The Development of Individualized Assignment Generator

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***Abstract* – The article discusses the development of a system that uses artificial intelligence (AI) to generate individualized mathematics assignments for bilingual students in Tatarstan, Russia. The goal is to enhance learning by tailoring assignments to students' linguistic preferences, cognitive styles, and knowledge levels. The system employs machine learning techniques and GPT-based models to create personalized tasks that align with curriculum goals while addressing linguistic diversity, particularly for Tatar-Russian bilinguals. The study evaluates several large language models (LLMs), including GPT-4, GPT-3.5 Turbo, YandexGPT, and GigaChat, based on their ability to generate math problems and content in the Tatar language. While GPT-4 and GPT-3.5 Turbo show superior performance in producing accurate and semantically correct problems, their proficiency in Tatar remains inconsistent. The research underscores the need for further development of LLMs to enhance content generation for bilingual educational contexts and highlights the potential of AI in advancing adaptive learning for mathematics education. Future directions include expanding the system's functionality and testing its effectiveness across diverse educational settings.**

Keywords – Natural Language Processing, Bilingual Education, Adaptive Learning, Large Language Models, Tatar-Russian Bilingualism.

I. Introduction

Modern educational technologies are rapidly evolving, offering innovative methods for creating personalized learning experiences. A significant aspect of digital learning is the capacity to adapt educational materials to the individual needs of students, which is particularly relevant in the context of teaching mathematics in the middle-school. At this educational stage, foundational mathematical concepts are critical for students' development, yet students often exhibit varying levels of understanding and preparedness. This necessitates approaches that can bridge these gaps and enhance learning outcomes.

In regions characterized by linguistic diversity, such as the Republic of Tatarstan in Russia, the creation of effective educational materials is further complicated by the need to address bilingualism. Tatarstan is distinguished by its cultural and linguistic richness, with Tatar and Russian being the two dominant and officially recognized languages. Many students are bilingual, fluently speaking both languages, which presents unique opportunities and challenges in secondary education. While bilingualism can confer cognitive advantages, it also requires educational materials that are sensitive to linguistic and cultural contexts (Bialystok, 2011).

Bilingual education in Tatarstan has deep roots, but recent years have witnessed challenges in balancing the use of both languages, particularly as Russian predominates in educational institutions. Efforts to preserve the Tatar language align with the region's aim to maintain its cultural heritage. However, bilingual students often require educational materials that not only meet rigorous academic standards but also reflect their linguistic and cultural backgrounds. This need is especially acute in subjects like mathematics, where precision and clarity are essential [1]. The demand for adaptive systems that cater to different levels of preparation and linguistic needs is therefore significant.

The advancement of artificial intelligence (AI) and machine learning technologies offers a promising solution to these challenges. Intelligent systems capable of generating assignments customized to each student's knowledge level and linguistic characteristics can provide personalized learning experiences that address individual needs [2]. In the context of mathematics, such personalization can enhance comprehension and engagement, laying a strong foundation for future mathematical learning.

The research question of this study is following: How can an AI-driven system be developed to generate individualized mathematics assignments for bilingual (Tatar-Russian) students, considering their language preferences, cognitive styles, and varying levels of preparedness?

To achieve this aim, the following objectives are established:

1. Analyze existing approaches to adapting educational materials for bilingual students in Tatarstan, Russia, focusing on identifying the specific challenges and requirements associated with learning mathematics in a bilingual context.

2. Develop an algorithm for generating mathematical assignments that considers students' levels of preparation and linguistic features, utilizing machine learning and AI techniques, particularly GPT-based neural network models, to create personalized and adaptive learning materials.

3. Test and evaluate the effectiveness of the assignment generator through empirical studies involving middle school students in the Republic of Tatarstan, assessing its impact on

learning outcomes, student engagement, and comprehension of mathematical concepts.

By addressing these objectives, the research aims to contribute to the development of adaptive educational technologies that enhance mathematical education for bilingual students. The proposed system seeks to bridge gaps in academic preparation, improve understanding of foundational mathematical concepts, and support the preservation of linguistic diversity within educational contexts. This work not only addresses a critical need within Tatarstan but also provides insights that may be applicable to other multilingual and multicultural educational settings.

II. Methodology

This research integrates pedagogical theories, adaptive learning principles, and advanced technological approaches to develop an individualized assignment generator for fifth-grade students studying mathematics. The theoretical and methodological framework encompasses works in adaptive learning, secondary education pedagogy, and contemporary advancements in machine learning and artificial intelligence.

Adaptive learning emphasizes the necessity for flexible delivery of educational content tailored to the learner's level of preparedness. Adaptive learning systems enhance educational efficacy by personalizing the learning process and accounting for the unique characteristics of each student [3,4]. In the context of secondary education, this personalization addresses the variability in students' proficiency with foundational mathematical concepts.

The concept of the zone of proximal development, introduced by Vygotsky [5], underscores the importance of providing learners with tasks that slightly exceed their current knowledge level to stimulate cognitive development. Applying this theory, the assignment generator formulates tasks aligned with each student's zone of proximal development, promoting deeper engagement and facilitating mastery of fundamental mathematical concepts.

Cognitive development and linguistic proficiency play critical roles in learning mathematics at the secondary education level. While students are developing foundational cognitive abilities, mathematical concepts can present challenges that require precise comprehension and application. For bilingual students, additional linguistic complexities may arise, necessitating educational materials adapted to their linguistic context [6]. Studies by Bialystok [7] have demonstrated that bilingual individuals possess unique cognitive advantages, such as enhanced executive functions, which can influence learning processes in academic subjects.

The effectiveness of utilizing artificial intelligence and machine learning for generating educational assignments has been substantiated by numerous studies. AI-based systems can automate task generation and adjust complexity based on student performance, significantly enhancing the personalization of the learning process [2]. Employing large language models (LLM), such as GPT-4, Claude and others, enables the consideration of both lexical and conceptual features of educational materials, which is particularly vital when designing assignments for young students studying foundational mathematics [8,9].

LLMs are built upon extensive neural networks trained on large-scale text corpora, enabling them to produce coherent and contextually appropriate assignments. Their ability to adapt to varying levels of student preparedness and to incorporate domain-specific knowledge makes them particularly suitable for generating assignments in mathematics, where precision and clarity are crucial [10].

The methodology involves systematic data collection and analysis to inform the adaptive algorithms guiding the assignment generation process. Detailed student profiles are developed, encompassing demographics, cognitive styles, motivational factors, language preferences, and historical performance data in mathematical topics. This information enables the system to tailor assignments that address each student's specific needs and areas for improvement.

III. Research Design

To explain the development process of the assignment generator, we will examine its application within the context of fifth-grade students learning topics such as "Natural Number Divisors" and "Addition and Subtraction of Fractions". The primary objective of this research is to develop and evaluate an automated system capable of generating individualized assignments. By leveraging advanced natural language processing techniques and adaptive learning principles, the system aims to enhance personalized education at the secondary level. It tailors assignments based on each student's performance metrics, cognitive styles, language preferences, and motivational factors. Central to this system is a GPT-based neural network model that produces assignments aligned with the students' specific learning needs while adhering closely to established curriculum goals.

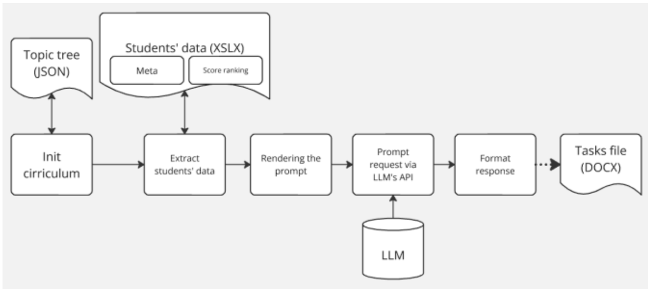


Fig. 1. Generator system workflow

The proposed system operates through a multi-stage workflow designed to ensure the delivery of highly personalized and educationally relevant assignments. Initially, a comprehensive dataset is meticulously prepared, encompassing a wide range of information for each student. This dataset includes demographic details such as age, gender, and language preference; cognitive style indicators like preferences for visual, auditory, or analytical learning; motivational types distinguishing between intrinsic or extrinsic motivation factors; and historical performance data detailing scores and feedback across various topics. This rich dataset serves as the foundational input for the system, enabling it to tailor assignments that address each student's specific needs and areas for improvement.

Subsequently, the curriculum under review is systematically structured into a JSON file that defines the hierarchy of topics and subtopics. This hierarchical structure includes topic relationships that illustrate connections between different concepts and relative difficulty levels that assign complexity ratings to each topic and subtopic. By mapping out the curriculum in this manner, the system can intelligently determine reinforcement needs by identifying foundational topics requiring review based on a student's past performance and can determine appropriate new topics for advanced learning. This ensures that the assignments are both relevant and appropriately challenging for middle school students.

```
"topics": [
  {
    "topic_id": 0,
    "title": "Делимость натуральных чисел",
    "matrix": [[0,1,2,3], [4], [5], [6]],
    "subtopics": [
      {
        "subtopic_id": 0,
        "title": "Свойства делимости",
        "contol": false

      },
      {
        "subtopic_id": 1,
        "title": "Признаки делимости",
        "contol": false

      },
```

Fig. 2. The example of curriculum structure within JSON file

The system employs a sophisticated template function to craft prompts for assignment generation. This function dynamically adjusts the content and complexity of the tasks based on each student's performance metrics. For areas where a student exhibits lower proficiency, it generates reinforcement tasks that revisit and strengthen foundational concepts. For areas where a student demonstrates higher proficiency, it introduces new, more complex tasks that extend learning into advanced topics. The template ensures that all generated tasks are aligned with the curriculum's topic matrix and adhere to the expected level of complexity.

The system communicates with the LLM through an API, sending constructed prompts that request personalized assignments. These prompts incorporate data from the student's profile, including language preference to ensure assignments are in the student's preferred language; motivational style to adapt tasks to include elements that motivate the student intrinsically or extrinsically; and cognitive traits and personal interests to customize content that matches learning styles and areas of interest, such as applications in computer science, physics, or philosophy. The AI model processes these prompts and generates assignments designed to engage the student effectively, making the learning experience more interactive and aligned with their academic and professional aspirations.

Once the assignments are generated, the system compiles them into a cohesive document for each student. This document includes a personalized heading outlining the student's background information and the specific topics covered, as well as formatted tasks aligning with the student's language preference and cognitive style. The assignments are organized in a logical sequence that is easy to follow, progressing from reinforcement tasks to new challenges. The final documents are saved in a format suitable for university-level coursework submission, facilitating easy distribution to students and allowing educators to review and assess the assignments as needed.

To illustrate the system's operation, consider the following example of how tasks are generated for an individual student. The system reads the student's profile, noting key details such as a lower performance in understanding natural numbers divisors, an analytical cognitive style, preference for the Tatar language, and an interest in Harry Potter.

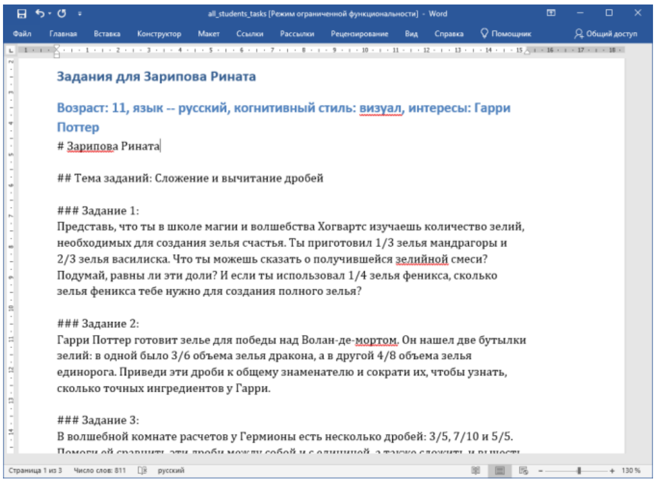
A	B	C	D	E	F	G	H
student	gender	age	language	psycho_type	hobby	motivation	topic0
Зарипова Рината	женский	11	русский	визуал	Гарри Поттер	внешняя	80
Данилов Андрей	мужской	12	русский	кинестетик	Формула-1	внутренняя	60
Хакимова Мадина	женский	11	английский	аудиал	футбол	внутренняя	80

Fig. 3. An example of students' profile in spreadsheet file

Based on the student's difficulties with natural numbers divisors, the system decides to generate reinforcement tasks focusing on these foundational concepts. A template function crafts a prompt that instructs the AI model to generate problems related to divisor, GCD, LCM, suitable for a student. It incorporates formal proof exercises and logical reasoning tasks to align with the student's analytical cognitive style.

The generated tasks are formatted into a text document with a personalized heading that includes the student's name and a brief overview. The problems are organized and sequenced to guide the student from reinforcing foundational knowledge to tackling more complex applications. The document is finalized and prepared for distribution, ensuring that it meets the academic standards expected at the university level.

The end result is a personalized document for each student, containing customized assignments that address their specific learning needs within proper math topic. These documents are easy to distribute in digital format, allowing for seamless integration into the university's learning management systems, and are designed to facilitate educators' ability to review assignments and monitor student progress. The assignments are student-centric, with tailored content that enhances engagement and effectiveness, and are aligned with the academic rigor expected in higher education.


all_students_tasks [Режим ограниченной функциональности] - Word

Файл Главная Вставка Конструктор Макет Ссылки Рассылки Рецензирование Вид Справка Помощник Общий доступ

Задания для Зарипова Рината

Возраст: 11, язык -- русский, когнитивный стиль: визуал, интересы: Гарри Поттер

Зарипова Рината

Тема заданий: Сложение и вычитание дробей

Задание 1:

Представь, что ты в школе магии и волшебства Хогвартс изучаешь количество зелий, необходимых для создания зелья счастья. Ты приготовил 1/3 зелья мандрагоры и 2/3 зелья василиска. Что ты можешь сказать о получившейся зелийной смеси? Подумай, равны ли эти доли? И если ты использовал 1/4 зелья феникса, сколько зелья феникса тебе нужно для создания полного зелья?

Задание 2:

Гарри Поттер готовит зелье для победы над Волан-де-мортом. Он нашел две бутылки зелий: в одной было 3/6 объема зелья дракона, а в другой 4/8 объема зелья единорога. Приведи эти дроби к общему знаменателю и сократи их, чтобы узнать, сколько точных ингредиентов у Гарри.

Задание 3:

В волшебной комнате расчетов у Гермионы есть несколько дробей: 3/5, 7/10 и 5/5.

Страница 1 из 3 Число слов: 811 русский 130 %

Fig. 4. The result file with generated tasks

IV. Results

This study presents a comparative analysis of several large language models (LLMs) utilized to generate mathematical problems on the topic of "Addition and Subtraction of Fractions". Each model was tasked with creating problem statements accompanied by answer options to evaluate their correctness, quality, alignment with educational objectives, and their ability to generate content in the Tatar language.

The evaluation criteria included the quality of task generation, difficulty level, grammatical and semantic correctness, generation time, variability of tasks, language support (specifically for Tatar), and pricing. Quality of task generation was assessed by examining the accuracy and clarity of the problem statements, the logical consistency of the answer options, and their relevance to the topic. The difficulty level considered the models' ability to produce tasks suitable for students with varying proficiency levels. Grammatical and semantic correctness involved assessing the proper use of language and the clarity of formulations. Generation time measured the efficiency of the models in producing responses. Variability of tasks evaluated the uniqueness and diversity of the tasks upon repeated requests. Language support examined the models' capability to generate content in multiple languages, focusing on Tatar to enhance accessibility for diverse student populations. Pricing analyzed the cost-effectiveness of each model in terms of subscription or usage fees.

The analysis revealed significant differences among the models in generating mathematical problems on addition and subtraction of fractions, particularly regarding their performance in the Tatar language.

GPT-4 [11] consistently produced high-quality, well-structured problems that were challenging, educationally relevant, and precisely aligned with the topic when using widely supported languages like English. However, its performance in generating content in Tatar was less consistent. While GPT-4 attempted to produce problems in Tatar, the outputs occasionally contained grammatical errors and unnatural phrasing, indicating limitations in its proficiency with less commonly supported languages. Despite these challenges, GPT-4 maintained efficient generation times and demonstrated high variability in task creation. Its advanced capabilities come at a higher cost, which may impact budget-conscious users.

GPT-3.5 Turbo produced generally acceptable problems in English but faced more significant difficulties when generating content in Tatar. The tasks often exhibited grammatical inaccuracies and ambiguous language, which could hinder student comprehension and the effectiveness of instruction. Although GPT-3.5 Turbo is more cost-effective than GPT-4 and offers faster response times, its limited proficiency in Tatar reduces its suitability for educators requiring content in that language.

YandexGPT [12] showed some proficiency in generating content in Russian and other regional languages but struggled with Tatar. The problems it produced lacked precision and clarity, often containing language errors and insufficient context. These shortcomings diminish its effectiveness for educational purposes in Tatar-speaking settings. YandexGPT may offer services at a lower cost and supports certain languages, but its limitations in Tatar content generation are notable.

GigaChat [13] exhibited significant challenges in generating meaningful educational content, especially in Tatar. The tasks were overly simplistic, lacked contextual relevance, and frequently contained vague or incorrect language. Its slow response times and low variability further detracted from its utility as an educational tool. While GigaChat may be more affordable and support some languages, its inability to produce high-quality content in Tatar limits its applicability for educators in that linguistic context.

V. CONCLUSION

In this study, we developed a system for generating individualized mathematical assignments for bilingual middle school students enrolled mathematics course. By integrating pedagogical approaches to adaptive learning with modern machine learning technologies, we created a program capable of tailoring tasks to each student's level of preparedness and linguistic characteristics.

The analysis of various large language models (LLMs)—specifically GPT-4, GPT-3.5 Turbo, YandexGPT, and GigaChat—revealed that GPT-4 and GPT-3.5 Turbo demonstrated superior performance across several criteria. These models provided high-quality generated tasks, precise mathematical content, adaptability in difficulty levels, grammatical and semantic correctness, and high variability in tasks with relatively quick generation times. This confirms the effectiveness of using these models in educational processes for personalized learning.

In contrast, YandexGPT and GigaChat exhibited less satisfactory results. Identified shortcomings included incorrect mathematical formulations, low variability of tasks, and grammatical errors. These findings indicate the need for further development and optimization of these models for educational applications.

The developed system makes a significant contribution to the advancement of adaptive educational technologies and offers new opportunities for improving the quality of mathematical education for bilingual students in the Republic of Tatarstan. It helps overcome challenges associated with differences in students' preparedness levels and linguistic features by providing a personalized approach to learning.

The limitations of this research are related to the limited scope of testing the system on actual students and dependence on the availability and cost of using certain language models. Future plans include expanding the system's functionality by incorporating additional topics and disciplines, as well as conducting more extensive testing involving different education levels and linguistic contexts. This will allow for a more comprehensive assessment of the system's effectiveness and help determine directions for its further development.

Thus, the results of the study confirm the promising potential of using modern artificial intelligence and machine learning technologies to create adaptive educational materials. The application of such technologies contributes to enhancing learning efficiency, meeting the individual needs of students, and improving the overall quality of education.

[1] *J. Cummins,* Language, Power and Pedagogy: Bilingual Children in the Crossfire. *Clevedon, UK: Multilingual Matters, 2000*.

[2] K. Holstein, B. M. McLaren, and V. Aleven, "Designing for complementarity: Teacher and student needs for orchestration support in AI-enhanced classrooms", in Artificial Intelligence in Education, Lecture Notes in Computer Science, vol. 11625. Cham, Switzerland: Springer, 2019, pp. 157–171.

[3] M. Bower and D. Sturman, "What are the educational affordances of wearable technologies?", Computers & Education, vol. 88, pp. 343–353, 2015.

[4] C. M. Chen and L. M. Duh, “Personalized web-based tutoring system based on an adaptive mechanism”, Computers & Education, vol. 44, no. 3, pp. 237–255, 2018.

[5] L. S. Vygotsky, Mind in Society: The Development of Higher Psychological Processes. Cambridge, MA, USA: Harvard Univ. Press, 1978.

[6] O. O. Adesope, T. Lavin, T. Thompson, and C. Ungerleider, “A systematic review and meta-analysis of the cognitive correlates of bilingualism”, Review of Educational Research, vol. 80, no. 2, pp. 207–245, 2010.

[7] E. Bialystok, “Reshaping the mind: The benefits of bilingualism”, Canadian Journal of Experimental Psychology, vol. 65, no. 4, pp. 229–235, 2011.

[8] R. Luckin, W. Holmes, M. Griffiths, and L. B. Forcier, Intelligence Unleashed: An Argument for AI in Education. London, U.K.: Pearson, 2016.

[9] R. Bommasani et al., “On the opportunities and risks of foundation models”, arXiv preprint arXiv:2108.07258, 2021.

[10] L. Floridi and M. Chiriatti, “GPT-3: Its nature, scope, limits, and consequences”, Minds and Machines, vol. 30, no. 4, pp. 681–694, 2020.

[11] OpenAI, “OpenAI API Documentation”. OpenAI, 2023. [Online]. Available: https://platform.openai.com/docs/introduction. [Accessed: Sep. 28, 2024].

[12] Yandex, “Yandex GPT3 API Documentation”. Yandex, 2024, [Online]. Avialable: https://ya.ru/ai/gpt-3 [Accessed: Sep. 28, 2024]

[13] Sber, “Interacting with APIs. GigaChat developer documentation”. Sber, 2024 [Online]. Avialable: https://ya.ru/ai/gpt-3 [Accessed: Sep. 28, 2024]