Personalized Computer Support of Performance Rates and Education Process in High School: Case Study of Engineering Students

Nadezhda Zhiyenbayeva
Abai Kazakh National Pedagogical University, Almaty, Kazakhstan

Elvira Belyanova (✉)
Bauman Moscow State Technical University, Moscow, Russia
elv-bel@mail.ru

Irina Petunina
Federal State Budgetary Educational Institution of Higher Education
"Kuban State Agrarian University named after I.T. Trubilin",
Krasnodar, Russia

Svetlana Dmitrichenkova, Elena Dolzhich
Peoples' Friendship University of Russia (RUDN University), Moscow, Russia

Abstract—The study demonstrates the superiority of personalized learning, an innovative 21st-century teaching method that encourages educators to transform traditional initiatives into modern learning situations in both traditional and virtual classrooms. Educational systems in many countries of the world are moving to a new paradigm of personalized learning, which adapts to the needs of students, allows one to choose individual educational trajectories, and respects unique skills and qualities. In promoting educational change, it is important to understand the role of information and communication technologies, which can act as catalysts for educational transformation, promote effective student-centered learning, and increase learners' motivation and engagement. The study aims to determine the impact of personalization on engineering students' academic performance in physics. For this, a personalized student support experiment was conducted during the 2018-2019 academic year at I.T. Trubilin Kuban State Agrarian University. Research sample consisted of 78 students. First of all, they underwent math skills assessment, as the physics study is based on mathematical analysis and interpretation. Physics test and Cronbach's alpha test (reliability is determined with a coefficient of 0.87) were used as a research toolkit. Apart from them, statistical tools and covariance analysis of data were employed. The research was supported by the SPSS statistical software package. According to the obtained results, higher post-test scores were recorded for experimental group students. It was found that personalized learning has a significant impact on students' academic performance. Those with low and average ability in mathematics demonstrated better academic results than students with high scores. The study established a

strong correlation between the method of learning and mathematical abilities. The influence of learning process personalization was determined to be moderately high (determinacy coefficient of 72.6%). In view of the results achieved, this study can be used while developing constructive approaches to help educators improve their teaching approaches and enhance students' academic achievements. Research findings may be of interest to those engaged in the field of education and university management.

Keywords—Computer technology; engineering education; mathematical skills; personalized training; support in the learning environment.

1 Introduction

Today, the world witnesses a new socio-economic reality in which personalization and customization of products and services are changing education [1]. Countries need to adapt to the new reality not only in business but also in other sectors, including education, to survive in a rapidly changing environment. Modern public education systems are still based on the principles of "standard size," i.e., the application of a fully functional education model suitable for all [2]. However, the unified approach is not able to maximize individual learning outcomes. Students today are more demanding and ready to discover new ways to apply and expand existing knowledge. In response to these challenges, educators are looking for personalized learning approaches to move beyond universal learning and towards new methodologies keeping pace with the needs of a constantly changing world [3].

Modern schools are aware of the need to create a new teaching and learning culture that will focus on developing abilities to find, choose, evaluate, and apply knowledge. Thus, education personalization implies that teaching personnel can decide what and how to teach according to the needs of each student [4]. Personalized learning is an educational strategy that allows students to participate in meaningful educational activities and demonstrate desired results [5]. In such a learning environment, teaching staff should use appropriate, up-to-date pedagogical technology-enhanced strategies [6].

The new generation of educational technologies creates numerous opportunities for personalization. These technologies are capable of adapting to students' learning needs automatically and allow selecting individual educational paths [7]. Personalized learning is an educational approach that, through flexibility and choice, respects the unique skills, hobbies, and qualities of each learner, as well as the challenges and obstacles they may encounter. The key attributes that make up a personalized learning model include an emphasis on inclusion, smaller class sizes, more individual teacher-student interaction, students' involvement, access to technology, and a diverse learning environment.

Personalized learning remains a new trend in many institutions; however, not all of them have an understanding of what it is, how it can be designed and implemented in a way that satisfies students, instructors, and administrative personnel. Personalized education is particularly important in an environment where more and more institu-

tions are working in an electronic educational environment. Today, these environments are developing under the influence of technological progress and the increasing availability of Internet learning resources. Such a negative factor as the COVID-19 pandemic led to the closure of educational institutions around the world. Therefore, according to the global business data platform Statista, more than 1.2 billion students in 186 countries did not attend or are still not attending classes due to the pandemic-related limitations. For this particular reason, further development of e-learning and personalized computer support for students remain crucial [8].

In the following sections of the study (section 2), personalized learning is considered with an emphasis on its 21st-century definitions and features (subsection 2.1) and ICT in providing personalized learning (subsection 2.2). Research methodology is disclosed in section 3. Section 4 presents study results, whereas sections 5 and 6 are discussion and conclusions.

2 Background and Literature Review

2.1 Personalized learning: Definitions and features in the 21st century

The idea of personalization in learning can be traced back to the XIX century when Helen Parkhurst created the Dalton plan. According to this plan, each student could program the curriculum to meet his/her needs, interests, and abilities, thereby promoting independence and reliability, improving social skills and a sense of responsibility [9]. Since then, the idea of education personalization has evolved, but still, no single definition of this concept exists. Thus, for example, representatives of the National College of School Leadership (United Kingdom) have defined education personalization as a highly structured and responsive learning approach. It is represented as the process of creating an environment in which all students can participate, develop, and achieve results. The Personalized Learning Foundation (California, United States) believes that a blended approach to learning combines the provision of education both within and outside the traditional classroom. This model promotes interaction between educators, parents, and students and provides an individualized training program for each student according to their needs and interests [10]. The B.C. Ministry of Education (Canada) suggests that personalized education means a transition from providing a set of broad, uniform learning outcomes to independent and interdisciplinary learning [3]. Personalized learning also means the process in which the goals, paths, and pace of learning are optimized to meet the needs, interests, and current performance of each student. It provides students with differentiated learning and support needed to acquire knowledge, skills, and competencies, as well as the flexibility for the development of personal interests [7]. Given this definition, personalized education can be described as a cycle of four stages: engagement, measurement, interpretation, and adaptation. Students are engaged in a learning experience according to which their individual needs, interests, and performance can be measured [11]. Afterward, they are interpreted following the criteria, and the interpretation itself is used to inform on the learning experiences that may differ in learners in terms of

goals, paths, and pace of achievement. Personalized learning consists of several basic components [3]: learning monitoring, learning assessment, the right to choose, approach to arranging the educational process, and effective learning (educational activities must go beyond a classroom or lecture hall).

The idea of personalized learning implies that this approach will improve students' performance both in the short term (e.g., higher achievement rates) and in the long term (e.g., successful completion of higher education). Therefore, some education systems initiated the personalization overdrive when attempts are undertaken to personalize learning for all students [12]. The education system has adopted the idea of every student to have diversity and progress at a different rate based on a large number of variables [13]. In 2014, the United States hosted the National Summit on Personalized Technology-based Learning [14] to discuss innovative teaching methods and personalized learning barriers. It concluded that different models are needed to support personalized learning and identified areas for promoting personalized learning practices such as data, technology architecture, human potential, curriculum, and research [15].

Researchers note several contradictions that teachers face in the process of personalizing learning [16,17]: the desire to reward talented students often outweighs the need to deal with the poor performance of others; heavy workload and time constraints of teachers; the need to master new technologies. The solution to these problems is facilitated by smart devices and technologies that allow creating an intelligent learning environment and contribute to the development of personalized and adaptive learning [18].

2.2 Information, communication, and computer technologies in ensuring learning personalization

Understanding the role that information and communications technology (ICT) play in promoting educational changes, flexibility, and personalization is of high relevance. ICT can catalyze education transformation by promoting learning that is more engaging, learner-oriented, adaptable to personal learning needs, interdisciplinary, and more closely related to real-life events [19]. ICT in education is able to increase the level of students' motivation and involvement, facilitate learning from students' own experience, and promote a learner-oriented approach [20]. Researchers note that personalized digital learning implies ensuring learner's ability to make effective educational decisions, recognizes different levels of abilities and knowledge in ICT application, and contributes to changing the learning environment through specific tools [11]. Thus, the development of ICT and digital content advancement tools has made personalized learning available to a broad audience.

ICT enables introducing the components of personalized learning into the educational process. For example, assessment in traditional higher education is usually limited to examinations, the main purpose of which is to compare students' achievements with the standards. Learning Management Systems (LMS) have introduced automatic assessment throughout the educational process and provide comprehensive data on student performance, including test results, portfolio, etc. Therefore, teachers

have the opportunity to adjust the learning of each student [21]. ICT also enhance learning efficiency by adapting it to each student when selective delivery of content becomes a part of personalized learning. The progress of talented students becomes less feasible when everyone follows the same curriculum at an average pace. Computers and mobile devices allow personalizing the learning paths of each student. Computers and mobile devices used for personalized learning are able to transform educational institutions [22,23]. The adjustment of resource allocation for a wider choice of a curriculum can be made through LMS. New technologies allow taking education outside the lecture room. Thus, using Web 2.0 tools and social networks, students can interact with each other and teachers almost anytime and anywhere [24].

Proceeding from data discussed above, the following benefits of technology-driven personalized learning approaches can be distinguished: improved learning and student engagement; ability to learn faster, deeper, or with greater breadth in subject areas; closing achievement gaps or improving graduation rates through the implementation of four components (Fig. 1) [25,26].
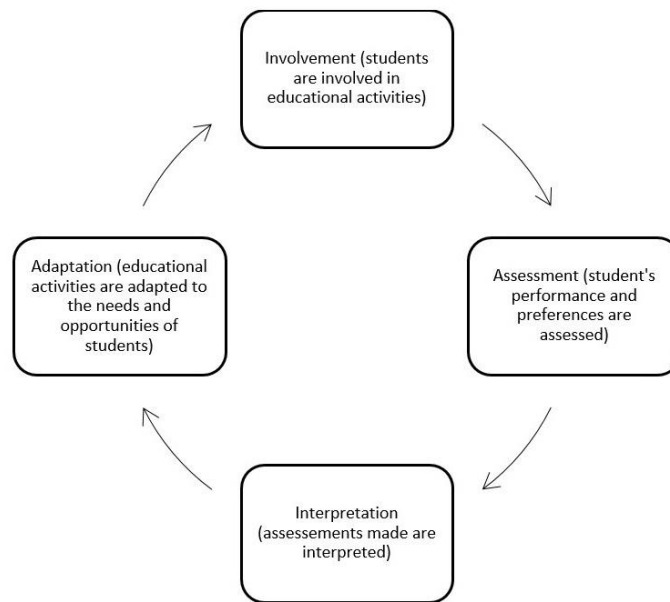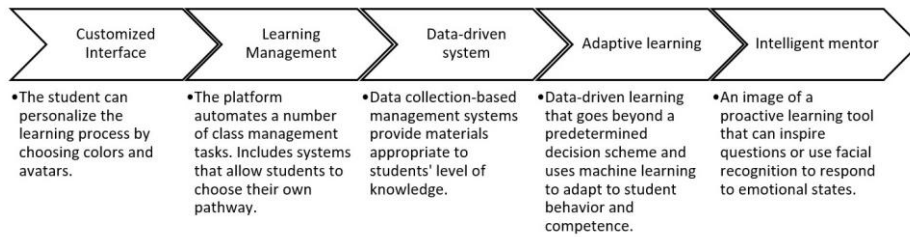

Fig. 1. Components of a personalized learning process

Note: compiled using [11,25,26].

Involvement makes it possible to adapt learning activities based on the assessment of student participation in learning. Assessment has tools for assessing student performance. Interpretation focuses on data and connects different patterns to potential learning adaptation models. Adaptation includes learning pace and timing, learning objectives, content choices and complexity, feedback nature and timing, etc. [11,25,26].

Adaptive systems are designed to functionally reflect and support a rather flexible and changing learning process nor stable one [27]. The typology of personalized learning systems with technological support provides a clear spectrum of possibilities described by personalized learning as a product. Personalized learning with technology can range from a simple learning interface setup to a system that adapts content depending on user performance (Fig. 2).

Customized Interface	Learning Management	Data-driven system	Adaptive learning	Intelligent mentor
• The student can personalize the learning process by choosing colors and avatars.	• The platform automates a number of class management tasks. Includes systems that allow students to choose their own pathway.	• Data collection-based management systems provide materials appropriate to students' level of knowledge.	• Data-driven learning that goes beyond a predetermined decision scheme and uses machine learning to adapt to student behavior and competence.	• An image of a proactive learning tool that can inspire questions or use facial recognition to respond to emotional states.

Fig. 2. Types of personalized learning systems with technological support

Note: compiled using [27-30].

These systems can be divided into five categories that increase the speed of response [27-30]: customized learning interface; learning management (includes platforms such as Blackboard, Class Dojo, Canvas, and Schoology); data-driven learning, adaptive learning, and intelligent mentoring (this category includes PracTutor, Amazon's TenMarks, McGraw-Hill Thrive, and Lexia from Rosetta Stone).

The individual learning approach is based on research on how students can study most effectively. Efficient learning mainly involves active teacher-student interaction, students' participation in management processes, access to ICT, and a flexible curriculum [26]. ICT is a tool that promotes understanding of how to learn instead of telling what to study by finding solutions to specific problems, developing students' curiosity and initiative, facilitating analytical thinking, and encouraging collaboration. The integration of ICT in a classroom enables continuous learning to be implemented in different learning contexts and provides on-demand support to students [31]. Different digital tools propose various interactive systems fostering collaboration, guiding students through the work process, and enabling teachers to interact effectively [32].

Advanced technologies implement activities that encourage higher levels of thinking and conceptual understanding of different topics through a range of software and online resources. They require teachers to rethink traditional approaches to pedagogy and curriculum management. These new social scenarios and content suggest a variety of new features that need to be considered in the curriculum [33]. A curriculum that integrates ICT contributes to better learning by providing a more powerful basis for developing abilities and sharing experiences [33]. In such a manner, new technologies offer a variety of benefits, meet students' needs, and increase learners' interest [6].

Even before the COVID-19 started, investment in educational technologies amounted to $18.66 billion (as of 2019). As for now, the possibilities of personalized learning are being expanded by companies developing the latest communication technologies. For example, Lark, a Singapore-based collaboration package developed by

ByteDance, offers students and teachers unlimited time for video conferencing, automatic translation, real-time collaborative editing of documents, and learning process planning. Teachers at the University of Jordan, which used the Lark package to teach students, argue that education has become more individual and communication through chats, video conferences and file sharing is more effective. For personalized learning, new competency-based learning platforms are also offered. These include Knewton, which uses adaptive learning technology to identify each student's specific strengths and weaknesses. Another adaptive learning provider, Education Elements, offers Highlight, a cloud-based personalized learning platform that tracks learners' progress through content providers. Some developments show that, on average, students memorize 25-60% more material during online learning with a personalized approach (World Economic Forum [8]), compared to 8-10% during traditional learning sessions. It can be explained by the fact that students learn online faster. E-learning requires 40-60% less time than studying in a traditional lecture room as students learn at their own pace by slowing down or speeding up the learning process with feedback from a teacher.

Certainly, some educators may face challenges in applying an individual approach to teaching, and therefore need to develop new pedagogical concepts. Today the role of an educator is transforming from teaching to mentoring and advising. Those adopting a personalized approach should combine it with mini-group learning, use ICT to improve personal interaction with students and activate social interaction through virtual social communities [10]. Researchers focus on electronic personalized learning, formalized assessment, giving feedbacks, and content creation tasks in the form of algorithmic tools that are to be integrated into the learning environment [34]. Machine learning algorithms are also supposed to help students and educators track progress and provide personalized feedback and assessments [35].

3 Methodology

The study demonstrates the superiority of personalized learning as an innovative method of teaching in the 21st century, which encourages educators to transform traditional classroom initiatives into modern ones that create learning situations in the in-class and online formats with greater dynamism, efficiency, and usefulness for engineering students. One of the main initiatives of the study was the personalization of study guides.

3.1 Research objectives

The main purpose of the study was to determine the effect of learning personalization on academic achievements of physics students. In this regard, the researchers have set the following objectives:

- To evaluate the mathematical abilities of the sample participants
- To evaluate the achievements of students from experimental and control groups for the block of physical disciplines
- To identify the extent to which personalized learning affects the performance of experimental and control group students
- To determine the difference in the average score of the sample participants after testing depending on their mathematical abilities
- To evaluate the impact of personalized learning on academic performance of students grouped by mathematical ability in physics.

3.2   Study hypotheses

The defined research objectives made it possible to develop the following hypotheses:

1. Personalized learning affects the academic performance of experimental group students insignificantly
2. There are no large differences in the average test score of students grouped by potential
3. There is no strong relationship between the learning method and the potential of students to study the course.

3.3   Formation of a research sample

The experiment was conducted during the 2018-2019 academic year. Research sample consisted of 78 students aged 19.7 years on average. The gender structure was 74% male and 26% female.

3.4   Design of the study

The educational architecture of I.T. Trubilin Kuban State Agrarian University was supplemented by a designed environment in which students supported their own academic programs. The use of personalized settings characterized by the interaction between the machine environment and a person (educators and students), as well as transparent, self-regulating protocols, allowed students to be encouraged and enabled them to take responsibility for the education.

The starting point of the research was the investigation of students' potential in mathematics, as the physical discipline includes scientific concepts studied through mathematical analysis and interpretation. Students were divided into high, medium, and low potential groups based on the average level of their academic achievement in mathematics. The ranges of 1.00-1.75 scores were classified as high potential, those of 1.76-2.5 were considered as medium potential, and scores of 2.49-3.00 built up a low potential.

Academic initiatives have been revised by educators to engage students in a series of meaningful learning activities that foster collaboration, research, and experimenta-

tion in a co-educational environment. Students were distributed into groups of five persons each (Buzz group). This facilitated the creation of a constructivist medium with positive interdependencies and extensive feedbacks before reaching the learning objectives, as well as promoted the active learning and participation of all group members. Transcripts of discussion and guidance were analyzed and verified by direct educators' observations. The training was conducted throughout the whole academic year (two academic semesters).

In order to better meet the goals of personalized learning, a flexible schedule was created and adjusted as groups and individual students developed their own pace of learning. Lessons in lecture rooms were designed to allow the experimental group to learn at their own pace. Mini-group work and collaborative learning, including feedback and additional instructions and explanations, were conducted at least once a week or more frequently if students needed. There was also introduced a module designed to meet students' own pace of learning in mini-groups. In parallel with the experimental group, the control group studied in a normal mode following the traditional schedule in lecture rooms and performed individual works and tasks for the theoretical and laboratory block.

The study applied pre- and post-testing design for the control group to provide a basis for the causal effect of an independent variable on a dependent one involving experimental and control groups of students. Each student approached the education process with distinctly defined intentions and objectives. The design of the learning environment considered the variability of students. Variability was provided by teaching tools, teacher support, and educational strategies and technologies designed to support the needs of students working independently and in groups. Besides, Google Calendar was used to easily schedule students' work.

The result of transcript analysis determined the number of control points established between teachers and students. The mathematics module was presented to students with low levels of ability to optimize their learning experience. Their performance was monitored using a testing method. When a student demonstrated a lack of knowledge and skills, the learning process was started again with another module and a mini-group.

3.5 Research methods

The following methods were used in the work:

- Theoretical (for the analysis and systematization of scientific, theoretical and methodological sources, generalization of experimental data);
- Empirical method (surveys of participants, discussions, testing);
- Experimental training (introduction of personalized settings for the interaction of the machine environment, teachers, and students);
- Mathematical and statistical methods for processing empirical data (Cronbach's alpha test, frequency counting, mean, percentage, and analysis of covariance).

3.6 Data collection procedure and research tools

The data in the analysis and interpretation tables are collected from the academic records of students. Analysis of transcripts, field research and observation, and evaluation of student portfolios were employed.

The instrument used in the study was a physics progress test consisting of 20 items. Cronbach's alpha criterion was applied when analyzing the results to determine the internal consistency of characteristics describing the object. This choice was provoked by the fact that it is as an effective tool for determining test reliability, which is crucial for the present research. Test reliability was determined with a factor of 0.87. Thus, the mutual correlations between elements in the test were consistent. The study also used statistical tools: frequency calculation, mean, percentage, and covariance analysis (ANCOVA) in processing the collected data. This tool was identified as optimal for analyzing experimental data, describing the patterns of change in a quantitative variable in several groups. SPSS Statistics software was used for applied research and data processing.

3.7 Ethical issues

Personal data, interview results, and academic performance data of research participants are considered as information of non-disclosure.

4 Results

At the initial stage of the study, research participants were tested on knowledge and skills in mathematical disciplines to determine their abilities and classify them into groups (Table 1).

Table 1. Mathematical Potential of Sample Participants

Mathematical Potential	Experimental Group	Control Group	Total	Percentage
High	10	12	22	28.21
Medium	8	14	22	28.21
Low	17	17	34	43.58
Total	35	43	78	100

Range: High potential - 1.00-1.75; Medium potential - 1.76-2.50; Low potential - 2.49-3.00 Note: developed by the authors

Table 1 shows the profile of the sample participants distributed by their mathematical abilities. The profile was formed based on the average index for mathematical disciplines. It was determined that most of the experiment participants had low mathematical potential, namely, 34 students or 43.58% of all involved. High and average potential in mathematical disciplines had 22 sample participants (each category included 28.21% of students). The formed groups, in general, were characterized by the prevalence of students with a high to an average level of mathematical abilities. However, the discrepancy with the number of students with low ability in mathematics was only 12.84%. There were not so few weak students; therefore, it was necessary to

take into account the interests of all categories for the training to have a convenient individual trajectory. The groups were supposed to form a constructive learning environment that will facilitate learning, skills, and competencies.

Then the students of the experimental and control groups started the classes. As mentioned above, the control group studied according to the traditional approach, whereas the experimental group received personalized training support. At the end of the academic year, students of the control and experimental groups underwent post-testing (Table 2).

Table 2. Average Student Scores for the Post-Test

Group	Value	Standard error	95% confidence interval	
			Lower limit	*Upper limit*
Control group	11.538[a]	0.303	10.935	12.141
Experimental group	13.762[a]	0.312	13.143	14.381

Covariates appearing in the model are evaluated at pre-test values amounting to 11.03.
Note: developed by the authors

The data in the table demonstrate that the average score of the control group was 11.538, while the experimental group received an average score of 13.762. The results were evaluated using a covariate pre-test value (11.03) and can be interpreted as follows: the experimental group students showed better results than their peers from the control group. Thus, one may assume a positive impact of personalized learning with an individual trajectory, complemented by a constructivist environment with useful feedback and work in a virtual environment.

Table 3 presents the results of assessing the impact of ability factors on student's performance.

Table 3. Testing the Impact of Ability Factors and Learning Methods on Academic Performance

| Source	Type III Sum of squares	Number of degrees of freedom (Df)	RMS value	F	P-value
Corrected model	644.200[a]	6	107.368	35.156	0.000
Interception	23.438	1	23.438	7.675	0.007
Pre-test	139.585	1	139.585	45.706	0.000
Method	79.138	1	79.138	25.913	0.000
Ability	2.516	2	1.259	0.412	0.665
Method*Ability	19.570	2	9.786	3.204	0.047
Error	216.837	71	3.055		
Total	13199.000	78			
Adjusted amount	861.039	77			

R in square = 0.747 (corrected R in square = 0.726). Note: developed by the authors

The table depicts a two-way covariance analysis of tests conducted between the two study groups (control and experimental). The results show that the average composite score obtained by experimental group students is significantly higher than that obtained by students in the control group (F=25.913 and p<0.001). Hence, students in the experimental group who studied in a personalized way learned the subject better

after the individualized learning method was introduced. Consequently, the hypothesis about the absence of a significant difference between the average academic performance of students who underwent personalized learning and that of students who have studied in a traditional way is rejected. Thus, personalized learning is believed to be significantly better than the traditional model in terms of its effect on students' overall academic performance.

At the same time, it can be noted that the impact of learning personalization is moderately high, as the determination coefficient, expressed by the adjusted R-square, amounts to only 72.6%. It means that the model of learning is only 72.6% of the variation in academic performance of students. Therefore, it can be assumed that other important variables or factors (e.g., student abilities or other teaching methods) may also explain the difference in academic achievement between the experimental and control groups.

The influence of learning conditions on the academic performance of students (depending on their mathematical abilities) in the experimental and control groups is shown in Fig. 3.
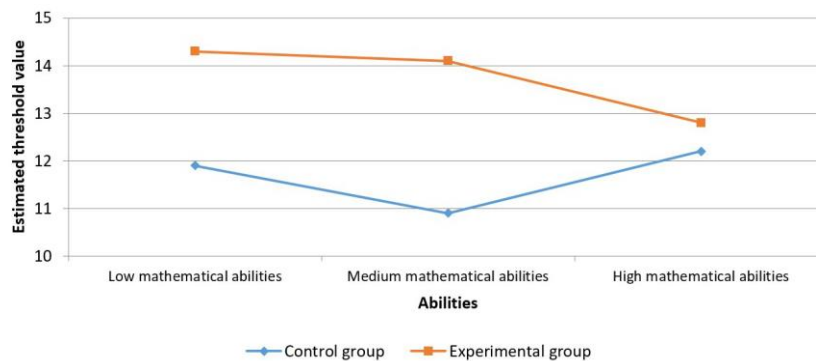
Fig. 3. Estimated Post-Test Threshold Value

Note: the average result of the post-test is estimated through the value of the pre-test covariate amounting to 11.05. Note: developed by the authors.

The figure illustrates the relationship between post-test average threshold values and mathematical abilities of students classified as low, medium, and high. The average post-test result was estimated using the covariate value of the pre-test amounting to 11.05. It was established that students with medium mathematical abilities received the greatest benefit from the personalized learning program. The next most useful result was shown by students with low mathematical ability. Quite surprising was the absence of significant differences in the scores of the most gifted students in math. The difference in academic achievement between the experimental and control student groups can be explained by the presence of other important variables, such as other student abilities and teaching methods. Personalized learning, which implies studying in mini-groups, is believed to be most useful for students who cannot show their potential in large student societies when only the brightest students take the

initiative. Students with distinct abilities in mini-groups have taken on the role of tutors, pulling up underachievers, but they have already felt confident in the background. For students with strong abilities, the most personalized way to learn can be offered that would help to show even more of their abilities.

5 Discussion

5.1 Comparative perspective

The thesis that the development of a personalized learning environment should be aimed not only at student performance in academic parameters but also at creating a transformative environment conducive to personal development coincides with the conclusions of this study [36,37]. The authors support the opinion that there is a need to explore how educators use data, how technologies are created to support learners, and how the content and curriculum are developed to support individual learning [14]. So do the findings of this study, other researchers argue that, with proper support, technology can enable educators to apply more personalized approaches in teaching and other activities [38]. An analysis of math and reading abilities of 5,500 students across 32 schools that had a personalized approach showed a 3% increase in performance [39].

The authors support the conclusion that machine learning algorithms help students and teachers track progress, provide personalized feedback, and recommend the best learning activity based on progress. For example, if a student is performing poorly, he/she is encouraged to use an artificial intelligence system called e-Tutor, which provides personalized corrective assistance [40]. Mental modeling, sensor technology, and smart cameras can detect if a student is attentive while sitting in a lecture, reading a book, or interacting with an online tool. They may suggest new activities and next steps in learning [41]. However, it should be noted that this is a problematic point. Many fully digital personalized environments rely on stimulus-response machine analytics to make decisions [42]. Many of these models replace teachers with digitally generated supervision, ignore student strengths, weaknesses, learning contexts, and ignore socio-emotional development [43]. As in this study, learners are shown to perform better when they have the opportunity to collaborate and discuss results in learning communities, for example, through supportive MOOC environments [44].

To study the impact of virtual learning environments on science and engineering education, the LabLife3D virtual laboratory in Second Life was developed and implemented for laboratory classes in biological sciences and chemistry, integrated with a system for collecting behavioral data during laboratory simulations for the purpose of teaching analytics [45]. An experience of introducing serious games (Serious Games, SG), which have educational potential, is also interesting [46]. The Activity Theory-based Model of Serious Games (ATMSG), for instance, promotes a systematic and detailed presentation of educational SG and pedagogical goals in many branches of engineering education, such as planning and design.

5.2   International experience

Scholars from Lithuania have investigated changes in the management of educational programs in an attempt to respond to the challenge of learning personalization using the creative method of digital storytelling. They have revealed that active participation in the classroom increased due to the individual approach and the use of digital media. Correspondingly, technology-supported learning personalization changes classroom management practices and strengthens teacher-student collaboration as well as peer-to-peer collaboration [47]. A national study in the United States focused on the systematical examination of the use of technology and the needs of teachers based on the conceptual framework of the Personalized Integrated Education System (PIES) has found that today 308 student-oriented schools in the country meet at least three of the five criteria for personalized learning. These criteria include personalized learning plans, criteria-based assessment, competency-based student achievement, problem- or project-based learning, and years of mentoring. However, it has been noted that only 12% of teachers can use technology systems that combine the four core functions, and 21% reported they do not have such systems at all [6,48].

6   Conclusion

The study aimed to foster the understanding of the personalized learning environment and explore its potential to support students. In particular, the researchers conducted observations, interviews, and analysis of academic performance data. Since teachers and students in a personalized learning environment rely heavily on data collected in the learning system, they need to be transparent, regular, and effective. These data are used to make decisions about student's progress and learning pathway in an individualized sequence. Their validity means that they are meaningful, accessible, and usable. For this reason, data must be visible to both a student and an educator, for example, in the LMS. In order to review the progress and discuss ways forward in learning, it is crucial to provide students with ongoing feedback and establish weekly tests. Student's self-regulation built into and used in personalized learning environments is of high relevance as well. To help students and teachers make decisions about established individual learning paths, this study developed and used specialized strategies. As a result, experimental group students became more active educational process participants and took greater responsibility for learning, which demonstrates the difference from the conventional approach where the primary responsibility was taken by teachers. Students' understanding was provided through forms, instructions, traditional reading, assignments, and consultations with teachers. Interviews with experimental group students demonstrated the usefulness of weekly meetings to discuss learning data. Such consultations helped to keep pace and take responsibility for learning. Passive students deserve special attention as they need help to develop more active learning strategies. An approach that can be effective in developing critical thinking skills and academic achievement among students was defined as the use of learning strategies compatible with a personalized learning environment.

The examination outcomes declare that experimental group students showed better results than control group participants, as evidenced by their average score after testing: 13.762 vs. 11.538. It was also established that personalized training significantly impacts students' academic performance in physics (p-value<0.001), which allowed rejecting the first of the formulated hypothesis. As a consequence, personalized learning was proved to be an effective mechanism for improving learning effectiveness.

No significant difference in students' average post-test results depending on their abilities (p-value=0.664) was noted, which enabled accepting the second hypothesis of the study. Individuals with low and average abilities in math showed a good level of academic achievement. However, a close relationship between the method of learning and the mathematical ability (p-value=0.047) was stated, which automatically rejected the third formulated hypothesis. In conclusion, one can infer that personalized learning is an important and effective tool for reconstructing the academic environment depending on students' abilities.

6.1   Research limitations

The research is restricted by the need for further elaboration. Even though observations were made during one academic year and the results confirm the personalized learning mechanism's success, the identification of specific outcomes and aspects of this learning environment might be influenced by the waiting effect. In order to avoid the possibility of misinterpretation, it is considered appropriate to carry out further research on personalized learning over a more extended period of time. Of particular interest is the absence of considerable difference in the scores of the most gifted students in mathematical subjects. Other important variables, like student abilities or teaching methods, require additional identification and investigation as it can better explain the difference in academic achievement between the experimental and control groups.

6.2   Research implications

The importance of research lies in the role of personalized learning: when studying physics, students must participate in a variety of quantifiable experiments, tasks, and exercises to master the necessary skills. Creative interventions must be carried out in a constructive learning environment for students to acquire competency. This research is important for developing constructive approaches that would help educators to improve their teaching methodology and students to improve their academic performance. It is offered to researchers, teachers, and administrative staff of higher education institutions.

7   Acknowledgement

8　References

[1] Russell, R. (2015). Adaptive and Personalized Learning: Stories from Districts Turning Themselves Around. EdNet conference. Retrieved from https://www.youtube.com/watch?v=qB0wJn32eu8&feature=youtu.be

[2] Sykes, A., Decker, C., Verbrugge, M., Ryan, K. (2014). Personalized learning in progress: Case studies of four Race to the Top district grantee's early implementation. Larium Evaluation Group, on behalf of United States Department of Education. Retrieved from https://rttd.grads360.org/services/PDCService.svc/GetPDCDocumentFile?fileId=7452

[3] Pane, J.F., Steiner, E.D., Baird, M.D., Hamilton, L.S. (2015). Continued Progress: Promising Evidence on Personalized Learning. Rand Corporation, Santa Monica, Calif. https://doi.org/10.7249/rr1365

[4] Klimienė, K. (2017). Personalizacijos problematical – reiškiniai, suformavę poreikį, ir jų sąveika su dizaino lauku. Mokslas – Lietuvos ateitis. Vilniaus Gedimino Technikos universitetas, 9(1): 99-110. https://doi.org/10.3846/mla.2017.992

[5] Zmuda, A., Curtis, G., Ullman, D. (2015). Learning personalised. The Evolution of the Contemporary Classroom. Jossey-Bass, San Francisco.

[6] Papadakis, St. (2020). Robots and Robotics Kits for Early Childhood and First School Age. International Journal of Interactive Mobile Technologies (iJIM), 14 (18), 34-56.

[7] Sss SRI International Using Technology to Personalize Learning in K–12 Schools. SRI International, Menlo Park, CA. Retrieved from https://www.sri.com/work/publications/using-technology-personalize-learning-k-12- schools

[8] World Economic Forum (2020). The COVID-19 pandemic has changed education forever. This is how. Retrieved from https://www.weforum.org/agenda/2020/04/coronavirus-education-global-covid19-online-digital-learning/

[9] Weichhart, G., Stary, C., Appel, M. (2018). The digital Dalton Plan: Progressive education as integral part of web-based learning environments. Knowledge Management & E-Learning, 10(1): 25-52. https://doi.org/10.34105/j.kmel.2018.10.002

[10] Arnesen, K.T., Graham, C.R., Short, C.R., Archibald, D. (2019). Experiences with Personalized Learning in a Blended Teaching Course for Preservice Teachers. Journal of Online Learning Research, 5(3): 275-310.

[11] Basham, J.D., Hall, T.E., Carter Jr, R.A., Stahl, W.M. (2016). An operationalized understanding of personalized learning. Journal of Special Education Technology, 31(3): 126-136. https://doi.org/10.1177/0162643416660835

[12] Enyedy, N. (2014). Personalized instruction: New interest, old rhetoric, limited results, and the need for a new direction for computermediated learning. National Education Policy Center, Boulder, CO.

[13] Rose, T. (2015). The end of average: How we succeed in a world that values sameness. HarperCollins, New York.

[14] Abbott, J., Basham, J., Nordmark, S., Schneiderman, M., Umpstead, B., Walter, K., Wolf, M.A. (2015). Technology-enabled personalized learning: Findings & recommendations to accelerate implementation. Friday Institute, Raleigh, NC.

[15] McDermott, S., Turk, M.A. (2015). What are the implications of the big data paradigm shift for disability and health? Disability and Health Journal, 8: 303-304. https://doi.org/10.1016/j.dhjo.2015.04.003

[16] Netcoh, S., Bishop, P.A. (2017). Personalized Learning in the Middle Grades: A Case Study of One Team's Successes and Challenges. Middle Grades Research Journal, 11(2): 33-48.

[17] Keeffe, M. (2017). Transition to Junior Secondary Schooling for Students with Learning Difficulties and Disabilities: A Study in Personalised Learning and Building Relational Agency in Schools. In Inclusive Principles and Practices in Literacy Education. Emerald Publishing Limited, pp. 213-230. https://doi.org/10.1108/s1479-363620170000011014

[18] Peng, H., Ma, S., Spector, J.M. (2019). Personalized adaptive learning: an emerging pedagogical approach enabled by a smart learning environment. Smart Learning Environments, 6(1): 9. https://doi.org/10.1186/s40561-019-0089-y

[19] Drigas, A., Karyotaki, M. (2014). Learning Tools and Applications for Cognitive Improvement. International Journal of Engineering Pedagogy, 4(3): 71-77.

[20] Scott, L. (2015). The Futures of Learning 1: Why must learning content and methods change in the 21st century? UNESCO Education Research and Foresight, ERF Working Papers Series.

[21] Huggins, E.S., Kellogg, S. (2020). Technology-enabled personalized learning: A promising practice in need of robust research. School Science and Mathematics, 120(1): 1-3. https://doi.org/10.1111/ssm.12384

[22] Johnson, D. (2013). Mobile support in cscw applications and groupware development frameworks. International Journal of Interactive Mobile Technologies, 7(2): 54-62. https://doi.org/10.3991/ijim.v7i2.2469

[23] Karabatzaki, Z., Stathopoulou, A., Kokkalia, G., Dimitriou, E., Loukeri, P. I., Economou, A., Drigas, A. (2018). Mobile Application Tools for Students in Secondary Education. An Evaluation Study. International Journal of Interactive Mobile Technologies, 12(2): 142-161. https://doi.org/10.3991/ijim.v12i2.8158

[24] Kaminskienė, L., Khetsuriani, N. (2019). Personalisation of learning through digital storytelling. Management: journal of contemporary management issues, 24(1): 153-166. https://doi.org/10.30924/mjcmi.24.1.10

[25] Means, B., Bakia, M., Murphy, R. (2014). Learning online: What research tells us about whether, when and how. Routledge, New York, NY. https://doi.org/10.4324/9780203095959

[26] Redding, S. (2016). Competencies and personalised learning handbook on personalised learning for states, districts, and schools. Temple University, Center on Innovations in Learning, Philadelphia, PA.

[27] Bulger, M. (2016). Personalized learning: The conversations we're not having. Data and Society, 22(1): 1-29.

[28] Anand, A., Schimke, A. (2015). Grade levels could be a thing of the past in schools focused on competency. PBS Newshour. Retrieved from http://www.pbs.org/newshour/updates/say-goodbye-fifth-grade-k12-schools-test-competency-based-learning/

[29] Bill and Melinda Gates Foundation (2015). Teachers Know Best: Making Data Work for Teachers and Students. Seattle: Bill & Melinda Gates Foundation. Retrieved from http://collegeready.gatesfoundation.org/wpcontent/uploads/2015/06/TeachersKnowBest-MakingDataWork.compressed.pdf https://doi.org/10.1787/ce9784a5-fr

[30] Dalgaard, L., Ventilla, M. (2015). A 'full-stack' approach to education. 16z Podcast, Andreessen Horowitz. Retrieved from http://a16z.com/2015/03/13/a16z-podcast-a-full-stack-approach-toeducation/

[31] Olivia, R., Bidarra, J. (2017) Video and storytelling in a digital world: Interactions and narratives in video clips. Academia Publications 32(4): 459-476.

[32] Richter, A., Courage, L.M. (2017). Comparing electronic and paper storybooks for preschoolers: Attention, engagement, and recall. Journal of Applied Developmental Psychology, 48(2): 92-102. https://doi.org/10.1016/j.appdev.2017.01.002

[33] Harman, C., Brelade, S. (2015). Using Human Resources to put Knowledge to Work. Knowledge Management Review, 3(1): 26-29.

[34] D'antoni, L., Kini, D., Alur, R., Gulwani, S., Viswanathan, M., Hartmann, B. (2015). How can automatic feedback help students construct automata?. ACM Transactions on Computer-Human Interaction (TOCHI), 22(2): 1-24. https://doi.org/10.1145/2723163

[35] Meier, Y., Xu, J., Atan, O., Van der Schaar, M. (2015). Predicting grades. IEEE Transactions on Signal Processing, 64(4): 959-972. https://doi.org/10.1109/tsp.2015.2496278

[36] Li, K.C., Wong, B.T.M. (2019). How learning has been personalised: a review of literature from 2009 to 2018. In International Conference on Blended Learning. Springer, Cham, pp. 72-81. https://doi.org/10.1007/978-3-030-21562-0_6

[37] Knewton (2017). Knewton Adaptive Learning: Building the world's most Powerful Education Recommendation Engine. Retrieved from https://www.knewton.com/wp-content/uploads/knewton-adaptive-learning-whitepaper.pdf https://doi.org/10.5465/amle.2016.0206

[38] Gang, W. (2015). Personalized Education in Globalization Era. Nanjing Journal of Social Sciences, 7: 104-110.

[39] Garden, S. (2015). Personalized learning is a big exciting idea but can funders get it right? Inside Philanthropy. Retrieved from http://www.insidephilanthropy.com/home/2015/8/27/personalized-learning-is-abig-exciting-idea-but-can-funders.html

[40] Tekin, C., Braun, J., van der Schaar, M. (2015). eTutor: Online learning for personalized education. In 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, pp. 5545-5549. https://doi.org/10.1109/icassp.2015.7179032

[41] Kopp, K., D'Mello, S., Mills, C. (2015). Influencing the occurrence of mind wandering while reading. Consciousness and cognition, 34: 52-62. https://doi.org/10.1016/j.concog.2015.03.003

[42] Wleklinski, N. (2017). Skinner's Teaching Machine and Programmed Learning Theory. Retrieved from: https://chip.web.ischool.illinois.edu/people/projects/timeline/1954teaching_machine.html

[43] Basham, J.D., Stahl, S., Ortiz, K., Rice, M.F., Smith, S. (2015). Equity matters: Digital & online learning for students with disabilities. Center on Online Learning and Students with Disabilities, Lawrence, KS.

[44] Coetzee, D., Lim, S., Fox, A., Hartmann, B., Hearst, M.A. (2015). Structuring interactions for large-scale synchronous peer learning. In Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing, pp. 1139-1152. https://doi.org/10.1145/2675133.2675251

[45] Qvist, P., Kangasniemi, T., Palomäki, S., Seppänen, J., Joensuu, P., Natri, O., Palomäki, E., Tiitu, H., Nordström, K. (2015). Design of virtual learning environments: Learning analytics and identification of affordances and barriers. International Journal of Engineering Pedagogy, 5(4): 64-75 https://doi.org/10.3991/ijep.v5i4.4962

[46] Callaghan, M., McShane, N., Eguíluz, A., Savin-Baden, M. (2018). Extending the activity theory based model for serious games design in engineering to integrate analytics, 8(1): 109-126. https://doi.org/10.3991/ijep.v8i1.8087

[47] Lindell, T.L. (2020). Teachers calling for organizational support to digitalize teaching. The International Journal of Information and Learning Technology, 37(5): 323-339. https://doi.org/10.1108/ijilt-02-2020-0017

[48] Al Mulhem, A. (2020). Exploring the Key Factors in the Use of an E-Learning System among Students at King Faisal University, Saudi Arabia. International Journal of Interactive Mobile Technologies, 14(3): 19-37. https://doi.org/10.3991/ijim.v14i03.11576

9   Authors

Zhiyenbayeva Nadezhda Bisenovna is a Doctor of Psychology, Professor of the Department of Special Education, Abai Kazakh National Pedagogical University, Almaty, Kazakhstan.

Belyanova Elvira Nikolaevna is a PhD of Physical and Mathematical Sciences, Associate Professor of the Department of Fundamental Sciences, Bauman Moscow State Technical University, Moscow, Russia.

Petunina Irina Aleksandrovna is a PhD of Technical Sciences, Professor of the Department of Higher Mathematics, Federal State Budgetary Educational Institution of Higher Education "Kuban State Agrarian University named after I.T. Trubilin", Krasnodar, Russia.

Dmitrichenkova Svetlana Vladimirovna is a PhD in Pedagogical Sciences, Head of the Department of Foreign Languages of Engineering Academy of RUDN University, Peoples' Friendship University of Russia (RUDN University), Moscow, Russia.

Dolzhich Elena Anatolyevna is a PhD in Philological Sciences, Assistant Professor of the Department of Foreign Languages of Engineering Academy of RUDN University, Peoples' Friendship University of Russia (RUDN University), Moscow, Russia.