# Chatbot algorithm for solving physics problems

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Abstract
The article is devoted to the use of chatbot capabilities, a product of artificial intelligence that can complement traditional learning formats. The article discusses the process of creating and testing a physics problem-solving algorithm implemented in a chatbot designed to teach users to solve typical physics problems. The training bot created by the authors offers the user to solve a typical problem, controls the correctness of the solution process, and asks guiding questions and tasks. A chatbot is a tool for sequential learning, so the purpose of creating a chatbot is to develop students' interest in the subject, familiarise them with typical problem-solving schemes, and assist teachers in individual work with students. The chatbot developed by the authors performs 4 main functions: educational, entertaining, motivational, and reminder. The technology of creating chatbots has wide possibilities for building different types of training courses. The effectiveness of the described method was tested in two groups of students. In the first group, the teacher provided explanations in the process of solving the tasks, and in Group 2, students solved the tasks independently using a chatbot. Statistical processing was based on the Mann-Whitney U test. It was found that there was no significant difference in the levels of problem-solving skills in the comparison groups.

**Keywords**
chatbot, algorithm, education, tasks, physics, mathematics



## 1. Introduction

The development of online education has had a significant impact on the methodology of teaching physics and mathematics, complementing traditional face-to-face learning formats

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with new online developments. Along with social networks, video blogs, and online platforms, one of the little-explored learning tools is a chatbot.

A chatbot is a computer program designed to simulate a real dialogue between a virtual interlocutor (artificial intelligence) and a user. A chatbot can ask questions, and respond with voice or written messages within the algorithm set by the administrator (bot moderator, author of its text and audio messages). The history of chatbots reflects the history of artificial intelligence and began before the creation of personal computers and the spread of the Internet. The founder of modern chatbots is considered to be the English mathematician and cryptographer Alan Turing, who developed the theory of machine learning in the 1930s. The first virtual voice assistant that answered the interlocutor's questions in natural language was ELIZA, created in 1966 by Joseph Weizenbaum and designed to simulate active listening by a psychotherapist. In the 2010s, chatbots became widespread with the advent of online messengers (WhatsApp, Facebook Messenger, Telegram, WeChat, etc.). In 2018, Facebook published statistics: the number of active chatbots on Facebook Messenger exceeded 300 thousand.

The use of chatbots is reasonable in areas where there are similar tasks that can be automated for convenience. Bots differ in the basic principle of operation: some work according to a ready-made algorithm (created by an administrator-moderator), while others use machine learning (i.e., they can learn from a corpus of texts and thus evolve).

Today, online chatbots are mainly used in marketing (customer advice, order acceptance, and processing), customer service (technical support, help desk), HR (employee search), education, and entertainment. Chatbots are broadly defined to include all voice assistants, including Siri (Apple), GoogleNow, Alexa, etc.

Chatbots solve a wide range of tasks by automating communication with users. When creating educational chatbots, the most useful features are the following: 1) providing information within the educational process – linearly and in a certain amount; 2) administering the learning process or submitting documents to an educational organization; 3) answering students' questions; 4) checking errors; 5) reminding of class times. Current developments in this area suggest that natural language interaction with technology is possible as technology evolves and users become more accustomed to interacting with digital objects. Instead of creating a human-like application for an intelligent machine, it is about creating effective digital assistants that can provide information, answer questions, discuss a specific topic, or complete a task.

Using machine learning techniques, these digital assistants can perform routine duties similar to those of a regular assistant or secretary. They excel at tasks such as organizing emails, and highlighting vital content and interactions, thereby increasing the efficiency of their users. A huge number of simpler and more subject-oriented text chatbots complement targeted functions such as collecting support tickets to leave feedback, distributing content for publication sites, and transferring tasks in digital and text formats. These rules or flows allow them to effectively answer queries in a specific domain but are not effective in answering questions whose structure does not match the rules the chatbot has been trained on.

Chatbots are still relatively underutilized in the education sector compared to the marketing and service industries. In an era driven by technological advancements, the education landscape has witnessed a remarkable transformation. With the proliferation of digital tools, chatbots have become valuable resources for facilitating learning and providing personalized assistance. In the field of physics, a subject that is often considered difficult for students to learn, developing a chatbot that can help solve physics problems can be a transformative solution. By leveraging the power of artificial intelligence (AI) and natural language processing (NLP), such a chatbot can improve student understanding, boost their confidence, and promote self-directed learning.

One of the key advantages of a physics chatbot is its ability to offer personalized guidance. By interacting with students in the form of a conversation, the chatbot can assess their strengths and weaknesses, identify specific areas of difficulty, and provide targeted explanations. With this personalized approach, the chatbot can effectively correct misconceptions, explain complex concepts, and offer step-by-step guidance on how to solve problems. This personalized assistance creates a favorable learning environment, empowering students to solve physics problems with confidence.

Feedback plays a crucial role in the learning process, allowing students to assess their progress and identify shortcomings that need to be addressed. A chatbot for solving physics problems can provide instant feedback on students' answers, helping them to identify mistakes and suggesting remedial measures. With instant feedback, students can correct their mistakes in real-time, improving their understanding of physics principles and problem-solving strategies. This rapid feedback loop promotes an iterative learning process, encouraging students to persevere in improving their approach and deepening their understanding of the subject.

A chatbot that solves physics problems can be available 24 hours a day, seven days a week, allowing students to get help whenever they need it. Unlike traditional teaching methods that adhere to specific schedules, a chatbot ensures that support is always available, regardless of time or location. This accessibility caters to a variety of learning styles and preferences, catering to individual needs and promoting self-directed learning. Whether the student is facing a problem during the day or late at night, the chatbot serves as a reliable companion, ready to provide guidance and help in solving the problem.

The ability of a physics chatbot to adapt and evolve based on student interaction is a significant advantage. This feature is difficult to ensure in the development process, but by analyzing student performance data, such a chatbot will be able to detect patterns, identify common difficulties, and refine its answers accordingly. This adaptive approach to learning allows the chatbot to continuously improve its effectiveness in addressing learner queries, thereby enhancing the overall learning experience. In addition, as the chatbot accumulates knowledge over time, it can develop a complete database of tasks, offering a large resource base for future learners.

Engagement is a vital component of effective learning. By incorporating elements of gamification and interactivity, a physics chatbot can make the learning process enjoyable and engaging. For example, a chatbot can present physics problems in the form of puzzles or riddles, encouraging students to think critically and apply their knowledge creatively. Incorporating interactive features such as simulations or visualizations can further enhance students' understanding of abstract concepts, making physics more understandable and accessible. By turning learning into an immersive experience, a chatbot fosters intrinsic motivation and deepens students' connection to the subject.

# 2. Theoretical Background

Modern dialogue systems are divided into closed-domain and open-domain virtual participants. Targeted dialogue systems are designed to solve specific predefined user tasks, and virtual participants are needed to engage the user in using the product by simulating a natural conversation with him or her. The dialogue is always conditioned by the context, which changes during the dialogue while setting a logical movement in a direction known to the interlocutors. If logical connections are lost, it causes emotional disappointment in the interlocutors. Thus, the main incentive for active interaction with a conversational agent is the user's emotional satisfaction from the dialogue with it.

The creation of a universal intelligent dialogue agent that combines not only the ability to execute specific daily user scenarios, but also to maintain the coherence of the conversation (coherence), and to issue responses that are consistent with each other in terms of content (imitation of messages from one person, coherence) is an interesting, promising and at the same time very difficult task that developers have yet to solve.

The conventional approach to the development of conversational agents includes three main blocks of tasks performed by them: natural language understanding, dialogue management, and user response synthesis. The core of the system is the process of analyzing a user's phrase in a natural language processing module, which converts the user's remark into another vector representation, usually by performing some text processing steps: segmentation, tokenization, normalization, parsing, named entity extraction, anaphora, and ambiguity resolution. The resulting vector representation is used by the internal model of the system to further respond to the next user. This text-processing cycle is the basis of any dialogue agent, and its complexity depends on the specific purpose of its creation [1].

The ELIZA virtual interlocutor was one of the first attempts to implement a natural human-machine dialogue between a person and a program. It was a chatbot based on a large number of manually created templates and heuristic rules. Such an approach requires huge human resources to predict possible branches of the conversation, which severely limits the set of answers. In an attempt to combat these limitations, researchers have developed a new way of looking at the possibility of creating a human-machine dialogue using data-driven chatbots and machine-learning models. The general idea is to create a chatbot that is trained with a large collection of human dialogue texts. Chatbots can be divided into generating and ranking chatbots according to the training methods.

Generating chatbots respond to user messages using text generation algorithms, predicting each subsequent word in the response. It was proposed not to define a script for the entire dialogue for a chatbot, but to try to teach the system to respond to the last user's remark using approaches from machine translation tasks. Today, the basis of the generating approach is recurrent sequential encoder-decoder architectures, which are multilayer LSTM and GRU neural networks that use the attention mechanism [2]. It is known that training-generating architectures often lead to the problem of answering with too general phrases (e.g., "I don't know", "okay"), as well as the problem of inconsistent answers (the bot answers the same questions but formulated differently).

Despite the prospects of using generating models, they are rather unpredictable in their performance for use in commercial products[3], so ranking chatbots that select a replica from a predefined set of answers are the most popular.

For single-turn conversation or multi-turn conversation pairs, vector representations of one dimension (encoder-encoder) are constructed from the data set, and then the most possible answers are ranked according to the values of some relevance function between the vectors (most often, a scalar product or cosine distance). This approach, which has gained popularity in information retrieval tasks, has subsequently been adapted in many works to create dialogue systems[4]. Dialogue ranking agents select answers from among pre-prepared responses, so an important advantage of this approach is the ability to limit the output of grammatically incorrect and unacceptable answers that may be present in the training dataset. In our experiment, we chose a chatbot ranking implementation.

To create a chatbot, you need a fairly large set of textual data containing dialogues on the topics it is supposed to support. The availability of additional contextual information, such as a unique identifier of the author of a sentence (or his or her name, age, and gender), as well as data about the dialogue (time of sentences, whether a sentence was answered), can improve the quality of chatbot responses.

Among the most popular open data sources where you can collect datasets suitable for creating a conversational chatbot, we would like to highlight the following: 1) Subtitles to films and TV series. They contain a lot of everyday dialogues on general topics. However, they also contain many specific phrases that may be inappropriate (for example, dialogues from fantasy and historical films) and there is no obvious separation of one dialogue from another; 2) Twitter microblogging service. Among the advantages of texts on Twitter is a precise breakdown into dialogues, and additional data about the authors and the addressee of the remark. However, most often, users engage in discussions around some multimedia content, which defines the topic to a greater extent. At the same time, dialogues on everyday topics are conducted by quite different groups of users, which may require additional research of the authors' profiles to ensure that the bot maintains the consistency of responses; 3) Public messenger chats (e.g. Telegram or Slack) is a source of replenishing the dataset with narrowly focused topics. When training a chatbot on such data, it should be remembered that in the absence of chat moderation by administrators, the texts may contain a significant number of replicas containing hate speech, political statements, and devalued vocabulary; 4) Other data sources. In addition to the sources mentioned above, we can also highlight comments on social media, various web forums on websites, film scripts and transcripts of TV programs, as well as texts of fiction and educational literature. As you can see, on the one hand, there are many sources where you can get open datasets with dialogues that are suitable for training a conversational chatbot. On the other hand, depending on the purpose of creating a bot, this data may not be enough, as there may be a required number of dialogues on the desired topic in the public domain.

Since when interacting with a ranking chatbot, the user is likely to write a sentence that is not in the pre-prepared set of answers, the relevant answers will be those whose context in the available data set is most semantically close to the entered sentence. In the work of R. Zhang et. al. [5], the authors propose many different ways to determine the context of a candidate answer for a chatbot with a ranking architecture. In our work, the context of a candidate's response is the chain of messages that precede the selected sentence, with this sentence being an explicit response to the penultimate phrase in the chain while being the last in the chain.

To be able to search for the most relevant answer based on the context of the cue, the original dialogue dataset was converted into a context-response format. The textual data was then processed in the following sequence: splitting the text of the cues into tokens; removing special characters, references, and punctuation; removing stop words, and lemmatizing the tokens. After the final processing stage, an updated dataset consisting of context-response text pairs was obtained. Given different variants of vector representations of the general dialogue dataset, the vectorization of the user's input query and the context from the response database can be calculated by averaging the word vectors of these models or sentences.

The most popular algorithms for creating vector representations of text today are based on the ideas of distributional semantics: words that occur in similar contexts with similar frequency are semantically close. In this case, the corresponding compressed vector representations (embeddings) are close to each other by the cosine measure in a certain vector space [6].

One of the most basic methods of representing a text document as a vector is the TF-IDF statistical measure [7], which is calculated as the product of the word frequency in the text and the inverse word frequency in the document collection. Information text vectorization models became popular after the emergence of the Word2Vec approach [8]. The vector representation reflects the contextual proximity of words: words that occur next to identical words in the text have a high cosine similarity, which means that we can talk about semantic proximity.

As a result of training the Word2Vec model, a fixed vocabulary is created, which requires training the model again. A solution to the problem of missing words was proposed within the fastText model [9], which is a modification of Word2Vec and calculates vector representations of word parts that make up the vector of a whole word. Today, there are many other models of text vectorization, including the GloVe model [10], which combines matrix decomposition and Word2Vec algorithms.

The above vectorization methods are called static, and they have the following limitation: such models do not take into account the ambiguity and context-dependent nature of words, i.e. for one word occurring in different contexts, there will be one average embedding. More recently, contextualized (dynamic) language models have been developed that allow calculating embeddings for a word (or a whole sentence) depending on its context of use. One of the main events of 2018 in the field of natural language processing and machine learning was the BERT model, which improved the solutions to many text processing and computational linguistics tasks known at the time of its introduction. Also, recent developments in the field of contextualized embeddings include such advanced models as ELMO, XLNet, and GPT-3 [11].

One of the common problems when working with texts in the case of chatbots is multilingualism: people often use borrowed words or entire quotes in their spoken language. In the case of ranking architectures, language mixing can affect the calculation of semantic proximity between vectors. A modern approach to ensuring multilingualism is to prepare a model that can generalize different languages in a common vector space, where vectors of identical sentences would be close to each other regardless of the language of the input sentence.

For many years, chatbots have played a significant role as pedagogical agents in educational institutions. Intelligent learning systems, also called digital learning pedagogical agents, date back to the early 1970s. These conversational pedagogical agents use artificial intelligence techniques to augment and personalize automated learning processes. Developing engaging, valuable, and practical pedagogical agents requires expertise in design and research, encompassing a deep understanding of emotional, cognitive, and social educational aspects while leveraging technological advances.

In addition, dialogue agents have been integrated into software and devices, extending their reach. Recently, organizations have been increasingly exploring the potential of chatbots beyond providing pre-programmed answers to simple information requests.

The integration of chatbots into education has seen a surge of interest over the past decade, especially in terms of their application in teaching and learning. These useful chatbot systems offer the benefits of instant accessibility and natural dialogue interactions similar to an interview. Furthermore, chatbots demonstrate the ability to facilitate casual interactions, promoting user engagement. Furthermore, this technology is a promising tool for teaching and learning in distance and online learning.

Mobile devices, with their diverse capabilities for collaboration, communication, and learning, have paved the way for the introduction of chatbot technology. However, the younger generation often blurs the lines between social media tools and mobile devices. Mobile devices offer advantages such as easy access to multimedia content, mobility, flexibility, and instant information search. At the same time, they pose challenges such as reading learning materials on small screens, reduced concentration and attention span, technological limitations (battery life, connectivity), and compatibility issues.

The problem of using various online services has also been increasingly studied since the beginning of the COVID-19 pandemic [12]. Despite these challenges, mobile devices allow students to receive quick feedback, creating a learner-centered environment. Research confirms the potential for interaction between students and teachers through social media, further highlighting the opportunities offered by the integration of chatbot technology into education. In education, the United States, Taiwan, and Hong Kong are the most prominent contributors to the use of chatbots. Research related to chatbots in education is still at an early stage, as few empirical studies investigate the use of effective instructional designs or learning strategies with chatbots. This provides a large scope for relevant research to stimulate innovative teaching in terms of improving the learning process and learning outcomes [13, 14, 15, 16]. S. Wollny et.al note that in terms of scalability and accessibility, they also offer unique opportunities as communication and information tools for digital learning [17]. Systems are being developed, for example, by F. Clarizia et. al that can process questions and provide answers to the student through the use of natural language processing methods and subject area ontologies [18]. A chatbot can act as an intelligent assistant that improves innovative educational services in educational institutions, reducing labor costs [19]. E. Kasthuri and S. Balaji use a practical MATLAB dataset to develop an educational chatbot [20]. A. Mondal et. al has applied an ensemble learning method as a random forest in the presence of extracted features from our prepared dataset [21].

## 3. Research Methods

The experiment described in our paper is based on the idea of creating a chatbot that could provide a coherent response to a given cue, thus giving the user the impression of a conscious dialogue. It is expected that this behavior will be demonstrated primarily in response to the pre-selected narrow topic (a typical physics problem). We chose physics textbooks as the data source for the chatbot implementation.

In this paper, we consider the creation of a chatbot to help students solve physics problems.

A physics problem refers to a small problem that is solved by applying the laws and methodology of physics, using logical inference, mathematical operations, and experiments. Solving such problems serves as both an end and a means of learning, encompassing various benefits, including 1) formation and enrichment of physical concepts; 2) development of physical thinking skills; 3) fostering the practical application of knowledge. In educational practice, physical tasks are used to 1) familiarisation with problem-solving scenarios and problem situations; 3) transfer new information; 4) development of practical skills and abilities; 5) assessment of the depth and strength of knowledge; 6) consolidation, generalization, and review of materials; 7) development of creative abilities. By solving problems, students develop hard work, curiosity, intelligence, independence of judgment, interest in learning, willpower, character, and perseverance in achieving their goals. Problem-solving is an integral part of most physics lessons and extracurricular activities.

## 4. Results

A chatbot designed to solve physics problems is based on a typical generalized sequence of problem-solving as follows:

1. Initial reading of the task statement.
2. Re-reading and clarification of the problem statement, including the meaning of new terms and expressions, with the participation of students.
3. Briefly write down the problem statement and convert physical quantities to the SI system.
4. Creating the necessary drawings, diagrams, and graphs.
5. Analysing the problem statement, understanding the physical nature of the phenomenon or process underlying the problem, and recalling the relevant physical laws and formulas.
6. Determining the method of solving the problem (analytical, synthetic, mixed).
7. Develop a plan for solving the problem.
8. Expressing the relationship between known and unknown quantities using formulas.
9. Solving equations or systems of equations to obtain the final formula.
10. Calculating the desired value.
11. Analysing the results and checking their reliability.
12. Study and analyze alternative approaches to solving a problem.

Although this is a generalized scheme, some steps may be omitted depending on the problem at hand.

For some physics problems, algorithmic and graph methods are used. Although they are rarely used in practice, the capabilities of a chatbot can radically change this situation. An algorithm consists of rules that, based on a certain system of elementary actions, allow you to reliably achieve the desired result. The development of skills and abilities to follow strictly defined rules is important in general education and practical applications. However, building such algorithms is a challenging task.

In general, problem-solving algorithms can be divided into three groups: 1) general algorithmic rules that outline the stages and guidelines for solving any problem; 2) algorithmic rules specific to certain types of problems; 3) algorithmic rules for individual operations.

The process of solving physical problems usually includes three stages of students' activities: 1) analysis of the physical problem or description of the physical situation; 2) search for a mathematical solution to the model; 3) implementation of the solution and analysis of the results.

The first step is to build a physical model of the problem based on the problem statement. This involves analyzing the conditions of the problem, identifying known and unknown parameters, and presenting the physical model using visual aids such as drawings, diagrams, or graphs.

The second stage involves the mathematical aspect of solving physical problems. This involves finding connections and relationships between known quantities and unknowns. The mathematical model of the problem is established by writing down general equations that correspond to the physical model. Additional parameters, such as initial conditions or physical constants, are considered based on the specific conditions described in the problem. Finally, the general equations are adapted to the specific conditions of the problem, and the relationship between unknowns and known quantities is expressed through partial equations.

The third stage involves the following steps: 1) analytical, graphical, or numerical solution of the equation relating to the unknown; 2) analysis of the result in terms of its probability and relevance, followed by recording the answer; 3) generalization of the methods used, specific to this particular type of physical problem, along with the search for alternative solutions.

It is important to emphasize that in physics education, a valuable approach to working with students is to have them solve problems whose physical content is similar to those solved in class, for example, inverse problems. This technique is highly effecttive in developing students' creativity and mental potential.

The algorithm for solving the problem can be outlined as follows: 1) reading the wording of the problem, understanding the terms and expressions; 2) summarising the conditions of the problem and creating appropriate diagrams; 3) analysing the content, clarifying the physical essence and forming a clear understanding of the phenomena, processes and states of the objects described in the problem; 4) identifying the concepts and laws necessary for solving the problem; 5) developing a solution plan, including possible experiments, including physical constants and tabular data, as well as analysing graphical materials such as graphs or diagrams; 6) converting the values of physical quantities into the appropriate SI units; 7) identification of regularities that establish relationships between the desired and given quantities and formulation of appropriate formulas; 8) drawing up and solving a system of equations in a general form, similar to setting up and conducting an experiment; 9) calculation of the desired value, parallel analysis of the results of the experiment; 10) analysis of the answer obtained, assessment of the impact of simplifications allowed in the formulation of the problem and during the solution process, similar to the evaluation of the experiment; 11) consideration of alternative approaches to solving the problem and selection of the most appropriate one.

Following this algorithm, students can systematically approach and successfully solve a wide range of physical problems.

In our study, we analyze modern approaches to the development of conversational agents in the task of maintaining a natural dialogue using the example of an experiment to create a chatbot that interacts with a user. As part of the experiment, we examined the process of creating a chatbot, identifying the main problems; we proposed a basic implementation and its improvement. We also generated a set of data, templates, and heuristic rules sufficient to ensure a variety of bot responses in a conversation on a relevant topic (as an example, we chose the topic of solving a physics problem).

Due to the urgency of introducing online resources into the educational process, an experimental chatbot was developed to help students solve physics problems independently. The chatbot communicates with the user via predefined text messages. The user who launched the bot can read the content of the problem, answer questions according to each stage of solving the problem, and read the next message from the bot to move on to the next stage.

Since the chatbot was intended for training purposes, its algorithm is simple and contains a pre-prepared set of rules for responding to user actions. Based on these stages, we created a flowchart of the algorithm (Figure 1).

The diagram of the chatbot algorithm for solving physics problems was created using the draw.io service (https://app.diagrams.net/) First, we set up the basic structure of the diagram. You can choose to create a flowchart or a sequence diagram to represent the chatbot algorithm. To add shapes, use the shape library on the left to add shapes to your diagram. For example, you can use rectangles to represent processes or actions, diamonds to indicate decision points, and arrows to show the process of executing the algorithm. Define the initial steps, which include actions such as greeting the user, asking for a problem statement, or collecting relevant data.

Added decision points: we identified decision points in the algorithm where the chatbot needs to make a choice based on user input or predefined rules. We used diamond shapes to represent these decision points. Connect steps and decision points: We used arrows to connect steps and decision points in a logical sequence. This helped to demonstrate how the algorithm progresses through different scenarios. Subroutines or functions were displayed as separate processes or steps in the diagram. They were connected appropriately to demonstrate the flow of control.

A well-designed algorithm should take into account error handling: They can be represented as additional decision points or steps that help the chatbot cope with invalid inputs or errors. The layout includes labels or annotations to provide explanations where necessary. The finished diagram is saved and exported in the desired format (for example, as a .drawio or .png file) using the options available in draw.io. You can export the diagram to different formats, such as PDF, SVG, or JPEG. These steps need to be adapted to the specific algorithm of the chatbot for solving physics problems. The key is to represent the logical sequence and decision points so that others can understand the algorithm at a glance.

The chatbot was developed in the Flow XO service and operates on the Telegram platform (Figure 2).

Flow XO is a universal platform that allows you to create chatbots and automate various tasks. Using its functions, we can create a chatbot to help students solve physics problems. The first step was to define the purpose of the chatbot. We started by clarifying the goals and objectives of the chatbot. We identified the sections of physics in which students might need help and the types of problems they might face. This helped to structure the chatbot's functions and responses accordingly. Next, we visited the Flow XO website and registered an account. Once registered, they got access to the platform's intuitive interface and some tools to build

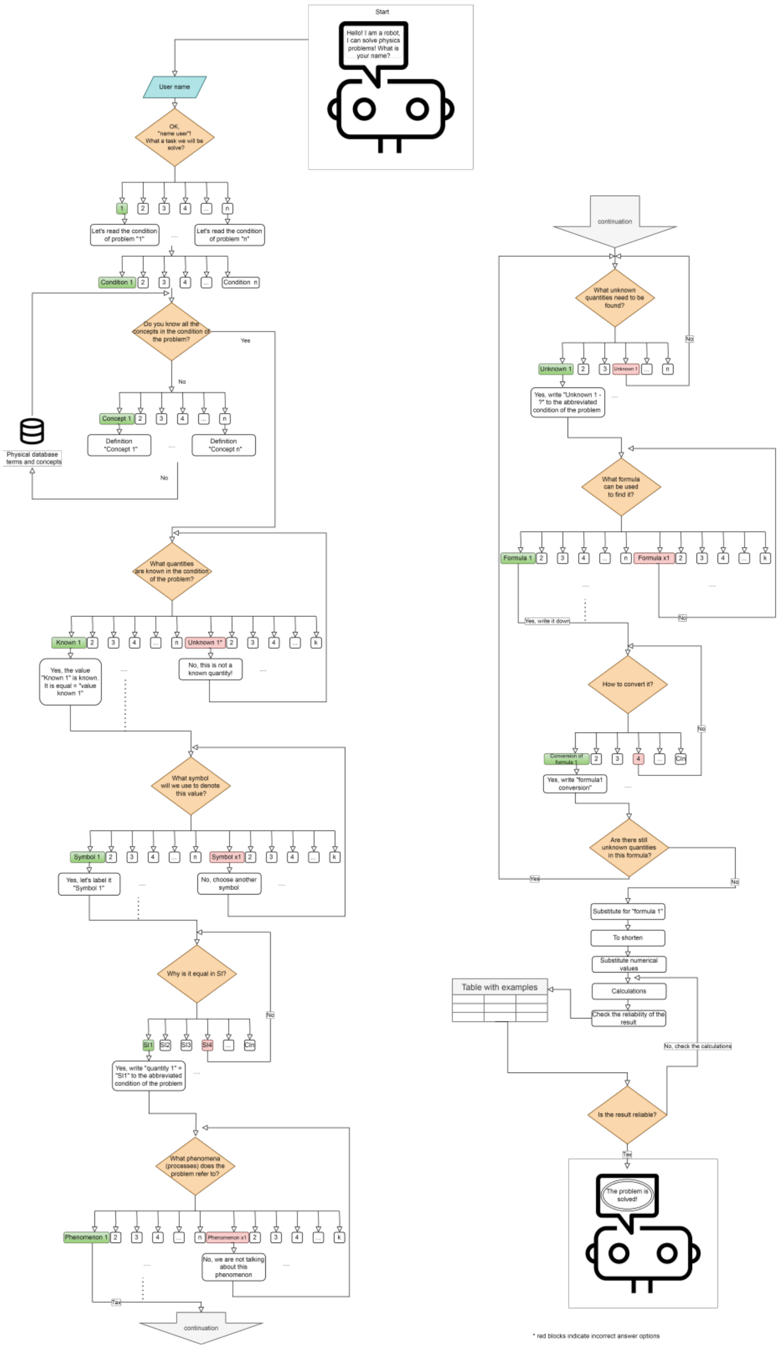

**Figure 1:** Flowchart of the chatbot algorithm for solving physics problems.

their chatbot. Using Flow XO's drag-and-drop interface, we designed the chatbot's conversation flow.

We defined the initial greeting, possible user actions, and bot responses. We developed

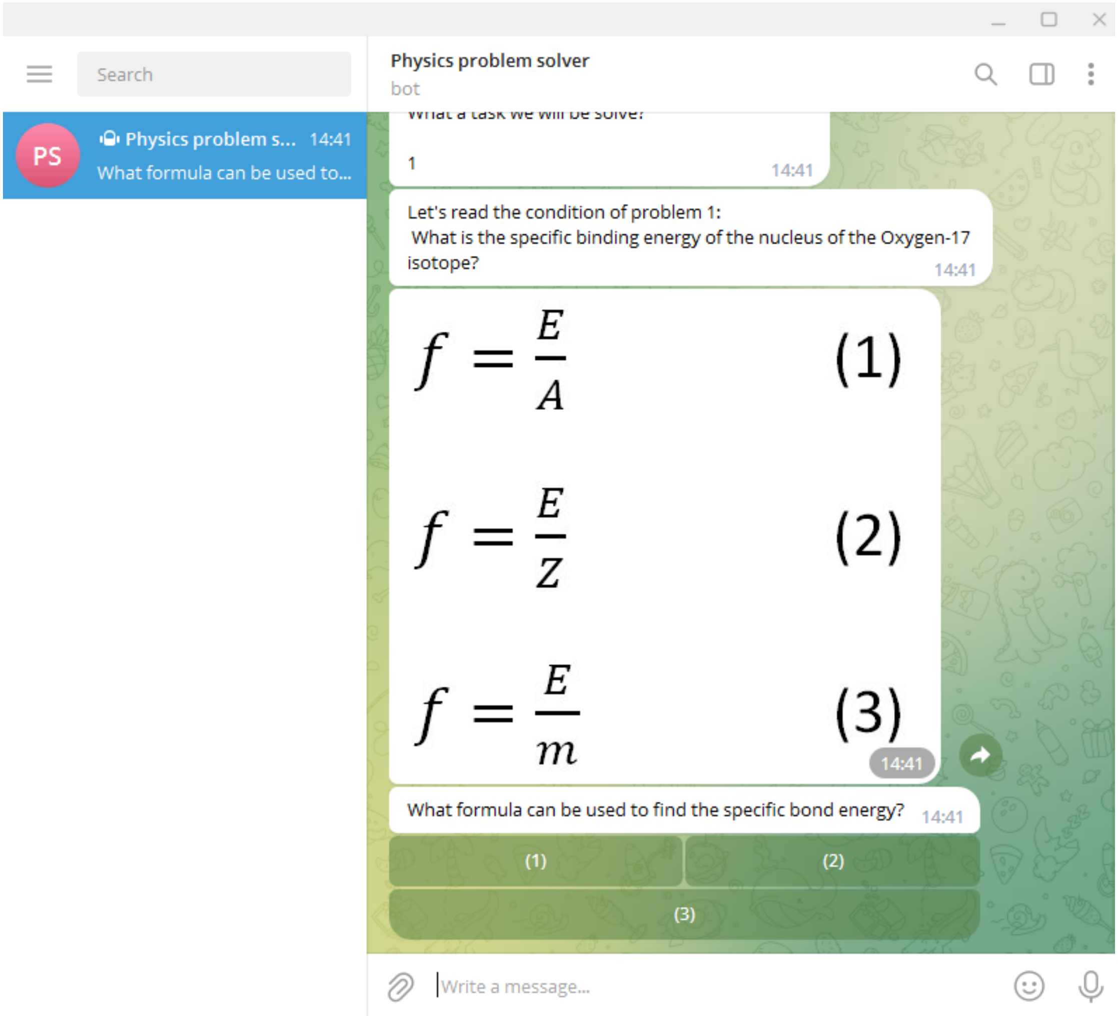


**Figure 2:** Chatbot Physics problem solver on the Telegram platform.

branching logic to efficiently handle different scenarios and user requests. We added predefined questions and answers. To help students instantly with typical physics problems, we created a database with predefined questions and answers. We included various types of problems covering different concepts and levels of difficulty. Flow XO allows you to enter these questions and corresponding answers using the "Ask a Question" action. Flow XO provides integration with external resources to enhance the chatbot's functionality. It is possible to integrate relevant physics resources such as textbooks, online reference books, or educational websites. This integration will allow the chatbot to provide students with additional information and reference materials when needed.

The most important task is to implement the algorithm for solving the problem. To help students solve physics problems step by step, you can create algorithms in Flow XO. To do this, we broke down the solution process into smaller logical steps and planned the chatbot's answers accordingly. This approach will help students to familiarise themselves with the necessary calculations, formulas, and concepts required to solve the problem.

To make the learning process more engaging, it is advisable to integrate interactive elements into the chatbot. For example, you can insert simulations, visualizations, or interactive tests to enhance understanding and facilitate hands-on learning. After creating the initial version of your chatbot, you should thoroughly test its functionality. Check for inconsistencies, errors, or gaps in the answers. At this stage, we also collected feedback from learners and made the necessary adjustments to improve the chatbot's efficiency. The final step is to deploy the chatbot on the platform of your choice. Flow XO allows you to integrate with popular messaging platforms such as Facebook Messenger, Slack, Telegram, or a website, making it available to students on their preferred platforms (Figure 3).

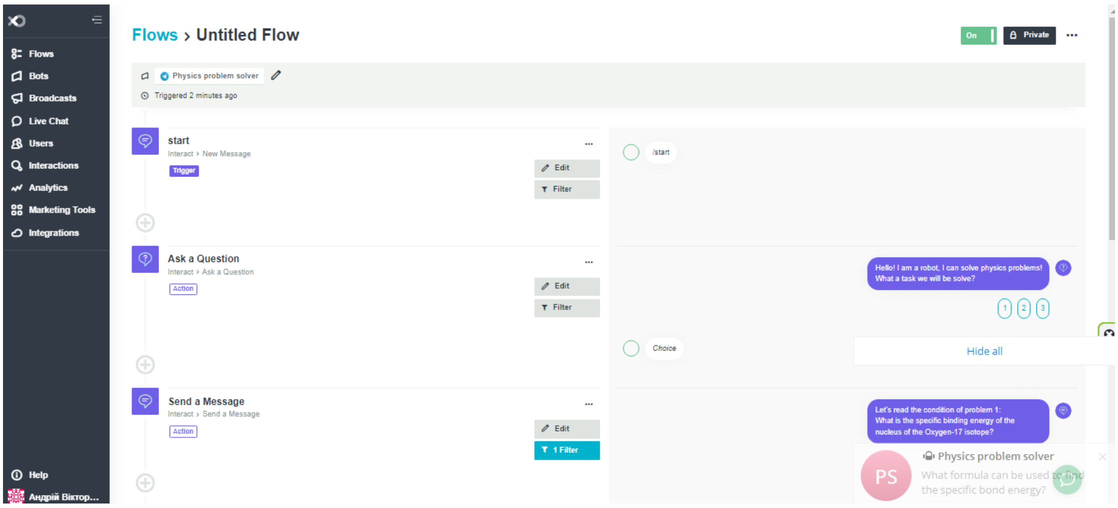


**Figure 3:** Flow XO service for chatbot development.

The performance of a chatbot needs to be constantly monitored and feedback from users should be collected. Feedback is needed to identify areas for improvement and update the chatbot accordingly. Regular updates ensure that the chatbot remains relevant and effective in helping students solve physics problems.

Two groups of students took part in an experiment to study the effectiveness of using a chatbot in solving physics problems. In the first group, the teacher provided explanations on how to solve the problem. In the second group, students worked independently to solve the same problems, but using the Physics problem solver chatbot, which works based on the algorithm developed by the authors of the article. Afterward, the students' solutions were checked and evaluated on a 100-point scale.

Data for the chat bot were taken from: 1) task conditions – school textbooks, problem collections recommended by the Ministry of Education; 2) answer options for the chat bot – from the practical experience of teaching physics, erroneous statements of students that they make most often.

The mention of artificial intelligence is made by us in the context of improving the work of the chat bot, which may lead to a more natural dialogue in the future, but this does not concern the actual educational content of the bot.

The non-parametric Mann-Whitney U test is used to assess the difference between two small samples in terms of significance according to the structure of students' results. The Mann-Whitney test is a nonparametric alternative to the t-test for independent samples. Its advantage is that it does not rely on the assumption of normal distribution or equal variances. It is suitable for data measured on an ordinal scale or higher.

The Mann-Whitney U test is used to compare two samples with sample sizes $n_1$ or $n_2 < 11$, thus satisfying the above conditions. Each sample must have at least three observations, and if one sample has two observations, the other sample must have at least five. The number of observations in each sample should not exceed 60, although ranking becomes more labor-intensive with 20 or more observations. Data should be presented on at least an ordinal scale.

The calculation of the Mann-Whitney U-statistic is conveniently presented in the form of an algorithm:

1. Check whether the conditions for applying the U-test are met.
2. Assign the data from the first sample to cards of the same color (e.g. red) and the data from the second sample to cards of a different color (e.g. blue).
3. Arrange all the cards in a single row in ascending order, ignoring the color of the cards.
4. Assign ranks to the values on the cards.
5. Divide the cards into two groups by color (red in one row, blue in the other).
6. Calculate the sum of the ranks separately for the cards in each group.
7. Find the greater of the two rank sums. The sample associated with the higher rank sum is considered sample 1, while the sample associated with the lower rank sum is considered sample 2.
8. State the null and alternative hypotheses:
   $H_0$: The level of significance in sample 2 is not lower than the level of significance in sample 1.
   $H_1$: The level of significance in sample 2 is lower than the level of significance in sample 1.
9. Calculate the empirical value of U using the appropriate formula:
   $$U_{ex} = n_1 n_2 + \frac{n_1(n_1+1)}{2} - S_1, \tag{1}$$
   where $n_1, n_2$ – sample sizes 1 and 2, respectively; $S_1$ – the sum of the ranks of sample 1.
10. Using the table of critical values of the Mann-Whitney test, determine the critical values $U_{0.01}$ and $U_{0.05}$ for the given $n_1$ and $n_2$.
11. If $U_{emp} \leq U_{0.01}$, the hypothesis H0 should be rejected, if $U_{emp} > U_{0.05}$, it should be accepted. If $U_{0.01} < U_{emp} \leq U_{0.05}$, the hypothesis H0 is rejected at the 0.05 (or 5%) significance level, although in practice this level of significance is considered unacceptable for the Mann-Whitney U test.

In our case, in two groups, the number of subjects was $n_1 = 8$, $n_2 = 10$, and the independent work on solving problems with the maximum possible score of 100 was tested. The students'

**Table 1**
Students' scores.

| Control group | | | Experimental group | | |
|---|---|---|---|---|---|
| No | Student code | Scores | No | Student code | Scores |
| 1 | A | 55 | 1 | A1 | 45 |
| 2 | B | 37 | 2 | B1 | 24 |
| 3 | C | 35 | 3 | C1 | 72 |
| 4 | D | 85 | 4 | D1 | 70 |
| 5 | E | 68 | 5 | E1 | 35 |
| 6 | F | 35 | 6 | F1 | 28 |
| 7 | G | 49 | 7 | G1 | 68 |
| 8 | H | 62 | 8 | H1 | 38 |
| | | | 9 | I1 | 45 |
| | | | 10 | J1 | 56 |

scores are presented in Table 1. Can we say that the level of problem-solving skills in these groups is different?

The hypothesis is formulated as follows:

$H_0$: there is no difference in the level of problem-solving skills between the groups;

$H_1$: students in Group 1 have a higher level of problem-solving skills.

It should be noted that in Group 1, the teacher provided explanations in the process of solving the tasks, while in Group 2, students solved the tasks independently using the chatbot. The number of students in the groups was different, but if we calculate the average number of points scored in the groups, they are equal to $x_1 = 53.3$ and $x_2 = 48.1$ points, which gives grounds for hypothesis H1. The U-test allows us to test it since the conditions for applying the method are met. Using the formula (1), we find $U_{ex} = 44.5$. The critical value Uk is found using the reference tables of the Mann-Whitney test. In our case, for $n_1 = 8$ and $n_2 = 10$ we find: $U_k = 20$.

The comparison of $U_{ex}$ and $U_k$ allows us to accept or reject the experimental hypothesis; in our case, $U_{ex} > U_k$, so $H_1$ is rejected and $H_0$ is accepted – there is no significant difference in the levels of problem-solving skills in the comparable groups (despite the difference in mean scores).

The Mann-Whitney U test confirmed the differences between the results in the control and experimental groups, which gives us grounds for improving the chat bot and conducting an experimental test of the methodology on a larger number of respondents using appropriate evaluation criteria.

## 5. Conclusions

The study considers the possibility of using a chatbot to teach physics problem-solving based on the developed algorithm. This learning format allows for achieving positive dynamics in physics learning. At the same time, the chatbot encourages students to use the structures being studied – to read the condition of the problem, consider the formulas describing the physical law, convert the formulas, represent the values of physical quantities in SI, perform calculations, etc. The chatbot allows you to complete tasks both synchronously and asynchronously.

The effectiveness of the described method was tested in two groups of students. In the first group, the teacher provided explanations in the process of solving the tasks, and in group 2, students solved the tasks independently using a chatbot. Statistical processing was based on the Mann-Whitney U test. It was found that there was no significant difference in the levels of problem-solving skills in the comparison groups.

We see the possibility of using a chatbot in several models of blended learning: 1) the Face-to-Face model, which allows supplementing the main educational process in the classroom with a teacher by performing online tasks of the bot; 2) the Online-lab model, in which the teacher uses the chatbot's capabilities in class with students and supplements them with tasks to solve atypical, creative and experimental physics problems; 3) the Online river model, which allows organizing a virtual educational world with the participation of a teacher and students.

It is important to emphasize that a chatbot is an additional and stimulating format that enhances the effectiveness of physics teaching. In addition, it has the potential to become a valuable and effective tool for both students and teachers, facilitating their work and improving their learning experience. In particular, a teacher can implement a chatbot in the classroom (homework, class work). A chatbot is a tool for sequential learning. A chatbot allows you to master the process of solving typical physics problems that can be fully or partially solved using an algorithmic approach. However, the chatbot technology itself has wide possibilities for implementing various educational tasks. Since its launch, the chatbot has been accumulating usage statistics and showing interest from users – pupils and students studying to become physics teachers.

The use of a chatbot to solve physics problems has the potential to change the approach to the process of solving physics problems. Using artificial intelligence and NLP technologies, this chatbot can provide personalized recommendations, immediate feedback, round-the-clock availability, adaptive learning, and an engaging learning experience. It is assumed that the use of chatbots can be effective in solving typical tasks in other academic subjects.

Chat bot technology is very dynamic these days. The description of the detailed implementation in comparison with other chatbot technologies is planned to be made in the following works.

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