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Artificial Intelligence Technologies in Biomedical Research on Human Adaptation and Maladaptation to Environmental Factors

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ABSTRACT

The number of environmental factors simultaneously affecting the human body is extremely large. Tracking these factors in time has become possible thanks to the development of artificial intelligence technologies, including machine learning algorithms, deep learning algorithms, and generative artificial intelligence. The integration of this new generation of technological solutions into biomedical sciences enables the identification of hidden interdependencies among studied elements and processes that were previously overlooked. In the context of research on the mechanisms of human adaptation and maladaptation, special attention should be given to exogenous hypoxia as one of the most significant environmental factors studied within ecology, physiology, and clinical medicine. The topic of individual markers of human resistance to hypoxia remains open and is regularly addressed in physiological and pathophysiological works. In recent works, methods of machine and deep learning have already found wide application, including the analysis of multimodal physiological data. For example, a machine learning model has been developed to predict the development of acute mountain sickness with a sensitivity of 0.998 and a specificity of 0.978. The model was trained using physiological indicators of test subjects and real-time climate data. Thus, the application of artificial intelligence tools for scientific research planning, data processing, and the creation of predictive models significantly expands the current understanding of physiological mechanisms of human adaptation to hypoxia and enables the analysis of other environmental factors to be carried out at a new technological level.

Keywords: artificial intelligence; environmental factors; hypoxia; machine learning; adaptation.

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Технологии искусственного интеллекта в медико-биологических исследованиях адаптации и дезадаптации человека к различным факторам среды

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АННОТАЦИЯ

Количество факторов внешней среды, воздействующих на человека одномоментно, чрезвычайно велико. Отслеживание их в динамике стало возможно благодаря развитию технологий искусственного интеллекта, включая алгоритмы машинного обучения, глубокого обучения и генеративный искусственный интеллект. Внедрение данного спектра технологических решений нового поколения в медико-биологические науки позволяет обнаруживать неявные взаимозависимости исследуемых элементов и процессов, упускаемые ранее. В контексте исследований механизмов адаптации и дезадаптации человека особое внимание следует уделить экзогенной гипоксии как одному из наиболее значимых факторов внешний среды, исследуемых в рамках экологии, физиологии и клинической медицины. Тема индивидуальных маркеров устойчивости человека к гипоксии до сих пор остаётся открытой и регулярно освещаемой в физиологических и патофизиологических работах. В последних методы машинного и глубокого обучения уже нашли широкое применение, включая анализ мультимодальных физиологических данных. Например, разработана модель машинного обучения, прогнозирующая развитие острой горной болезни с чувствительностью 0,998 и специфичностью 0,978. Для обучения модели использовались физиологические показатели испытуемых и климатические данные, фиксируемые в режиме реального времени. Таким образом, применение инструментов искусственного интеллекта для планирования научных исследований, обработки полученных данных и создания прогностических моделей существенно расширяет горизонт актуального понимания физиологических механизмов адаптации человека к гипоксии и позволяет на новом технологическом уровне подойти к анализу других факторов внешней среды.

Ключевые слова: искусственный интеллект; факторы среды; гипоксия; машинное обучение; адаптация.

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人工智能技术在医学-生物学研究中用于分析人类对不同环境因素的适应与失调

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摘要

在同一时刻作用于人体的环境因素数量极为庞大。随着人工智能技术的发展，特别是机器学习、深度学习以及生成式人工智能算法的广泛应用，动态监测这些因素已成为可能。新一代人工智能解决方案在医学-生物学研究中的引入，使得研究者能够识别出此前未被发现的研究要素与生理过程之间的隐性相互关系。在探讨人类对环境适应与失调机制的研究背景下，外源性低氧应作为生态学、生理学及临床医学中最重要的环境因素之一被重点关注。个体对低氧耐受的标志物仍是一个开放性议题，至今仍频繁出现在生理学和病理生理学研究中。机器学习和深度学习方法已被广泛应用于该领域，尤其是在多模态生理数据的分析方面。例如，研究人员已构建出一种预测急性高原病发生的机器学习模型，其灵敏度达0.998，特异性为0.978。该模型基于受试者的生理参数与实时采集的气候数据进行训练。因此，在科研设计、数据处理和预测建模过程中应用人工智能工具，显著拓宽了对人体低氧适应生理机制的当前认识，并使我们能够在新的技术层面上开展对其他环境因素的分析。

关键词：人工智能；环境因素；低氧；机器学习；适应。

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INTRODUCTION

Artificial intelligence (AI) technologies have become central to the emerging sixth technological cycle. The impact of new tools on scientific research across diverse fields cannot be overstated. According to an analytical report on publication activity, from 2019 to 2023 the number of publications by Russian authors at A*-level AI conferences increased by 70%, and the economic effect of AI implementation is projected to reach tens of trillions of rubles by the end of the decade [1]. AI also holds immense potential in the biomedical sciences. For instance, it is used to analyze medical images—such as X-rays, CT scans, and MRIs—for the early detection of diseases. A novel direction enabled by AI technologies includes virtual assistants and wearable devices that collect health data from patients and assist in the management of chronic diseases [2]. AI is applicable not only in clinical practice but also in fundamental research. The analysis of large datasets accelerates the development of new drugs and delivery systems. Artificial intelligence capabilities are actively being utilized in the Russian healthcare system. For example, the TOP-3 and AIDA services have been integrated into the medical information system to support general practitioners in diagnosing patients, with the cumulative number of confirmed final diagnoses already exceeding 1.3 million [3]. The development of next-generation clinical decision support systems has become possible due to the emergence of generative AI technologies, which are applied across a wide spectrum of medical tasks—from the analysis of electronic health records to medical education, drug development, and scientific research [4–7]. In Russia, generative AI is also advancing rapidly in the medical domain. For example, in February 2024, the large language model GigaChat successfully passed the final state examination in the specialty 31.05.01 General Medicine at the V.A. Almazov National Medical Research Centre [8].

This paper focuses on the integration of AI technologies into research projects related to the study of human physiological functions. Some attempts have already been made to summarize the existing applications of machine learning in various physiological research methods [9]. However, due to the rapid development of AI, up-to-date reviews of the current state of this direction are especially valuable.

KEY DIRECTIONS IN THE DEVELOPMENT OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES: MACHINE AND DEEP LEARNING

Modern AI development is marked by the rapid evolution of methods and approaches applied across diverse fields—from medicine and pharmacology to natural language processing and computer vision. In this work, we focus on analyzing three key directions in AI development: machine learning, deep learning, and generative AI. Although these technologies share common origins, they differ substantially in their architectural principles, learning methods, and practical implementation, which makes them applicable to solving different classes of problems.

Machine learning, as a classical approach, is based on statistical models and feature engineering, enabling effective work with structured data and the integration of expert knowledge [10]. However, its limitations in processing complex unstructured data and its dependence on feature quality have driven the development of more advanced methods. Deep learning, based on multilayer neural networks, has revolutionized the processing of unstructured data—such as images, audio, and text—due to its ability to automatically extract hierarchical features. In the context of deep learning, neural networks are hierarchical architectures capable of extracting multilevel features from data through multiple hidden layers. Each layer transforms the input data using linear and nonlinear operations, allowing the model to learn complex dependencies and patterns in the data. A foundational publication in the field of deep learning is the article by LeCun et al. [11]. Nevertheless, its high demands for computational resources and data, as well as the "black box" problem, remain significant limitations. Generative AI, representing the next stage in AI evolution, focuses on the creation of new data and solutions. This opens the door to creative applications such as image and text generation and even the design of new materials, all made possible by a new neural network architecture—transformers [12]. However, this direction also presents its own challenges, including the complexity of managing large parameter sets and ensuring the feasibility of the generated outcomes.

Each of these directions addresses specific tasks—from working with structured data and extracting hierarchical features to generating new data and solutions. The combination of these methods constitutes the generalized concept of AI, where each technology complements and enhances the capabilities of the others despite their inherent limitations. Thus, AI is an integrative discipline that brings together diverse methods and approaches to solve a broad range of problems. A comparative table of the AI technologies discussed above—machine learning, deep learning, and the distinct features of generative AI—is presented below (Table 1).

ARTIFICIAL INTELLIGENCE AS A DISRUPTIVE TECHNOLOGY IN MEDICAL AND BIOLOGICAL SCIENCES

Application of Artificial Intelligence in Clinical Practice

Computer vision is the first AI technology to be widely adopted in clinical practice. Using neural networks, physicians can quickly identify pathological changes, estimate their size and volume, and determine the most probable diagnosis [13]. Automated medical image analysis is already widely used in diagnostic radiology to detect retinal diseases, identify melanoma and other skin tumors, identify and classify malignant cells in histological sections, detect colon polyps during colonoscopy, and perform automated ECG interpretation [14–19]. In the Russian Federation, the MosMedAI project enables all medical institutions nationwide to submit radiological studies for AI-based processing to support clinical decision-making. As of the end of 2023, over 250,000 studies had been processed [20].

Natural language processing is the second major group of AI technologies widely used in medicine. A patient's electronic health record contains a vast amount of medical information that may influence physician decision-making. A significant portion of this information is free-text data describing symptoms, examination findings, and diagnostic conclusions. Machine learning models for natural language processing are capable of analyzing large amounts of unstructured data and drawing conclusions [21]. Natural language processing in electronic health records is used to determine the onset of allergic diseases, identify patients at high risk of developing asthma based on clinical notes and laboratory data, automatically extract cancer-related information, and detect a history of delirium [22–24]. In Russia, several AI-based services for processing medical records have received regulatory approval and are used in clinical settings, including AIDA, TOP-3, Webiomed, and MedicBK.

The main challenge for AI in this domain lies in supporting clinical decision-making regarding interventions, ordering diagnostic tests, and making a clinical diagnosis. With the advent of multimodal AI systems capable of processing numerous parameters, medicine now has the opportunity to develop recommendation systems that take into account chronic diseases, sex, age, results of laboratory and instrumental studies, and social determinants of health [25, 26].

Application of Artificial Intelligence in Molecular Biology

Deep learning models are capable of identifying complex patterns in high-dimensional data, making them especially useful in omics research. Hwang et al. [27] trained a genomic language model (gLM) to predict protein function based on genomic information, classify genomic sequences, and identify co-regulated gene modules such as bacterial operons. The model was validated on the *E. coli* K-12 genome and demonstrated an absolute accuracy of 59.2%. This study is unique as it was the first to show that deep learning models can capture "context" within nucleotide sequences using the same algorithms employed in language processing.

In another study, the machine learning model MethylBoostER effectively predicted the pathomorphological subtype of renal tumors based on DNA methylation profiles [28]. On a test dataset, the model achieved a prediction accuracy of 0.960. Such high accuracy indicates that, following validation in clinical trials, this model could be used to assess patient prognosis preoperatively.

AI has also transformed and accelerated the drug discovery process. Until 2021, researchers lacked a tool capable of predicting the three-dimensional structure of a protein based on its amino acid sequence. That changed when Google DeepMind researchers developed the artificial intelligence model AlphaFold, which solved this problem with high precision [29]. This innovative tool marked a breakthrough in chemistry and molecular biology, earning its creators the Nobel Prize in Chemistry in 2024. That same year, Nature published an article introducing AlphaFold 3 [30]. The updated model can accurately predict the structures of proteins, nucleic acids, small molecules, and modified residues, and it can also model protein–ligand interactions. The root-mean-square deviation in structure prediction is less than

Table 1. Comparison of machine learning, deep learning and generative artificial intelligence

Aspect	Machine Learning	Deep learning	Generative artificial Intelligence
Computational approach	Utilizes feature engineering and statistical models Requires variable computational resources	Employs multilayer neural networks for hierarchical feature extraction Requires high computational power and large datasets	Applies techniques such as variational autoencoders and generative adversarial networks to model the data generation process
Learning mechanisms	Uses supervised, unsupervised, and reinforcement learning on structured data	Applies backpropagation and deep reinforcement learning to large sets of raw data	Involves adversarial and variational probabilistic learning using large, domain-specific datasets
Practical implementation	Integrates expert knowledge via engineered features, but may miss novel patterns	Performs well on unstructured data (e.g., image recognition, natural language processing), but lacks transparency ("black box")	Generates novel multimodal content: text, images, videos, and more
Advantages	Ease of interpretation and integration of expert knowledge	High performance in handling complex unstructured data	Ability to generate new data and solve complex tasks without task-specific training
Limitations	Limited in capturing complex patterns; heavily reliant on feature quality	High computational and data requirements, low interpretability	High training cost; requires massive datasets for learning

0.2 nanometers. Today, neural network models are widely used in the pharmaceutical industry to identify molecular targets, screen candidate molecules, and predict their pharmacokinetic and pharmacochemical properties [31].

PROSPECTS FOR APPLICATION OF GENERATIVE ARTIFICIAL INTELLIGENCE IN HEALTHCARE

Large language models, such as GPT (Generative Pretrained Transformer), have become important tools in healthcare and have enabled new scenarios for physician–patient interaction. Trained on vast amounts of textual data, these models successfully pass various formats of medical examinations. In a 2023 study, the large language model ChatGPT surpassed the passing threshold on the United States Medical Licensing Exam (USMLE), and in February 2024, the GigaChat model passed the state certification exam in the General Medicine specialty [32]. AI chatbots that generate text in response to user queries are capable of optimizing physicians' workflows. ChatGPT-4, having received a transcript of a doctor–patient consultation, is able to summarize the conversation and generate a structured medical note [33]. In December 2024, Sechenov University and Neuromed LLC announced clinical trials of an AI assistant for cardiologists [34]. The AI assistant generates visit notes and discharge summaries, provides access to drug reference information, offers diagnostic and treatment recommendations based on current clinical guidelines, and automatically assesses individual patient risks.

Large language models also hold promise for delivering psychological support. In 2022, the AI-enabled psychotherapeutic platform Wysa was approved by the FDA for use in patients with musculoskeletal pain, anxiety, and depression, following evidence from a cohort study [35]. The study included 153 participants divided into three cohorts: the first cohort received no psychological support; the second cohort received at least one in-person counseling session; and the third cohort was given access to a digital platform featuring a mobile chatbot powered by a neural network that provided cognitive behavioral therapy. In addition to the chatbot, patients could also receive remote consultations from specialists via the platform. In the group with access to Wysa, symptom scores for depression and anxiety improved by 2.8 to 3.7 points compared with the group that received no psychological counseling. Physical function, as measured by the PROMIS questionnaire, improved by 2.4 points in the Wysa group compared with the traditional counseling group.

ARTIFICIAL INTELLIGENCE TOOLS IN PHYSIOLOGICAL RESEARCH

AI is becoming an essential tool in studying the pathogenesis of pathological conditions. Machine learning models can analyze millions of scientific articles and identify complex relationships, thereby synthesizing scientific data in a more comprehensive and less biased manner. Wei et al. [36] used machine learning models to identify overlaps in the molecular pathophysiology of Alzheimer disease, amyotrophic lateral sclerosis, and frontotemporal dementia. Specifically, machine learning methods were applied to compare and reveal shared molecular mechanisms among these diseases. To this end, a semantic knowledge network, SemNet 2.0, was built based on over 33 million biomedical publications. AI models identified the most significant nodes in the network related to each disease using a machine learning–based ranking algorithm. These nodes represented protein molecules playing a key role in the pathogenesis of the diseases. This scientific data mining approach makes it possible to identify the most promising directions in the study of the pathogenesis of Alzheimer disease, amyotrophic lateral sclerosis, and frontotemporal dementia.

Researchers in the field of physiology also use AI to uncover new relationships between genotype and phenotype in various pathologies. Asencio et al. [37] applied a machine learning model to process temporal features of cardiac contractions and classify different types of sarcomere pathological changes based on these characteristics. Using this model, the researchers achieved an accuracy of 78.5 ± 0.1% in classifying sarcomere mutations. This study demonstrates the potential of AI for investigating the mechanisms of cardiomyopathy associated with various mutation types.

Neural networks are widely used to detect physiological signals under pathological conditions. Peng et al. [38] described a model based on nasal airflow pressure and blood oxygen saturation (SpO_2) for detecting apnea and hypopnea episodes. According to the researchers, integration of data from electrocardiography, electroencephalography, and body movement patterns may enable the development of even more accurate diagnostic systems for obstructive sleep apnea.

AI can also serve as a tool for identifying "red flags" to predict life-threatening events (such as cardiac arrest, sepsis, hemorrhagic shock, or respiratory failure) by analyzing large volumes of human physiological data [39]. AI technologies are facilitating the development of novel methods for studying physiological processes. Cai et al. [40] demonstrated the effectiveness of AI-based velocimetry for the quantitative assessment of blood flow velocity and shear stress. The researchers successfully combined imaging, experimental data, and physical principles using neural networks, enabling automated analysis of experimental data and extraction of key hemodynamic indicators. These findings allow for the investigation of processes occurring in vessels affected by microaneurysms.

Pretrained language models may have a sufficiently high level of knowledge in physiology to be applied in education. In a study by Soulage et al. [41], the large language model ChatGPT-3.5 performed better on a physiology exam than most medical students enrolled in a physiology course. Large language models trained on physiology content may become effective tools for educating students. Potential educational use cases for ChatGPT include generating introductory material for complex topics, creating self-assessment questions, developing study plans, and finding additional resources [42].

APPLICATION OF ARTIFICIAL INTELLIGENCE IN STUDYING THE IMPACT OF ENVIRONMENTAL FACTORS ON HUMAN HEALTH

Until recently, most studies on childhood obesity examined the impact of external factors only at a single level of the socioecological model (e.g., individual or community level) [43]. Investigating the combined effects of environmental, social, and individual factors on obesity had been a challenging task prior to the advent of machine learning tools. Allen et al. [44] used the random forest method as a machine learning algorithm, which is commonly applied in studies of gene–gene interactions. The study confirmed the hypothesis that young individuals with similar levels of education and family wealth have varying risks of obesity depending on the economic and educational resources available in their neighborhoods. The model also revealed that environmental pollution significantly influences obesity development in children from low-income families. However, machine learning methods require further study and interpretation, as the models used cannot establish the mechanisms behind the identified associations. One fundamental issue is model interpretability. Most AI models function as “black boxes,” making it impossible to determine the specific decision-making algorithms used by neural networks.

Ojha et al. [45] investigated the influence of urban environmental factors on physiological responses using machine learning models. Thirty study participants, equipped with wearable sensors (Empatica E4) and backpacks containing environmental monitoring devices—measuring noise levels, temperature, humidity, light intensity, and particulate matter concentration—moved through the city. The wearable devices recorded electrodermal activity, which reflects arousal levels and is commonly used in neurophysiological research to assess the impact of external stimuli. In retrospective analysis, a binary classification algorithm predicted participants' arousal states with a sensitivity of 0.89 and specificity of 0.84. Using a deep learning algorithm, the researchers identified patterns of how external factors trigger arousal: sounds exceeding 66 dB, low light levels (<580 lux), and temperatures above 22 °C were most frequently associated with physiological arousal. The researchers used a self-organizing map (SOM) clustering model to group participants based on the degree of their reactivity to environmental changes. The researchers confirmed that machine learning can automate the analysis of complex interactions among multiple factors and accurately predict physiological responses to stimuli across different population groups. The main limitation of the study was the low quality of electrodermal activity data, which contained a large amount of noise and artifacts, leading to the exclusion of data from 10 out of 30 participants from the analysis.

In addition to retrospectively analyzing the impact of environmental factors on human health, AI can process real-time data. This tool can be used to investigate how sudden environmental changes affect the functional state of the human body and to detect pathological changes. Wei et al. [46] demonstrated the high efficacy of machine learning methods in predicting the risk of high-altitude hypoxia by analyzing real-time individual physiological parameters and environmental factors. The AI system analyzed heart rate, heart rate variability, blood oxygen saturation, and environmental factors (ambient temperature, atmospheric pressure, relative humidity, and ascent rate). Based on these inputs, 25 machine learning algorithms were trained and tested. The most accurate model achieved a sensitivity of 0.998 and specificity of 0.978 in diagnosing mild acute mountain sickness.

Wearable devices equipped with biosensors that track environmental conditions and physiological parameters are routinely used in medicine, particularly in sports medicine. Shen et al. [47] described biosensors for noninvasive measurement of lactate levels, the elevation of which serves as a marker of hypoxia due to a metabolic shift toward anaerobic glycolysis. For example, electrochemical sensors can measure the electrical current generated during lactate oxidation by enzymes (e.g., lactate oxidase or lactate dehydrogenase) and convert it into lactate concentration. These sensors can operate across a wide range of concentrations (from micromolar to millimolar levels) and are characterized by high accuracy. Potentiometric sensors register changes in the electric potential at the electrode depending on lactate concentration, whereas impedance sensors detect variations in resistance or capacitance resulting from the interaction of lactate with the biosensing layer. Optical biosensors detect optical signal changes (such as fluorescence intensity or colorimetric shifts). For instance, hydrogen peroxide generated during enzymatic oxidation of lactate reacts with chromogenic substrates (e.g., tetramethylbenzidine), leading to a color change measurable by a smartphone camera or portable spectrometer. Semiconductor biosensors, such as field-effect transistors and organic electrochemical transistors, detect changes in channel conductivity upon lactate binding to a bioreceptor (e.g., an enzyme). These are especially sensitive to low lactate concentrations and can be integrated into flexible substrates. Self-powered biosensors, such as piezoelectric devices, convert mechanical energy (e.g., body movement) into electrical signals modulated by lactate concentration. Biofuel cells generate current from lactate oxidation, with current magnitude correlating to lactate levels. As the number of biosensors increases, the amount of available data also grows, enabling the assessment of functional body status and informing lifestyle modifications, therapeutic decisions, and disease risk evaluation. Kimball et al. [48] described a machine learning model that incorporates both physiological and environmental parameters to predict the development of hypovolemia. Physiological inputs included photoplethysmography, electrocardiography, seismocardiography, as well as cardiac output, stroke volume, heart rate, blood pressure, skin and core temperature, total peripheral resistance, and blood volume. Such technologies are especially relevant for athletes and military personnel subjected to high physical loads and varying environmental conditions.

The use of neural networks to predict pathological conditions is currently an area of active research. However, AI has yet to find widespread application in the study of human adaptation to altered environmental conditions. Training such algorithms requires the accumulation of physiological data collected under hyperbaric conditions and during states of hypo- and hyperoxia. These studies could help identify physiological parameters that respond positively to training in such environments. Thus, the development of AI may lead to new discoveries in sports medicine.

Despite its promising potential, several limitations currently hinder the widespread implementation of AI in studies of environmental effects on the human body. Machine learning algorithms used in existing research are effective at identifying correlations but cannot reliably explain why certain environmental factors elicit specific responses. At present, most machine learning models can be used to generate hypotheses but not to verify them. Developing interpretable models remains a major challenge for future research in human physiology [49].

Most studies to date have involved small sample sizes, as noted by the researchers themselves. The development of accurate predictive models necessitates a large number of labor-intensive experiments simulating altered environmental conditions. It is essential to maintain a balanced distribution of environmental conditions and subject groups to ensure that the training data are sufficiently representative. In addition, biosensors used to detect physiological changes are often susceptible to noise and artifacts, which significantly complicates research in this domain.

PROSPECTS FOR APPLICATION OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES IN RESEARCH ON HUMAN HYPOXIC POTENTIAL UNDER EXTREME CONDITIONS

Hypoxic potential refers to the human body's ability to adapt to conditions of reduced oxygen availability—such as high-altitude environments, intense physical exertion, or other extreme situations. Studying hypoxic adaptation is important for medicine, sports, space biology, and other scientific domains. Within the field of adaptive medicine, interest in machine learning models is only beginning to grow, and the number of published studies is still minimal.

Machine learning models can be used to design personalized training programs that account for individual responses to hypoxic stress. This is particularly important in elite sports, where even small improvements can be decisive. In one study [50], a machine learning model was developed based on selected physiological parameters (red blood cell count and hemoglobin concentration) collected from 64 professional speed skaters who underwent a 10-week training program (3 weeks of baseline training at sea level, 4 weeks of hypoxic training, and 3 weeks of recovery). The machine learning model demonstrated higher accuracy in assessing physiological variables compared with a polynomial model and enabled the development of an effective system for predicting physiological changes under hypoxic training based on baseline sea-level measurements.

Beyond sports medicine, AI is also applied in aviation. In another study [51], researchers explored the use of wearable sensors and machine learning algorithms to enable early detection of hypoxia and prevent in-flight emergencies. As part of the experiment, 85 participants underwent a two-phase study in which they used aviation masks that regulated oxygen supply. The participants performed cognitive tests and flight simulations whereas the oxygen level was gradually reduced to simulate high-altitude ascent. The data collected via dry EEG electrodes were processed using machine learning algorithms, and the extracted features of brain activity were transformed. The machine learning models showed high sensitivity (0.83 to 1.00) and specificity (0.91 to 1.00) in detecting hypoxia. This research highlights major progress in developing real-time systems for in-flight hypoxia detection.

Mazing et al. [52] demonstrated machine learning models' ability to detect tissue hypoxia during reduced inspired oxygen levels and to assess individual hypoxia tolerance. Using an optical sensor, the researchers measured tissue hypoxemia in participants. The collected data were used to train a self-organizing map (SOM), a type of neural network used to uncover hidden patterns and cluster objects into groups. As a result, the model divided the participants into three groups with differing levels of hypoxia tolerance and functional physiological states. This study demonstrates the feasibility of creating a simple, reproducible test to assess individual hypoxia tolerance based on neural networks.

The use of AI models in the study of hypoxic adaptation mechanisms represents a promising area of research. Machine learning models can serve as tools for processing and analyzing large datasets, identifying latent patterns, and predicting individual responses to hypoxic exposure. For example, there are still no precise and clearly defined parameters that allow for an objective assessment of a person's hypoxia tolerance during a hypoxic test. Many additional parameters may indirectly help to complete the picture of an individual's hypoxia tolerance [53]. Numerous contentious questions remain concerning the selection of an intermittent hypoxic stimulation regimen, such as the oxidative and inflammatory processes induced by intermittent hypoxic training [54, 55], and the involvement of reactive oxygen species during recovery [56, 57].

The undeniable advantages of AI-based approaches for detecting hypoxia lie primarily in their ability to rapidly process multimodal data—such as biosensor readings from wearable devices (lactate, SpO_2, heart rate, heart rate variability) and environmental parameters (temperature, humidity, atmospheric pressure), among others—and to identify complex patterns within these data. Traditional approaches would require predefined hypotheses and lengthy statistical processing, along with preprocessing to enable data comparability. This paper described earlier how neural networks can process unstructured data—such as EEG, ECG, microcirculation images, and examples of nasal airflow and SpO_2 analysis for apnea detection—which would not be feasible using standard polysomnography due to its high cost and interpretive complexity.

AI applications in this field are likely to offer new perspectives on data related to hypoxia tolerance, the implementation of adaptive mechanisms at molecular and systemic levels, and the interrelationships among these processes.

CONCLUSION

The modern environment is characterized by numerous simultaneously acting external factors, the impact of which on the human body can now be monitored thanks to advances in AI, such as machine learning algorithms, deep learning, and generative models. These technologies open new frontiers in the biomedical field, enabling the identification of hidden relationships between elements and processes. Of particular importance is the study of exogenous hypoxia—one of the key environmental factors explored in ecology, physiology, and clinical medicine. Questions concerning individual tolerance to hypoxic conditions remain highly relevant and are actively discussed in the scientific data. Contemporary research increasingly employs machine learning and deep learning methods to analyze multidimensional physiological data. The application of these methods in the planning of scientific experiments, data analysis, and the development of predictive models significantly improves our understanding of human adaptation mechanisms to hypoxia and facilitates further investigation into the effects of other environmental factors. Ongoing developments demonstrate considerable potential for future progress in this area by improving the efficiency of research procedures through optimized statistical analysis, data processing, and experimental design. A particularly important direction of research involves the study of human adaptive capacity, wherein the development of classification models to distinguish groups with differing levels of stress resilience holds relevance for various fields, including medicine, biology, and psychology. The creation of predictive models for assessing hypoxia tolerance holds potential for enhancing machine learning methodologies and for addressing applied challenges in clinical, aerospace, and space medicine. However, several limitations hinder the widespread use of AI in adaptation studies, including difficulties in acquiring sufficient data, the limited quality of biosensors, and the lack of interpretable machine learning models for studying environmental factors.

ADDITIONAL INFORMATION

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