The object of this study is the impact of using generative artificial intelligence (AI) on the resource efficiency of enterprises in the context of sustainable development. The issue relates to the fact that despite the ability of generative AI to optimize management and production processes, its use is accompanied by an increase in electricity consumption (grid, mostly non-renewable) and water, which creates new environmental risks.

This paper systematizes existing methods for indirectly estimating energy and water consumption in the process of generative AI model functioning. Based on this, an approach to assessing the ecological footprint of generative AI has been devised, which takes into account four indicators such as query length, complexity, task type, and industry. A special feature of the proposed approach is a combination of quantitative analysis, regression modeling, and query classification to assess resource intensity.

An empirical study has shown that high-volume queries (analytical and creative) generate significantly higher resource consumption (2.1–2.3 Wh of electricity and more than 0.8 liters of water) while factual queries create a minimal load (< 0.12 Wh). This difference is explained by the complexity of information processing and the involvement of significant computing power in cloud data centers.

To evaluate the feasibility of AI implementation, a sustainability index has been proposed to assess the balance between the efficiency achieved and resources spent. The proposed approach could be used by enterprises under conditions of limited access to energy and water resources, in particular during post-war recovery and implementation of the principles of sustainable development

Keywords: generative artificial intelligence, GPT-models, sustainable development, energy efficiency, ecological footprint

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ENSURING SUSTAINABLE USE OF GENERATIVE ARTIFICIAL INTELLIGENCE BY ENTERPRISES BASED ON RESOURCE CONSUMPTION OPTIMIZATION

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1. Introduction

Post-war restoration of enterprises is accompanied by a complex strategic dilemma. On the one hand, it is worth integrating the principles of sustainable development as a foundation for reconstruction, energy modernization, and ensuring long-term competitiveness. On the other hand, the lack of resources and the need for quick, innovative solutions complicate the implementation of this goal. In the context of the destruction of individual natural ecosystems, increasing energy costs and socio-economic instability, there is an urgent need for fundamentally new approaches to strategic management of enterprises.

In this context, solutions based on artificial intelligence (AI) are appropriate as it is a powerful tool for optimizing production processes at enterprises, increasing energy efficiency, and accelerating management decision-making. These technologies are particularly relevant given the priority of digitalization and stimulating the development of the IT sector in Ukraine. There are known cases of the use of AI in various aspects of enterprise management. This concerns waste management optimization [1], production planning [2, 3], management of "smart" energy networks [4, 5], management of marketing and sales activities [6], etc. This is relevant under the conditions of limited resources of the post-war period.

Although currently there are a small number of data centers operating in Ukraine (as of March 2024, 58 data centers, 25th place in the world in terms of the number of such facilities) [7, 8]), the further development of AI technologies will inevitably lead to an increase in their number and capacity. This creates potential challenges in the field of energy consumption and environmental impact. Large language models, machine learning systems, as well as the infrastructure to support them, will require significant consumption of electricity and water resources for cooling. Under such conditions, a situation arises when technology designed to make enterprises more sustainable and energy efficient becomes an additional burden on the environment.

This makes scientific research aimed at determining the impact of AI on resource intensity and the environment relevant. The task of sustainable use of AI requires a thorough analysis based on determining the economic benefits, taking into account the energy, water, and carbon impacts of the implementation of modern digital technologies. At the stage of rebuilding the Ukrainian economy, such research forms the basis for devising policies and methods for using AI in the interests of sustainable development.

2. Literature review and problem statement

Research in the field of sustainable development and AI demonstrates significant interest of the scientific community and business in the integration of innovative technologies in solving environmental, social, and economic challenges. It is emphasized [9, 10] that AI can contribute to achieving sustainable development goals, especially through increasing energy efficiency, innovation, and infrastructure development. At the same time, potential risks of their negative impact due to ethical, social, or environmental challenges are noted. The issue of ensuring a comprehensive, responsible implementation of AI, which simultaneously takes into account positive results and risks, remains unresolved.

Works [11, 12] emphasize the potential of AI for optimizing energy systems and the importance of implementing energy-efficient algorithms. However, the studies do not take into account the ecological footprint of AI systems themselves, in particular generative models. There are also no methods for quantifying energy and water consumption during their operation. This is due to both the closed nature of infrastructure data and the researchers' focus mainly on the benefits of AI, rather than its costs. Therefore, the question of the balance between the benefits of AI and the resource cost of its use remains open.

Studies [13–15] focus on the use of AI to improve energy efficiency of production, reduce greenhouse gas emissions, and optimize resource use in the Ukrainian context. In particular, the authors of [13] outlined positive directions for business digitalization using AI, including for efficient energy and water consumption. However, the analysis is limited to the strategic level without considering the real technical or energy characteristics of the systems' functioning. The analytical report [14] focuses on the potential of using AI in energy, in particular in consumption management and forecasting. However, there are no quantitative assessments of the energy consumption of the models themselves and their environmental impact. Paper [15] proposes conceptual approaches to the use of AI in environmental forecasting. At the same time, there is no analysis of how AI itself can create additional environmental challenges, in particular due to high energy consumption during training and generation. These and other scientific studies by Ukrainian scientists focus mainly on general strategic opportunities and theoretical premises, without being accompanied by a quantitative assessment of the impact of AI on resource consumption. In particular, no specific tools or methods for assessing the energy or water consumption of AI systems are considered. This is explained by the lack of open data and the methodological unsoundness of assessing the resource footprint of technologies.

References [16–18] focus on the potential of AI in energy management systems, in particular in energy consumption automation, increasing the efficiency of energy systems and forecasting demand. Study [16] considers the implementation of intelligent energy consumption control systems in commercial buildings using machine learning and IoT technologies. The authors focus mainly on reducing energy consumption by consumption objects, without taking into account the energy costs of the AI solutions themselves, in particular at the stages of data processing and forecast generation. Paper [17] analyzes the prospects for the application of AI in energy markets and networks, emphasizing the potential for optimizing energy production and distribution. However, there is no analysis of how the large-scale implementation of AI affects the overall load on the energy system, which is especially critical in the context of sustainable development. Paper [18] proposes a model of the impact of AI on resource efficiency and CO_2 emissions reduction. Although an attempt is made to quantitatively analyze the impact of AI on sustainability, the authors do not include in the assessment the actual resource consumption of intelligent systems, in particular their water or energy footprint. Thus, despite the relevance of the research topic and the recognition of AI as a tool for energy optimization, the sources mentioned overlook the actual energy and water footprint of AI systems that are implemented in the energy sector.

The relationship between AI and energy consumption is complex and multifaceted. The authors of [19] point to the "rebound effect", when increased efficiency due to AI can lead to an increase in overall energy consumption due to increased demand. In addition, studies [20] show how the use of AI can reduce energy intensity in the industrial sector, and argue that although AI can increase productivity, it requires a critical study of its energy needs. There are currently no clear estimates under which conditions the positive effect of AI will outweigh its increasing energy consumption. This is due to both the lack of integrated methods for assessing the life cycle of technology and insufficient attention to the cumulative impact on the resource base.

AI systems are notoriously energy-intensive. Studies show that not only the use but also the training of neural networks is particularly energy-intensive. Some models consume as much energy as several households over their entire lifetime [21]. For example, one ChatGPT (GPT-4) response, according to various sources, requires approximately 0.5–2 Wh of electricity (depending on the length of the response and the complexity of the query), which is equivalent to charging a smartphone for 10–20 min or using an LED lamp for 10–20 min. One query to GPT-4 consumes 0.5–1 l of water, depending on the location of the data center, temperature, and infrastructure load. According to various estimates, ≈ 10 GWh of energy (equal to the consumption of a small city for several months) and ≈ 700 thousand liters of water for cooling (equal to 3 Olympic-sized swimming pools) were spent on training GPT-4 [22, 23].

This raises questions about the sustainability of AI technologies, as the energy required to train and run these models can contribute to increased carbon emissions if they are generated from non-renewable energy sources. It is clear that as datasets and algorithms become larger and more complex, the computing resources required to process them increase, leading to increased energy demand [24]. In addition, the importance of optimizing AI hardware in training systems to minimize energy use has been discussed [25]. This suggests that improving AI hardware and algorithms is essential to reducing the energy footprint of AI. The authors of [19] argue that while AI can increase efficiency, it could also lead to increased energy consumption if not managed properly. However, existing studies lack a systematic assessment of the relationship between hardware, energy sources, and carbon emissions. This is due to both the technological opacity of commercial models and the limited empirical data to compare the impact of different configurations, making it difficult to devise unified approaches to assessing AI sustainability.

Therefore, although AI is actively used by enterprises to optimize production and business processes, increase energy efficiency, and promote sustainable development, the energy and water efficiency of such systems remains insufficiently studied. In particular, there are no metrics for assessing the impact of AI models on energy and water consumption. There is uncertainty about whether the resource savings due to AI compensate for its own environmental footprint. In addition, the question remains open about the superiority of environmental and economic benefits from the use of AI over its resource costs, especially in the long term. It is advisable to devise a methodology for assessing this balance under specific enterprise conditions.

3. The aim and objectives of the study

The purpose of our study is to substantiate approaches to the sustainable use of AI by enterprises by assessing its energy and water footprint, modeling factors influencing resource consumption of generative models. This will make it possible to compile practical recommendations for minimizing environmental risks and increasing the efficiency of its use.

To achieve the goal, the following tasks were set:

– to identify application areas and characteristic features of the use of AI by enterprises in various sectors of the economy in the context of ensuring sustainable development;

– to systematize existing methods for assessing energy and water consumption of generative AI models;

– to conduct experimental modeling of the impact of ChatGPT (GPT-4) query characteristics on conditional energy consumption and water consumption;

– to determine the balance between the efficiency of generative AI use and its resource consumption to justify the feasibility of use under conditions of limited energy and water resources.

4. The study materials and methods

The object of our study is the impact of the use of AI on the resource efficiency of enterprises in the context of sustainable development.

The hypothesis of the study assumes that the presence of a comprehensive approach to assessing the conditional energy consumption and water consumption of generative AI based on query parameters could allow us to propose mechanisms for optimizing its use under conditions of limited resources.

During the experiment with the ChatGPT generative model, certain assumptions were accepted:

– energy consumption is directly proportional to the number of tokens and the complexity of the query;

– average energy consumption indicators and water footprint coefficients of data centers are constant throughout the experiment.

The study adopted the following simplifications:

– conditional energy consumption of ChatGPT-4 was determined based on averaged indicators from open sources (0.05–0.1 Wh per 1000 tokens);

– water consumption – based on the averaged water footprint (1–2 l per 1 kWh) without taking into account geography and type of cooling systems;

– the level of complexity of the requests was determined on a subjective scale (1–4) based on expert assessments;

– typology of requests (factual, creative, analytical, etc.) was carried out without the use of specialized classifiers.

The research was conducted in stages using theoretical and empirical methods, taking into account the interdisciplinary nature of the problem, which covers aspects of digital technologies, energy, and sustainable development. The methodology involved experimental interaction with the GPT-4 generative language model (based on ChatGPT from OpenAI, version for March 2024).

The first stage involved identifying application areas and characteristic features of the use of AI by enterprises in various sectors of the economy in the context of promoting sustainable development. For this purpose, methods of systematization, logical and content analysis were used, which allowed us to identify priority areas for further experimental assessment.

At the second stage, a review and comparative analysis of approaches to assessing energy and water consumption using generative models was conducted. General scientific methods of analysis were used, as well as adaptation of existing approaches to the research conditions: the carbon calculator method, statistical modeling, correlation weighting, and estimation of conditional energy consumption based on text query parameters. The criteria for selecting methods were their accessibility to the user and the lack of direct access to the hardware environment of data centers.

The third stage involved conducting an experiment with the ChatGPT generative model (GPT-4), during which a series of queries of various types and complexity (short factual, analytical, mathematical, creative, medical, and scientific and technical) were generated and analyzed.

For each, the following quantitative indicators were recorded: the number of tokens (length of the query and response); complexity level (1 – low, 4 – very high); scope of application (medicine, business, ecology, philosophy, etc.); conditional energy consumption (Wh); conditional water consumption (liters). Owing to this, regression models of the dependence of energy and water consumption on the length of the query and its level of complexity were proposed. Visualization, correlation analysis, and classification of queries by areas were carried out in order to identify the most resource-intensive areas of AI application. To build mathematical dependences, linear and nonlinear regression methods, coefficients of determination, correlation analysis were used. These methods were chosen as the most appropriate tools for identifying dependences between user query parameters and conditional resource consumption.

Modeling of generative responses was carried out through the official ChatGPT web interface. Data systematization, basic statistical processing, and construction of data tables were carried out using Microsoft Excel. Regression model construction, calculation of correlation and determination coefficients, visualization of dependences were performed in Python. A personal computer with an Intel Core i7 processor was used as the hardware platform.

At the fourth stage, applied recommendations and approaches to the adaptive use of generative AI were devised. Methods of generalization, expert evaluation, comparative analysis of resource consumption models and principles of optimization of sustainable use of digital technologies in the production and management environment of enterprises were used.

5. Results of investigating the resource consumption by generative artificial intelligence

5. 1. Using artificial intelligence to increase the sustainability of enterprises

Ukrainian enterprises face deep sustainability challenges: power outages, water supply losses, staff shortages due to mobilization and migration, as well as uncertainty in market demand. Under such conditions, the need to integrate innovative technologies based on AI technologies that can increase production efficiency and environmental responsibility becomes critical. Analysis of a large data set allowed us to systematize the sustainability problems of enterprises by individual industries and determine the potential impact of AI on their solutions and specific technologies with examples of their use (Table 1).

Table 1

Sustainability issues in business sectors and how to address them with AI

Field of activity	Sustainability issues	Potential impact of AI	Global experience in the application of AI
Industry	High CO_2 and pollution emissions. High energy consumption. Production waste and inefficient use of resources. Equipment breakdowns and costly downtime	Predictive maintenance – predicting failures and minimizing waste. Process optimization – reducing energy consumption and raw material losses. Emissions and waste monitoring – controlling environmental impact. Automation of production processes – increasing efficiency	Siemens MindSphere – IoT+AI for plant performance analysis, reduces energy consumption by 10–20%. IBM Maximo AI – predictive maintenance of equipment, reduces downtime by 25%. CarbonChain – carbon footprint monitoring in metal and cement production
Energy	Imbalance between energy generation and consumption. High carbon footprint from traditional sources. Difficulty integrating renewable energy sources	Smart Grid – intelligent networks for energy balancing. Consumption forecasting – reducing excess production. Optimization of solar and wind power plants. CO_2 emission monitoring	Google DeepMind for Energy – reduces energy consumption of Google data centers by 40%. AutoGrid – optimizes network operation, saves up to 15% energy. Climeworks – monitoring and reducing CO_2 emissions
Agriculture	Excessive use of water, fertilizers, and pesticides. Crop losses due to climate change. High carbon footprint of the agricultural sector	Precision farming – optimizing irrigation and fertilization. Monitoring soil and plant health. Forecasting weather conditions and disease spread. Automation of agricultural machinery	John Deere See & Spray – reduces pesticide use by 70%. Prospera AI – crop condition analysis, reduces crop losses. CropX – AI soil monitoring, saves water up to 30%
Construction and real estate	High CO_2 emissions during construction. Significant construction waste. High heating and air conditioning costs	Design of energy-efficient buildings. Optimization of the use of building materials. Monitoring of energy consumption of buildings. Automation of construction processes	Autodesk Spacemaker – analyzes energy consumption at the design stage. BrainBox AI – reduces building energy consumption by 25%. Cove.Tool – reduces CO_2 emissions during construction
Transport and logistics	High CO_2 emissions from transport. Low efficiency of routes. Problems with vehicle disposal	Route optimization – reducing mileage and emissions. Predictive transport maintenance. Electric vehicles and autonomous transport	Optibus – reduces emissions from urban transport by 15%. Geotab – fleet monitoring, fuel economy. Tesla Autopilot – autonomous driving to reduce accidents
IT and digital technologies	High energy consumption of data centers	Green AI – energy-efficient computing. Optimizing cloud services	Google TPU – reducing power consumption of ML algorithms. Microsoft Azure Sustainability – "green" cloud computing
Retail and trade	Low energy efficiency of algorithms	Inventory and logistics optimization. Personalization to reduce returns	Symphony RetailAI – Minimizing Waste in Retail Vue.ai – AI Personalization for Retail
Consulting and business services	High costs of management and decision-making. Inefficient use of resources. The need to personalize approaches to customers	Business process optimization through big data analytics. Using chatbots to automate consultations. Risk forecasting and strategy modeling	IBM Watson – market analysis and trend forecasting. ChatGPT – automation of client consultations
Education (online and offline courses)	Lack of personalized learning. Unequal access to quality education. High cost of traditional education	Adaptive learning based on student needs. Automation of student assessment and support. Translation and adaptation of materials for broad access	Duolingo AI – personalized language learning. Coursera AI Tutor – adaptive online courses. Grammarly – writing assistance
Medical services and pharmaceuticals	Shortage of medical personnel. High cost of diagnostics and treatment. Inefficient allocation of medical resources	Automated disease diagnosis. Analysis of medical data for early detection of pathologies. Optimization of drug and resource allocation	IBM Watson Health – medical image analysis. DeepMind Health – disease prediction. BioGPT – drug development assistance
Hospitality and tourism	High resource consumption. Low personalization of service. Long booking and registration processes	Optimizing energy use in hotels. Automation of reservations and registration. Analysis of reviews and personalization of services	Google Travel AI – personalized recommendations. Hilton's Connie AI – virtual assistant in hotels. TripAdvisor AI – analysis of tourist reviews
State-owned enterprises and public services	Bureaucracy and inefficiency of the public sector. High administrative costs. Corruption and lack of transparency	Document processing automation. Analytics and forecasting for decision-making. Using blockchain for transparency	AI–driven chatbots (GovChat) – automation of public services. Data Analytics in Public Policy – forecasting social trends. AI-based fraud detection – fighting corruption

Note: compiled from [26–28].

Thus, enterprises in mechanical engineering, metallurgy, food industry are faced with traditional problems of high energy consumption, significant technological losses, and insufficient automation of technological processes. In this context, AI acts as a tool for intelligent equipment management, predicting equipment failures, reducing product shortages, and optimizing logistics processes.

The biggest problem in the agricultural sector, which is being solved in precision farming systems with the help of AI, is the decrease in yield under the influence of climate change and limited access to water. Analysis of satellite data, weather changes and soil conditions makes it possible to save resources and ensure the stability of agricultural production even under risky conditions.

In transport and logistics, which have suffered from disruptions in supply chains, AI is used to optimize routes, predict the risks of delays, and reduce greenhouse gas emissions by reducing idling.

Construction and housing and communal services need to increase energy efficiency and control water consumption. For example, the implementation of intelligent building management systems makes it possible to automatically regulate lighting, ventilation, and heating depending on user needs and weather conditions, which directly affects the reduction of energy costs.

Healthcare in the context of post-COVID-19 and wartime system overload requires accurate forecasting, efficient resource allocation, and waste minimization. Here, AI is already being used for patient triage, medical image analysis and drug logistics optimization. However, from a sustainability perspective, the excessive use of computing resources requires a critical reassessment of the infrastructure of healthcare facilities.

In the public sector and education, the main barriers remain fragmented digitalization, lack of analytical systems, and high maintenance costs of legacy systems. In these areas, AI can not only increase the efficiency of decision-making, but also contribute to transparency, inclusiveness, and cost reduction through automation.

Analysis of the application of AI in various sectors of the economy already demonstrates significant benefits in solving environmental, social, and economic problems.

The main areas of AI's impact on sustainability include resource optimization (reducing energy consumption, reducing waste) and reducing greenhouse gas emissions (through forecasting and optimization). We should not forget about the automation of processing large amounts of data, as well as monitoring and analysis of environmental impact through tracking climate change, air quality, soil condition, etc. However, it faces significant challenges: the need for significant computing power, which increases energy consumption (in this aspect, studies on "green AI" are well-known); limited access to high-quality data; high implementation costs. Despite the wide range of applications of AI to support the sustainable development of enterprises, the results of the analysis reveal that the key challenge for them is the significant energy consumption of both the production processes themselves and information and communication systems. Combined with damage to the energy infrastructure, dependence on energy imports and rising tariffs, this issue is key to the further viability of enterprises. The role of water consumption is also growing, especially in industrial areas where water supply networks are disrupted or access to water is limited.

The implementation of AI systems, especially generative models operating in large data centers, often aims to optimize resource use. At the same time, the very process of their operation creates an additional burden on the energy and water infrastructure. In this regard, for further scaling of such solutions, it is advisable to estimate and model energy and water consumption during the operation of generative AI. The ChatGPT model was chosen as an example for analysis.

5. 2. Systematization of methods for estimating energy and water consumption when using generative artificial intelligence

Despite the widespread use of AI in various fields of activity, its ecological footprint has not yet been assessed, since there is no access to monitoring energy and water consumption during response generation and calculations. However, taking into account the available tools, it is advisable to single out methods for indirectly determining the ecological footprint of the use of generative AI.

The method using carbon calculators [29, 30] is based on the use of average energy consumption indicators in data centers published by large providers (Google, Microsoft) and research institutions. In particular, it is known [22] that the generation of 1000 GPT-4 text tokens consumes approximately 0.05–0.1 Wh. Taking into account the PUE (Power Usage Effectiveness) indicator of data centers and the average water footprint (1–2 liters per 1 kWh), the average load on resources is calculated as:

$$E = L \cdot e, \tag{1}$$

$$W = E \cdot w, \tag{2}$$

where E is the electricity consumption (Wh), L is the length of the text (tokens), e is the energy consumption per 1 token, W is the water consumption (liters), w is the water footprint per 1 Wh.

This method is recommended for an approximate estimate at the early stages of analysis or in the absence of access to accurate data.

A statistical modeling method (based on historical cases), which is based on finding the relationship between the parameters of the ChatGPT query array (length, complexity, topic) and the conditional energy and water consumption [31], which makes it possible to predict resource consumption in new queries. This approach can be used at any enterprise without direct access to servers.

The time window measurement method is a technically complex, accurate approach that is advisable to apply in cases where there is access to the server, or a local model is used. The essence of this method is to determine the difference between the energy consumption indicators before, during, and after the query execution [32]. The water footprint per kWh is used to estimate water consumption. This method is extremely useful for internal assessments at enterprises deploying their own AI models.

The correlation weighting method is based on the assumption that the characteristics of AI queries (type, complexity, volume) have a stable statistical relationship with the energy and water consumption during their processing [33]. That is, there is a correlation between the complexity and length of the query and the resources required to generate it. Queries are classified by type (factual, analytical, creative, etc.), and each type is assigned an average consumption coefficient (for example, a simple fact – 0.03 Wh/token, 0.01 l/token; analytical review – 0.07 Wh/token, 0.025 l/token). These coefficients are determined empirically by processing a large set of queries and summarizing the average costs for each category.

Analysis of methods for indirectly determining the ecological footprint of generative AI reveals that a combination of statistical modeling and correlation weighting is the optimal solution when an enterprise does not have full access to servers. With this in mind, at the next stage of the research, an empirical experiment was conducted aimed at modeling the impact of query characteristics to the generative AI Chat GPT-4 model on energy and water consumption.

5. 3. Experimental modeling of energy and water consumption by generative artificial intelligence

To understand the quantitative impact of query parameters to generative AI on electricity and water consumption, empirical modeling was conducted in the form of a sequential experiment using the GPT-4 model. The main goal of this stage of the study was to verify the possibility of applying statistical modeling and correlation weighting, as well as to build an indicative database that would make it possible to predict the environmental load for different types of queries.

More than 30 queries were formulated from a wide range of areas and types of interaction with the generative model – from factual queries to complex analytical and creative tasks. For each request, the following were recorded: the number of tokens (the total length of the request and the response), a subjective assessment of complexity (on a scale from 1 to 4), the topic (medicine, ecology, business, philosophy, creative studios, science, etc.), and conditional values of energy consumption and water consumption were calculated. The limitation of the study was the conditional nature of the energy and water consumption estimates, which are based on well-known scientific estimates and do not take into account the specifics of a particular data center infrastructure. Based on the collected data, regression relationships were constructed that reflect the dependence of resource consumption on the request parameters:

$$E = 0.04T + 0.5C, \tag{3}$$

$$W = 0.015T + 0.2C, \tag{4}$$

where E is the conditional energy consumption (Wh), W is the conditional water consumption (liters), T is the number of tokens in the query and response, C is the level of complexity of the query.

The experiment showed that there is a relationship between the length of the query and the amount of resources required to process it (Fig. 1, 2). Long analytical and creative queries, in particular the creation of literary works, the construction of mathematical models, medical recommendations, as well as complex philosophical queries, have the largest ecological footprint. For them, energy consumption reached 2.1–2.3 Wh, and water consumption was more than 0.8 liters. The smallest footprint was recorded for simple factual queries, where consumption did not exceed 0.12 Wh.

Analytical queries consumed an average of about 1.5 Wh and 0.6 l of water. Creative queries consumed over 2 Wh and almost 1 l of water. Technical (mathematical and econometric) queries consumed about 1.1 Wh. The lowest energy consumption was recorded for short factual answers, at an average of 0.25 Wh (Fig. 3). Long queries can significantly distort general trends, so they should be analyzed separately.

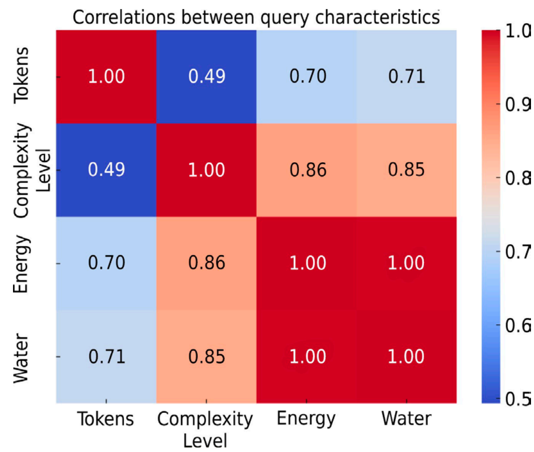

Fig. 1. Heatmap of correlation among experimental parameters (Imagined with AI)

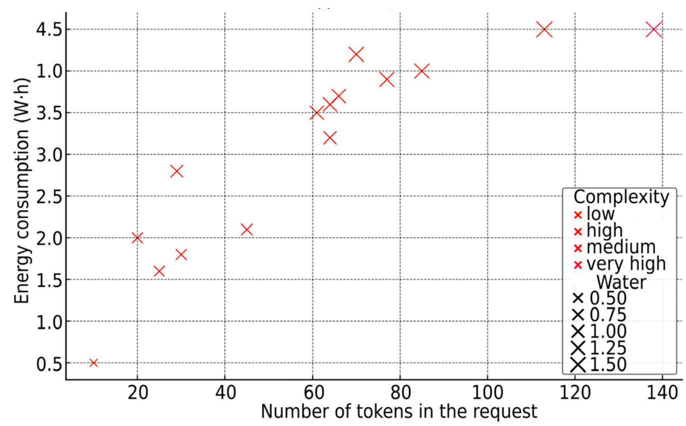

Fig. 2. Dependence of energy consumption on the volume of the request (Imagined with AI)

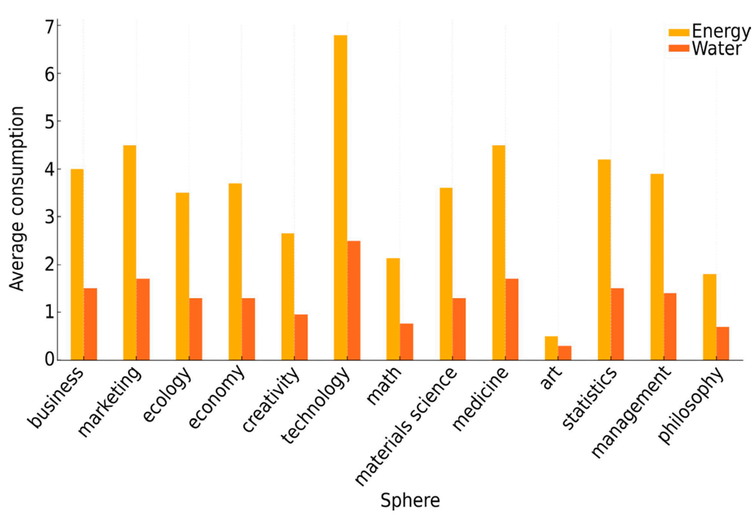

Fig. 3. Comparison of average energy and water consumption for requests from different sectors (Imagined with AI)

Our results confirm that the energy and water load when using generative AI is not a constant indicator but depends on the complexity, length, and type of the query. This indicates the need for further optimization of the use of AI, especially for enterprises that follow the principles of sustainable development.

5. 4. Balance between efficiency and environmental sustainability of generative artificial intelligence

The high efficiency of AI in solving a wide range of tasks cannot be the basis for its unconditional implementation without taking into account energy and water costs. Therefore, the final stage of the study was to define recommendations for improving the environmental friendliness of the use of AI and find a balance between the benefits of the technology and its impact on the environment.

In order to quantitatively substantiate such a balance, we shall use an integral indicator – the Sustainability Index (SI), which makes it possible to correlate the benefits of using AI-based solutions with the resource costs for their operation

$$SI = \frac{B-R}{R+e}, \tag{5}$$

where B is the benefits of using AI (time savings, increased accuracy, reduced production losses), R is the total consumption of resources (energy, water, carbon footprint), e is a constant that prevents division by zero.

In the case when SI exceeds 1, the benefits significantly outweigh the resource losses, therefore, the use of AI is sustainable. If SI approaches 1, then this is a balance zone in which each new decision should be made with caution. Conversely, if the SI value is less than 1, then the environmental damage or resource load exceeds the benefits received. In this case, it is worth either changing the model of using AI or abandoning its use at this stage.

When analyzing the sustainability index of the use of generative AI, it is important to understand that it has both potentially positive and significant negative consequences for sustainable development. On the one hand, the negative impact of AI is manifested through high energy consumption, large water losses for cooling data centers, as well as the growth of electronic waste that is difficult to recycle. At the same time, AI can bring a positive environmental effect by optimizing energy networks, balancing energy supply and demand, reducing losses. And also contribute to reducing CO_2 emissions through logistics optimization. Important areas are the forecasting of climate change and environmental risks based on big data analysis, reducing printed documentation and automating processes. Therefore, to find a balance between benefits and risks, it is advisable to focus on environmental efficiency parameters that make it possible to determine whether the use of AI is justified in a specific case (Table 2).

The data obtained during the experiment allowed us to offer a number of recommendations for optimizing the use of generative AI, which is especially relevant for enterprises that strive to adhere to the principles of sustainable development.

At the user level, rationality in query formulation and tool selection plays an important role. First, it is advisable to choose less powerful models for processing factual tasks, while GPT-4 or similar models should be used only for complex queries. Second, it is effective to reduce unnecessary tokens in queries, i.e., more precise formulation of the question can reduce energy consumption. Instead of complex multi-factor queries, it is advisable to break queries into separate stages, which makes it possible to avoiding excessive calculations in one cycle. In this context, it is considered advisable to introduce courses in school, vocational or university programs to teach the effective use of generative AI.

Table 2

Criteria for assessing the environmental sustainability of the use of artificial intelligence

Criterion	AI has a negative impact if	AI is environmentally sustainable if
Energy consumption	Overcomes resource and time savings	Optimizes business processes and reduces overall consumption
Water resources	Data centers require significant cooling	Uses alternative methods with a low water footprint
Energy source	Powered by hydrocarbon sources	Infrastructure runs on renewable sources
Request efficiency	Powerful models are used for simple tasks	Uses an adaptive model selection system

It also turned out to be advisable to pre-classify queries by type (e.g., factual, creative, analytical) using models that are optimized for this type of task. A promising direction is the introduction of energy consumption indicators in responses, similar to "calories" in food products, which will stimulate the environmental awareness of generative AI users.

Attention should also be paid to organizational and infrastructure aspects. For example, the implementation of optimized hardware solutions, the use of "green" data centers, the transition to local learning or deployment models – all this will significantly reduce energy and water loads. In addition, from the point of view of AI regulation, it is possible to stimulate developers to design systems with built-in monitoring of environmental impact, devise certification procedures for "sustainable" AI solutions, as well as support the implementation of such technologies in sectors that are critical to the state – energy, agriculture, and industry.

6. Discussion of results related to the resource consumption by generative artificial intelligence

AI is a powerful tool for increasing the efficiency of enterprises on the basis of sustainable development, but its use is accompanied by significant environmental challenges. Our results indicate that the energy and water consumption of generative models, such as GPT-4, depends on the complexity and length of queries (Fig. 1–3). The significant load of the model is controversial, as the technology aimed at optimizing resources itself acts as an additional load on the environment. This is consistent with studies [21, 22] that emphasize the significant energy footprint of large language models.

Our results confirm the findings reported in [19] on the "rebound effect", where efficiency gains through AI can lead to an increase in overall energy consumption. However, unlike previous works that focused mainly on energy aspects, our study also takes into account the water footprint.

The proposed AI Sustainability Index (SI) allows for a quantitative assessment of the balance between the benefits of using AI and its environmental impact. This approach complements work [10], which focused on the qualitative aspects of sustainable AI but did not propose a specific tool for assessment. The proposed index could become a useful metric for enterprises that seek to integrate AI into their processes, adhering to the principles of sustainable development.

A key aspect that was identified is the need to stimulate environmental awareness among users of generative AI. Our study showed that many users are not aware of the resource costs associated with each request to AI. Introducing energy consumption indicators in the responses could raise awareness and promote more responsible use of the technology. Introducing educational activities at school, vocational, or university programs on the effective use of generative AI would also contribute to increasing environmental awareness. This approach is consistent with the concept of "green AI" [12, 24] and emphasizes the importance of informing users about the environmental impact of their actions.

It is also worth noting that the proposed recommendations for optimizing the use of AI (e.g., adaptive model selection, reduction of redundant tokens) are consistent with the ideas of "green AI" [12, 24]. However, our study offers specific practical steps for users, enterprises, and regulatory institutions, which makes its results more applicable.

The study has a number of limitations that must be taken into account when interpreting the results. First, the assessment of energy and water consumption was not carried out on the basis of actual data but using indirect methods (correlation weighting, statistical modeling) using coefficients from open sources (e.g., 0.05–0.1 Wh per 1000 tokens). Therefore, the values obtained are conditional and may vary depending on the computational architecture and query execution conditions. Our study was conducted without access to the ChatGPT–4 server infrastructure, which limits the accuracy of calculating the real load. Water consumption for server cooling was also estimated indirectly by extrapolation based on an average coefficient (1–2 l per 1 kWh), which also has regional variability. Second, the study is focused on the ChatGPT-4 application model and does not take into account the specificity of other types of generative AI. In addition, the types of queries covered are not exhaustive for the entire spectrum of applications in enterprise activities.

However, there are certain shortcomings of our study that may limit its practical application. In particular, the lack of real-time resource consumption monitoring tools for users of generative models does not allow for accurate verification of the results of the experiment. This means that recommendations for optimizing resource consumption remain approximate. The impact of hardware and power sources was also not taken into account, which under real conditions could significantly change the actual energy consumption and water dependence. The limited number of cases and topics on which the modeling was based also narrows the generalizability of the obtained patterns.

It is advisable to direct further development of the study along several directions. First, it is to deepen the accuracy of assessing the ecological footprint of generative AI by integrating tools for direct monitoring of energy and water consumption. This would allow us to move from conditional to actual calculations, increasing the reliability of the conclusions. Second, to expand the database of queries that takes into account different areas of enterprise activity, the variability of languages, usage scenarios, and the intensity of data processing. This approach would contribute to the construction of more general models relevant to a wide range of industries. Third, it is advisable to conduct a comparative analysis of different models of generative AI in terms of efficiency, resource dependence, and ecological footprint, which would allow enterprises to choose the optimal technologies from the perspective of sustainable development. A separate area is likely to be the development of digital tools for assessing the sustainability of generative AI, in particular, the design of calculators for energy consumption, ecological footprint, and the index of sustainability of AI use.

7. Conclusions

1. AI is being implemented in the activities of enterprises in various sectors of the economy (mechanical engineering, agriculture, logistics, energy, healthcare) as a tool for increasing productivity, planning accuracy, minimizing losses, and automating routine processes. In the context of sustainable development, AI contributes to achieving the goals of energy efficiency, reducing emissions, and effective resource management. At the same time, it has been found that the use of generative AI is not environmentally neutral. Large-scale models require significant consumption of electricity and water both during training and in the process of generating responses. This leads to the emergence of a new class of risks and management dilemmas: how to ensure technological advantages without harming the environmental sustainability of enterprises, especially in conditions of resource scarcity. Such a focus of research puts in the spotlight not only the benefits of AI but also the need to assess its impact on the environment.

2. Despite the widespread implementation of generative AI in various fields of activity, its ecological footprint remains poorly studied due to the lack of data on the actual consumption of energy and water during the generation of responses. In this context, analysis of existing methods for indirect determination of environmental load allowed us to choose the most appropriate combination of statistical modeling and correlation approach. A feature of the proposed approach is its adaptability: it allows for approximate estimates of electricity and water consumption depending on the length, complexity, and type of query without the use of expensive tools.

3. Our indirect quantitative determination of the dependence of the environmental load on the type of query of the generative AI model (GPT-4) allowed us to determine the quantitative patterns of resource consumption. In particular, it was found that simple factual queries consume 10–15 times less energy and water than large-scale creative or analytical queries. This ratio is due to the computational complexity of queries, the number of activated model parameters, and the length of generation. The constructed regression models of the dependence of conditional energy consumption and water consumption on the number of tokens and query complexity allowed us to predict the impact of the user's digital activity on the environmental load. This opens up opportunities for designing personalized systems for assessing the sustainability of digital interaction with AI.

4. An approach to assessing the balance between the efficiency of AI use and resource load has been proposed, which is implemented in the form of an AI sustainability index. This indicator makes it possible to quantitatively correlate the benefits of using generative AI with energy and water costs. The type, complexity, length, and scope of queries are key variables in this approach. Using the sustainability index could allow us to make informed decisions about the feasibility of

using generative AI in a resource-constrained environment. Based on this index, a number of practical recommendations have been proposed. In particular, the use of less powerful models for simple tasks, precise formulation of queries, limitation of generation length, classification of queries by resource intensity, and use of local models for routine tasks. In order to increase the environmental awareness of AI users, it is proposed to implement ecological footprint visualization systems, develop training programs to raise awareness, and design tools for monitoring resource consumption.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

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Data availability

All data are available, either in numerical or graphical form, in the main text of the manuscript.

Use of artificial intelligence

The authors used generative artificial intelligence (in particular, ChatGPT-4) to conduct a research experiment aimed at modeling conditional energy and water consumption when processing queries of varying complexity. The data obtained as a result of experimental interaction with the GPT-4 generative model were recorded, classified, mathematically processed, and analyzed by the authors. The methodology for conducting the experiment, the principles of measuring and modeling resource consumption, as well as the criteria for classifying queries are set out in the relevant section of the paper. Generative technologies were not used in creating the text of the paper, except for treating the experiment results and generating query examples. All conclusions, analytical generalizations, and scientific statements are the result of authors' hard work.

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