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Personalized distance-learning experience in determining students' performance

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Abstract

One way or another, students face certain difficulties and disadvantages of distance learning. This can affect students physically and emotionally if appropriate measures are not taken. The solution might be the personalization of distance learning process, which implies the application of individual approaches to learning. The article aims to determine the academic performance of students who use the system of personalized distance learning Quiz Guide. For this study, 140 students were selected. The results of the performance analysis showed that the experimental group scored higher on the final test, indicating that students using the Quiz Guide learning system had significantly better academic achievement than those who took the traditional approach to learning. According to the post-test results, the control group scored (average) 65.14 points, the experimental group, 74.71.

Keywords: Academic performance, computer learning system, individualized approach, personalized distance learning, Quiz Guide system.

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1. Introduction

1.1. Conceptual or theoretical framework

Helping students learn effectively online, address barriers, and meet learning goals relies on a student's educational and individual characteristics to shape key personalized learning materials and learning pathways (Hsu, 2012).

Big educational data aiming to provide technical support for this type of educational process is a foundation of personalized learning (Raphaeli et al., 2017). With regard to the individual characteristics of student learning, personalized learning is a breakthrough in the generally accepted teaching methods. Clearly, the digital development of society has influenced cognitive styles and methods of distance learning (Xu et al., 2019).

It is now relevant to find a new meaning for traditional education (Al-Sheeb et al., 2018; Zhao et al., 2017). A system for facilitating personalized distance learning has been created (Salehi et al., 2014).

Given students' difficulties during the distance learning period, lack of time to learn, self-learning skills can help extract and analyze data about the distance education process (Makhambetova et al., 2021).

There is now a high demand for online learning due to the fast progress of Internet technology. There are now no time or space constraints, allowing the online learning environment to be increasingly student-centered. It is imperative to create a personalized learning environment that meets the needs and demands of students, and to evaluate student learning in individual distance learning. As students often have no choice and online learning problems cannot be resolved in time, effective personalized learning will address these issues (Nada & Brenda, 2004).

In the context of this study, it is necessary to actualize the role of a teacher in the implementation of personalized distance learning, which involves the following:

- multilevel updating of educational outcomes;

- transformed student-centered learning;

- the use of modern technologies and organizational forms of student assessment in personalized distance learning;

- academic self-assessment and assessment of achieved results in an actively developing digital environment to dramatically improve educational outcomes (Makhambetova et al., 2021).

The suitability and effectiveness of the Quiz Guide personalized distance learning system for measuring student achievement is further supported by important indicators of learning transformation:

- relevance (new-format teacher training in the liberal arts style);

- polyparadigmality (integration of digital, personalized, and individualized educational paradigms);

- variability of training, adaptation of the learning process to the individual capabilities and needs of students;

- a navigable form of teacher-student communication that becomes parity (Makhambetova et al., 2021).

1.2. Related research

In personalized learning, the speed and methods of instruction are aligned directly to students' needs. Teaching approaches, learning objectives, and course content are modified according to each student's individual characteristics (Garcia-Delmuro, 2019).

Personalized Learning (PSI) was created in the late 1960s to help students in Brazil learn material without a teacher around (S. Kumar & R. Kumar, 2021).

Because the basis of the program is largely behavioral, it was quickly supported by psychology professors and other professionals (Eyre, 2007). Keller (1968) identified key elements important to PSI classes: (1) mastery of the course base, (2) involvement of observers, (3) independent study, (4) emphasis on writing, and (5) use of lectures and demonstrations to motivate students.

A study by Makhambetova et al. (2021) clearly demonstrated the components of individualized learning strategies. Individualized strategies help create a digital pathway for teachers to increase student achievement and motivation.

In Europe and the United States, online education is at an advanced level and a certain scale has emerged (Qi, 2018).

The authors of one study proposed a personalized course model built on a flexible personalized learning model that uses input tests to identify students' initial knowledge and digital skills. The proposed model is more effective than an earlier model of similar courses (Bekmanova et al., 2021).

Web-based information and traditional data mining methods make up web mining (Kasemsap, 2017; Srivastava et al., 2000). The primary goal of web mining is realized by examining user browsing patterns, such as user data about site usage (Carmona et al., 2012).

To provide personalized education support services, the following series of data collection methods can be applied by first creating a supercube of student access data (Junus, 2017).

(1) Modernizing site structure and interface with path analysis can be used to identify groups of frequent access paths on sites and other information from path analysis (Hamdani & Suherman, 2021). (2) Dynamic hyperlinks to students and association rules can help identify connections between specific knowledge and student interests (Li et al., 2021). (3) By following the classification algorithm, different learning for different participants in the learning process is provided. (4) The clustering algorithm identifies and combines similar students from the web access information database. (5) Consistent connections in student learning can be identified by searching for consistent patterns (Han & Ellis, 2019).

The author of another study proposed a personalized learning system model based also on data mining (web mining) technology to improve the low-level service learning system in modern distance education (Qi, 2018). This can help universities in organizing personalized assessments (Chawinga & Zozie, 2016).

A cloud-based adaptive learning system was created using mobile devices in the classroom (Brusilovsky et al., 2007). Survey results showed that students were very interested in mobile learning as a supplement to e-learning.

Researchers studied a personalized e-learning system called Quiz Guide (Kornepati, 2017). The system was originally designed to support introductory C programming courses. The Quiz Guide contains over 100 interactive self-testing exercises (Ueta et al., 2021). Personalization in the Quiz Guide takes the form of prompts that students use to self-identify appropriate assignments (S. Kumar & R.

Kumar, 2021). The system provides students with information about their knowledge through icons. To help students distinguish between related questions, the system adds a checkmark to each correctly completed question (Kornepati, 2017).

1.3. Purpose of the study

A review of scientific publications has shown that the study of the complexities of learners in distance education is a relevant problem for many educational systems. The personalized distance learning system is no exception.

The main motivation for writing the article was the goal to optimize the personalized distance learning process for students, to create a favorable atmosphere for them to learn.

The purpose of our work is to determine the performance of students, using the system of personalized distance learning Quiz Guide.

The study tasks were as follows:

- assess the level of students' performance in the context of computer science course by means of testing;

- identify whether there were significant differences in students' achievements in both groups.

2. Methods and materials

2.1. Research model

To examine the impact of the Quiz Guide personalized distance learning system, a quasi-experimental study was conducted in a computer science course. The quasi-experimental design is a more scientific approach to research because it explores causal relationships between independent and dependent variables in a well-controlled context. For some experimental studies that are not easily conducted, a quasi-experimental research method can be applied to develop some controls to minimize potential factors affecting the validity of the study (Thyer, 2012).

2.2. Participants

The 1st-year students of Abay Kazakh National Pedagogical University and Yelabuga Institute of Kazan Federal University took part in the study. 140 students were selected for this study, of which 74 students (42 women and 32 men) were randomly selected as an experimental group and 74 students (41 women and 33 men) as a control group. The average age of the participants was 18 years old.

The experimental group used the Quiz Guide personalized learning system, while the control group studied using the traditional distance learning approach. All participants gave informed consent to participate and were completely anonymous. Their personal data were neither collected nor stored or used during the study. The research process did not affect respondents' academic performance or personal development. The course "Information Technology" was chosen for experimental teaching, because this discipline is mandatory for almost all specialties and directions - it was interesting to explore how one can organize personalized learning for this discipline.

2.3. Data collection tools

The measurement scale instruments adopted in this study were carried out before and after the study. All tests were developed by three instructors with many years of experience in the field. Initial testing was carried out to determine the skills of the students, prior to the experiment. It consisted of true/false questions with a maximum score of 100. A follow-up test was designed to assess students' concepts and knowledge of the computer science course. In addition, two computer science experts were recruited to ensure that the tests were adequate for assessing student performance in this unit, and experienced Sechenov University teachers who use information technology in research were recruited.

2.4. Data collection process

The beginning of the experimental training was preceded by a pre-testing procedure. This was necessary to determine the available knowledge of the students in the field of IT and to establish whether the students of the two groups were equal in this parameter. For this purpose, the participants were gathered in the computer lab of the institution, where they took a PC pre-test for 30 minutes under the strict supervision of three teachers. This was followed by experimental training.

In the control group, distance learning was organized using the MOODLE online platform. The experimental group was trained using the Quiz Guide system. The principles of personalized learning provided by this system are described in the literature review. One can also read about it in detail in the scientific paper of the developer. Training in groups lasted for 3 months. The groups were taught by the same instructor, who was well trained in the Quiz Guide system.

The information technology program included the following topics:

1. network preservation technologies in information systems.

2. organization, storage, and protection of databases.

3. protection of e-commerce systems and multiservice systems.

4. modern technologies for developing, deploying, and protecting applications and data in a cloud environment.

5. organization and information support of managerial activity.

6. selection of office applications for data analysis.

After graduation, students should be able to:

- collect, formalize, systematize, structure, and work through data to solve applied problems in the professional sphere;

- select and use the tools of office applications for data analysis;

- automate workflow using information and communication technologies and networks, office and hypertext technologies;

- conduct research work and present their results using multimedia presentations and in the Internet space.

Next, students took a post-test according to the same procedure as the pre-test.

2.5. Data analysis

Test reliability was tested using Cronbach's alpha. The scale for interpreting Cronbach's Alpha values, according to Mallery and George (2000).

Cronbach's alpha of both tests values were 0.88 and 0.90, respectively, indicating acceptable internal consistency (Cortina, 1993). Piloting to determine internal consistency between test questions was not performed; SPSS version 18 software was used to calculate the value.

ANCOVA analysis of covariance was used to rule out differences between prior knowledge of the two groups and to examine the effectiveness of the proposed instructional approach to student achievement. ANCOVA treated the pre-test score as the predictor variable (or control variable) of the post-test score, and then determined whether the adjusted post-test score had intergroup differences after adjusting the pre-test score.

The Shapiro-Wilk test was used to calculate the normality of the data obtained in the study. The result of this test was 0.97 (p=0.23), which indicates normal data distribution. In addition, the Levene test was performed to determine homogeneity of variance (F=3.11, p>0.05), showing that the assumption is reasonable and that there were no significant differences in the variance of the two groups. The assumption of homogeneous regression slopes was confirmed, indicating that a one-way ANCOVA analysis could be performed (F=0.26, p>0.05).

3. Results

The results of the analysis are presented in Table 1 reflect the ratio of student achievement. The adjusted mean and standard error were 74.71 and 3.45 for the experimental group and 66.8 and 3.57 for the control group. According to the data, there was a significant difference between the test results of the two groups (F = 10.84, p <0.05).

Table 1. Results of analyzing (ANCOVA) student achievement

Group	N	Value	SD	Adjusted average value	SE	*F*	η^2
Experimental group	74	75.14	12.43	74.71	3.45	10.84*	0.62
Control group	74	65.44	19.75	66.8	3.57		

*p<0.05.

The experimental group scored significantly higher on the final test than the control group, indicating that students using the Quiz Guide learning system had significantly better academic achievement than those who took the traditional approach to learning. Moreover, the effect size (η 2) of learning achievement was 0.62, meaning a small to medium effect (Cohen, 2013).

Figure 1 shows post-test results in the control and experimental groups, namely the number of points (average) on a 100-point scale.

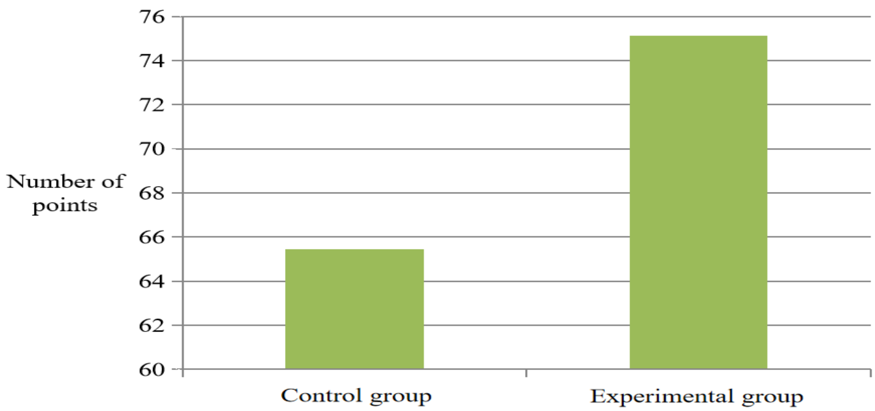

Figure 1. Post-test results

Experimental group students had a good level of mastering the educational material in the discipline "Information Technology". This indicates that the applicant has a thorough knowledge, can apply it in practice, but can make inaccuracies, individual errors in the formulation of answers. They also complete practical assignments based on theoretical knowledge, but can make inaccuracies, separate errors in the analysis. They apply consistently and methodically correct program practical skills.

Participants in the control group mastered the curriculum at a satisfactory level. This indicates that the applicant of higher education knows the program material completely, has practical skills, but is not able to independently justify and interpret the results, cannot go beyond the topic.

The data obtained showed that compared to the classical approach to learning, the system of personalized learning Quiz Guide can lead to better student achievements in the context of computer science learning. One can assume that students were more interested in working with interactive tests and examples.

4. Discussion

The possibilities of personalized distance learning have also been investigated by educational researchers. Bekmanova et al. (2021) proposed an individualized learning model for the course "Innovation skills for the modern teacher in an e-learning environment". This model is based on entry tests to identify students' knowledge and innovation skills. The interface is made using a variety of courses and is a connecting component between the assessment unit of the learning system and the student. Researchers concluded that this model of learning provides an opportunity to enhance learning personalization, which was confirmed by a survey of students at the end of training (Aljawarneh, 2020). It is concluded that the application of promising data science methods allowed the model of personalized learning for making distance learning courses to improve its efficiency in higher education. These programs and methods, together with personalized assessments carried out, can contribute to the improvement of the higher education system as a whole (Zaoudi & Belhadaoui, 2020).

The authors from the Russian Federation reviewed the main approaches to personalization of distance education and proposed algorithmic approaches to personalization design for automated distance education support systems (Kovalev & Kozlova, 2017). The positive influence of individual learning strategies on the performance of learning process participants was confirmed by content analysis and methodological triangulation. Individualized, personalized learning approaches have proven to be effective for teaching and learning. A positive attitude of students towards personalized forms of education was determined. They believe that a personalized approach to learning in vocational education is a means of increasing academic achievement and motivation (Dwiyanti & Sari, 2021; Makhambetova et al., 2021).

To date, two main ways to personalize distance learning have been identified: by testing students after passing the new material, as well as by taking into account learners' behavioral factors (Ghazali et al., 2015). Testing involves creating a model of a student, the properties of which are his/her intellectual abilities and preferences. On their basis, the system corrects the order of the topics studied. The second approach of designing a distance learning process is based on behavioral factors, in addition to identifying a student's knowledge, the system enters information about how s/he got this knowledge. The authors defined uncertainty as the main problem in identifying a student's knowledge of a particular material. To solve this problem, they proposed the use of fuzzy logic, which involves working in conditions of fuzzy and blurred data (Supangat et al., 2021).

The authors also suggest creating a personal weekly or bi-weekly schedule when a student enrolls in a course. When creating the schedule, zeros mark the main activity, units mark periods that can be used for independent work. The coefficient of readiness to achieve the result is put by agreement with a student, intensity - by agreement, but with the basic periodicity. To establish a comfortable study load, for each period, its basic binary value is multiplied by the coefficient of readiness to achieve the result and the coefficient of intensity. The load is summed up by periods for each day during the week, and taking into account the total duration of the course an indicator of the comfortable length of training is obtained (Kozlova, 2016).

5. Conclusions

The personalized model of distance education is a new mode of learning that has emerged with the development of web technologies. In this case, distance education becomes student-centered rather than teacher-centered, and more importantly, it motivates them to take the initiative in learning.

The study results allowed assessing the level of students' performance in personalized distance learning, as well as identifying whether there are significant differences in students' performance between both groups. The results of the performance analysis showed that the experimental group scored significantly higher on the final test, indicating that students using the Quiz Guide learning system had significantly better academic achievement than those who took the classical approach to learning. According to the post-test results, the control group scored (average) 65.14 points, the experimental group scored 74.71. It is also important to note the limitations of the present study. First of all, future research might consider conducting a longer experiment. For example, researchers might run the experiment for one year and test the robustness of the experimental results. Stability and robustness of the study results are issues to be explored further. Second, it is worth considering increasing the sample size of the experiment to improve the accuracy of the experiment results. Finally, factors such as different learning styles, different characteristics, academic performance, and gender can also be taken into account to further expand the scope and depth of the study.

The results obtained can help develop a set of activities that can contribute to a comfortable personalized distance learning, as well as provide new insights into personalized learning.

Future research may examine the positives and negatives of personalized distance learning systems, particularly the Quiz Guide, as well as examine how user-friendly they are for students.

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