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## INCLUSIVE NEXT-GENERATION DIALOGUE SYSTEM: LINGUISTIC ASPECT

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### **Abstract**

**Aim.** To identify strategies for developing language models using artificial intelligence to support the inclusion of people with mental disabilities.

**Methodology.** The study compares two approaches to building dialogue systems: information retrieval question-answering systems and generative question-answering. A collection of texts on inclusive education was compiled. Additionally, a complex of question-answering systems was created using neural network transfer learning methods to analyze the performance of the approaches. A linguistic analysis of the collected data and the results of the dialogue system was conducted.

**Results.** The study showed that both approaches to building dialogue systems have their advantages and limitations. Information retrieval question-answering systems provide high answer relevance. Generative models offer greater flexibility in a broader context. Linguistic analysis revealed that for optimal results, it is advisable to combine both approaches, leveraging the strengths of each depending on the specific task and interaction context.

**Research implications.** The significance lies in the development of dialogue system theory, deepening the understanding of the interaction between structural and semantic aspects of language and their impact on the effectiveness of different approaches to creating dialogue systems, as well as the possibility of applying the research results in the educational system.

**Keywords:** dialogue systems, generative models, inclusive education, linguistic analysis, neural network models

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Научная статья

## ИНКЛЮЗИВНАЯ ДИАЛогоВАЯ СИСТЕМА НОВОГО ПОКОЛЕНИЯ: ЛИНГВИСТИЧЕСКИЙ АСПЕКТ

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### Аннотация

**Цель.** Выявление стратегии разработки языковых моделей с помощью искусственного интеллекта для поддержки инклюзии людей с ментальными нарушениями.

**Процедура и методы.** В исследовании сравниваются два подхода к построению диалоговых систем: вопросно-ответные системы на основе извлечения информации и генеративные модели. Собрана коллекция текстов на тему инклюзивного образования. Методами нейросетевого трансферного обучения также создан комплекс вопросно-ответных систем для анализа производительности рассматриваемых подходов. Проведён лингвистический анализ собранной коллекции данных и результатов работы диалоговой системы.

**Результаты.** Исследование показало, что оба подхода к построению диалоговых систем имеют свои преимущества и ограничения. Вопросно-ответные системы на основе извлечения информации обеспечивают высокую релевантность ответов. Генеративные модели, в свою очередь, обладают большей гибкостью в широком контексте. Лингвистический анализ показал, что для достижения наилучших результатов целесообразно комбинировать оба подхода, используя сильные стороны каждого из них в зависимости от конкретной задачи и контекста взаимодействия.

**Теоретическая и/или практическая значимость** заключается в развитии теории диалоговых систем, углублении понимания взаимодействия между структурными и семантическими аспектами языка и их влияния на эффективность различных подходов к созданию диалоговых систем, а также в возможности применения результатов исследования в образовательной системе.

**Ключевые слова:** генеративные модели, диалоговые системы, инклюзивное образование, лингвистический анализ, нейросетевые модели

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## Introduction

According to the World Health Organization (WHO), about one in six people globally experience significant disability. Persons with disability face inequities in healthcare, education, and employment<sup>1</sup>. According to reports, people with mental health impairments experience stigmatization; bullying at school and discrimination at work result in low social participation and mental deterioration. Evidence from World Psychiatric Association shows that raising awareness of mental health conditions through media campaigns and inclusion reduces stigma and discrimination in the long-term run [1].

There are different types of mental disorders [2]. Nevertheless, this study does not intend to cover every single category. The scope of this study addresses the challenges of people with neurodevelopmental disorders, such as Autism Spectrum Disorder (ASD) and Attention Deficit Hyperactivity Disorder (ADHD). Neurodevelopmental disorders impact behavior and cognition<sup>2</sup>. What distinguishes them from other mental impairments is their potential to affect learning and language acquisition, meaning that neurodevelopmental disorders are a primary concern within the domain of inclusive education research presented in this study.

People with ASD face challenges with social interaction<sup>3</sup>, ADHD is associated with trouble having attention<sup>4</sup>, various learning<sup>5</sup> and language disorders<sup>6</sup> cause difficulties un-

derstanding concepts, patterns, and words. Inclusive education of students with neurodevelopmental disorders has been widely described globally [3], but the analysis of the use of Artificial Intelligence (AI) technologies in those practices lacks proper depth.

The rapid development of Generative AI resulted in numerous neural network apps in various fields, including psychology, psychotherapy, and psychiatry. Some research proves the use of such Conversational AI agents as ChatGPT as a psychotherapist assistant; the model successfully collects client information and generates reports for therapists [4].

One can also find individual initiatives, like Spectrums AI<sup>7</sup>, that use AI algorithms to develop virtual assistance for people with neurodevelopmental disorders. Such cases prove the need to adapt AI-powered technologies for inclusive education. Nevertheless, there is a lack of AI regulations<sup>8</sup> and research on applying novel technologies for inclusion.

The study aims to discover the development strategies for building AI-powered apps that assist the inclusion of individuals with neurodevelopmental disorders and propose evidence-based recommendations for stakeholders, including educators, policymakers, and healthcare providers. The research basis is the AI-powered app development case experienced by the paper author. The study results could be tested in various settings, including education institutions, workplaces, and inclusive communities, to evaluate the success of the proposed practices and predict potential challenges.

The paper consists of a Related Work section and two chapters. The Related Work

<sup>1</sup> Disability. In: *World Health Organization (WHO)*. URL: <https://www.who.int/news-room/fact-sheets/detail/disability-and-health> (accessed: 17.08.2023).

<sup>2</sup> Mental Disorders. In: *World Health Organization (WHO)*. URL: <https://www.who.int/news-room/fact-sheets/detail/mental-disorders> (accessed: 22.08.2023).

<sup>3</sup> Autism Spectrum Disorder (ASD). In: *Centers for Disease Control and Prevention*. URL: <https://www.cdc.gov/autism/index.html> (accessed: 22.08.2023).

<sup>4</sup> Attention-Deficit / Hyperactivity Disorder (ADHD). In: *Centers for Disease Control and Prevention*. URL: <https://www.cdc.gov/adhd> (accessed: 22.08.2023).

<sup>5</sup> Language Disorders. In: *Centers for Disease Control and Prevention*. URL: <https://www.cdc.gov/ncbddd/developmentaldisabilities/language-disorders.html> (accessed: 22.08.2023).

<sup>6</sup> Facts about Intellectual Disability. In: *Centers for Dis-*

*ease Control and Prevention*. URL: <https://www.cdc.gov/disability-and-health/media/pdfs/2024/12/intellectualdisability.pdf> (accessed: 22.08.2023).

<sup>7</sup> Helping Neurodivergent Minds with Artificial Intelligence. In: *Spectrums AI*. URL: <https://www.spectrums.ai> (accessed: 22.08.2023).

<sup>8</sup> Tobin J. Artificial Intelligence: Development, Risks and Regulation. In: *House of Lords Library*. URL: <https://lordslibrary.parliament.uk/artificial-intelligence-development-risks-and-regulation> (accessed: 22.08.2023).

section aims to explore and evaluate existing AI-based apps that address the unique needs of individuals with neurodevelopmental disorders. The first chapter proposes various AI architectures for building inclusive apps, such as Information Retrieval techniques, Natural Language and Image Generation models, and Conversation AI agents, and the second chapter illustrates the realization of the proposed architectures in an app. The source code and supplementary material are available at: [vifirsanova / empi](https://github.com/vifirsanova/empi): Empathic Machine Processors for Inclusion (EMPI). In: GitHub. URL: <https://github.com/vifirsanova/empi> (further – *vifirsanova / empi*).

### Related Work

According to the Cambridge Dictionary<sup>1</sup>, in education, inclusion is a concept describing an opportunity for everyone to participate in activities. Thus, a disabled individual should be able to take the same advantage from an activity as any other member of an inclusive group.

Numerous inclusive education technologies for students with neurodevelopmental disorders include computer-assisted learning. Information technology is a crucial part of our everyday life, and computer assistance helps disabled students to acquire independence, communication skills, and knowledge [4].

Mobile devices are particularly useful when it comes to encouraging autonomy. For example, mobile apps for planning and scheduling help to organize routines, achieve goals, and psychologically prepare for social activities [5]. Knowing how to greet a classmate, answer a teacher's questions, or ask to use the bathroom step by step brings more confidence and allows one to pay more attention to studying.

There are different classes of computer-assisted technologies for students with neurodevelopmental disorders. For example, Augmentative and Alternative Communi-

cation (AAC) comprises tools and practices for communication to support individuals with speech difficulties. Augmentative communication supplements speech with signs, pictures, or other indicators, while alternative communication replaces speech with a different communication strategy<sup>2</sup>. Proloquo2Go<sup>3</sup> is an AAC app suitable for non-verbal individuals with neurodevelopmental disorders and other disabilities. The use of Proloquo2Go in inclusive education was approved by its users<sup>4</sup>.

AI technologies augment inclusive education. For example, the InnerVoice app<sup>5</sup> uses Microsoft Azure AI<sup>6</sup> to teach language. A user should take a picture of an object, and then an AI model will recognize, label, and pronounce its name. As a result, autistic individuals can learn the relations between objects and their names and the connection between text and speech.

Another example is Empowered Brain<sup>7</sup>, a set of Augmented Reality (AR) apps for mobile devices and smart glasses. Empowered Brain provides games that teach how to make eye contact, recognize emotions, and explore environments such as classrooms. AI algorithms analyze emotions and user's speech commands.

Overall, the technologies observed in this section use the power of AR and AI and the advantages of portable devices. They help individuals with neurodevelopmental disorders to enhance learning capabilities and communication skills. Most of the observed

<sup>1</sup> Inclusion. In: *Cambridge Free English Dictionary and Thesaurus*. URL: <https://dictionary.cambridge.org/dictionary/english/inclusion> (accessed: 15.04.2025).

<sup>2</sup> ASHA Practice Portal. In: *American Speech-Language-Hearing Association*. URL: <https://asha.org/practice-portal/> (accessed: 26.08.2023).

<sup>3</sup> Proloquo2Go – AAC app with symbols. In: *AssistiveWare*. URL: <https://assistiveware.com/products/proloquo2go> (accessed: 26.08.2023).

<sup>4</sup> Blazing a Trail for Inclusion. In: *AssistiveWare*. URL: <https://assistiveware.com/learn-aac/12-ways-to-include-everyone-to-communicate-in-your-community> (accessed: 15.04.2025).

<sup>5</sup> InnerVoice. In: *iTherapy*. URL: <https://www.ithera-pyllc.com/innnervoice> (accessed: 26.08.2023).

<sup>6</sup> Azure AI Platform. In: *Microsoft*. URL: <https://azure.microsoft.com/en-us/solutions/ai> (accessed: 26.08.2023).

<sup>7</sup> Empowered Brain. In: *Brain Power*. URL: <https://brain-power.com/empowered-brain> (accessed: 26.08.2023).

AI algorithms process images and speech. They do not take advantage of natural language processing, although Conversational AI models such as ChatGPT are gradually evolving in psychiatry, psychology, and psychotherapy.

The observed apps are broad in their domain, meaning they do not highlight specific situations that an individual with a neurodevelopmental disorder might face in an inclusive classroom. Another detail is that the apps are not inclusive themselves. They provide tools for people who experience some difficulties, for example, non-verbality, but they cannot be used as a training tool for members of a diverse group inclusively. These features and limitations will form the basis of the following research.

### **Chatbot**

The research is two-fold; the first part proposes the Conversational AI architecture suitable for the inclusive education of individuals with neurodevelopmental disorders, and the second part describes a design for a mobile app for the proposed architecture realization.

The proposed Conversational AI architecture, or the Chatbot, uses Transfer Learning (TL) [6] to fine-tune pre-trained models with a custom dataset about inclusive education and neurodevelopmental disorders. The TL concept reveals itself compared with traditional Machine Learning (ML). Traditional ML implies training a new model from scratch each time we process a new dataset or try to solve a new task. For example, if we need to adapt an English conversational model for Russian data, we should train the same ML architecture from scratch on a Russian dialogue corpus. This approach would require significant time and computing power, and the results will not likely be satisfactory on a low-resource corpus or specific conversational domain, such as inclusive education and neurodevelopmental disorders (compared to open-domain tasks).

Transfer Learning allows preserving knowledge gained during model training

and transferring (expanding) it to a new data type or task. Thus, adapting an English conversational model for the Russian language requires using the English model as a pre-trained one and fine-tuning it (re-training it using weights learned by a model during training on English material) on a Russian dialogue corpus. This process usually takes significantly less time and computing power, opening an opportunity to make language- and domain-specific adjustments.

This study focuses on specific TL techniques: domain adaptation and cross-lingual learning. The domain adaptation enables model pre-training on an open- or broad-domain dataset and transferring knowledge gained during the training to a narrow- or low-resource domain. For example, one can train an open-domain question-answering system and use it to fine-tune a question-answering model that covers information about inclusive education. The cross-lingual adaptation allows transferring knowledge from a high-resource language, such as English, to lower-resource language models.

### **Data**

Both domain adaptation and cross-lingual transfer require a dataset representing a closed domain or a target language. The dataset used in this study fulfills both purposes; it is a collection of texts about inclusive education of individuals with neurodevelopmental disorders (the research domain) in Russian (the target language). The proposed dataset is called ASD QA (Autism Spectrum Disorder Question-Answering) and collected by the author of this paper. The ASD QA dataset inherits the structure of the Stanford Question Answering Dataset (SQuAD) [7; 8], a multipurpose collection of questions, answers, and reading passages. SQuAD allows building Machine Reading Comprehension (MRC) models that take paragraphs and relevant questions as input data and use ML algorithms to extract answers to given questions from the paragraphs [9].

The ASD QA dataset was collected through Toloka.AI<sup>1</sup> crowdsourcing. The crowdworkers were to read a set of paragraphs about Autism Spectrum Disorder (ASD) extracted from an information web resource Autistic City (the data is used with the resource administration agreement)<sup>2</sup>, ask one or several questions to each of the given paragraphs, and find answers to their questions. An additional task was to create several generic questions irrelevant to the dataset topic. This study proposes using irrelevant questions as a textual noise that makes the task of automated question-answering difficult for machine learning and results in the development of rather sophisticated models.

One can compare the technique of irrelevant questions collection used in the ASD QA with SQuAD version 2.0 “impossible” questions [8]. “Impossible” questions are relevant to the reading passages’ information but are slightly inaccurate and contain only plausible answers to given questions. The difference between the SQuAD 2.0 and the ASD QA dataset is that the latter contains irrelevant questions that do not have answers in reading passages. “Impossible” questions make SQuAD 2.0 difficult even for robust language models, and one can use SQuAD 2.0 as a tool for algorithm enhancement, while irrelevant questions in the ASD QA dataset are required to filter the input data

from uninformative questions and teach a model to focus on the dataset domain exclusively.

This study uses the knowledge gained by open-domain algorithms enhanced with SQuAD 2.0 to create new closed-domain models through TL. Thus, the ASD QA dataset should reflect differences between the target and all the other domains and filter the input data. Also, the dataset does not need to be as voluminous and difficult as SQuAD 2.0 because TL allows skipping the stages of training where the model learns universal dependencies and other basic linguistic knowledge [10; 11].

One can download the ASD QA dataset from Figshare<sup>3</sup>. Table 1 shows the ASD QA dataset statistics. The detailed statistics is given at *vifirsanova / empi*. The ASD QA dataset contains around 4,000 question-answer pairs and more than 500 reading passages about inclusion and neurodevelopmental disorders. Circa 5% of the questions in the dataset are irrelevant; they form noise in the data and allow input filtering. The ASD QA dataset has four modifications. The first modification permits up to 3 answers to each question. The second modification contains 50% of the whole dataset (its short randomized version). The third modification has shortened answers cut up to 1 word where possible. Another dataset version does

Table 1 / Таблица 1

The ASD QA dataset statistics / Статистика датасета ASD QA

<i>The number of question-answer pairs</i>	<i>4138 pairs</i>
<i>The number of irrelevant (noisy) questions</i>	<i>352 questions</i>
<i>The average length of a question</i>	<i>8 words</i>
<i>The average length of an answer</i>	<i>20 words</i>
<i>The average length of a reading passage</i>	<i>63 words</i>

Source: compiled by the author.

<sup>1</sup> Toloka AI. URL: <https://toloka.ai> (accessed: 03.09.2023).

<sup>2</sup> Autistic City. URL: <https://aspergers.ru> (accessed: 03.09.2023).

<sup>3</sup> Firsanova, V. (2020). Autism Spectrum Disorder and Asperger Syndrome Question Answering Dataset 1.0. In: *figshare*. URL: [https://figshare.com/articles/dataset/Autism\\_Spectrum\\_Disorder\\_and\\_Aasperger\\_Syndrome\\_Question\\_Answering\\_Dataset\\_1\\_0/13295831](https://figshare.com/articles/dataset/Autism_Spectrum_Disorder_and_Aasperger_Syndrome_Question_Answering_Dataset_1_0/13295831) (accessed: 03.09.2023). DOI: 10.6084/m9.figshare.13295831.v19.



not contain irrelevant questions. On the Figshare page, one can find an additional corpus of texts written by random crowdworkers of different ages. The study proposes using this data to learn textual features indicating the user's age. That might be useful to tune the tone of voice of a Conversational AI system.

**Information Retrieval  
Question-Answering**

The study proposes using the ASD QA dataset to build an Information Retriever Question-Answering (IR QA) system. The proposed IR QA system takes the user's question as input, extracts keywords, and searches [12] through an informational source, such as Autistic City, an article that could contain an answer. A Machine Reading Comprehension module takes the user's question and the article as input and extracts an answer to the user's question.

The advantage of the proposed algorithm is that the model does not generate content but cites it from a reliable information source. That guarantees the absence of generic, misleading, and computationally biased content in the output. The disadvantage is that the expected model performance should be at least twice as low as the performance of a pure open-domain MRC system.

The possible explanation for the expected IR QA system limitation is that the MRC module relies on the search engine performance; if the engine extracts an article that does not contain an answer to the user's question, the MRC module will have nothing to work with, and even if a search engine extracts several plausible articles, it does not guarantee the exception of failure. Another explanation is that although Transfer Learning technology is robust, it does not ensure high performance on closed-domain and low-resource data [13]. The study proposes to train a Machine Reading Comprehension model on the ASD QA dataset and test it using a search engine and the Autistic City content.

The ASD QA dataset was split into train, validation, and test sets. The samples are

available on the HuggingFace platform<sup>1</sup>, and the coding script is available at *vifirsanova / empi*. The dataset was used for the model fine-tuning with HuggingFace Transformers. The demo versions of the Transfer Learning process, making predictions with the model and its evaluation are available at GitHub.<sup>2</sup> After several trials on the model fine-tuning with different Transformer [14; 15] based models and various model parameters, the most efficient version was published on HuggingFace<sup>3</sup>. Table 2 shows the model parameters, Table 3 indicates metric scores achieved by the fine-tuned model, and Figure 1 presents the model performance on HuggingFace UI.<sup>4</sup>

Table 2 / Таблица 2

**The model parameters / Параметры модели**

Model Parameter	Parameter Value
Hardware	Tesla T4 GPU
Model type	XLM-RoBERTa
Learning rate	2e-5
Number of training epochs	3
Batch size	1
Optimizer	Adam

Source: compiled by the author.

Table 3 / Таблица 3

**The achieved metric scores / Значения метрик оценки**

Loss	1.5
Exact Match	0.51
F1-Score	0.54

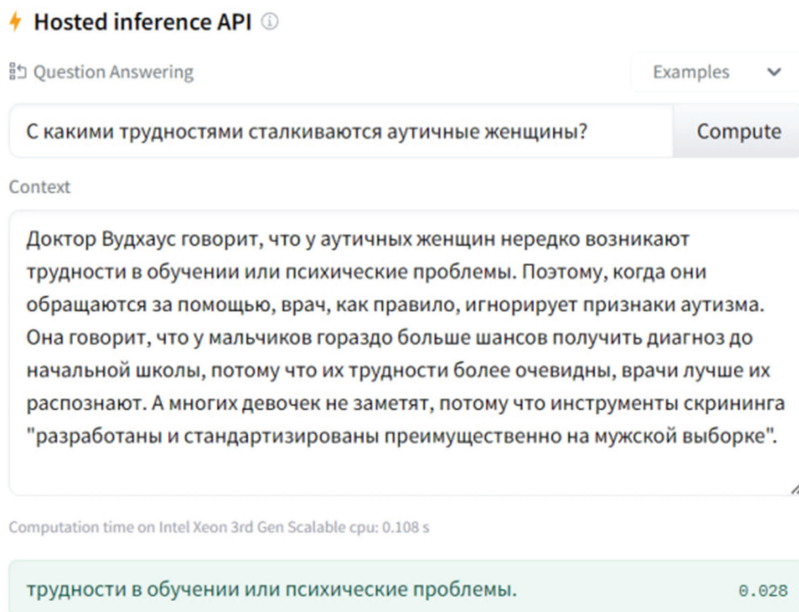
Source: compiled by the author.

<sup>1</sup> missvector. Dataset Card for The ASD QA Dataset. In: *HuggingFace*. URL: <https://huggingface.co/datasets/missvector/asd-qa-test> (accessed: 13.09.2023).

<sup>2</sup> vifirsanova. Empathic Machine Processors for Inclusion (EMPI). In: *GitHub*. URL: <https://github.com/vifirsanova/empi/tree/main/demos> (accessed: 15.04.2025).

<sup>3</sup> missvector. Model Card for Ru-ASD-QA-BERT. In: *HuggingFace*. URL: <https://huggingface.co/missvector/ru-asd-qa-bert> (accessed: 13.09.2023).

<sup>4</sup> Ibid.



**Fig. 1 / Рис. 1.** The model performance on HuggingFace UI / Производительность модели на интерфейсе HuggingFace

Source: compiled by the author.

Satisfactory results in Figure 1 rely on proper input formatting. The MRC task requires two input elements; a question and a reading passage that must contain an answer. Thus, an MRC algorithm as a chatbot engine should be provided with a separate search engine or an information retriever that extracts a proper reading passage from a database or the web. One solution is to build a two-fold retriever-reader model that searches through a database in the first processing stage and extracts an answer to a user question, like MRC, on the second stage [16].

One way to build a retriever is to convert the data stored on the information source into a corpus. The study proposes using a scraping technique described at *vifirsanova / empi*. The data was parsed with BeautifulSoup and then used as a corpus for information retrieval. The data was split into chunks of equal length. Each chunk contained 512 characters, i.e. the maximum input length for BERT-based systems. The corpus comprised 10,706 chunks. The study

proposes searching the corpus with the Okapi BM25 ranking function [17]<sup>1</sup>.

Searching the input questions presented in Figure 1 resulted in different reading passages, although they were posed to the same passage in the ASD QA dataset. Figure 2 shows the extracted reading passages. Empirically, it is evident that some passages contain plausible answers, and the first-ranked passage does not always contain an answer. Presumably, the combination of the passages might lead to higher precision. Nevertheless, the extracted passages were tested on the ASD QA model, and Figure 3 shows some results. The results in Figure 3 show a significant decrease in the model performance even if the extracted passages were similar to the passages from the original dataset. One of the solutions is to switch the base algorithm to Generative AI.

<sup>1</sup> The search process is shown at: *vifirsanova / empi.retriever\_reader/BM25\_search.ipynb*. In: *GitHub*. URL: [https://github.com/vifirsanova/empi/blob/old\\_ver/retriever\\_reader/BM25\\_search.ipynb](https://github.com/vifirsanova/empi/blob/old_ver/retriever_reader/BM25_search.ipynb) (accessed: 15.04.2025).



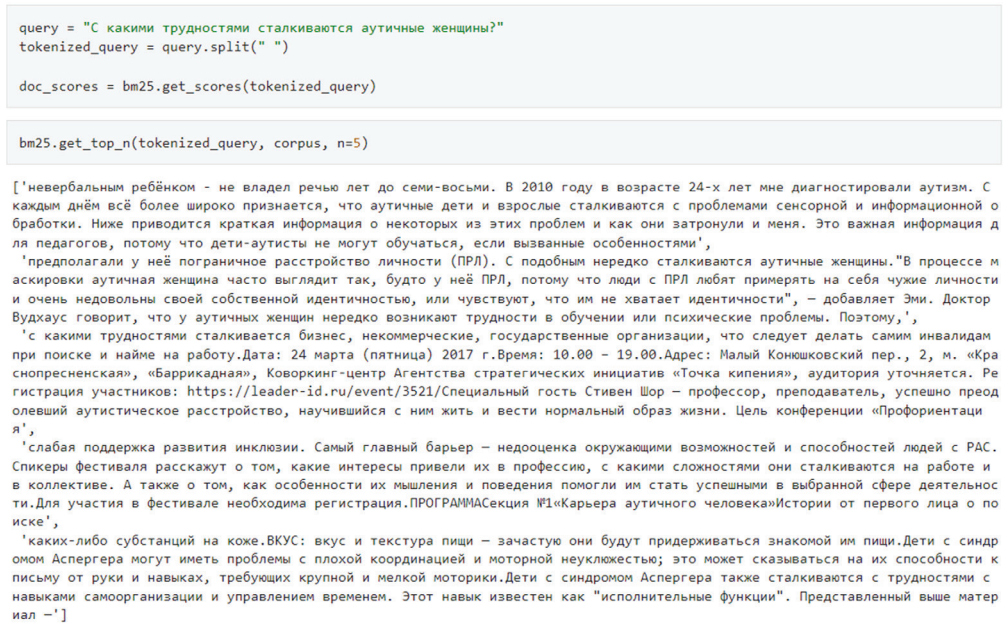


Fig. 2 / Рис. 2. The results of Okapi BM25 retrieval / Результаты извлечения информации методом Okapi BM25

Source: compiled by the author.

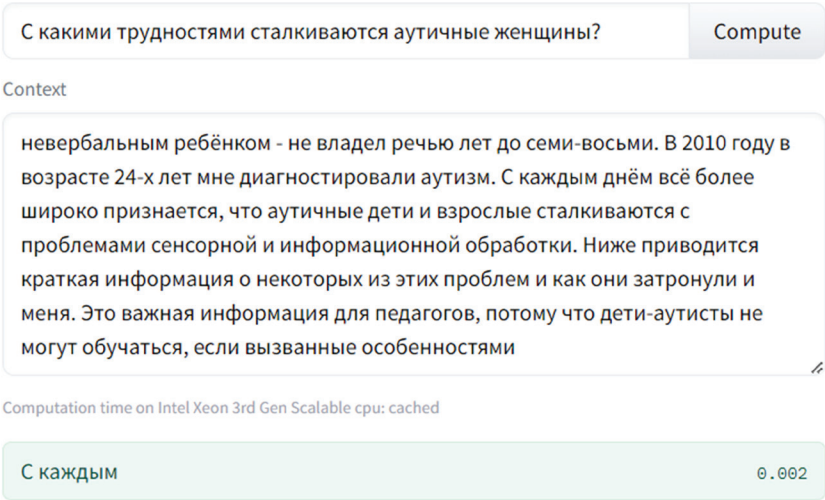


Fig. 3 / Рис. 3. The model performance after Information Retrieval / Производительность модели после извлечения информации

Source: compiled by the author.

Generative algorithms allow sequentially generating content by learning the probability distribution of tokens through training data. Zero-shot learning is a capability of a generative algorithm to learn a new task without “seeing” similar samples in the training data, while few-shot learning allows a model to solve a new problem successfully with only a few examples of the task in a sample [18]. That means that it is possible to fine-tune generative algorithms for a wide range of Natural Language Processing tasks including question-answering.

One significant limitation of generative algorithms is their “hallucination”, i.e. gibberish content, such as non-existing words, grammar mistakes, or false facts. ChatGPT based on GPT 3.5 and GPT 4 is the state-of-the-art Generative AI model. The study proposes several experiments on adapting ChatGPT for inclusive education.

### Generative Question-Answering

Figure 4 shows ChatGPT responses to questions from the ASD QA dataset. The model generates correct answers, however, the given information is excessive and it does not contain specific facts about inclusive education. The study proposes the improvement of the model by integrating a graph. Firstly, it is important to build a graph that would contain necessary information about inclusion and neurodevelopmental disorders. The study proposes creating a graph [19] that describes skills, practices, forms of communication, and inclusive environment, i.e. factoid information for different inclusive community members, such as psychiatrists, tutors, volunteers, and individuals with neurodevelopmental disorders. Figure 5 shows the nodes and links of the proposed graph.

Secondly, one should form a query to access the encoded information. For example, one can use SPARQL query language to form queries, such as `SELECT * WHERE {?disorder rdfs:label "Autism"@en ; dbo:abstract ?text . FILTER (LANG ( ?text ) = 'ru' )}`, which means extracting all the instances containing textual information about Autism Spectrum

Disorder in Russian from DBPedia (Wikipedia-based graph knowledge base).

Finally, the extracted information can be used to form prompts (instructions in natural language) for ChatGPT or similar Conversational AI models. Figure 6 shows possible prompts for question-answering and ChatGPT outputs. The prompt should contain the question (for example, a question from the ASD-QA dataset) and the information extracted from DBPedia or any other custom knowledge base (see Figure 5). The prompt should also contain styling instructions that set the length of a generated answer, tone of voice, and other formatting variations.

### App

The proposed technology forms a Conversational AI chatbot. The chatbot is a part of a larger development project, an app for inclusive education. The proposed idea is to build a virtual assistance app for psychiatrists, tutors, volunteers, and individuals with neurodevelopmental disorders. The app might help to exchange information about inclusion and instantly use popular tools for psychological support.

Figure 7 shows some of the app prototypes created in Figma by the author of this paper. The proposed app includes a Conversational agent that automatically answers various questions about inclusion and neurodevelopmental disorders, a catalog of educational illustrated novels about communication in an inclusive community, a planning calendar, and a messenger. The app design is a result of numerous consultations with psychiatrists, neurotypical university students, and individuals with neurodevelopmental disorders.

The study proposes using AI-generated images to illustrate the catalog of novels about communication, as well as chatbot responses. Figure 8 shows an image generated by DALL-E 2 with a prompt “greetings, illustration, simplified image”. The knowledge of content format that would be acceptable and psychologically comfortable for people with neurodevelopmental disorders combined



Аутизм бывает только у детей?



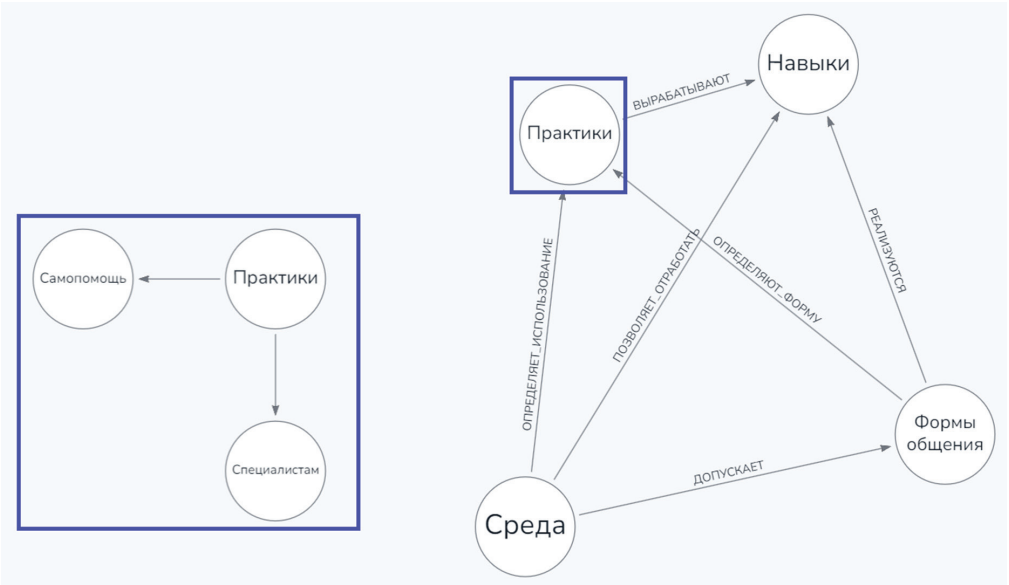
Нет, аутизм (расстройство аутистического спектра) не ограничивается только детским возрастом. Аутизм является пожизненным неврологическим расстройством, которое может сопровождать человека на протяжении всей его жизни. Признаки аутизма проявляются в раннем детстве, и некоторые дети с аутизмом могут испытывать значительное улучшение в развитии и адаптации к окружающему миру с возрастом, благодаря поддержке, реабилитации и обучению.

Однако аутизм также остается частью жизни многих взрослых людей. Некоторые люди с аутизмом могут развиваться и находиться в состоянии независимой жизни, в то время как другие могут нуждаться в продолжительной поддержке и адаптации для успешной интеграции в общество.

Важно помнить, что аутизм проявляется разнообразными способами, и каждый человек с аутизмом уникален. Это расстройство может сказаться на социальной коммуникации, поведении, интересах и чувствах, и воздействие его может быть различным у разных людей независимо от возраста.

**Fig. 4 / Рис. 4.** ChatGPT answers questions from the ASD QA dataset / ChatGPT отвечает на вопросы по данным ASD QA

Source: compiled by the author.



**Fig. 5 / Рис. 5.** Nodes and links of the proposed graph / Рёбра и вершины графа

Source: compiled by the author.

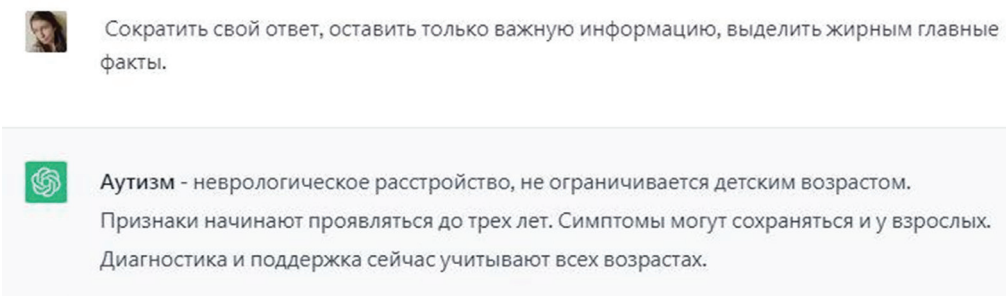


Fig. 6 / Рис. 6. Proposed prompts and ChatGPT responses / Подсказки для ChatGPT

Source: compiled by the author.

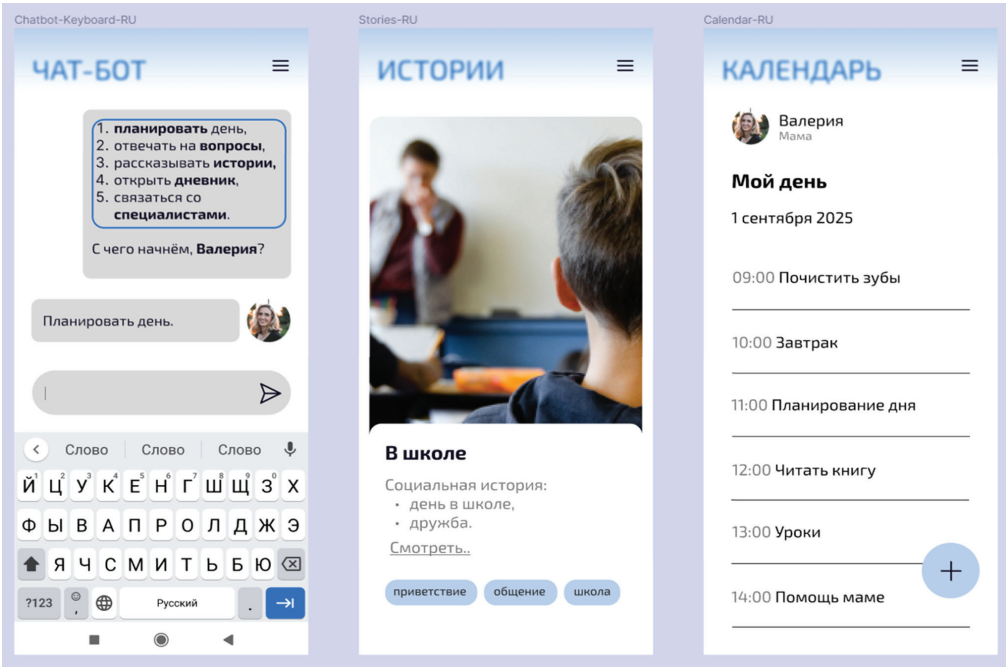


Fig. 7 / Рис. 7. App prototypes / Прототипы мобильного приложения

Source: compiled by the author.

with the power of prompt engineering could solve the problem of creating unique illustrations that explain the basic concept of communication.

### Conclusion

The study proposes a Conversational AI system and a mobile app for inclusive education of individuals with neurodevelopmental

disorders. The study describes data collection, the Conversational AI architecture development process, and the app prototype.

The proposed Conversational AI architecture uses Transfer Learning to fine-tune pre-trained Transformer-based language models with the ASD QA dataset. The ASD QA dataset collected by the paper author covers various topics related to inclusive ed-



**Fig. 8 / Рис. 8.** An illustration generated with DALL-E 2 / Иллюстрация создана с DALL-E 2

Source: compiled by the author.

ucation and neurodevelopmental disorders. The dataset compiled through crowdsourcing includes different types of questions to encourage domain-specific learning.

The research probes two approaches to building dialogue systems: Information Retrieval Question-Answering (IR QA) and Generative Question-Answering. The IR QA system searches for an article that might contain an answer to a user question and extracts information from the extracted passage. This approach reduces the risk of gene-

rating misleading or biased content. However, the extraction quality might be limited by the effectiveness of the underlying search engine. Generative Question-Answering, on the other hand, allows for more flexible responses but may introduce hallucinations by generating incorrect information.

The study proposes integrating a knowledge graph with factoid information about inclusive education and neurodevelopmental disorders to enhance the Generative QA model performance. The model would access accurate information through the knowledge graph and generate high-quality responses with Generative AI.

The study proposes using the Conversational AI system in a mobile app to assist psychiatrists, tutors, volunteers, and individuals with neurodevelopmental disorders. The app offers several features: the Conversational agent, educational aid, a planning calendar, and a messenger to support inclusive education.

Overall, the study reflects various approaches towards building a Conversational AI for inclusion: Transfer Learning techniques, knowledge graphs, and Generative AI. The proposed system might positively impact the field of inclusive education. However, it is important to recognize such challenges as Generative AI hallucination and maintain the quality of responses.

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