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DEVELOPMENT OF AN APPROACH TO CHAT-BOT PERSONALIZATION WITH GENERATIVE ARTIFICIAL INTELLIGENCE WHEN REALIZE AN ONLINE ASSISTANT

The object of research is the interaction in the "human – machine" system during the user's interaction with generative artificial intelligence. The relevance of the research topic is due to the need to provide assistance to users in a narrow professional topic. To implement the goal set in the work, a model of operator decomposition was developed using the "Goals, Objects, Methods, and Selection rules" GOMS technology, taking into account the multi-level cognitive functions of a person. For this purpose, microoperators were used, which are responsible for combining various actions to find an answer to a question. A model with the decomposition of the operator μ *was developed, which is responsible for cognitive functions when creating a request during human interaction with a chatbot based on artificial intelligence. The work used interaction with the ChatGPT chatbot.*

The proposed decomposition algorithm was used as the basis for the online assistant plugin. The implementation is made in JavaScript, which allows it to be used on any sites and portals. The main components of the plugin are the interface for entering a query, a multi-level search mechanism on the site and in connected specialized libraries. The API integration of the plugin with ChatGPT was implemented.

As a result of the work, a study was conducted to experimentally determine the values of action and movement operators that are related to human mental activity and algorithmized in the online assistant. According to the results of the experiment, it was taken into account that for a chatbot, queries using foreign language signs and symbols and queries in the user's usual natural language are equivalent. To communicate with ChatGPT using the plugin, it is necessary to adhere to uniqueness and clarity when forming narrowly professional queries. The result was obtained that when querying in natural language on a topic familiar to the user, the online assistant adapts to the requirements more slowly. But at the same time, the speed of finding an answer and its formulation is accelerated. The problem of personalizing the online assistant was solved. This became possible thanks to the analysis of user behavior through the detailing of the query by micro-operators in the GOMS model. This allows to personalize the online assistant without user registration, only based on its behavior when forming a request.

The proposed approach can be used to create online assistants for the implementation of highly specialized complex projects on web platforms.

Keywords: *plugin, GOMS model, operator decomposition, cognitive functions, natural user language.*

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1. Introduction

The modern development of generative artificial intelligence (AI) has led to the development and use of various widgets and plugins to help users use web services and web information processing tools. For example, a number of basic AI plugins are currently used for the WordPress content management system, such as AI Engine, AI Power, RankMath, and others [1]. This allows the user to be assisted from content generation with subsequent optimization to image creation and page coding. However, the work does not mention that these plugins cannot be used in other development environments without appropriate costly adaptation. Among WordPress widgets, ChatBot is popular as an online AI-based assistant from Google, which works through Dialog Flow V2 [2]. These widgets are implemented on the basis of Hypertext Preprocessor (PHP) development, which allows them to be easily integrated into the WordPress template environment to perform any current tasks related to working on the site. Plugins are mostly implemented in Python, C++ or JavaScript, depending on the tasks and functions that are designed to facilitate the user's work on the site. However, plugins do not allow for personalization, which complicates the work of users and makes it impossible to use on other platforms of website developers.

Personal AI assistants are becoming more in demand by users every year due to the increase in accuracy and semantic understanding when working in the web environment [3]. However, the problem still remains the insufficient maturity of the service and the insignificant degree of personalization of the assistant. This leads to a deterioration in the interaction in the "human-computer" system due to the cognitive load [4]. Although the authors note the problem, they do not offer approaches to its solution.

When solving complex tasks by the user, for example, conducting scientific research related to the systematization and processing of large amounts of information, there is a need for timely receipt and transmission of data. In addition, on scientific, research and educational sites there is always the problem of timely updating of content. For example, forming lists of scientific publications, creating information about user activity, systematizing entered data to prevent duplication. An online assistant based on generative artificial intelligence could solve these issues, but so far there is a lack of integrated solutions with appropriate adaptation to the personal tasks of a particular specialist [5]. Available widgets and plugins, similar to those used in WordPress, are not flexible enough. They cannot be used in other content management systems. In addition, they do not allow for personalization [6]. This affects user work and makes it impossible to implement applied tasks. It is difficult to solve the above problem by simply connecting chatbots with generative artificial intelligence (Copilot, ChatGPT, DeepSeek, and others) to sites, since such a solution does not take into account the cognitive component of the user.

Few works have been devoted to the development of approaches to creating various online assistants based on generative AI. This is due to the fact that the personalization of the practice of communicating with AI has only just begun. An example of such personalization is given in [7], which presents the results of the work of an artificial agent on moderation of discussions. For this, reasoned messages with content that depend on the previous messages of the participants are used. However, the experiment conducted with the participation of the developed agent increased the number of problems, since the chatbot polarized the discussions due to the inability to connect the statements of different people in time to perceive a holistic event. That is, cognitive misunderstanding arose due to the generalized perception of the people who participated in the discussion.

In [8], another problem was noted – inaccurate content and poor-quality information when searching for answers to narrowly professional questions using OpenAI chatbots. This applies to a number of medical issues that have limitations in search when used through publicly available AI tools. The study compares the information obtained using ChatGPT and the professional tool FootCareMD®.

A similar conclusion follows from work [9] regarding the choice of a product by consumers through chatbots with AI. It is noted that with a clear definition of the problem, the answer of the chatbot is more satisfactory for the user. However, for well-known products, a clear definition of the problem does not affect their choice due to the redundancy of information that does not reflect the cognitive perception of the user.

The described problems can be solved by implementing a chatbot cognition system with AI, close to human. This is possible by increasing the accuracy of the analysis of data received by the chatbot when communicating with a human user. In [10], the Generative Pre-trained Transformer 4 (GPT-4) and Large Language Model Meta AI 2 (LLAMA2) models with special training of generative AI based on semantic evaluation of user's natural language utterances are considered. However, the authors do not consider the possibility of personalizing such systems.

Research [11] presents the results of the development of a specialized tool to improve the efficiency of experiment planning. The implementation of one of the modules in Python with the ChatGPT plugin allows for interactive analysis during the modeling process. However, the module does not take into account personalization for the needs of individual researchers, which is why a number of experimental tasks remain unresolved.

In [12], a study was conducted on the possibility of a chatbot to take the user's position to provide meaningful online assistance. It is noted that the interaction between efficiency and flexibility benefits the intellectual experience of the online assistant. The work is based on a study of customers on the sale of a product with a strong or weak impact on cognitive intelligent experience. The paper recommends deploying AI chatbots on special-purpose Internet platforms, but does not take into account personalization for performing individual tasks.

The need for universality of chatbots for receiving online assistance is emphasized in [13]. In particular, it was found that a cluster of technologies consisting of machine learning and related data science technologies allows solving highly specialized tasks. The only problem remains the construction of algorithms for performing multi-level cognitive functions. That is, solving the problem of personalizing a chatbot when creating an online assistant with generative artificial intelligence is relevant. This will allow coordinating the user's work taking into account its cognitive characteristics and the speed of learning the artificial intelligence model in order to increase work productivity.

Thus, *the aim of research* is to develop an approach to personalizing a chatbot with generative artificial intelligence when implementing an online assistant. Such an online assistant can be connected as a plugin to any sites or portals designed for processing big data, converting specialized scientific information, and controlling complex robotic devices.

2. Materials and Methods

The object of research is the interaction in the "human-machine" system during the user's interaction with generative artificial intelligence. The study of such interaction allows to develop approaches to creating online assistants capable of fulfilling requests personalized to the requirements of a specific user.

The subject of research is the personalization of work with chatbots based on generative artificial intelligence to the professional needs of the user.

As follows from the analysis of sources, there is a question of implementing a technology that will allow using chatbots with generative artificial intelligence in a more personalized way, in accordance with the user's needs and tasks. The main criteria should be ensuring the speed of the user's work, the efficiency of the chatbot's training, and the accuracy of the information received upon request. The latter is related to the implementation of the cognitive function of the online assistant in accordance with the user's cognitive function.

The above can be implemented in the form of a plugin for connecting a chatbot with generative AI with additional rules. And the implementation of the cognitive function can be represented through the improved model "Goals, Objects, Methods, and Selection rules" (GOMS).

To conduct the study, computer modeling methods were selected to reproduce in detail the consumer's behavior when interacting with a chatbot. Statistical methods of comparison, grouping by features, and systematization were also used to analyze and process the experimental results. The study is based on modeling using a simplified GOMS model – Keystroke-level Model (KLM) for testing the developed online assistant plugin in highly specialized tasks [13].

The input data are time measurements of individual actions in the user's behavior when creating a request to the online assistant. The online assistant is a plugin that combines the user and an AI-based chatbot into an interaction system. This system records user requests, details them by features, and compares them by cognitive features.

The limitations of research are the conditioned user interaction response [12]. This allows to choose the required measurement accuracy when decomposing the GOMS-KLM model operators, which simplifies calculations and facilitates the plugin algorithmization process.

The assumptions in the work are the occurrence of information noise at a given step when executing queries depending on the selected cognitive feature of the user's behavior. That is, when reproducing the experiments, an assumption was made about a certain cognitive behavior of the user.

In this work, the plugin is considered as a software module with a dynamic connection to the ChatGPT chatbot with generative AI [14]. The GOMS model is a model of a human information processor in human-computer interaction [15]. The four components of the user's cognitive structure are represented by the methodology, method, object and rules for making a choice when searching for an answer to a question. Regarding the aim of research and the objectives set, the GOMS model

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is used to accept or reject the answer from the online assistant to the question posed. The use of the simplified GOMS-KLM model is due to the reaction of the user and the online assistant to the mental training operators. The limitation is that the user may not be prepared to work with the specified technology and learns to work with the online assistant in parallel with the training of this assistant.

Machine learning with reinforcement was chosen to implement the online assistant. This is due to the possibility of implementing the process of making consistent decisions without interfering with the time spent due to high variance, the need for explanations and online training [16]. The plugin is directly implemented with an example of a plugin for evaluating the created code [17]. The basic structure of the created plugin is GPT-4. The search rules serve as limitations for searching through GPT-4: first, a keyword is searched and an answer is generated based on the information available on the site where the plugin is installed. At the same time, the search time is estimated. Provided that the time to search for an answer on the site may be greater than the time for the user to type the keyword, a search is performed in all available resources.

This approach allows for communication and cooperation between a person and a machine using "soft skills" [18]. For this purpose, fuzzy logic rules can be used to introduce both machine learning methods based on user feedback during interaction and to form an explanation/interpretation response from the chatbot. The latter can be a modification of the traditional representation of the GOMS-KLM model [15].

According to the GOMS model, the elementary actions of the user when forming a request to an online assistant can be divided into several stages. The first stage is the logical formation of a question to an online assistant. The primary information carrier here is the user's memory. The request can be formed both in the user's natural language and using code. In this study, natural language is the user's native language, in which the request is formed in meaningful, logically literate sentences. Code in this work means the formation of a request in an illogical way, without the use of keywords, using signs, symbols, and numbers.

When forming a request and its subsequent typing from the keyboard in the online assistant window, the user performs a cycle with n-fold repetition of movements and actions. In this case, n is the number of letters entered by the user. These are the following actions: searching for a character on the keyboard, moving hands, pressing a key, analyzing the next word that will be entered into the query, reviewing the typed text to find an error, identifying the error, correcting it, making a decision to complete the query entry. The last stage of query formation is the decision to confirm the query entry into the online assistant dialog box.

GOMS technology for quantifying the labor costs of entering a query H suggests using two standard operators. These are M (considering the next step), which lasts 1.2 s, and K (pressing a keyboard/mouse key) with a recommended value of 0.28 s. During this period, the user calculates the actions to enter the next character/word to explain its question. This can be described by the formula

$$H = n(K + xM) + yM, \tag{1}$$

where $x, y = \{0,1\} x, y = \{0,1\}$.

Formula (1) can be explained as an assessment of entering a query of n characters into the online assistant dialog box and visually checking the input to determine the correctness of the posed question. In this formula, the operator M corresponds to the component of consciousness within the framework of the implementation of the cognitive function, which sets the period of consideration of the next step in solving the posed question. In this case, the choice of values of x and y in formula (1) is the solution to the problem of arranging the operator M. Three main solutions can be of practical importance here: $x=0$, $y=1$; $x=1$, $y=0$; $x=2$, $y=0$. The GOMS methodology assumes the possibility of various solution options [19].

Using (1), it is possible to assess the accuracy of the online assistant's response in the process of machine learning with reinforcement. Training involves constant interaction of the AI model with the user, in which the minimum response to the answer is "like/dislike". That is, in the software implementation, this algorithm reacts to the message from the user "true/false".

It is assumed that it is not known in advance how many characters $\bar{v}$ ($\bar{v} = < n$) will be used to enter the query explaining a certain keyword. The keyword acts as a hint for the online assistant and sets the search direction. In this case, the calculation of the time t_1, t_2, t_3 for the three possible search solutions x, y will have the following form:

$$t_1 = K\bar{v} + M + P + BB, \tag{2}$$

$$t_2 = (K + M)\bar{v} + P + BB, \tag{3}$$

$$t_3 = (K + M + M)\bar{v} + P + BB, \tag{4}$$

where $K = 0.28$ s, keystroke; $P = 1.1$ s, mouse pointer; $BB = 0.2$ s, mouse click to send a request [19].

The value t_1 is calculated with the condition that only one operator M is needed to enter $\bar{v}$ characters in a query consisting of one keyword. The value t_2 assumes the condition that operators M are needed after each input word to formulate a full-fledged query. The value t_3 assumes a thorough check and analysis by the user of each word to formulate the most accurate query possible, taking into account the keyword as a hint to the online assistant.

To modify the representation of the GOMS model in order to form a multi-level online assistant AI knowledge system, similar to the user's knowledge system, some conditions should be accepted. Thus, operators M in this case are considered multi-level. The number of levels of such operators depends on the area of knowledge, the area of solving the problem. In this case, three basic components can be distinguished [15, 19], according to which the logic of the online assistant's work can be built:

– preparation of the next step of forming the answer depends on the user's previous actions;
– operators K, $t(n)$, P also have a cognitive component associated with the time of reflection on the next action;
– the GOMS model will differ when solving tasks of different classes, which implies changes in the scope of application of various operators and leads to the division of individual tasks into simple subtasks.

Taking into account the specified components, it can be predicted that the online assistant algorithm will track the user's actions. This will allow it to adapt to the logic of constructing user queries with each new request and launch the personalization algorithm by operators.

In general, based on the analysis of scientific sources, it can be generalized that existing methods and approaches do not satisfy user requirements for the development of online assistants due to the lack of personalization capabilities. This, in turn, is related to the implementation of the cognitive function of the online assistant. The implementation of such a function in online assistants based on generative artificial intelligence will allow for rapid personalization of artificial intelligence tools.

3. Results and Discussion

The operator decomposition model taking into account representations (2)–(4) is shown in Fig. 1. Multilevel human cognitive functions are presented in the form of microoperators $\mu_1 - \mu_5$, K:

μ_1 – logicality of the text, its "understandability" when analyzing a query by an AI chatbot;

μ_2 – complexity of searching for symbols when typing a query by the user itself from the keyboard with the time of moving the hand to the key;

μ_3 – visual analysis of the user's entered query, making decisions about entering additional explanations to the query;

μ_4 – complexity of forming an additional query that explains the previous one;

μ_5 – comparing the response of the AI chatbot with the user's expectations, making a decision about further actions;

K – directly pressing a key on the keyboard, complexity of actions from typing a query.

That is, microoperators μ_1, μ_3, μ_5 – operators describing cognitive actions, k – movement operator, μ_2 and μ_4 – combinations of cognitive functions and movements to perform them. The values are presented in symbols per second (sym/s).

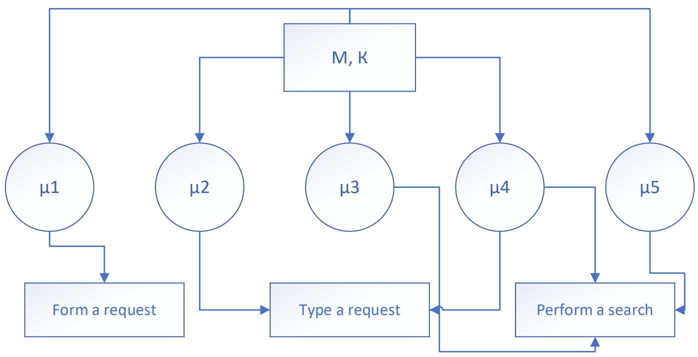

Fig. 1. Operator decomposition model according to the GOMS model

To obtain the values of μ and K, the following is taken into account: the complexity of the information for forming a query and the ability to work with modern technology.

When determining the complexity of the information for forming a query, the use of special symbols and words is taken into account. This is important when developing an online assistant that will be used in specialized projects. Three types of information can be used in such projects:

1) *digital and alphanumeric codes*. When forming a query using them, it is important not to make mistakes to shift the emphasis of interpretation when forming an answer to the query. The user's cognitive functions are not a priority;

2) *text in natural language*. Here, the correct use of terms and words and compliance with the rules of communication with the chat bot are a priority. Cognitive understanding of the search direction is important for obtaining a correct and accurate answer;

3) a query in natural language on a topic that is not familiar to the user. In this case, the user's cognitive capabilities occupy a somewhat intermediate position.

The ability to work with computer technology must meet the requirements for a typical level. That is, the online assistant must be designed for a user with low digital competence.

The values of μ_1–μ_5 according to the model shown in Fig. 1 are obtained using the following algorithm.

Step 1. Measurements t_1 (symbols/s) – the time of entering the query text with reflection. That is, visual control of the entered text is taken into account, errors and inaccuracies of the formulation are corrected

$$t_1 = K + \mu_1 + \mu_2 + \mu_3 + \pi_c \mu_4. \quad (5)$$

The statistical probability of entering erroneous symbols, symbols and statements when forming a query is denoted by π_c.

Step 2. Measurement t_2 (symbols/s) – the time of entering a fragment of query clarification after understanding the need for such clarification. This step takes into account visual control of the input and correction of errors noticed by the user

$$t_2 = K + \mu_2 + \mu_3 + \pi_c \mu_4. \quad (6)$$

Step 3. Dimension t_3 (sym/s) – time of entering a query without visual control, immediately after the user needs to use the online assistant

$$t_3 = K + \mu_1 + \mu_2. \quad (7)$$

Step 4. Dimension t_4 (sym/s) – time of entering a clarification to the query immediately, without studying the previous answer

$$t_4 = K + \mu_2. \quad (8)$$

Step 5. Dimension t_5 (sym/s) – time of visual analysis of the answer received from the online assistant before forming the next query

$$t_5 = \mu_5. \quad (9)$$

Step 6. Comparison of answers with user control and without user control with memorization of the most accurate and correct option. User confirmation of the correct answer is mandatory to reinforce the machine learning of the online assistant.

The above algorithm allowed to develop the basic foundations for creating an online assistant with the function of adapting to user requirements. The computer model for the study was developed in Python. Direct implementation in the form of a plugin for placement on the site is using JavaScript.

When the user enters an entry into the online assistant dialog box, a search is performed. The plugin rules state that initially the search is performed directly on the hosting site or portal (using content indexing on the page). If the answer is found, the plugin displays it. If the search time exceeds 4 seconds, the plugin refers to an external library for further search. If the search time on libraries exceeds 7 seconds, the plugin refers to the ChatGPT application programming interface (API) to search for an answer on the Internet.

The main components of the plugin are:
– *interface for entering a query:* a dialog box for entering a question;
– *site search mechanism:* an algorithm for searching on the page (search by keywords based on the entered query);
– *libraries for search:* the ability to connect external libraries for search depending on the topic of the portal;
– API integration with ChatGPT via API for searching for an answer on the Internet.

As an extension for training an online assistant with AI, which is connected to the site via a plugin, content analysis using regular expressions is used. This allows to more accurately find relevant information on the page. The plugin interface, in addition to the dialog box, keeps a progress mark of the search for an answer to the query. The history of queries is stored for further training of the online assistant. External libraries are connected via API. This allows to reduce the search time and obtain more accurate information.

In addition, after a series of tests, a response caching mechanism was introduced. This allowed avoiding repeated requests to the same sources if the query was similar. In addition, the ability to re-search by results was added.

The web implementation of the online assistant takes into account the self-learning process through the collection and analysis of query history. This is presented as follows:

```
document.getElementById('search-btn').addEventListener('click', async
function () {
  const query=document.getElementById('query-input').value;
  if (!query) {
    alert(«Будь ласка, введіть запит.");
    return;
  }
```

The specified code allows to store user queries and analyze them, improving the functionality of the online assistant.

Clearing previous results:

```
document.getElementById('result').innerHTML='';
 document.getElementById('loading').style.display='block';
 const start=Date.now();
```

allows to proceed to checking cached results without assuming the creation of information noise, which can lead to an error in forming the answer. After this, the process of adapting the search logic according to the model occurs (Fig. 1). If there are no similar results in the cache, then the search mechanism is launched using a chatbot with AI, with the obtained search results entered into the cache for analysis before forming the answer to the query.

The developed pilot version of the online assistant performs a number of functions that allow to implement the personalization of the ChatGPT chatbot according to the requirements and rules of the online assistant. Among these functions are the following:

– adaptation of the search logic based on user queries:

```
function adaptSearchLogic(query) {
 let queryHistory=JSON.parse(localStorage.getItem('queryHistory')) || [];
```

– implementation of logic to determine the most common queries:

```
 let frequentQueries=getFrequentQueries(queryHistory);
```

– outputting the frequency of requests to adapt the behavior of the online assistant to the user's requirements:

```
 console.log("Часті запити користувача:", frequentQueries);
```

– function for searching the most common queries:

```
function getFrequentQueries(queryHistory) {
 const frequencyMap={};
 queryHistory.forEach(query=>{
  frequencyMap[query]=(frequencyMap[query] || 0)+1;
 });
```

– function for searching for a result in the cache:

```
function getCachedResult(query) {
 const cachedData = localStorage.getItem(query);
 if (cachedData) {
  return cachedData;
 }
 return null;
}
```

– function for saving the result to the cache:

```
function cacheResult(query, result) {
 localStorage.setItem(query, result);
}
```

The obtained online assistant was tested on the basis of the Educational and Methodological Laboratory of Digital Education and Artificial Intelligence of the Hryhoriy Skovoroda University in Pereiaslav. This allowed to obtain experimental values of operators related to human mental activity and algorithmized in the online assistant.

To experimentally determine the values of operators of actions and movements related to human mental activity, it was assumed that there is some unknown value t, which was measured when users worked on m various personal devices when working with the online assistant. The value t means the time to obtain the most accurate answer that satisfies the user's request. The hypothesis is accepted that the time to obtain a positive answer decreases when adapting the online assistant according to user requests.

The measurement process and results may have random errors and deviations. Therefore, the request is formed on the basis of a given keyword. Based on the results of each user's work, a table is obtained consisting of N_j values τ_{ij} of measurement results ($i=1, N$). The processing of the values τ_{ij} consists in calculating the mathematical expectation $\tau(m) \approx t(m)$ and the standard deviation $\sigma(m)$. The value $\tau(m)$ is the expected value of t, and $\sigma(m)$ is the deviation from the value $\tau(m)$. This is due to the fact that the online assistant is designed for users with different levels of knowledge and skills, and accordingly, the characteristics of the work, including cognitive ones, will be different for each user.

The experiments for evaluation t_1–t_4 are implemented according to the following scheme:

1) each keyword launches a series of experiments on user queries and receiving a response to the query;

2) between queries, after receiving a response, an arbitrary pause T is set;

3) each query consists of S_i – a text packet with S_i characters in each ($s=1, N_i$);

4) each query involves measuring the values τ_{ij} of the online assistant's response time;

5) each user j ($j=1, m$) processes a certain number of packets N_j for different queries with specified keywords.

The experiments assume a maximum use of foreign language signs and symbols of no more than 12 ($n \le 12$) using queries in natural language on a topic unfamiliar to the user, and queries in natural language on a topic familiar to the user. The number of devices participating in the experiment is 3 (computer, laptop, tablet). The number of packets N_j for each user is 20 (one packet is a query to the online assistant for one keyword with clarifications). The use of symbols S_i for one query is approximately 300.

Table 1 shows the results of text processing by the online assistant for queries created in natural language on a topic well known to the user.

In Table 1, the values τ_{ij} are given without taking into account the user's preparation before entering the query. The mean value of the sample $\tau(m)$, the confidence interval $\Delta\tau(m)$ and the deviation were calculated.

In Table 2, the summarized values of the estimates $t_1 \div t_4$, K, the variance $D_{t_1} \div D_{t_4}$, D_k, the standard deviation $\sigma_{t_1} \div \sigma_{t_4}$, σ_k, the measurement errors $\Delta t_1 \div \Delta t_4$, ΔK when creating queries using foreign language signs and symbols, using queries in natural language on a topic unfamiliar to the user, and queries in natural language on a topic familiar to the user are presented.

From Table 2, it can be noted that the expected relative error in measurements does not exceed 4.3% even with the worst result.

Using equations (5)–(8) as a system for unknowns $\mu_1 \div \mu_4$, the following solutions can be obtained

$$\mu_1 = t_1 - t_2,\ \mu_2 = t_4 - K,\ \mu_3 = t_1 - t_3 - \pi_c,$$
$$\mu_4 = 2(\mu_2 + K) = 2t_4. \qquad (10)$$

Taking into account (10), it is possible to give estimated values $\mu_1 \div \mu_4$, $\sigma_{\mu_1} \div \sigma_{\mu_4}$, $\Delta\mu_1 \div \Delta\mu_4$ for queries using foreign language signs and symbols, using queries in natural language on a topic unfamiliar to the user, and queries in natural language on a topic familiar to the user (Table 3).

Table 1

Results of text processing by the online assistant for a topic known to the user

No.	τ_1	τ_2	τ_3	τ_4
1	0.57	0.44	0.59	0.4
2	0.59	0.42	0.52	0.44
3	0.54	0.45	0.55	0.42
4	0.62	0.4	0.58	0.38
5	0.58	0.42	0.56	0.44
6	0.64	0.5	0.54	0.4
7	0.52	0.44	0.57	0.4
8	0.66	0.43	0.61	0.37
9	0.67	0.46	0.62	0.41
10	0.58	0.42	0.62	0.4
11	0.57	0.4	0.58	0.43
12	0.61	0.45	0.6	0.39
13	0.62	0.44	0.55	0.43
14	0.55	0.41	0.57	0.34
15	0.56	0.46	0.51	0.42
16	0.61	0.48	0.64	0.4
17	0.59	0.42	0.5	0.42
18	0.7	0.45	0.53	0.38
19	0.68	0.51	0.55	0.43
20	0.53	0.43	0.55	0.43
21	0.62	0.48	0.5	0.41
22	0.64	0.47	0.61	0.32
23	0.58	0.42	0.56	0.36
24	0.55	0.45	0.56	0.41
25	0.55	0.5	0.58	0.4
26	0.6	0.4	0.51	0.33
…				
58	0.68	0.43	0.52	0.41
59	0.56	0.43	0.52	0.42
60	0.66	0.41	0.58	0.4
$\tau(m)$	0.6	0.44	0.54	0.4
$\sigma(m)$	0.048	0.031	0.036	0.030
t	0.012	0.008	0.009	0.0076
$\tilde{t}$	0.6±0.012	0.44±0.008	0.54±0.009	0.4±0.076

Table 2

Summary values of processing estimates by query types

Characteristics	Query type		
	Foreign language signs and symbols	Natural language, unfamiliar topic	Natural language, familiar topic
t_1	1.20	1.13	0.60
D_{t1}	0.0033	0.0016	0.0023
σ_{t1}	0.0586	0.041	0.048
Δt_1	±0.02	±0.015	±0.012
$\Delta t_1 / t_1$	0.016	0.013	0.02
t_2	0.73	0.69	0.44
D_{t2}	0.007	0.0067	0.00096
σ_{t2}	0.0875	0.082	0.031
Δt_2	±0.03	±0.03	±0.008
$\Delta t_2 / t_2$	0.04	0.043	0.018
t_3	0.98	0.91	0.54
D_{t3}	0.0028	0.0014	0.0036
σ_{t3}	0.053	0.038	0.009
Δt_3	±0.019	±0.014	±0.009
$\Delta t_3 / t_3$	0.019	0.015	0.016
t_4	0.53	0.50	0.40
D_{t4}	0.00053	0.0067	0.0009
σ_{t4}	0.023	0.026	0.030
Δt_4	±0.008	±0.009	±0.0076
$\Delta t_4/t_4$	0.015	0.018	0.019
K	0.15	0.15	0.15
D_k	0.00002	0.00002	0.00002
σ_k	0.0042	0.0042	0.0042
ΔK	0.001	0.001	0.001
$\Delta K / K$	0.007	0.007	0.007

Table 3

Estimated values for queries by text types

Characteristics	Query type		
	Foreign language signs and symbols	Natural language, unfamiliar topic	Natural language, familiar topic
μ_1	0.47	0.44	0.16
$D_{\mu 1}$	0.0103	0.0083	0.00326
$\sigma_{\mu 1}$	0.1	0.091	0.057
$\Delta\mu_1$	±0.025	±0.023	±0.0144
$\Delta\mu_1 / \mu_1$	0.053	0.052	0.09
μ_2	0.38	0.35	0.25
$D_{\mu 2}$	0.00055	0.00672	0.00092
$\sigma_{\mu 2}$	0.023	0.082	0.03
$\Delta\mu_2$	±0.0058	±0.021	±0.0076
$\Delta\mu_2 / \mu_2$	0.022	0.06	0.03
μ_3	0.214	0.214	0.055
$D_{\mu 3}$	0.0061	0.003	0.0059
$\sigma_{\mu 3}$	0.078	0.055	0.077
$\Delta\mu_3$	±0.02	±0.014	±0.019
$\Delta\mu_3 / \mu_3$	0.09	0.065	0.33
μ_4	1.06	1.00	0.80
$D_{\mu 4}$	0.00212	0.0268	0.0036
$\sigma_{\mu 4}$	0.046	0.164	0.06
$\Delta\mu_4$	±0.011	±0.04	±0.015
$\Delta\mu_4 / \mu_4$	0.01	0.04	0.015

The calculation $\sigma_{\mu_1} \div \sigma_{\mu_4}$ was carried out taking into account the unconditional relationships and assumptions of the variance $D_{\mu_1} \div D_{\mu_4}$ values:

$$D_{\mu 1} = D_{t1} + D_{t2},$$

$$D_{\mu 2} = D_{t4} + D_k,$$

$$D_{\mu 3} \approx D_{t1} + D_{t3},$$

$$D_{\mu 4} = 4D_{t4}.$$

The above assumptions are based on the model (5) regarding π_c.

The measure of adequacy of the calculated operators in relation to the values of t_i is the degree of approximation of the calculated sum $t_p = K + \mu_1 + \mu_2 + \mu_3 + \pi_c \mu_4$ to the measurements of t_1. For the three types of requests, the values differ slightly. Thus, for requests using foreign signs and symbols, the ratio is $t_p / t_1 \approx 1.01$; for requests using natural language on a topic unfamiliar to the user, it is $t_p / t_1 \approx 1.02$; and for requests using natural language on a topic familiar to the user, it is $t_p / t_1 \approx 1.025$.

The definition of the micro-operator μ_5, which according to the model (Fig. 1) is responsible for further actions to compare the response of the chatbot with AI with the user's expectation, is calculated as the average value of the random variable μ_{5i}

$$\mu_5 = \Sigma_i \mu_{5i} / N, \tag{11}$$

where $\mu_{5i} = \tau_i / C_i$; N – the total number of experiment series; C – the number of query characters.

Table 4 shows the summarized values of μ_5, $D_{\mu 5}$, $\sigma_{\mu 5}$ for queries using foreign language signs and symbols, the use of queries in natural language on a topic unfamiliar to the user, and queries in natural language on a topic familiar to the user by experiment series.

The result obtained (Table 4) has the following explanation: in the created software implementation, the operator M does not have rules for language recognition. The plugin is responsible for communication

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with ChatGPT, and for the chatbot, queries using foreign language signs and symbols and queries in the user's usual natural language are equivalent. To communicate with ChatGPT using the plugin according to [8], it is necessary to adhere to uniqueness and clarity when forming narrowly professional queries. In this case, a query in natural language on a topic familiar to the user should lead to faster adaptation of the online assistant. In this case, human cognitive abilities allow to form a query in such a way that the search is accelerated, and the adaptation of the online assistant is somewhat slowed down.

Table 4

Values for queries by text types of experiment series

Characteristics	Query type		
	Foreign language signs and symbols	Natural language, unfamiliar topic	Natural language, familiar topic
μ_5	0.0435	0.045	0.045
$D_{\mu 5}$	$1.1\cdot10^{-4}$	$6.8\cdot10^{-5}$	$1.2\cdot10^{-4}$
$\sigma_{\mu 5}$	0.01	0.0082	0.0081
$\Delta\mu_5$	±0.0025	±0.0019	±0.0021
$\Delta\mu_5/\mu_5$	0.057	0.044	0.046

The obtained experimental results significantly improve the results of [7]. This is due to the function of adapting the logic to the user's logic in the online assistant. These results complement the work [10] on semantic evaluation of user natural language utterances and on this basis the implementation of the logic function for determining the most common queries. This allows to "distinguish" users even without prior registration. That is, by analyzing the cache, the user is differentiated and the online assistant is personalized based on the first query. The latter is implemented after the online assistant training process.

Unlike work [11], the online assistant is implemented using JavaScript. This allows for simplified installation on any site or portal. And unlike work [12], the developed online assistant does not simply take the user's position, but reproduces the user's cognitive process based on the processed queries.

That is, the advantages of this research are the ability to implement the online assistant personalization using (5)–(9). This is achieved by executing an algorithm that tracks the user's cognitive characteristics when entering queries. After that, the query is analyzed and remembered. The results of Table 4 allow to track user behavior regardless of the language or characters used to create the request. The difference in the request execution time is relatively insignificant (approximately 1.04%). However, according to other characteristics of the obtained values (Table 2 and Table 3), it can be seen that depending on the complexity of the request, the system gradually adapts to the user's requirements.

The practical significance of research is to improve interaction with users when using online assistants in the web environment when implementing various projects. Thanks to personalization, chatbots can provide the necessary information faster and more accurately. This is important in terms of increasing work productivity and saving time when performing complex tasks. Personalized online assistants can contribute to the formation of long-term relationships with users. In addition, personalized online assistants can collect and analyze data on the main problems that the user has. This will allow to respond in a timely manner to the emergence of problematic issues.

The limitations of research are the conditioned reaction of the user's interaction with the chatbot. The condition that the number of words in the query should not exceed the specified number of characters in the dialog box is also a limitation of the study.

The disadvantages of the study include the fact that for the accuracy of the decomposition of operators according to the GOMS model, the solution (2)–(4) requires a preliminary estimate. In this case, the calculation of the detailed values of the operators *M* and *K* and their arrangement requires deeper detailing and abstraction from the text typing operators.

Under martial law, the specified research can be used in control programs for unmanned aerial vehicles and various robotic platforms. Such development will contribute to rapid adaptation during the interaction of the operator and the device. This can significantly improve the responsiveness and accuracy of work.

The prospects for further research lie in the further decomposition of the model according to other operators. Another direction of work may be the expansion of the user base with the deepening of questions without limiting the query symbols. This will allow to deepen the functionality of online assistants and their use in the implementation of scientific projects, work in virtual laboratories, and cloud computing. This is a step towards creating chatbots that understand and respond to user requests even better, taking into account the context and emotions.

4. Conclusions

The proposed operator decomposition model using GOMS technology did not prove the possibility of using this model in a new direction of research. The results obtained allowed to investigate micro-operators μ in relation to human cognitive function when interacting with an online assistant based on AI. The results of the calculations proved the positivity of the relative error values μ for the studied group of users.

A pilot version of the online assistant with the function of adaptation to user requirements has been developed. JavaScript was used for the universality of the development.

The values of micro-operators μ, the reaction time of the online assistant for creating a response and adapting to the user's requirements based on the reproduction of cognitive functions were experimentally investigated.

Analysis of user behavior when implementing the online assistant according to the above algorithm allowed obtaining results for different scenarios. It was determined that depending on the complexity of the request, the system gradually adapts to the user's requirements. The final results for requests using foreign language signs and symbols were obtained, the time ratio of time spent was 1.01 s. For the use of natural language requests on a topic unfamiliar to the user and for a natural language request on a topic familiar to the user, the results were 1.02 s and 1.025 s.

The proposed approach can be used to create online assistants for the implementation of highly specialized complex projects on web platforms. Also, this can be used to improve existing plugins for interaction with chatbots with generative artificial intelligence.

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Conflict of interest

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Data availability

The manuscript has no related data.

Use of artificial intelligence

The authors used artificial intelligence technologies within the permissible framework to provide their own verified data, which is described in the research methodology section.

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