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OPPORTUNITIES TO IMPROVE THE QUALITY OF STUDENT LEARNING THROUGH ADAPTIVE KNOWLEDGE TESTING USING GOOGLE FORMS

OPORTUNIDADES PARA MEJORAR LA CALIDAD DEL APRENDIZAJE ESTUDIANTIL MEDIANTE PRUEBAS DE CONOCIMIENTO ADAPTATIVAS CON

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ABSTRACT

The aim of the article is to analyze the feasibility of applying adaptive knowledge testing for philology students using the electronic system Google Forms. The study employed methods such as analysis of scientific and methodological literature, case studies, and a pedagogical experiment. The focus was placed on comparing the results of adaptive testing using Google Forms in the experimental group with traditional testing conducted via the Moodle system in the control group. The analysis involved the use of Pearson's chi-squared test (χ^2) to identify statistically significant differences in student learning success. The article highlights the importance of adaptive testing in the educational process and substantiates the requirements for preparing adaptive tests. The results of the pedagogical experiment confirmed the research hypothesis that the use of adaptive knowledge testing via Google Forms significantly improves the quality of student learning. It is concluded that adaptive testing is an important and effective tool in the educational process, helping to better assess the knowledge and skills of students.

Keywords:

Adaptive testing, Google Forms, Adaptive test, Students, Teachers, Learning success.

RESUMEN

El objetivo del artículo es analizar la viabilidad de aplicar pruebas adaptativas de conocimiento a estudiantes de filología mediante el sistema electrónico Formularios de Google. El estudio empleó métodos como el análisis de literatura científica y metodológica, estudios de caso y un experimento pedagógico. El enfoque se centró en comparar los resultados de las pruebas adaptativas con Formularios de Google en el grupo experimental con las pruebas tradicionales realizadas a través del sistema Moodle en el grupo de control. El análisis incluyó el uso de la prueba chi-cuadrado de Pearson (χ^2) para identificar diferencias estadísticamente significativas en el éxito del aprendizaje estudiantil. El artículo destaca la importancia de las pruebas adaptativas en el proceso educativo y fundamenta los requisitos para su elaboración.

Los resultados del experimento pedagógico confirmaron la hipótesis de investigación de que el uso de pruebas adaptativas de conocimiento a través de Formularios de Google mejora significativamente la calidad del aprendizaje estudiantil. Se concluye que las pruebas adaptativas son una herramienta importante y eficaz en el proceso educativo, que ayuda a evaluar mejor los conocimientos y las habilidades del alumnado.

Palabras clave:

Pruebas adaptativas, Formularios de Google, Prueba adaptativa, Alumnos, Profesores, Éxito del aprendizaje.

INTRODUCTION

Adaptive testing (hereinafter referred to as AT) is a relevant approach to assessment in higher education, characterized by its flexibility and ability to respond to the individual needs of students. Its core concept lies in the real-time modification of tests based on each student's responses (Tomashev et al., 2018). This approach offers numerous advantages, enabling more accurate evaluation of students' knowledge, the development of effective learning programs, and an increase in student interest and motivation.

The work by Moreira-Segovia & Zambrano-Barros (2025) provides a set of key theoretical and pedagogical foundations that strengthen academic coherence and support the interpretation of the results obtained through adaptive assessment using Google Forms.

First, the authors offer a solid conceptual framework on knowledge management in educational contexts, emphasizing that high-quality learning depends on the institutional capacity to organize, transfer, and strategically use knowledge. This perspective directly supports the approach of the article, as adaptive assessment is presented as an effective mechanism for managing relevant information on student performance and transforming it into input for improving learning outcomes.

Likewise, the work emphasizes the importance of efficient educational management oriented toward evidence-based decision making, which aligns with the use of digital assessment tools that allow for the systematic collection, analysis, and comparison of results. In this regard, the comparison between Google Forms and Moodle conducted in the study finds theoretical support in the idea that assessment instruments should actively contribute to the improvement of educational processes rather than being limited to the traditional measurement of performance.

Another relevant contribution of the work is its defense of personalized learning as a core axis of educational innovation, an aspect that is directly linked to adaptive testing. Assessment adjusted to the student's level and progress, as analyzed in the article, responds to the need to address the diversity of learning paces and styles, a principle widely developed by the authors within the framework of quality-oriented educational action.

Finally, the source helps to reinforce the pedagogical validity of the experimental results by emphasizing that learning quality increases when there is coherence among educational objectives, assessment methods, and the technological tools used. In this way, Moreira-Segovia & Zambrano-Barros (2025) provide theoretical support for the article's conclusion by considering adaptive assessment not only as a technical innovation but also as a comprehensive strategy to improve student learning success in higher education.

At the same time, educators face several significant challenges when implementing adaptive testing (AT). One of the main difficulties lies in determining an appropriate level of test difficulty, especially when working with large and heterogeneous student groups that exhibit wide variations in knowledge and skills.

This requires the development of systems capable of automatically adjusting to students' evolving performance levels during the testing process. In addition, notable technical challenges emerge in the design of adaptive tests, as their implementation demands substantial resources, including an extensive pool of test items, reliable response-processing mechanisms, and adequate technological infrastructure to ensure valid and secure testing procedures (Koliada et al., 2020). Another critical issue concerns the need to create a large volume of test questions across multiple difficulty levels, a task that is highly time-consuming and places a considerable workload on instructors (Yavorskiy et al., 2017).

Furthermore, test item databases must be regularly updated to reflect changes in academic curricula and learning objectives, which entails continuous revision and maintenance efforts (Zhuang et al., 2022). The implementation of AT also generates large datasets that require careful and systematic analysis in order to ensure accurate interpretation of results and meaningful pedagogical feedback (Wulandari et al., 2020). Finally, there is a potential risk of overemphasizing adaptive testing at the expense of other teaching and assessment methods, as excessive focus on testing may limit opportunities for fostering critical thinking, creativity, and other essential dimensions of the learning process.

These factors demand considerable practical effort. However, research in this area can contribute to improving the quality of education and expanding the possibilities for individualized learning. Furthermore, AT is aimed at enhancing the efficiency and validity of educational outcome assessments, as well as student skills, thereby supporting a better understanding of their needs and capabilities.

The issue of adaptive testing (AT) in higher education has been the focus of numerous studies aimed at exploring the effectiveness of AT and identifying potential problems and challenges associated with its implementation.

A significant number of scholarly works devoted to the development of methodological foundations for AT include the creation of algorithms for question selection, models for response evaluation, and systems for data processing (Tagirova & Zubkova, 2023). However, researchers continue to search for ways to achieve more accurate assessments and are developing methods to prevent the underestimation or overestimation of students' knowledge levels in AT (Wang & Kingston, 2019).

Another line of research focuses on identifying effective strategies for integrating AT into higher education practice. This includes issues related to the development of technical infrastructure (Lin et al., 2018), teacher training (Rodríguez et al., 2023), updating question databases (Eggen, 2018), and the interpretation and use of test results.

Despite the substantial body of existing research, certain aspects of the problem still require further investigation. One such study is presented in (Frey et al., 2016), where the focus is on examining the impact of AT on student motivation. The authors hypothesize that adaptive tests, which better match students' knowledge levels, can enhance their motivation to learn.

Another study (Kimura, 2017) explores the potential of AT for assessing students' cognitive abilities, opening up new prospects for using AT from the perspective of learning psychology. Study (Istiyono et al., 2020) examines the influence of AT on educational inequality and sheds light on how adaptive testing may affect equal learning opportunities. Researchers in (Flens et al., 2016) propose a new approach called "feedback-based adaptive testing," which involves using student feedback to adjust the test in real time.

According to the authors Oppl et al. (2017) investigated the use of AT in the context of online learning. Their work highlights how adaptive testing can support remote education while also revealing various challenges students may face when using this method in an online environment.

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Adaptive testing (AT) is a computer-based method of assessing learning outcomes that adjusts to the abilities of each individual student during the testing process. This technology creates personalized versions of the test based on the student's previous answers, allowing for a more accurate assessment of knowledge and skills than traditional methods.

First and foremost, an adaptive test must include a large number of questions of varying difficulty, covering the entire spectrum of assessed competencies or knowledge. A broad question pool is necessary to provide the system with enough options to select the next question based on the student's previous responses. In addition, each question must be clearly defined in terms of its difficulty level (Bezrukov & Akimova, 2023). This requires prior testing of the questions on a student sample to determine their level of difficulty and to ensure they are valid and reliable indicators of the knowledge they are intended to measure.

Student feedback is also an essential element of the AT process, as it helps improve the testing procedure and content, contributing to better understanding and student engagement. A scientific approach to evaluating student feedback is based on several key principles: first, it is important to develop clear and consistent criteria for evaluating feedback. These criteria may include factors such as the completeness of the response, its relevance to the test content, constructiveness, and objectivity; second, it is necessary to consider the context in which the feedback is provided (Chrysafiadi et al., 2018).

Special attention must be paid to differentiating question difficulty levels, their relevance to the learning context, and their alignment with broader educational goals. It is also important to take into account curriculum changes, new teaching methods, or learning technologies that may affect the relevance or validity of the test, which in turn requires revisiting the test's structure and format.

Let us outline the approaches to creating an adaptive test in Google Forms. This involves preparing several question sections. Each section should include questions corresponding to a certain difficulty level. The form can be configured to transition between sections based on the student's answers. For example, if a student answers correctly in one section, they can be directed to a section with more difficult questions. If the answer is incorrect, they may be redirected to a section with easier questions or be provided with additional study materials.

Google Forms also allows automatic grading of answers and providing immediate feedback. This is beneficial for students, as they can instantly see their results. It also relieves teachers from the need to manually grade tests. The use of Google Forms for AT can make the assessment process more personalized and efficient, as it better addresses individual student needs and knowledge levels (Medina-Díaz & Verdejo-Carrión, 2020).

Using the drop-down menu for question types in Google Forms, instructors can choose various formats such as short or long text responses (for open-ended questions), multiple choice (single or multiple answers), drop-down lists, and linear scales (used to rate responses on a specified scale) (Noroozi et al., 2023).

To create an AT system in Google Forms, different levels of question difficulty must be considered. According to Bloom's taxonomy, these levels can be categorized into three main types: easy, medium, and difficult.

The easy level typically focuses on assessing basic knowledge and understanding of the course material. Questions at this level involve recalling facts, listing items, defining terms, or explaining basic concepts.

The medium level requires a deeper understanding of the material and the ability to analyze information. These questions may involve comparing and contrasting ideas, explaining cause-and-effect relationships, or analyzing data.

The high level demands a demonstration of advanced critical thinking skills, including evaluation, synthesis, and the application of knowledge in new contexts. It is important to note that question difficulty levels are not necessarily tied to how complicated a question appears, but rather to the depth of cognitive processing it requires.

One particularly relevant issue in this context is selecting the appropriate difficulty level for the first question. Like most researchers, we support starting adaptive testing with a medium-difficulty question, which has several scientific justifications. First, it is efficient: starting at a medium level allows for a quick approximation of the student's knowledge level, optimizing the testing process and making it easier to deliver relevant questions. Second, it saves time: the system can quickly narrow down the possible knowledge range, reducing the overall testing time. Third, it increases accuracy: adaptive tests that begin with medium-difficulty questions tend to yield more precise assessments of student knowledge compared to those that start with either easy or difficult questions

Based on the above, the aim of this article is to analyze the feasibility of using adaptive knowledge testing for philology students through the Google Forms electronic system. This aim allows us to formulate the following research objectives:

- To justify the requirements for preparing adaptive tests;
- To describe approaches for creating an adaptive test in Google Forms;
- To conduct an experimental study on the effectiveness of learning outcomes among philology students using AT in the Google Forms platform.

Research hypothesis: The use of adaptive testing through Google Forms in philology education significantly improves the quality of student learning.

MATERIALS AND METHODS

To achieve the stated objective, the authors employed a range of methods, most notably the analysis of scientific and methodological literature, case study analysis, and a pedagogical experiment.

The literature review focused on an in-depth study of academic works related to the research subject in order to determine the current state of the problem, identify unresolved issues, and outline directions for future research.

The case study method was used to examine a specific case—the potential use of Google Forms—within the context of the study.

The primary method employed was a pedagogical experiment, which was conducted during the second semester of the 2023–2024 academic year. A total of 152 second- and third-year students participated in the experiment. They were divided into an experimental group (EG, 75 students) and a control group (CG, 77 students), based on their existing academic group assignments.

To measure students' knowledge using adaptive testing via Google Forms, the following procedure was implemented:

- a system of tests at varying difficulty levels was developed for a selected academic subject;
- the tests were uploaded to Google Forms and configured in accordance with adaptive testing requirements;
- testing was conducted using Google Forms, followed by processing and interpretation of the results.

At the organizational stage of the study, a course taught to philology students was selected. The total number of test results amounted to 152, as each student in both EG and CG completed the test. Traditional testing for the CG was conducted using the Moodle system, while the EG underwent adaptive testing via Google Forms.

The full test included 30 items (31 items for EG), with 10 questions at each difficulty level (easy, medium, and hard), where the point value varied according to difficulty. The scoring system was based on a 100-point scale: 2 points for easy questions, 3 points for medium, and 5 points for hard, which together totaled 100 points.

For the adaptive testing in the EG, one additional, non-scored question was included at the beginning to determine the initial difficulty level. Ideally, this question was designed to assess logical thinking. Thus, the number of medium-level questions was 11 instead of 10.

To ensure proper functioning of adaptive testing in Google Forms, each question was placed in a separate section containing only that one question. After answering the first question, the system guided the student along a pre-set path determined by the instructor. A correct answer would lead the student to the next question at a higher difficulty level, while an incorrect answer would lead to an easier question or additional learning material. The algorithm was structured so that after a brief introduction, students were directed to the first question at the medium difficulty level, followed by either an easy or hard question depending on the response.

The results of the pedagogical experiment were processed using methods of mathematical statistics to identify differences in the distribution of a specific indicator—learning success—by comparing two empirical distributions. For this, Pearson's chi-squared test (χ^2) was applied. The measurement scale consisted of two categories: "successful" and "unsuccessful," with the degrees of freedom calculated as v = 1.

A score of 70 or more points was considered indicative of successful learning.

The null hypothesis (H_0): there are no differences in learning success between the CG and the EG. The alternative hypothesis (H_1): there are significant differences in learning success between the CG and the EG.

RESULTS AND DISCUSSION

Let us examine the results of evaluating student learning success.

Before the implementation of adaptive testing using Google Forms, an analysis was conducted to assess the academic performance of the experimental group (EG) and the control group (CG) in the previous semester. The findings showed that both groups had similar levels of success—66% for EG and 68% for CG. After completing the adaptive testing, the overall quality level in terms of pass rates in the subject showed results of 87% for EG and 76% for CG (see Table 1).

Table 1. Comparative analysis of learning success in EG and CG.

No.	Group	Number of Students	Learning Success (%)	
			Previous Semester	Current Semester
1	CG	77	68%	72%
2	EG	75	66%	83%

As shown in Table 1, the pedagogical effect amounted to 17% in the experimental group and 4% in the control group, which confirms the pedagogical effectiveness of adaptive testing using Google Forms.

According to the chi-squared distribution table for a significance level of α = 0.05 and 1 degree of freedom (v = 1), the critical value is χ^2_crit = 3.841. Since before the pedagogical experiment the calculated value χ^2 < χ^2_crit (1.242 < 3.841), it does not fall into the critical region, indicating that there was no significant difference in academic success between the EG and CG at the beginning of the experiment.

After the pedagogical experiment, the calculated chi-squared value showed that χ^2 > χ^2_crit (19.342 > 3.841). This provides grounds for rejecting the null hypothesis (H_0) and accepting the alternative hypothesis (H_1), thus confirming the existence of statistically significant differences in learning success between the two groups.

Given that the experimental group underwent adaptive testing using Google Forms, it can be concluded that this factor contributed to the higher level of academic success among EG students. Therefore, the research hypothesis has been experimentally confirmed.

Thus, the results of the pedagogical experiment demonstrated that the Google Forms electronic system offers a wide range of opportunities for adaptive testing (AT), allowing educators to easily create and manage tests, as well as process the results (Noroozi et al., 2023). Google Forms is user-friendly, with an intuitive interface that enables teachers to quickly design tests and students to complete them with ease. The platform includes built-in analytical tools that allow for rapid analysis of test results, including automatic grading and point allocation.

Google Forms also has integrated capabilities for adaptive testing. For instance, it supports response-based branching logic, which allows students to be automatically directed to specific questions depending on their previous answers (Chrysafiadi et al., 2018). To prevent cheating during testing, it's possible to set restrictions on the number of attempts and the time allowed to complete the test.

In adaptive testing, it is essential to maintain logical structure that enables automatic navigation of students to specific questions or sections based on their responses. This feature is a crucial component of AT, as it helps tailor the test to each student's needs based on their prior performance. Creating branching logic based on answers involves several steps.

First, a new form with multiple sections must be created, where each section may contain one or more questions. Each section can be seen as a separate "path" within the test. Second, each question needs to be configured so that the student's response determines which path they follow. To do this, the instructor selects a question to act as a branching point. Then, for each possible response, the teacher selects which section the form will direct the student to (Zhuang et al., 2022). This enables transitions between questions from easier to more difficult levels. It is recommended to label each section and question with a number to simplify navigation.

Regarding the distribution of the test, Google Forms offers several options. The first is to generate a link to the form, which can be sent via email or through any messaging service. The second is to embed the form directly into the university's website.

It is also important to manage form access settings. The teacher can either allow access to all students or restrict it to specific groups. Additionally, it should be monitored whether students are allowed to complete the form multiple times or only once.

Google Forms provides convenient tools for analyzing student responses and displaying test results. After testing is complete, instructors can access general response statistics as well as detailed individual results. It's possible to view how many students selected each answer and in what percentages. This helps identify which questions posed the greatest difficulty, or which topics may need further explanation or revision (Oppl et al., 2017). Moreover, instructors can review each student's individual responses to assess their level of understanding and identify areas where additional support may be needed (Lin et al., 2018). This not only enables quick and efficient assessment of test results, but also helps reveal knowledge gaps among students.

CONCLUSIONS

Adaptive testing is an important and effective tool in the educational process, helping to more accurately determine students' levels of knowledge and skills. Its core principle is the dynamic selection of questions based on students' previous responses. The process of adaptive testing involves many components, including question development and evaluation, determining difficulty parameters, collecting and analyzing student feedback, as well as regularly reviewing and updating test content. The main goal of adaptive testing is to provide a more precise and individualized assessment of students' competencies.

In the educational context, adaptive testing serves as a critically important instrument that requires in-depth analysis and the creation of accurate difficulty parameters. These parameters should be based on real performance data rather than only theoretical expectations for the questions. By incorporating student feedback, the testing process can be continually improved to meet students' current needs and align with the curriculum. It is essential to consider differentiation in task difficulty, relevance to the learning context, and alignment with overarching educational goals. Thus, adaptive testing is a highly valuable means of enhancing the quality of higher education. A key part of the adaptive testing process is the development of high-quality tests that require a large number of well-prepared questions at various difficulty levels.

The pedagogical experiment identified several key advantages of Google Forms, which proved to be a flexible and effective tool for creating tests with varying levels of difficulty. This platform offers a wide range of response types and customization options, including single choice, multiple choice, and text-based answers. Of particular value is the response-based branching logic, which automates the routing of students through different test sections depending on their previous answers—an especially useful feature for implementing adaptive testing. The automatic grading of student responses in Google Forms reduces the workload for instructors and simplifies the assessment process. Additionally, using Google Forms to analyze student responses enables instructors to identify knowledge gaps and adapt the learning process to better meet students' needs.

In light of the above, Google Forms can be a highly effective tool for organizing adaptive testing in higher education, provided its capabilities are used correctly. With the ongoing advancement of technology, further improvements in the adaptive testing process can be expected in the future, including the integration of artificial intelligence and big data analytics.

REFERENCES

Bezrukov, A. I. & Akimova, S. A. (2023). Modelirovaniye adaptivnogo testa po rezul'tatam klassicheskogo testirovaniya. ***Modern Information Technologies and IT Education, 19***(2), 498–507. https://doi.org/10.25559/SITITO.019.202302.498-507

Chrysafiadi, K., Troussas, C., & Virvou, M. (2018). A framework for creating automated online adaptive tests using multiple-criteria decision analysis. ***2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC)***. Miyazaki, Japan.

Eggen, T. J. H. M. (2018). Multi-segment computerized adaptive testing for educational testing purposes. ***Frontiers in Education, 3***, 111. https://doi.org/10.3389/feduc.2018.00111

Flens, G., Smits, N., Carlier, I., van Hemert, A. M., & de Beurs, E. (2016). Simulating computer adaptive testing with the Mood and Anxiety Symptom Questionnaire. Psychological Assessment, 28(8), 953–962. https://doi.org/10.1037/pas0000240

Frey, A., Seitz, N.-N., & Brandt, S. (2016). Testlet-based multidimensional adaptive testing. ***Frontiers in Psychology, 7***, 1758. https://doi.org/10.3389/fpsyg.2016.01758

Istiyono, E., Dwandaru, W., Setiawan, R., & Megawati, I. (2020). Developing computerized adaptive testing to measure physics higher-order thinking skills of senior high school students and its feasibility of use. ***European Journal of Educational Research, 9***(1), 91–101. https://doi.org/10.12973/eu-jer.9.1.91

Kimura, T. (2017). The impacts of computer adaptive testing from a variety of perspectives. ***Journal of educational evaluation for health professions***, ***14***, 12. https://doi.org/10.3352/jeehp.2017.14.12

Koliada, M., Bugayova, T., & Miklashevich, N. (2020). Intelligent testing systems based on adaptive algorithms. ***CEUR Workshop Proceedings***, 2770, 172–186. https://ceur-ws.org/Vol-2770/paper21.pdf

Lin, G.-H., Huang, Y.-J., Lee, Sh.-Ch., Huang, Sh.-L., & Hsieh, Ch.-L. (2018). Development of a computerized adaptive testing system for functional assessment of stroke. ***Archives of Physical Medicine and Rehabilitation, 99***(4), 676–683. https://doi.org/10.1016/j.apmr.2017.09.116

Medina-Díaz, M. D. R., & Verdejo-Carrión, A. L. (2020). Validez y confiabilidad en la evaluación del aprendizaje mediante las metodologías activas. ALTERIDAD. ***Revista de Educación, 15***(2), 270–284. https://doi.org/10.17163/alt.v15n2.2020.10

Moreira-Segovia, R. V. & Zambrano-Barros, N. A. (2025). ***Cultura, conocimiento y acción: hacia una gestión educativa eficiente***. Sophia Editions.

Noroozi, O., Banihashem, S. K., Biemans, H. J., Smits, M., Vervoort, M. T., & Verbaan, C. L. (2023). Design, implementation, and evaluation of an online supported peer feedback module to enhance students' argumentative essay quality. ***Education and Information Technologies, 28***, 12757–12784. https://doi.org/10.1007/s10639-023-11683-y

Oppl, S., Reisinger, F., Eckmaier, A., & Helm, C. (2014). A flexible online platform for computerized adaptive testing. ***International Journal of Educational Technology in Higher Education, 14***(1), 2. https://doi.org/10.1186/s41239-017-0039-0

Rodríguez, I., Rubio, D., & Rubio, F. (2023). Complexity of adaptive testing in scenarios defined extensionally. ***Frontiers of Computer Science, 17***, 173206. https://doi.org/10.1007/s11704-022-1673-9

Tagirova, L. F. & Zubkova, T. M. (2023). Intellektual'naya sistema adaptivnogo testirovaniya. ***Scientific and Technical Journal of Information Technologies, Mechanics and Optics, 23***(4), 757–766. https://doi.org/10.17586/2226-1494-2023-23-4-757-766

Tomashev, M. V., Avdeev, A. S., & Krasnova, M. V. (2018). Adaptivnoye testirovaniye kak sredstvo upravleniya kachestvom obrazovaniya. ***Informatics and Education, 9***, 27–33. https://doi.org/10.32517/0234-0453-2018-33-9-27-33

Wang, W. & Kingston, N. (2019). Adaptive Testing With a Hierarchical Item Response Theory Model. ***Applied psychological measurement***, ***43***(1), 51–67. https://doi.org/10.1177/0146621618765714

Wulandari, F., Hadi, S., & Haryanto. (2020). Computer-based adaptive test development using fuzzy item response theory to estimate student ability. *Computer Science and Information Technology, 8*(3), 66–73. https://doi.org/10.13189/csit.2020.080302

Yavorskiy, V., Zhaxybayeva, G., Chvanova, A., & Baidikova, N. (2017). *Information and communications technologies provision of distance learning in a technical university*. In *Proceedings of the CSIT 2017 Conference*. Karaganda State Industrial University. https://csit.am/2017/Proceedings/W_ITM/W_ITM20.pdf

Zhuang, Y., Liu, Q., Huang, Z., Li, Z., Shen, S., & Ma, H. (2022). Fully adaptive framework: Neural computerized adaptive testing for online education. *AAAI Conference on Artificial Intelligence, 36*(4), 4734–4742. https://doi.org/10.1609/aaai.v36i4.20399

CONFLICT OF INTEREST:

The authors declare no conflicts of interest.

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