

ARTIFICIAL INTELLIGENCE IN HYPERBARIC MEDICINE: EXAMPLES OF APPLICATIONS

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ABSTRACT

Artificial Intelligence (AI) and Machine Learning (ML) are revolutionizing modern medicine and hyperbaric oxygen therapy (HBOT) is currently on the threshold of this transformation. This narrative review analyses current AI applications in HBOT, focusing on four key areas: prognostic modelling, safety monitoring, chamber automation, and precision medicine based on omic data.

In predictive modelling, ML algorithms demonstrate high efficacy in forecasting outcomes for sudden sensorineural hearing loss and chronic wound healing. Regarding safety surveillance, the fusion of autonomic signals (e.g., EDA, HRV) represents a breakthrough in the early detection of CNS oxygen toxicity, allowing preventive introduction of air breaks. Advanced control algorithms allow high-precision protocol execution and personalised compression kinetics. Furthermore, integrating transcriptomic and metabolic data paves the way for a deeper understanding of the mechanisms underlying the response to hyperbaric stress.

Despite promising results, most available evidence comes from single-center retrospective studies. Key obstacles include a lack of standardization for oxygen "dose" variables, limited external validation, and regulatory challenges. This paper identifies translational priorities, such as development of multicenter data registries and implementing "human-in-the-loop" clinical decision support systems. Standardization and prospective validation are essential for AI to become a cornerstone of personalized hyperbaric medicine.

Keywords: hyperbaric oxygen therapy, artificial intelligence, machine learning, oxygen toxicity, precision medicine.

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INTRODUCTION

Hyperbaric oxygen therapy (HBOT – Hyperbaric Oxygen Therapy) is a unique treatment used for selected indications where increasing the partial pressure of oxygen in tissues can support repair processes, modulate the inflammatory response, and improve microcirculation [1-4]. In practice, HBOT involves administering oxygen at a concentration close to 100% under elevated ambient pressure (usually 1.4–3.0 ATA, depending on the indication), which increases the amount of oxygen dissolved in plasma and the oxygen tension in tissues [1, 3-5]. Clinically, HBOT is used for selected indications (e.g., radiation-induced tissue injury, hard-to-heal wounds, carbon monoxide poisoning), most often as an adjunctive therapy [5-7]. Unlike many pharmacological interventions, HBOT is strictly parameter-driven, as pressure, exposure time, number of sessions, compression/decompression rate, and planned “air breaks” jointly determine both efficacy and risk. Despite documented benefits, contemporary clinical practice still relies largely on local, often empirical protocols, and the lack of high-quality comparative data hinders full standardisation of treatment [4,5,8]. At the same time, the availability of large clinical registries and electronic medical records has created a foundation for building predictive mathematical models to support qualification for HBOT. This forms a natural bridge between classical biostatistics and modern artificial intelligence methods.

In the era of precision medicine, a key challenge is moving from uniform therapeutic schemes to data-driven personalisation. Simultaneously, we can see rapid development of artificial intelligence (AI) methods, including machine learning (ML) and deep learning (DL), which are revolutionising the analysis of heterogeneous data (clinical data, device parameters, physiological signals, imaging) and the construction of predictive models and decision-support systems [9-12]. Although AI already supports optimization of treatment and the automation of imaging diagnostics in diabetology, cardiology, and radiology, hyperbaric medicine is currently entering a similar transformation. Potential AI applications in this area include not only precise patient selection and protocol personalization, but also advanced real-time safety monitoring, including early detection of oxygen toxicity and barotrauma, and objective evaluation of wound-healing progress using computer vision methods.

Despite the growing number of reports, the literature on AI in hyperbaric medicine remains highly scattered between clinical and engineering journals and is characterised by substantial heterogeneity of metrics and input data [11, 12]. This narrative review was prepared to map the existing evidence systematically, organize the domains of AI applications, and identify priorities for future clinical implementation. The aim of this work is to analyze the use of machine learning and deep learning algorithms in key HBOT domains: patient qualification, therapeutic dose personalization, safety surveillance, and monitoring of treatment effects.

METHODOLOGY

We conducted a narrative literature review to provide a synthetic description and critical assessment of current applications of artificial intelligence (AI), machine

learning (ML), and deep learning (DL) in hyperbaric medicine. We applied an approach aimed at identifying studies of the greatest clinical and translational relevance, with an emphasis on: (1) prognostic models and prediction of response to HBOT, (2) safety monitoring and detection of adverse events, (3) image analysis and wound assessment, (4) automation and chamber control, and (5) omics/bioinformatics approaches related to hyperbaric exposures.

The search was performed in MEDLINE (PubMed), Embase, Web of Science Core Collection, Scopus, and IEEE Xplore, supplemented by snowballing and reference lists of key publications. The time window covered the period from 1 January 2015 to 20 January 2026. The search relied on combinations of hyperbaric medicine terms (e.g. “hyperbaric oxygen therapy”, HBOT, “hyperbaric chamber”) and AI/ML/DL terms (e.g. “machine learning”, “deep learning”, “computer vision”, “predictive model”, “anomaly detection”, “reinforcement learning”). The strategies were adapted to the specific properties of individual databases.

The study selection was purposeful and iterative. Following the initial selection of titles and abstracts, we identified the publications most relevant to clinical HBOT practice and hyperbaric chamber safety engineering. In domains with a limited number of clinical studies, we also included technical papers (full conference proceedings) if they contained potentially translational components (e.g., control algorithms, real-time monitoring systems).

Inclusion and exclusion criteria:

- **Included:** original full-text studies (journals or complete conference articles) involving the use of ML/DL for prediction, classification, risk stratification, signal processing, image analysis or control in the context of HBOT or clinically relevant hyperbaric/hyperoxic exposures, involving humans; preclinical studies were included only if clearly orientated towards a translational pipeline and discussed validation for future clinical applications.
- **Excluded:** editorials, commentaries, and abstracts without full text; studies not related to HBOT/hyperbaric exposures (e.g. general AI in wound disease without a hyperbaric component); purely conceptual reports without data or without method/evaluation description.

From publications, the following key information was extracted: population and indication, sample size, type of input data (clinical, laboratory, signals, imaging, chamber logs), algorithm type, validation method (internal/external, temporal), reported metrics (e.g., AUC, sensitivity/specificity, segmentation metrics) and limitations identified by authors. The findings were integrated in thematic synthesis, structuring the literature by application domain and implementation readiness level (proof-of-concept → potentially deployable solutions). Particular attention was paid to methodological risks typical of predictive models (e.g. overtraining, dependence on data-distribution strategy, lack of external validation, limited calibration reporting).

RESULTS: DOMAINS OF APPLICATION

PROGNOSTIC MODELLING AND PREDICTION OF RESPONSE IN PATIENTS EXPOSED TO HBOT

models are trained within cohorts of patients undergoing HBOT to predict treatment outcomes or complication risk. It should be emphasised that these studies are usually not designed to estimate the causal effect of HBOT. The variables describing HBOT exposure (e.g., number of sessions, protocol parameters) are sometimes included as predictors alongside baseline patient characteristics, allowing prediction in real-world conditions but not justifying the conclusion that the observed effect is caused by therapy intensification itself. This distinction is essential for interpreting results and limiting the risk of overinterpretation in clinical practice.

The best-developed clinical prediction domain is sudden sensorineural hearing loss (SSNHL), where a short “therapeutic window” favours the deployment of decision-support tools aimed at rapid identification of patients standing the highest probability to improve. In the study by Koo et al., an ML model was developed to predict outcomes in severe SSNHL, treating HBOT as part of therapeutic exposure (including number of sessions). The authors reported high predictive performance (accuracy 89.36%; AUC 0.87), and key predictors included age, diabetes comorbidity, presence of vertigo, and cumulative number of sessions, with a suggested threshold of ≥ 10 treatments as a cut-off in predictive analysis [13]. At the same time, similar to many single-center studies, an important limitation is the need for external validation and assessment of generalizability in different populations and under different treatment schemes.

Explainable AI (XAI) is gaining importance in this group of studies, allowing assessment of the contributions of individual variables’ to predictions and potentially generating biological hypotheses. Wu et al. used a Random Forest model supported by SHAP analysis which achieved very high discrimination (AUC 0.998) in a retrospective study [14]. In the result interpretation, they attributed the predictive value not only to standard clinical factors, but also to mean corpuscular volume (MCV) and albumin concentration. However, such high AUC values in retrospective studies often require cautious interpretation due to the risk of overtraining, dependence on the data-distribution strategy, and potential data leakage which makes replication, external validation, and evaluation of calibration and clinical usability (e.g., decision-curve analysis) crucial.

The second important area of AI applications in HBOT involves chronic wounds, including diabetic foot ulcers (DFU), where ML can support decision-making in two complementary dimensions. Firstly, image analysis and computer vision approaches that integrate multiple modalities (e.g., clinical photography, dermoscopy, and thermography) with deep learning architectures such as convolutional neural networks (CNNs) are being developed to detect ischaemic signs or prognostic healing features [15]. In addition, models that use molecular profiling and omics data are being developed. For example, transcriptomic analyses with feature selection (including LASSO, SVM, Random Forest) identified the CXCR4 gene as a potential biomarker and therapeutic target in DFU [16]. In the context of predicting complete wound healing, a Support Vector Machine (SVM) algorithm showed the highest stability and precision, achieving AUC of 0.922, outperforming Random Forest (AUC = 0.917) and Extreme Gradient Boosting (XGBoost) (AUC = 0.889) [17]. This suggests that classical support-vector approaches may outperform more complex methods for smaller but well-defined clinical datasets.

In general, the reference works analysis indicates that the development of prognostic models in hyperbaric medicine is moving towards personalized data-driven therapy; however, the evidence maturity is uneven. Translational priorities include standardization of HBOT exposure data (granular “dose” parameters and session course), multicenter validation and generalizability assessment, reporting calibration and clinical utility measures, and integration of models with safe patient monitoring systems and clinical workflows (e.g., telemetry solutions).

SAFETY MONITORING AND EARLY WARNING FOR OXYGEN TOXICITY

Patient safety in a hyperbaric environment requires real-time monitoring systems [18]. These systems integrate analysis of physiological signals with technical chamber data, enabling early detection of anomalies and prediction of adverse events such as central nervous system oxygen toxicity (CNS-OT) [19]. Safety has traditionally been monitored primarily through clinical observation and periodic measurements of vital signs. Introducing AI/ML methods allows this process to be transformed into a continuous automated surveillance of the patient condition and infrastructure [20].

Machine learning models can be trained to detect patterns that precede adverse events during HBOT sessions. Inputs include:

- physiological signals monitored in real time,
- data from chamber atmosphere monitoring systems,
- a patient’s previous session history,
- information on medications, comorbidities, and ventilation parameters.

Numerous studies show that sequential models (LSTM, RNN, LSTM-XGBoost hybrids) and other ML algorithms can predict clinical deterioration, hypoxia, or critical vital sign values in advance [21-23]. Anomaly detection methods can flag deviations from a typical course of an HBOT session before an obvious clinical incident occurs. In practice, this can shorten the response time of staff and reduce the severity of the complication.

Applying AI/ML to large retrospective datasets from hyperbaric centers enables identification of risk patterns that are not intuitively obvious: (1) therapy parameter configurations (pressure, exposure time, oxygen fraction); (2) chamber type and safety procedures; (3) patient profiles associated with complications; (4) timing and dynamics of symptoms relative to the session course.

Experience in other areas shows that retrospective clinical data and registries can serve as bases for building predictive models for adverse events with higher performance than classical regression models [21-23]. In HBOT, analogous approaches could be used for individualized risk assessment before therapy and to design modified protocols (e.g., slower compression/decompression, change in working pressure) [24]. Moreover, reinforcement learning and adaptive control algorithms are being studied for automatic adjustment of hyperbaric chamber environments to improve safety, comfort, and system stability [25]. The greatest threat to HBOT is oxygen-induced seizures. A breakthrough in their prediction is moving beyond EEG-only analysis towards autonomic-

signal fusion. Studies have shown that electrodermal activity (EDA) or, more specifically the TVSymp spectral index, increases rapidly ca. 2 to 4 minutes before the onset of the seizure. ML models integrating EDA with heart rate variability (HRV) achieve 100% sensitivity in detecting a pre-ictal state in animal and human models, giving staff time to pre-emptively remove the oxygen mask ("air break"). This is a significant advance when compared to traditional monitoring which often registers the event as late as the tonic-clonic phase [26].

Safety monitoring is likely the domain of AI with the highest readiness for implementation in hyperbaric medicine because the sessions are standardized, repeatable, and take place in a controlled environment.

PROTOCOL OPTIMIZATION AND HYPERBARIC CHAMBER CONTROL

Hyperbaric oxygen therapy (HBOT) is inseparable from the use of advanced engineering systems which require rigorous and precise regulation of baric parameters and strict management of oxygen exposure. Although automation of chamber environment control algorithms has a well-established tradition, contemporary research increasingly implements machine learning methodologies to optimize process control, including decision-time learning approaches and integrated control planning. These solutions are applied, among others, when modelling chambers with a mild pressure profile and in strategies to prevent altitude sickness. Although many reports focus on technical aspects, they have key translational potential for developing customized clinical protocols. Ultimately, integrating individual patient risk factors, such as a specific predisposition to barotrauma, with adaptive control systems will allow dynamic modulation of compression and decompression kinetics and precise design of air breaks [27-29].

In the automation of multiplace hyperbaric chambers, highly precise tracking of a target pressure profile has been demonstrated using a controller which includes deliberate compensation of the system's zero-pole characteristics. In an automated hospital room, the mean relative tracking error was 0.35% (SD 0.58%), while maintaining stable control under typical operational disturbances such as controlled air releases or medical lock operations, and while executing complex therapeutic sequences including pauses and "alleviation" procedures automatically during compression [30]. The authors reported that the solution has been routinely used in clinical practice since 2015, supporting > 3000 treatments, with operational benefits such as improved repeatability, reduced staff workload, and potential improvement in patient comfort (smoother compression and lower noise) [30]. This example illustrates effective translation of validated engineering solutions into everyday workflow in a hyperbaric medicine center.

Contemporary analyses of safety profiles in monoplace chambers emphasise the determining role of protocol operational parameters, including working pressure, exposure time, air-break architecture, and oxygen delivery modality, in shaping adverse event frequency. In a large retrospective study analyzing patients with epilepsy (N = 634 HBOT sessions), a rigorous therapeutic scheme was implemented with pressures of 1.8 to 2.0 ATA and sessions lasting 90 to 120 minutes. By introducing mandatory 5-minute air breaks, the incidence of seizures fell to just 1:634, proving high mitigation effectiveness of appropriately designed protocols in

populations with increased neurological risk [27]. Data from more than 180,000 sessions cited in this context suggest that even a single 5-minute air break is a statistically significant factor that reduces the risk of CNS-OT seizures. These findings are fundamental for workflow optimization and indicate the need for a rigorous implementation of air breaks as a preventive standard in hyperbaric medicine [27].

Analysis of adverse events recorded in computer-controlled monoplace chambers showed that otalgia (ear pain) was the most commonly reported symptom (33%), and a substantial proportion of therapy interruptions occurred already at relatively low pressure levels (1.2–1.4 ATA). The authors noted that high-resolution session logs, including pressure-time profiles and pause characteristics, may provide a basis for determining optimal compression and decompression rates and defining "heightened vigilance zones" in control algorithms aimed at reducing barotrauma risk and improving patient adherence [28]. Moreover, in a cohort of carbon monoxide poisoning sufferers, specific clinical and laboratory factors associated with barotrauma risk were identified, including altered consciousness and lower albumin and magnesium concentrations, implying the rationale for integrating clinical variables into adaptive control strategies (e.g. further compression slow-down, modification of session termination criteria in high-risk populations) [29].

Contemporary clinical studies cover a wide range of HBOT protocols that differ in terms of target pressure, total number of exposures, and structure structure—from long regimens (e.g., 60 sessions at 2.0 ATA) to shorter programs, including 10–15 treatments at 2.2 to 2.4 ATA with structured air breaks [31-34]. A meta-analysis concerning fibromyalgia indicates that exposure to lower pressures (<2.0 ATA) may be associated with fewer adverse events while maintaining the observed clinical effect [31]. Clinical trials in long-term COVID and COVID-19-related ARDS (2.0–2.4 ATA, limited number of sessions, fixed-structure breaks) report a favorable safety profile, although the results regarding clinical efficacy remain inconclusive [33,34].

The diversity of schemes suggests a significant, yet underused space for systematic protocol optimization based on quantitative modelling of oxygen "dose", individual patient risk profiles, and dynamic assessment of clinical response during therapy.

From the perspective of clinical AI applications, existing automatic control systems and high-resolution logs generated by hyperbaric chambers (pressure-time profiles with recorded interventions and adverse events) constitute a valuable database for developing and training adaptive control policies. Such policies could be optimized in terms of multiple criteria—aiming to maximize expected clinical benefits and minimize the risk of adverse events simultaneously—while maintaining a "human-in-the-loop" model in which the physicians remains accountable for decisions to start, modify, or stop therapy.

PRECISION HBOT BASED ON OMICS AND ML

An emerging research direction at the intersection of hyperbaric medicine and data science uses omics data and machine learning (ML) to identify biological states that may predict response to HBOT, modulate its efficacy, or mediate mechanisms of action. Unlike traditional prognostic models based solely on clinical data, omics approaches enable more granular

patient phenotyping and formulation of mechanistic hypotheses regarding tissue sensitivity to hyperoxia and pressure stimuli.

In the more extensive reference works, including precision oncology, graph-based ML models (e.g., graph neural networks) add value by embedding transcriptomic and other omics data into network structures, identifying response biomarkers, and modelling complex interactions between the genome, transcriptome, and proteome [35]. Similar analytical frameworks may be useful in HBOT for prioritizing genes and pathways conditioning tissue sensitivity (e.g., neuronal, vascular/endothelial) to therapy-related stimuli.

A key translational step is the design of prospective cohort protocols that integrate transcriptomic data with clinical information and clearly defined endpoints. Studies using such approaches in severe inflammatory and infectious conditions indicate that different gene-expression patterns can be linked to measurable outcomes (e.g. mortality, organ failure), and then their stability in independent cohorts can be verified, increasing credibility and generalizability [36]. This research “template” supports planning of HBOT studies in which the transcriptomic profiles of the patients (e.g. necrotizing soft tissue infections) are analyzed together with granular HBOT exposure data (“dose” parameters, session course, adverse events) and clinical results to identify response signatures, stratification markers, and possible intervention targets.

In studies of response to hyperbaric stress, plasma proteomics and metabolomics are used to map molecular pathways associated with oxygen toxicity and generalised organism responses to varied “doses” of hyperoxia systematically. Short hyperbaric exposures (1.4 vs 2.5 ATA for 60 min) have been shown to induce a comparable increase in reactive oxygen species (ROS) kinetics and activation of the antioxidant response (including SOD, catalase, glutathione), while immunomodulation and inflammation biomarkers show a dose-response relationship, increasing proportionally to the magnitude of oxygen exposure [37]. At the cellular level, hyperoxia reviews indicate that elevated pO_2 promotes excessive ROS production from mitochondria and NADPH oxidases, leading to dysregulation of key signaling axes (Nrf2, NF- κ B, MAPK), activation of damage-response mechanisms (DAMPs, e.g., HMGB1) and innate immune receptors (including TLR4), and the initiation of various programmed cell death mechanisms [38]. Such well-characterized molecular networks can serve as “anchors” for ML models which—following appropriate validation—could support the prediction of pulmonary toxicity thresholds and the identification of HBOT therapeutic windows as a function of a patient’s individual omics profile.

Future precision HBOT models will likely require multimodal data integration, including: baseline clinical risk profile, high-resolution exposure parameters recorded by chamber systems (e.g., pressure, time at pressure, compression/decompression dynamics, session structure and breaks), high-frequency physiological responses, and molecular signatures reflecting patient biological state. Multi-omics literature emphasises that such integrative approaches are critical for capturing the multilayer nature of disease processes and improving endpoint prediction, while heterogeneous graph representations (graph ML methods) allow modelling relationships between omics layers and clinical data,

potentially increasing model generalizability [35]. Similar conclusions can be drawn from studies on the prediction omiczne umożliwiają bardziej granularne fenotypowanie of the response to anticancer therapy where integrated omics profiles and deep learning analyzed phenotypic data (including graph networks and transfer learning) support the construction of highly complex predictive models while striving to maintain clinical interpretability [39,40].

EVIDENCE MAP: REPRESENTATIVE STUDIES

To structure the heterogeneous literature at the interface between AI/ML and hyperbaric medicine, we applied the evidence mapping approach that provides a concise overview of the scope, methodological maturity and translational potential of the available studies. Table 1 summarizes selected peer-reviewed publications representing the main application domains.

- prognostic modelling and prediction of treatment response in HBOT cohorts;
- safety monitoring and early warning systems (e.g., for CNS oxygen toxicity);
- automation and process control in hyperbaric chambers; and
- use of multimodal data, including omics, to support therapy customization and generation of mechanistic hypothesis.

The selection is illustrative and focuses on studies which (a) provide comparable information on inputs and validation strategies, (b) address clinically relevant endpoints or adverse events, and (c) show practical implications for the design of future decision-support systems in HBOT. The summary also highlights typical limitations of the current evidence base, such as predominance of retrospective and single-center analyses, limited external validation, insufficient calibration reporting, and lack of standardization of variables describing HBOT “dose” (session parameters, breaks, interruptions). Consequently, Table 1 is not an exhaustive systematic inventory, but an orientation map that points to areas with the highest concentration of studies and gaps that require further work prior to clinical implementation.

Tab. 1

Representative studies of AI/ML applications in hyperbaric medicine (selected).

Study	Application	Data and inputs	Model and validation	Key findings / limitations
Koo et al. 2026 (Front Neurol) [41]	Prediction of outcomes in severe SSNHL; HBOT as a predictor	Retrospective, 1 center (N=231); clinical + laboratory + audiometry + number of HBOT sessions	MLP (best among compared ones); internal split	Test AUC ~0.87; effectiveness drop vs training suggests overtraining risk; no external validation.
Wu et al. 2026 (Braz J Otorhinolaryngol) [14]	Explainable prognostic model for unilateral SSNHL	Retrospective cohort (~N=453); clinical + laboratory + hearing measurements	Random Forest + SHAP; internal validation	Best RF; SHAP indicated the severity of hearing loss and laboratory signs (e.g., MCV, albumin); external validation was needed.
Xu et al. 2025 (Front Neurol / PMC) [42]	Stratification of risk of pulmonary infection after deep intracerebral hemorrhage; HBOT variable included	Retrospective (N=649); clinical variables + biomarkers + HBOT exposure	Random Forest + SHAP; internal train/test	Test AUC ~0.93; interpretability supports bedside use; HBOT appears protective, but without causal inference.
Hossain et al. 2024 (Biocybern Biomed Eng) [43]	Early warning of CNS oxygen toxicity symptoms	Controlled exposures (N=49); EDA-derived features	Standard ML; leave-one-subject-out	Sensitivity 100%, specificity 84%, median leading time ~250 s; requires prospective evaluation in routine HBOT.
Banou et al. 2024 (BioMedInformatics, MDPI) [44]	Genomic/omics analysis related to HBOT in Parkinson's disease (generation of biomarker hypotheses)	scRNA-seq: iPSC-derived dopaminergic neurons in the midbrain; 4,495 cells / 18,098 genes; PD vs control groups	Hybrid gene selection: Wilcoxon + XGBoost + Borda; classifier benchmarking (PyCaret); enrichment and PPI/graph analyses	MAP2, CAP2, WSB1 identified as associated significantly with PD and 'indicatively' with HBOT; limitations: <i>in vitro</i> data, no HBOT exposure or clinical endpoints, no external validation.
Gracia et al. 2018 (PLoS One) [30]	Automation and control of a multiplace hyperbaric chamber	Engineering implementation in a hospital	System identification + control; real-world validation	Stable pressure tracking and automation of complex procedures; important for safety engineering of future learning systems.
Zhang et al. 2025 (Algorithms) [25]	Learning-based control for a mild hyperbaric chamber	Engineering study; sensor/actuator logs	Decision-time learning + planning; simulations/bench tests	Feasibility of adaptive control; clinical translation requires safety certification and human oversight design.

GAPS AND TRANSLATIONAL PRIORITIES

Regardless of the application domain (response prediction, safety monitoring, chamber automation, image analysis, or omics approaches), the current evidence base for AI in hyperbaric medicine is limited by recurring methodological and implementation barriers that reduce clinical readiness. The most common include predominance of retrospective and single-center studies, insufficient standardization of variables describing HBOT exposure ("dose"), limited reporting of calibration and clinical usefulness, and deficits in external validation, generalizability assessment, and drift control following deployment. In addition, implementing AI systems in hyperbaric chamber settings requires addressing specific technical, organisational, and regulatory safety constraints (including human–system interaction, alarm fatigue, cybersecurity, redundancy, and fail-safe modes).

Table 2 provides a concise overview of key gaps with practical research priorities which—if pursued consistently—may accelerate the transition from proof-of-concept prototypes to solutions with verified clinical value. A major priority is building data infrastructure that enables prospective multicenter studies with granular capture of the HBOT session course, linking these data with high-frequency physiological monitoring and adverse events, and applying standardized reporting and evaluation frameworks (including calibration metrics, decision analyses, and assessment of the impact on the treatment process). Such a development programme is necessary for credible clinical deployment of decision-support systems and adaptive therapy control in hyperbaric medicine.

Tab. 2

Key gaps and translational priorities for AI in HBOT.

Area	Gap	Why it matters	Practical next steps
External validation	Most studies are single-center and limited to internal validation.	Models may fail when protocols, populations, and devices change.	Multicenter registries; temporal and geographic validation; center-specific reporting.
Calibration and clinical usability	Mostly AUC/accuracy, calibration and decision analyses are rare.	Poorly calibrated risk can mislead qualification and monitoring intensity.	Report calibration plots, slope/intercept, Brier score; assess decision curves and clinically meaningful thresholds.
HBOT 'dose' data	Chamber logs (pressure ramps, air breaks, interruptions) are rarely used.	Without dose granularity, protocol personalisation is limited and inter-center comparisons are poor.	Define a minimal HBOT dataset that includes session logs and adverse events; standardize protocol descriptions.
Real-time safety systems	Early warning studies are promising, but small; the false alarm burden is often unreported.	Alarm fatigue and unnecessary session interruptions can compromise treatment.	Prospective studies with predefined intervention algorithms; report false alarms per session, lead time, PPV/ NV.
Imaging data standards	Wound imaging lacks acquisition and annotation standards.	Models may learn confounding factors (lighting, camera) rather than biology.	Standardise acquisition; include scale/metadata; validate across devices and centers; report Dice/IoU and generalizability tests.
Ethical and legal issues	Limited discussion concerning privacy, liability, and regulatory pathways.	Hinders deployment and may expose patients and centers to risk.	Apply TRIPOD+AI/CONSORT-AI; bias audits; define human oversight; align with MDR/FDA and EU AI Act obligations.

ETHICAL, LEGAL, AND GOVERNANCE CONSIDERATIONS

AI systems developed for hyperbaric medicine most often play the role of clinical decision support (CDS – Clinical Decision Support Systems), and in certain configurations may meet criteria for software as a medical device (SaMD). Therefore, their design, validation, and deployment should follow established principles of trustworthy AI in healthcare, including privacy protection and data security, clear definition of intended clinical use and target population, rigorous assessment of effectiveness and safety in clinically relevant subgroups, transparency, and maintenance of the human-in-the-loop role in clinical decision-making.

In the European Union, AI tools dedicated to HBOT fall under the Medical Device Regulation (MDR), with particular attention to guidance on Rule 11, and under the EU AI Act which classifies medical systems as high-risk solutions. In the United States, FDA guidance distinguishes decision-support functions not requiring certification as a medical device from software subject to stringent oversight, emphasizing the role of qualified professionals in verifying machine-generated suggestions.

Operationally, hyperbaric centers planning deployments should consider the specific chamber environment constraints, including:

- a) cybersecurity and safe integration with control infrastructure and monitoring systems;
- b) continuous monitoring of dataset shift and performance drift after deployment;
- c) full traceability (model versioning, origin of training data, update pathway);
- d) interface and procedure design with clinicians and technical staff (clinician-in-the-loop) to reduce excessive alarms and alert fatigue;
- e) clear rules for secondary use of physiological and imaging data, including compliance with data protection and minimisation requirements.

In practice, a governance-by-design approach is recommended, meaning embedding oversight mechanisms at the design stage: formal documentation of the model purpose, inclusion/exclusion criteria and usage scenarios; predefined thresholds for acceptable performance, calibration, and safety; description of alarm escalation and intervention pathways; and clear division of responsibilities between treating physicians, chamber staff (hyperbaric technicians), and software developers/suppliers. Such oversight structure reduces systemic error risk, facilitates regulatory compliance, and increases the likelihood of safe, scalable implementation of AI in hyperbaric medicine.

LIMITATIONS

This work is holistic, pilot evidence mapping intended to structure a rapidly evolving research area at the intersection of clinical medicine and systems engineering. The following methodological limitations should be considered:

- Nature of synthesis: As a narrative review, the work focuses on identifying research gaps and mapping the thematic field rather than comparing therapeutic effects quantitatively or conducting a meta-analysis.

- Source heterogeneity: A substantial portion of AI in hyperbaric medicine is published in engineering venues and technical conference papers with reporting standards differing from those in clinical literature, potentially affecting metric consistency.
- Publication dynamics: Due to the high pace of AI data growth and delays in indexing early online articles, some of the latest reports may not have been captured despite a multi-level search strategy.
- No formal quality assessment: At this pilot stage, no structured assessment of the bias risk (e.g. PROBAST for predictive models) was conducted, which is typical for hypothesis-generating exploratory work.

These limitations define a pathway for future work, which should be expanded into an exhaustive systematic review based on a complete PRISMA-ScR protocol. Further stages should include rigorous methodological evidence quality assessment and validation of identified predictive models in independent multicenter cohorts.

CONCLUSIONS

AI applications in hyperbaric medicine have been evolving from isolated, mainly retrospective predictive models towards solutions with increasing clinical utility, including early-warning safety systems, adaptive support for protocol selection and modification, and precision patient phenotyping based on multimodal data. The most likely short-term implementation impact concerns tools for monitoring and predicting the risk of adverse events (particularly CNS oxygen toxicity) as well as structured prognostic models for time-sensitive indications such as SSNHL. However, achieving credible, scalable implementations requires development of data infrastructure and clinical evidence: standardisation and granular capture of HBOT “dose”, multicenter validation with generalizability assessment, prospective studies of impact on decisions and workflow, and consistent adherence to reporting standards and regulatory requirements relevant to CDS/SaMD.

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