interdisciplinary Studies*. 11(3): 50-59. DOI: 10.36941/ajis-2022-0067

Tolmachev et al., 2022 – *Tolmachev, M., Korotaeva, I., Zharov, A., Beloglazova, L.* (2022) Development of students' digital competence when using the "Oracle" electronic portal. *European Journal of Contemporary Education*. 11(4): 1261-1270. DOI: 10.13187/ejced.2022.4.1261

Tretyakova et al., 2023 – *Tretyakova, G., Arutyunian, V., Ginzburg, O., Azarova, O., Belozerova, E.* (2023). Formation of the speech competence in students – future economists to the level of independent English proficiency (B2). *Perspectives of Science and Education*. 63(3): 253-270. DOI: 10.32744/pse.2023.3.16

Uralbaeva et al., 2023 – *Uralbaeva, S., Rakimzhanova, S., Malikova, A., Abdimaulen, G*. (2023). Reconstructing the European experience of eloquence in the context of pedagogical rhetoric: Philosophical research and cultural studies. *Academic Journal of Interdisciplinary Studies*. 12(2): 273-281. DOI: 10.36941/ajis-2023-0048

Uteuliyev et al., 2023 – *Uteuliyev, N., Madiyarov, N., Drobyshev, Y., Azhibekov, K*. (2023). Assessment of the readiness of future mathematics teachers to use digital educational resources in the study of geometry in Kazakh Universities. *European Journal of Contemporary Education*. 12(2): 667-677. DOI: 10.13187/ejced.2023.2.667

Voskresensky et al., 2023 – *Voskresensky, A., Stetsko, A., Chistaleva, T*. (2023). Artificial intelligence in the system of higher education in modern Russia and the states of the former USSR. *Revista Conrado*. 19(S3): 41-47.

Zhang et al., 2019 – *Zhang, Y., Wang, D., Gao, X., Cai, Y., Tu, D*. (2019). Development of a computerized adaptive testing for Internet addiction. Frontiers in Psychology. 10: 1010. DOI: 10.3389/fpsyg.2019.01010