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Research And Evaluations In The Field Of Health Science

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CHAPTER 1

ARTIFICIAL INTELLIGENCE IN IMMUNOLOGY: ALGORITHMS, PLATFORMS, AND APPLICATIONS

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Introduction

The field of immunological data analysis now uses advanced machine learning and computational approaches to enhance its sophistication. Through these algorithms researchers gain the ability to detect intricate patterns and make accurate predictions while discovering biomarkers in immunological research. Artificial Intelligence is transforming immunological research by enabling efficient analysis of complex biological data. Machine learning techniques, including supervised and unsupervised learning, enhance disease classification, biomarker discovery, and immune response modeling. Deep learning methods, such as Convolutional Neural Networks and Natural Language Processing, facilitate genomic analysis and automated extraction of immunological insights. AI-driven research is supported by platforms like TensorFlow, PyTorch, and Scikit-learn, alongside specialized bioinformatics tools such as Cytoscape and Galaxy. Cloud-based solutions, including AWS and Google Cloud AI, provide scalable infrastructure for large-scale immunological data analysis. By improving diagnostic accuracy and enabling personalized treatments, AI is revolutionizing immunology. Its ability to process high-dimensional data fosters new discoveries in immune-related diseases and therapeutic interventions. As AI technologies evolve, their role in immunological research and clinical applications will continue to expand. This chapter presents an extensive review that classifies different algorithms by their practical applications and functional characteristics in immunological research as well as types of immunological data to be anaylzed.

Types of Immunological Data

Immune system research relies on multiple biological data types to gain distinctive understanding of immune system functionality and dysregulation. Research and clinical applications depend on an integrative framework created by genomic, transcriptomic, proteomic, metabolomic data and clinical data from real-world patients. The potential of AI is significantly enhanced by its capacity to integrate various layers of research and clinical applications, thereby offering a comprehensive perspective.

Studying immune disorders requires genomic data as a fundamental resource. Research on an organism's entire DNA through genomic data allows scientists to study genetic differences that affect immune system function and disease susceptibility. The progress in genomic sequencing technology has enabled genome-wide association studies (GWAS) to identify genetic markers associated with cancer, infectious diseases, and autoimmune diseases such as rheumatoid arthritis (RA) and systemic lupus erythematosus (SLE) (Chu et al., 2021). Genomic studies usually focus on genetic variants linked to immune system disorders. AI-powered deep learning transforms genomic data interpretation through its ability to process extensive datasets which enhances disease diagnostics and genetics research (Alrefaei et al., 2022). Artificial Intelligence demonstrates proficiency in genomic sequence annotation and pathogenic variant detection while predicting genetic effect outcomes which are essential for immune response comprehension and disease understanding specifically for autoimmune disorders and cancers (Arivanantham et al., 2023).

Transcriptomic analysis displays gene expression alterations that relate to immune system activation and its control mechanisms. The analysis of peripheral blood leukocyte transcriptomic profiles helps understand active immunological pathways during infections and autoimmune reactions (Tsaliki et al., 2018). Genomic data together with transcriptomic data enables researchers to study the genetic basis of immune system variation thoroughly. Artificial Intelligence enhances transcriptomic analysis by detecting patterns of gene expression associated with immune system activation. Research shows that artificial intelligence can evaluate RNA-Seq data to identify specific disease profiles (Gupta & Vyas, 2023). Deep learning methods have elucidated complex genetic interactions, providing insights into tumor heterogeneity and patient responses to immunotherapies (Zhu, 2020). Degroat et al. (2024) indicated that the application of multimodal AI systems can reveal novel biomarkers and mechanisms that may be otherwise neglected. AI plays a crucial role in addressing batch effects, a common challenge in transcriptomic studies that integrate datasets from various sources (Degroat et al., 2024). Narayanan et al. (2024) illustrated that AI-driven preprocessing tools enhance genomic data quality, resulting in more dependable machine learning outcomes (Narayanan et al., 2024).

Proteomic and metabolomic data add another layer to immunological evaluations. Proteomics studies proteins, their functions, structures, modifications, and interactions, using techniques like mass spectrometry to identify disease-related protein biomarkers (Gegner et al., 2022). AI enhances the identification, quantification, and interpretation of proteins and metabolites involved in immune responses and disorders. For instance, proteomic analysis benefits from AI algorithms optimizing data processing. The “AutonoMS” platform by Reder et al. (2024) automates metabolomic fingerprinting, streamlining experimental design and data interpretation, which supports rapid hypothesis testing (Reder et al., 2024). These technologies significantly improve protein detection sensitivity and specificity, revealing disease mechanisms and therapeutic targets. Conversely, metabolomics focuses on metabolites in biological samples, crucial for understanding metabolic changes during immune responses. Advanced techniques facilitate the identification of metabolic pathways linked to immune activation and inflammation (Coman et al., 2016; Maecker et al., 2021). The combined analyses of proteomic and metabolomic data can further clarify how metabolic dysregulation affects immune disorders. Additionally, platforms like "Galaxy" aid in metabolomics, processing complex liquid chromatography-mass spectrometry (LC-MS) data effectively (Rob et al., 2016). The quick analysis of large datasets is critical for identifying metabolic signatures related to autoimmune diseases, infections, or cancer. Machine learning applications enhance biomarker identification, with Capaci et al. (2024) showcasing the Chimerys algorithm's effectiveness in discovering proteins linked to endometrial cancer. AI platforms facilitate personalized diagnostics and treatments based on individual proteomic profiles (Capaci et al., 2024). Moreover, metabolomic research elucidates metabolic changes during immune responses, with comprehensive metabolomic profiles relating closely to immune dynamics. Tools like MetaboAnalyst enable pathway enrichment analyses that reveal metabolic shifts linked to immune functions, essential for identifying biomarkers (Bhargava & Calabresi, 2016; Chong et al., 2018). In addition, AI-enhanced visual data tools are transforming metabolomic data interpretation. Yu et al. (2019) noted that these platforms promote standardization and improve metabolite-health outcome correlations through advanced probabilistic models, enhancing diagnostic accuracy for immune-related diseases (Yu et al., 2019).

Clinical and real-world patient data is increasingly being studied by AI technologies in the discipline of immunology, which helps to enhance the understanding and treatment of immune-related diseases. These advanced technologies serve to increase diagnosis accuracy, optimize treatment plans, and enhance patient outcomes by allowing researchers and medical practitioners to extract insightful analysis from complicated and diverse data sets. Clinical data supplies essential context to findings from various omic analyses, including patient demographics, treatment outcomes, laboratory results, and clinical diagnoses, thus validating experimental outcomes in clinical settings. Longitudinal data enhances understanding of disease progression and treatment responses. Research that merges clinical data with multiplexed omic data delivers a comprehensive perspective on factors influencing patient outcomes (Maecker et al., 2021; Yang et al., 2017). Predictive modeling of clinical outcomes, which uses patient data from electronic health records (EHRs), is one interesting use of artificial intelligence. Machine learning algorithms can examine vast amounts of both organized and unstructured data, finding patterns and correlations across variables like demographic information, laboratory results, prescription history, and clinical symptoms. A study by Culos et al. (2020) shows that adding mechanical insights from immunological knowledge into machine learning models can strengthen the predictive power of these algorithms, therefore reducing the patient sample size needed for efficient training and validation (Culos et al. 2020). Ultimately, this combination guides treatment plans customised to particular patient demands by means of more precise forecasts based on clinical data.

AI's relevance is also evident in the study of infectious diseases, particularly during the COVID-19 pandemic. For example, Du et al. (2021) employed machine learning to evaluate clinical data, including blood tests and imaging results, to forecast the severity of SARS-CoV-2 infection and associated mortality risks (Du et al., 2021). According to their findings, AI has great promise for improving prognostic capacities through patient categorization based on clinical features. By examining a variety of clinical factors, machine learning models have also been created to forecast issues including the need for intubation in COVID-19 patients (Arvind et al., 2021). These models show how well artificial intelligence can combine clinical data and generate relevant recommendations for quick medical interventions. Moreover, artificial intelligence methods have been included into clinical decision support systems (CDSS), which seek to enhance doctors' performance by means of individualized recommendations based on actual patient data (Mahadevaiah et al., 2020). By producing insights particular to individual situations, these technologies help clinical decision-making by use of machine learning models. One study shows how AI can help with decision-making and better patient treatment for disorders such atrial fibrillation (Siontis et al., 2020). AI is also quite important in emergency medicine and trauma treatment, too. AI is acknowledged to help track patient data and forecast results in emergency medical situations (Khorsand et al., 2024). In complicated scenarios, such as controlling sepsis or heart disorders, where quick treatments are absolutely vital, this capacity is very important. Moreover, integrating patient-reported outcomes (PROs) into AI analytics deepens the comprehension of treatment responses and the quality of life linked to immunological therapies. By utilizing these perspectives, machine learning can enhance the understanding of how treatments influence patients individually, promoting the advancement of personalized medicine (Lau et al., 2022).

Types of Algorithms for Immunological Data Analysis

AI algorithms are transforming immunology through Machine Learning (ML), Deep Learning (DL), and Natural Language Processing (NLP). These methods help analyze complex biological data, identify patterns, and deepen our understanding of the immune system. ML includes supervised, unsupervised, and reinforcement learning. Supervised learning predicts immune responses and classifies disorders using labeled data. For instance, Tomic's "Immunaut" employs unsupervised learning techniques like t-distributed Stochastic Neighbor Embedding (tSNE) to predict reactions to Live Attenuated Influenza Vaccines (LAIV) (Tomic, 2024). Unsupervised learning helps uncover patterns in unlabeled data, as shown by Lee et al.'s work on metabolic reprogramming in T cells using such algorithms (Lee et al., 2023). Though currently less common, reinforcement learning is being explored to optimize treatment strategies and aid clinical decision-making. As a subset of ML, DL includes neural networks, convolutional neural networks (CNNs), and recurrent neural networks (RNNs), demonstrating significant potential in immunology for analyzing high-dimensional data. Boushehri et al. used a ResNet CNN framework to study the immunological synapse, enabling better characterization of therapeutic antibodies (Boushehri et al., 2022). CNNs serve image classification purposes, while RNNs help analyze sequential data, such as immune response variations over time. NLP is increasingly important in immunology for extracting insights from unstructured data sources like clinical records and scientific literature. NLP techniques streamline the extraction and summarization of immune-related information from extensive datasets. This capability enhances AI models by integrating existing knowledge on immune responses and diseases. NLP is vital for literature mining pertaining to biomarkers and treatment responses, supporting hypothesis generation and guiding future research. Therefore, AI algorithms, through various ML, DL, and NLP forms, are essential for advancing immunology research, improving data analysis, enhancing predictions related to immune responses, classifying conditions, and informing clinical decisions.

Supervised Learning for Immunological Data Analysis

Supervised learning plays a vital role in immunological data analysis, using labeled datasets to build predictive models that improve understanding of immune responses, disease diagnosis, and treatment outcomes. These models support clinical decision-making and advance precision medicine in immunology.

Supervised learning algorithms are widely used to establish relationships between input variables and outcomes. For example, Fernandes et al. (2020) introduced a probabilistic multi-domain integration model utilizing immune and inflammatory biomarkers to predict bipolar disorder (BD) and schizophrenia (SZ), demonstrating its clinical utility in distinguishing complex disease states (Fernandes et al., 2020). Similarly, Малашенкова et al. showed that models based solely on immune parameters could achieve over 70% accuracy in diagnosing schizophrenia (Малашенкова et al., 2023). These findings underscore the diagnostic potential of supervised learning in immunology.

Supervised learning algorithms are usefull for diagnosing immunological conditions. For instance, T cell receptor sequencing data can be used to classify antigen-specific T cells. DeepTCR, a deep learning framework developed by Sidhom et al. (2021) reveals structural patterns in T-cell repertoires, aiding classification related to immunotherapy (Sidhom et al., 2021). Such approaches enable precise diagnoses based on biological markers. Moreover, supervised learning enables predictive modeling of patient outcomes based on immunological characteristics. Meier et al. developed models assessing immune responses to new *Mycobacterium tuberculosis* antigens, demonstrating the potential of these algorithms in infectious disease diagnostics (Meier et al., 2021). Predicting immune responses allows clinicians to tailor treatments and improve therapeutic outcomes. Furthermore, supervised learning is instrumental in identifying biomarkers associated with immune responses or disease states. Classification algorithms reveal patterns in large immunological datasets, supporting the discovery of immune signatures relevant to specific conditions or therapies (Farzan, 2024). This contributes to advancing personalized medicine in immunology. On the other hand, combining supervised learning with multi-omics data—such as genomic, transcriptomic, and proteomic information—allows for comprehensive analysis of immune responses. These methods uncover relationships across biological domains, enhancing insights into immune system dynamics (Bhattacharya et al., 2021). Handling high-dimensional data strengthens the predictive capabilities of supervised models in immunology.

Applying supervised learning to electronic health records (EHRs) supports predictive modeling for clinical decision-making. Algorithms can identify patients at risk of developing severe conditions based on immunological profiles, enabling early interventions (Coppard et al., 2023). This enhances patient management in immunological care. Also, supervised learning refines treatment strategies by analyzing patterns in historical patient data. Models can predict the effectiveness of therapies based on prior outcomes, guiding clinicians toward more personalized treatment plans (Tjaden & Tjaden, 2023). This supports the advancement of precision medicine in immunology.

Unsupervised Learning for Immunological Data Analysis

Unsupervised learning algorithms are vital for analyzing immunological data, as they uncover patterns and structures in complex, high-dimensional datasets without requiring labeled outcomes. This makes them especially valuable when prior knowledge or annotated data is limited, enabling the discovery of novel insights into immune responses and disease mechanisms.

These algorithms have been effectively used to identify disease subtypes. For instance, Orange et al. (2018) applied machine learning to integrate synovial histologic features with RNA sequencing data, identifying three distinct subtypes of rheumatoid arthritis (Orange et al., 2018). This demonstrates the power of unsupervised learning to reveal hidden structures within immunological datasets.

A primary application of unsupervised learning in immunology is cluster analysis, which organizes data based on similarity. Techniques such as K-means and hierarchical clustering are commonly used to categorize immunological data. For example, scientists employed a random forest dissimilarity matrix to classify renal cell carcinoma tumors based on immunohistochemical markers, helping distinguish patient groups with varying tumor characteristics (Chen & Ishwaran, 2012). This facilitates the recognition of unrecognized disease subtypes and supports personalized treatment strategies. Moreover, high-dimensional immunological datasets often require dimensionality reduction to simplify analysis. Techniques like Principal Component Analysis (PCA) and t-distributed Stochastic Neighbor Embedding (t-SNE) condense complex data while preserving essential features. Eckhardt et al. (2022) demonstrated how PCA improves data interpretability, which is crucial for navigating large immunological datasets (Eckhardt et al., 2022). Unsupervised learning also aids in extracting key features from large datasets, a critical step for downstream analyses. For instance, self-organizing maps (SOMs) help detect meaningful patterns in unlabeled immune data, facilitating the identification of important cellular or molecular markers (Liu et al., 2023). This is particularly useful when analyzing novel datasets where conventional methods may miss significant relationships.

Unsupervised learning is effective in detecting anomalies—unusual patterns or outliers—that may indicate unique immune responses or undiagnosed health issues. Clustering algorithms can identify atypical immune profiles, potentially signaling distinct disease mechanisms or treatment responses (Dai et al., 2024). This is essential for understanding variability in patient responses and advancing personalized medicine. Furthermore, unsupervised learning naturally supports exploratory data analysis, enabling researchers to derive insights without predefined hypotheses. This approach can generate new research questions and deepen the understanding of immune system dynamics (Warchol et al., 2023). The ability to visualize and interpret underlying structures in immunological data contributes to the development of future research directions.

Applying unsupervised learning to multi-omics data—such as genomics, transcriptomics, and proteomics—enhances the understanding of complex biological systems. These methods can reveal interactions across omics layers that influence immune responses, leading to comprehensive models that better reflect biological complexity.

Ensemble Methods for Immunological Data Analysis

Ensemble methods, which combine predictions from multiple models, offer substantial advantages in immunological data analysis. By leveraging the strengths of various algorithms, they enhance classification accuracy, reduce overfitting, and improve generalization across complex datasets.

Techniques like Random Forests and Gradient Boosting Machines are known for their ability to improve classification in high-dimensional immunological data Xin et al. (2024) demonstrated the effectiveness of ensemble learning in feature selection for identifying biomarkers in renal cell carcinoma (Xin et al., 2024). By aggregating predictions from multiple base learners, ensemble methods can detect key immunological markers that distinguish disease states or patient responses, offering valuable diagnostic tools.

Ensemble methods mitigate overfitting by training models on different data subsets, reducing variance and increasing generalizability—an important advantage in immunological studies with many features but limited samples, such as gene expression datasets. Moreover, by incorporating varied algorithms or feature subsets, ensemble methods benefit from model diversity, which has been shown to outperform single-model approaches (Wang et al., 2013). This allows researchers to explore different perspectives within the data, enhancing understanding of immune mechanisms. Furthermore, in immunology, integrating data from diverse sources enhances insight. Ensemble methods can consolidate findings from different studies or experimental conditions, producing more reliable and generalizable conclusions (Helmut & Murdiansyah, 2023). Also, ensemble approaches have proven effective in predicting clinical outcomes, such as treatment responses in autoimmune diseases. By incorporating various clinical and biological variables, these models improve prognostic accuracy and support clinical decision-making (Arnal Segura et al, 2025). Moreover, ensemble methods are valuable for detecting atypical immune responses or irregular biomarker patterns, which may reveal novel disease mechanisms or treatment effects. This is particularly useful in high-dimensional datasets, where traditional methods may overlook significant outliers (Arnal Segura et al, 2025).

As new data becomes available, ensemble methods can be updated more easily than single models. Their flexibility allows researchers to integrate recent findings into existing frameworks, maintaining the relevance and accuracy of immunological analyses over time (Xin et al., 2024). In multi-omics research, ensemble methods enable the integration of genomics, transcriptomics, and proteomics data, supporting a systems-level understanding of immune function. These techniques help uncover interactions across biological layers, offering insights into disease mechanisms and potential therapies (Fu et al., 2022). Thus, ensemble methods are thus highly applicable to immunological data analysis. Their ability to improve prediction, support integrative analyses, and adapt to evolving datasets makes them a powerful tool for both research and clinical applications.

Deep Learning Algorithms for Immunological Data Analysis

Deep learning algorithms have become integral to immunological research, enabling the analysis of complex biological datasets and offering new approaches for understanding immune responses and related diseases. These methods effectively manage the high-dimensional, nonlinear nature of immunological data, enhancing predictive accuracy and generating deeper insights.

Artificial neural networks (ANNs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs) are among the most prominent deep learning techniques used in immunology. Hu et al. (2020) proposed an end-to-end deep learning model for cytometry data, directly linking raw inputs to clinical outcomes. Their findings underscore deep learning's capacity to improve the accuracy and interpretability of analyses derived from high-dimensional datasets (Hu et al., 2020).

CNNs are especially effective for image-based analyses, such as evaluating microscopy images of immune cells and tissues. In immunology, CNNs have been applied to automatically classify cells in cytometric data, interpret histological images, and detect disease markers (Chuai et al., 2018). For example, CNNs used in immunofluorescence microscopy have significantly enhanced the differentiation of cell types and their interactions within immune microenvironments (Pound et al., 2016), offering valuable diagnostic support in clinical settings.

RNNs are suited for analyzing sequential or time-series data, making them useful for modeling dynamic immune responses. They have been used to track changes in immune cell populations following vaccination or infection, helping forecast outcomes based on prior temporal patterns. This modeling aids in understanding fluctuating immune responses and disease progression (Zhang et al., 2023).

Autoencoders are unsupervised deep learning models used for dimensionality reduction and feature extraction, particularly in high-dimensional datasets. By compressing and reconstructing input data, they can uncover latent features associated with immune responses or disease states. Autoencoders have been applied to gene expression data to identify biomarkers and distinguish immune profiles across diseases (Dhuri et al., 2022), reducing data complexity while retaining critical information.

Generative Adversarial Networks (GANs) generate synthetic data, which is beneficial when labeled immunological datasets are limited. These models produce realistic samples that augment existing data, supporting the development of more robust predictive models for immune-related conditions by increasing data diversity without the need for extensive experimental datasets (Beltrán et al., 2023).

Transfer learning allows the adaptation of pre-trained models to specialized immunological datasets, reducing training data requirements and improving model performance. For instance, CNNs trained on general image datasets have been successfully re-applied to identify and classify immune cell types (El-Hussieny et al., 2023). This approach is especially valuable in immunology, where large, annotated datasets may be scarce.

Deep learning models—particularly CNNs and RNNs—have been integrated with genomic and transcriptomic datasets to explore associations between immune gene expression and clinical outcomes. Such models enhance our understanding of the genetic basis of immune responses and their implications for disease progression and treatment efficacy (El-Hussieny, 2024; El-Batrawy et al., 2020).

Natural Language Processing for Immunological Data Analysis

Natural Language Processing (NLP) has emerged as a valuable tool in immunology, enabling researchers to extract insights from unstructured text such as clinical records, scientific literature, and patient-reported outcomes. While immunological data analysis often focuses on structured datasets, NLP allows the integration of textual information, enhancing the depth and utility of available data.

A primary application of NLP in immunology is the automated extraction of relevant information from unstructured clinical notes and research documents. Sheikhalishahi et al. (2019) demonstrated how NLP techniques can transform clinical narratives into structured formats suitable for machine learning analysis, successfully identifying immunological conditions, treatments, and outcomes from electronic health records (EHRs). This capability is essential for managing large volumes of health data and streamlining the data preparation process (Sheikhalishahi et al., 2019).

NLP also supports the analysis of qualitative data from patient-reported outcomes (PRO), which are critical for evaluating treatment effectiveness.

As shown by Lu et al. (2021), NLP techniques can interpret unstructured PROs to yield insights into patients' experiences, helping guide therapeutic decisions and improve treatment satisfaction in clinical immunology (Lu et al., 2021). Furthermore, beyond textual data, NLP techniques have been adapted to analyze biological sequences and proteomic data by treating them as language. Le (2023) noted that applying linguistic methods to proteomics can enhance the understanding of immunological mechanisms and aid biomarker discovery (Le, 2023). Moreover, NLP contributes to improving clinical documentation by detecting ambiguities, redundancies, and inaccuracies in electronic medical records. Lo et al. (2022) demonstrated that NLP tools can support clinicians in identifying and interpreting key medical information, improving documentation quality and consistency (Lo et al, 2022).

In summary, NLP enhances immunological data analysis by enabling automated information extraction, integrating patient perspectives, interpreting biological data, and supporting clinical documentation. As its applications expand, NLP is expected to further enrich immunological research and clinical decision-making.

AI Platforms for Immunological Data Analysis

AI is transforming immunological data analysis, with the emergence of advanced machine learning algorithms and bioinformatics platforms tailored to the field. Both general-purpose and domain-specific platforms are increasingly being developed, offering comprehensive environments for handling, analyzing, and storing structured and unstructured immunological data (Pandya et al., 2021). These platforms provide off-the-shelf tools that allow researchers—including both bioinformaticians and experimental biologists—to initiate analyses quickly and efficiently in multidisciplinary settings.

Modern AI platforms offer access to a wide array of algorithms, computational resources, and preprocessing tools within a unified interface. Some are specifically designed to promote collaboration between professionals from different disciplines, supporting the integration of machine learning workflows into immunological research. These platforms are often linked with existing data repositories and software suites to create a seamless research environment (Li et al., 2022; Shiwlani et al., 2023; Zhao et al., 2024; Sharma et al., 2022).

The increasing complexity and heterogeneity of immunological data, particularly with the rise of high-throughput technologies, has heightened the demand for accessible AI tools. In response, new platforms have been developed to enable even non-expert users to manage large datasets, perform preprocessing, apply statistical analyses, visualize data, and implement state-of-the-art machine and deep learning models. Many platforms also support workflow automation, collaborative project tracking, and integration of diverse services, facilitating interdisciplinary research and streamlining computational tasks.

These innovations democratize access to advanced data analysis methods, allowing immunology researchers with limited computational training to adopt AI-driven approaches. As a result, they can reduce the time and cost typically required for implementing machine learning into routine workflows. However, challenges such as data privacy, secure access, and the need for trained personnel remain important considerations in deploying these platforms effectively. Several real-world applications and test cases have demonstrated the successful integration of AI platforms into immunological research, highlighting their potential to enhance discovery and clinical translation (Sebastian & Peter, 2022; Durmuş et al., 2024; Wang et al., 2023; Martinson et al., 2024).

Open-Source Platforms

Open-source machine learning libraries have become indispensable tools in immunological data analysis, offering scalable, flexible, and customizable frameworks for applying AI techniques to complex biological questions. Among the most widely adopted are TensorFlow, PyTorch, and Scikit-learn—each serving different needs within the research community.

TensorFlow

Developed by Google, TensorFlow is a powerful open-source library that supports the development and deployment of deep learning models across a wide range of applications, including immunology (Pavlović et al., 2021; Denset et al., 2024; Davalos et al., 2023). Researchers and data scientists are increasingly leveraging TensorFlow to construct complex neural networks capable of analyzing high-dimensional biological data, such as gene expression profiles and protein interaction networks. These models contribute significantly to understanding immune responses and disease mechanisms, offering insights that drive the development of innovative therapies (Baskaran et al., 2024). TensorFlow's flexibility and scalability make it a preferred platform for interdisciplinary applications that integrate data science, biology, and artificial intelligence (Pertseva et al., 2021).

PyTorch

Another leading open-source library, PyTorch has gained popularity for its dynamic computation graph, which facilitates intuitive and efficient model building. Its flexibility makes it particularly suited for tasks like image analysis and sequence modeling in immunological research (Zeng et al., 2024; Wilman et al., 2022). PyTorch encourages rapid experimentation, enabling researchers to test hypotheses, refine models, and explore new approaches with minimal friction. This adaptability is especially valuable in immunology, where evolving data types and biological complexity demand continuous model development (Anter & Yakimovich, 2025; Zaslavsky et al., 2025).

Scikit-learn

Known for its simplicity and accessibility, Scikit-learn is a highly versatile library geared toward traditional machine learning. It supports a broad range of supervised and unsupervised learning tasks, making it a reliable tool for immunological studies that require data preprocessing, feature selection, and model evaluation (Arshad et al., 2024; Singh et al., 2024). Scikit-learn's ease of use allows researchers with varying levels of programming expertise to apply robust analytical methods to complex biological datasets, thereby facilitating the extraction of meaningful insights and accelerating discoveries in immunology (Veljkovic et al., 2021).

Together, these open-source platforms play a pivotal role in the modern immunological research ecosystem, enabling scalable and reproducible analyses while promoting innovation through collaboration and accessibility.

Specialized Bioinformatics Tools

Cytoscape

Cytoscape is an exceptionally valuable and widely employed tool that serves the purpose of visualizing intricate and multifaceted networks while seamlessly integrating diverse types of attribute data. In the specialized field of immunology, it holds a crucial function in assisting researchers to effectively represent, analyze, and comprehend protein-protein interaction networks, in addition to cellular signaling pathways and gene regulatory networks. These fundamental elements are indispensable for achieving a more profound understanding of molecular interactions and dynamics operating within the immune system, which is critical for a wide range of applications in both research and clinical practice (Lu et al., 2022). This adaptable and robust platform constantly provides priceless insights that significantly contribute to the ongoing advancements in the exploration of immunology and network biology, thereby enhancing our knowledge and facilitating progress in this important scientific domain. (Mousavian et al.,2021; Khattak et al., 2021; Lima et al., 2021)

Galaxy

Galaxy is an incredibly powerful and highly versatile, open-source, web-based platform that has been specifically designed to effectively support a wide array of data-intensive biomedical research projects across various disciplines. This remarkable platform not only accommodates an extensive range of bioinformatics workflows but also offers a comprehensive suite of tools, making it an invaluable resource for researchers who are focused on analyzing, visualizing, and deriving meaningful insights from large and complex genomic and proteomic datasets that are particularly relevant and crucial to the field of immunology. One of the standout features of Galaxy lies in its highly user-friendly interface, which allows individuals without extensive technical expertise or specialized training to efficiently conduct intricate analyses and interpret their results with significant ease. This level of accessibility is essential for fostering collaboration among researchers and driving innovation in biomedical research, ultimately leading to important breakthroughs in understanding complex biological systems and processes (Singh et al., 2023; Priyadarsinee et al., 2024; Royaux et al., 2025)

Cloud-Based Solutions and Big Data Platforms

Amazon Web Services (AWS)

AWS offers an extensive and comprehensive range of cloud-based solutions that provide not only robust but also highly scalable storage, along with powerful computational capabilities designed to meet a variety of needs. These critical features enable researchers to conduct extensive and sophisticated analyses while efficiently training machine learning models on large, complex, and diverse immunological datasets. Among the many available services, Amazon SageMaker plays a pivotal and influential role by streamlining the development, training, and deployment processes of AI models that are carefully customized to cater to specific immunological applications and requirements (Eldin & Kaboudan, 2023). With AWS, researchers can effectively leverage advanced analytical tools and cutting-edge technologies in a highly flexible and cost-effective manner, significantly enhancing their overall ability to derive meaningful insights from vast amounts of biological data and further driving innovations in the field.

Google Cloud AI

Google Cloud AI provides an extensive and diverse collection of advanced machine learning tools that are specifically designed to assist researchers in the critical areas of data analysis as well as model training within the dynamic and ever-evolving field of immunology. These powerful tools not only enable researchers to conduct large-scale genomic analyses effectively but also empower them to integrate numerous datasets from multiple distinct studies. By utilizing these tools, researchers can generate comprehensive, meaningful, and impactful insights into complex immune functions and various immune disorders. This capability is crucial, as it significantly facilitates remarkable advancements in both research methodologies and treatment strategies in healthcare and medical science (Thuan et al., 2024).

Challenges and Future Directions

The healthcare industry is experiencing a significant transformation as advances in AI continue to facilitate the discovery of new biomarkers, drug targets, and therapeutic approaches. Disease diagnosis and prognosis stand to gain substantially from the implementation of AI algorithms and platforms for the analysis of an increasing wealth of biomedical and healthcare data, including next-generation sequencing data analysis. Yet, key challenges need to be addressed in order to integrate AI-driven solutions successfully with healthcare frameworks. These include the need for scalable AI models that comply with data privacy, regulation, and ethics frameworks throughout their lifecycle, interoperability with a diverse range of end-serving systems, and the development of inferable and explicable AI algorithms. Considering the scale, complexity, structural heterogeneity, and dynamics of immunological data, these challenges are further amplified in immunotherapy research and patient care (Pandya et al., 2021; Wang et al., 2023; Lou et al., 2023; Naskar et al., 2025; Gupta & Kumar, 2023)

With the explosion of immunological data and advances in single-cell technologies, significant progress has resulted in computational immunological studies that can help to decipher the structure of immune systems and predict therapeutic targets. In this context, the development and adoption of AI algorithms and platforms tailored for immunological data analysis is seen as an unprecedented opportunity to revolutionize understanding, diagnosis, and treatment strategies to cure immunological-related diseases. Possible pandemics and the urgent need to accelerate the development of advanced therapies, drugs, and vaccines make this need even more pressing and paramount. (Olawade et al., 2024; Mohseni and Ghorbani, 2024; Zhao et al., 2024)

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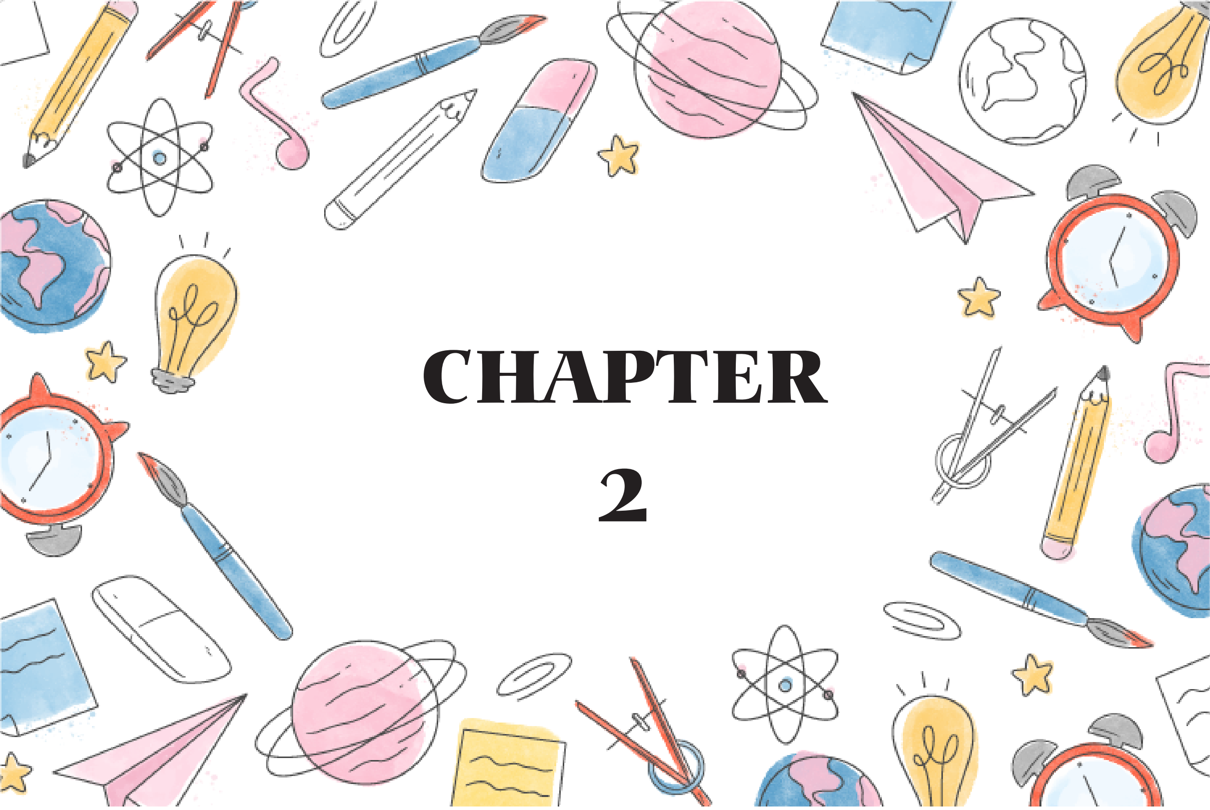

CHAPTER 2

A BIBLIOMETRIC ANALYSIS OF MACHINE LEARNING APPLICATIONS IN RESPIRATORY PHYSIOTHERAPY AND REHABILITATION

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INTRODUCTION

Respiratory or pulmonary physiotherapy is a collection of therapeutic procedures to increase pulmonary function and promote rehabilitation for patients with respiratory disorders. This discipline incorporates breathing control exercises, postural adjustments, mobilization techniques, sputum clearance methods, and patient education (Valenza-Demet et al., 2014). Such interventions are especially critical for patients post-operatively, such as those recovering from pulmonary surgeries or individuals on mechanical ventilation who experience complications like pneumonia (Lähteenmäki et al., 2020; Nandanwar et al., 2024).

A branch of artificial intelligence (AI) called machine learning focuses on developing statistical models and algorithms that let computers do specific tasks without human supervision using data inference and pattern recognition. The fundamental objective of machine learning is to enable machines to acquire information from data inputs, enhance their learning continuously, and make predictions or conclusions using that data (Ling, 2023). The many methods and algorithms used in machine learning may be broadly categorized as reinforcement learning, unsupervised learning, and supervised learning. When a model is trained on a labeled dataset, supervised learning occurs, enabling the model to predict outputs based on input characteristics (Krishna, 2021). In this field, decision trees and logistic regression are standard techniques. On the other hand, unsupervised learning uses methods like clustering and dimensionality reduction to analyze unlabeled data to uncover hidden patterns or internal structures. However, reinforcement learning provides feedback through rewards or penalties to educate models to make decisions sequentially (Omar, 2021). Several machine learning techniques are included in hybrid models, which have also demonstrated promise in raising projected accuracy in various applications (Khan et al., 2023). In summary, machine learning encompasses diverse algorithms and methods designed to analyze large datasets, facilitating advancements across many fields and indicating its robust role in modern technology and AI (Ling, 2023).

Machine learning (ML) finds diverse applications in respiratory physical therapy, enhancing clinical practice and patient outcomes. One significant application is in assessing and monitoring patient movements using machine learning-based computer vision techniques. For instance, a Kinect-based system has been shown to evaluate therapeutic movements remotely, providing real-time feedback and promoting continuous care, which is essential for chronic respiratory patients (Zhou et al., 2025). Additionally, while machine learning algorithms are utilized to improve predictive accuracy in different medical contexts, there is a need for specific studies directly linking ML applications to tailoring therapy interventions for conditions like lung diseases. A current systematic review reported that ML methods accurately predicted weaning results in mechanical ventilation, with XGBoost outperforming the other models, but the lack of studies using newer architectures, such as transformer models, emphasizes a need for future research and development in this field (Ahmed et al., 2025).

A bibliometric study on machine learning applications in respiratory physical therapy is essential for several reasons. First, it gives a complete assessment of the existing research environment, assisting in identifying common trends, significant themes, and research demands in this emerging topic. Given the rapid advancements in machine learning and its use in healthcare, a complete bibliometric investigation can indicate the amount of published literature and identify key research that has transformed the subject (Medić et al., 2019; Tran et al., 2019). Moreover, bibliometric analysis facilitates the identification of collaborative networks among researchers and institutions, which is vital for fostering interdisciplinary partnerships necessary for advancing complex fields like respiratory therapy (Saleh et al., 2024). Furthermore, knowing the empirical data supporting machine learning approaches in healthcare can help influence clinical operations and promote evidence-based procedures (Tran et al., 2019). Such analysis can also elucidate the evolution of research, documenting shifts from traditionally focused studies toward novel applications involving big data analytics and AI in respiratory health (López-Belmonte et al., 2020). Finally, the findings from a bibliometric analysis can guide future research directions, emphasizing under-explored areas that present opportunities for innovation and improvement in patient outcomes (Huang et al., 2024).

METHODS

Data sources and search strategy

Clarivate PLC's Web of Science Core Collection was used as a data source for bibliometric research. Searching keywords were primarily based on Medical Subject Headings of the National Library of Medicine in the United States of America (USA). This comprehensive search was carried out in a single day on April 15th, 2025. The search results were exported as plain text files for further analysis. *Figure 1a* details the search methodology and corresponding results.

Eligibility criteria

A topical search was performed to find all publications about respiratory physiotherapy and machine learning. The inclusion criteria comprised only papers published in English, classed as articles, and indexed in Science Citation Index Expanded or Emerging Sources Citation Index, with no restrictions on the country of publication, the type of study, or the period. Irrelevant articles such as aquaculture, rat studies, noninvasive imaging, and mutation/gene studies were excluded. Retracted articles were also excluded.

Data synthesis

Simple descriptive statistics, such as frequency counts, were employed to determine similarities and differences. Biblioshiny function of Bibliometrix package in R version 4.4.3. (R Foundation for Statistical Computing, Vienna, Austria) was used for data synthesis and analysis in RStudio version 3.6.0 (Posit Software PBC, Boston, MA, USA). It is an interactive, web-based interface built for bibliometric analysis, designed to be user-friendly and accessible to researchers from various disciplines (Aria & Cuccurullo, 2017). This comprehensive performance analysis examined publications to identify annual scientific production, average citations per year, the most relevant sources, most locally cited sources, most relevant authors, most locally cited authors, most relevant affiliations, publishing countries, most relevant documents, most cited documents, and most frequent words. Trend topics, thematic analysis, and factorial analysis were also performed. Visualization and scientific mapping were used to reveal cumulative production and co-citation network of sources, authors' production, collaboration networks and co-citation networks, production, collaboration networks and world maps of the countries, co-citation network of documents, word clouds and co-occurrence network of the most frequent words, trend topics, and thematic maps.

RESULTS

Initially, 1514369 records associated with machine learning (1461232) or respiratory physiotherapy (53137) were identified. After truncation for the intersection of these two fields, 301 records were screened according to eligibility criteria, and 31 records were excluded. After refining the records according to document types, Web of Science index, and languages, 50 were excluded, and 220 were eventually analyzed (*Figure 1b*). For bibliometric analysis, the status of metadata of abstract, author, document type, journal, language, publication year, science categories, title, and total citation was excellent. The status of metadata of affiliation, cited references, corresponding author, and Digital Object Identifier was good. Metadata of keywords and keywords plus had an acceptable status.

Main information

Between 1992 and 2025, 207 articles and 13 reviews were published in 132 sources, with an annual growth rate of 9.5 percent. The average citations per document and the average document age were 9.168 and 4, respectively. Documents had 1482 authors, 614 author's keywords, and 7786 references. Co-authors per document was 7.61, and the ratio of international co-authorships was 27.73 percent.

Annual scientific production

Annual scientific production from 1992 to 2025 is shown in *Figure 1c*. Minor fluctuations were observed in the early years. 3, 4, and 5 articles were published in 2009, 2013, and 2017, respectively. In 2019 and 2020, seven articles each were published. Since 2021, significant increases have been observed in articles published. 2021, 2022, 2023, and 2024 hosted 32, 38, 38, and 48 articles, respectively. Twenty articles were published from the beginning of 2025 until April 15th, 2025. The annual growth rate was found to be 9.5 %.

Average citations per year

Average article citations per year from 1992 to 2025 were presented in *Figure 1d*. Fluctuations were observed in the early years. Annual averages of 3.7, 2.0, and 1.6 citations were found in 2000, 2006, and 2009, respectively. In 2015 and 2018, the average number of citations per year was 2.6 and 2.7, respectively. The most cited year was 2020; its average citation number was 6. The year 2021 came in second place with an average of 3 citations per year. The year 2011 resulted in 0 citations.

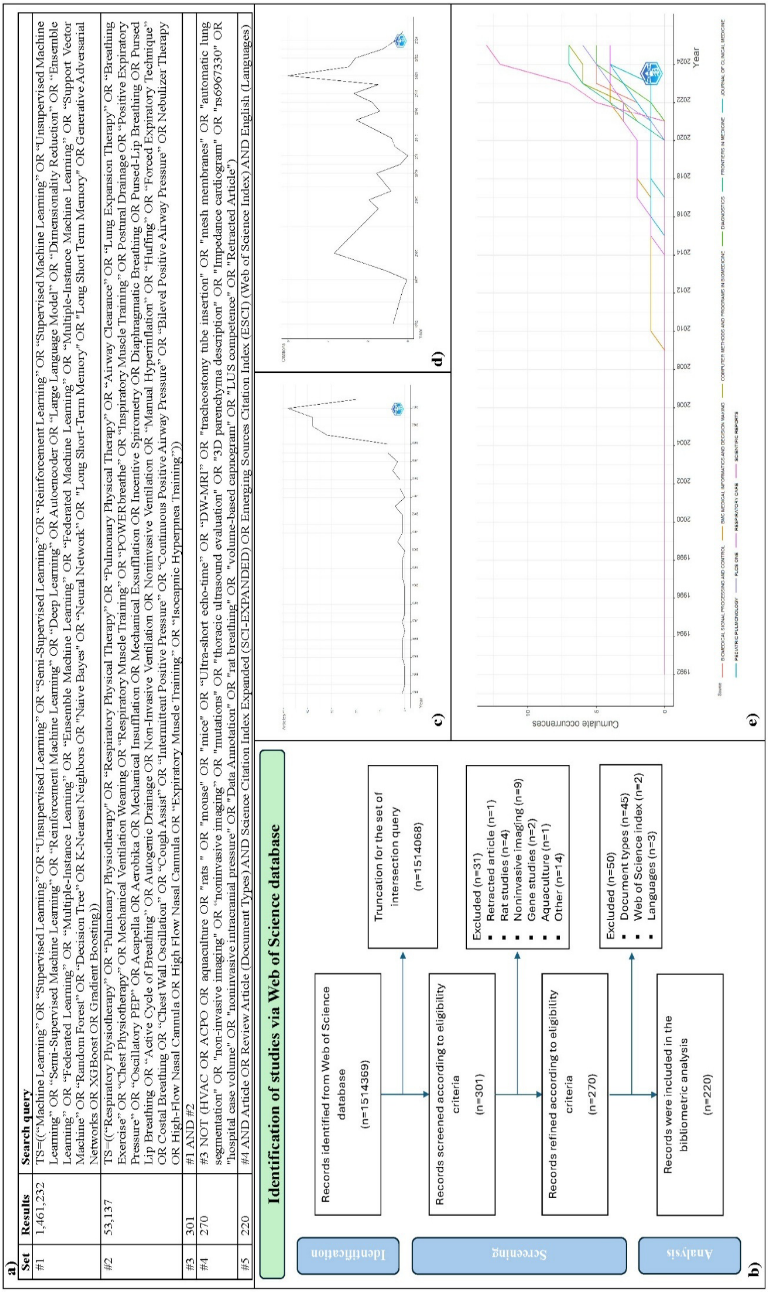
Most relevant sources

The top 20 journals publishing the most analyzed literature are as follows. *Scientific Reports* published 13 articles. *Computer Methods and Programs in Biomedicine* and *Frontiers in Medicine* contributed to the literature with seven articles each. *PLOS One* published six articles, while *Biomedical Signal Processing and Control*, *BMC Medical Informatics and Decision Making*, and *Diagnostics* published five articles each. Other journals were *Journal of Clinical Medicine (4 articles)*, *Pediatric Pulmonology (4 articles), Respiratory Care (4 articles), Applied Sciences-Basel (3 articles), Critical Care (3 articles), Frontiers in Pediatrics (3 articles), IEEE Access (3 articles),* and *Journal of Anesthesia Analgesia and Critical Care (3 articles).* These journals were the core sources according to Bradford's Law. *Physiological Measurement (3 articles), Algorithms (2 artic-*

les), Bioengineering-Basel (2 articles), BMC Pediatrics (2 articles), and *BMC Pulmonary Medicine (2 articles)* were sources in zone 2 according to Bradford's Law.

Scientific Reports (H-index: 5 points) demonstrated the highest local impact based on H-index, G-index, and M-index values. According to H-index, other journals with the most local high impact were *Computer Methods and Programs in Biomedicine (4 points)*, *Frontiers in Medicine (4 points)*, *PLOS One (4 points)*, *Respiratory Care (4 points)*, *BMC Medical Informatics and Decision Making (3 points)*, *Algorithms (2 points), Bioengineering-Basel (2 points)*, *Biomedical Signal Processing and Control (2 points)*, and *BMC Pulmonary Medicine (2 points)*, respectively.

The cumulative production of the most relevant sources over time is demonstrated in *Figure 1e*. In the early period before 2021, *BMC Medical Informatics and Decision Making*, *Respiratory Care, Pediatric Pulmonology,* and *Journal of Clinical Medicine* published their first article in 2010, 2015, 2016, and 2018, respectively. In 2021, *PLOS One* and *Biomedical Signal Processing and Control* published one article each, and *Computer Methods and Programs in Biomedicine* and *Frontiers in Medicine* published two articles each. In 2022, *Scientific Reports* published two articles. In the following years, dramatic increases in the production of publications were observed in each journal.



a)

Set	Results	Search query
#1	1,461,232	TS=((“Machine Learning” OR “Supervised Learning” OR “Unsupervised Learning” OR “Semi-Supervised Learning” OR “Reinforcement Learning” OR “Supervised Machine Learning” OR “Unsupervised Machine Learning” OR “Semi-Supervised Machine Learning” OR “Reinforcement Machine Learning” OR “Deep Learning” OR Autoencoder OR “Large Language Model” OR “Dimensionality Reduction” OR “Ensemble Learning” OR “Federated Learning” OR “Multiple-Instance Learning” OR “Ensemble Machine Learning” OR “Federated Machine Learning” OR “Multiple-Instance Machine Learning” OR “Support Vector Machine” OR “Random Forest” OR “Decision Tree” OR K-Nearest Neighbors OR "Naive Bayes" OR “Neural Network” OR "Long Short-Term Memory" OR "Long Short Term Memory" OR Generative Adversarial Networks OR XGBoost OR Gradient Boosting))
#2	53,137	TS=((“Respiratory Physiotherapy” OR “Pulmonary Physiotherapy” OR “Respiratory Physical Therapy” OR “Pulmonary Physical Therapy” OR “Airway Clearance” OR “Lung Expansion Therapy” OR “Breathing Exercise” OR “Chest Physiotherapy” OR Mechanical Ventilation Weaning OR “Respiratory Muscle Training” OR “POWERbreathe” OR “Inspiratory Muscle Training” OR Postural Drainage OR “Positive Expiratory Pressure” OR “Oscillatory PEP” OR Acapella OR Aerobika OR Mechanical Insufflation OR Mechanical Exsufflation OR Incentive Spirometry OR Diaphragmatic Breathing OR Pursed-Lip Breathing OR Pursed Lip Breathing OR “Active Cycle of Breathing” OR Autogenic Drainage OR Non-Invasive Ventilation OR Noninvasive Ventilation OR “Manual Hyperinflation” OR “Huffing” OR “Forced Expiratory Technique” OR Costal Breathing OR “Chest Wall Oscillation” OR “Cough Assist” OR “Intermittent Positive Pressure” OR “Continuous Positive Airway Pressure” OR “Bilevel Positive Airway Pressure” OR Nebulizer Therapy OR High-Flow Nasal Cannula OR High Flow Nasal Cannula OR “Expiratory Muscle Training” OR “Isocapnic Hyperpnea Training”))
#3	301	#1 AND #2
#4	270	#3 NOT (HVAC OR ACPO OR aquaculture OR "rats " OR "mouse" OR "mice" OR "Ultra-short echo-time" OR "DW-MRI" OR "tracheostomy tube insertion" OR "mesh membranes" OR "automatic lung segmentation" OR "non-invasive imaging" OR “noninvasive imaging” OR "mutations" OR "thoracic ultrasound evaluation" OR "3D parenchyma description" OR "Impedance cardiogram" OR "rs6967330" OR "hospital case volume" OR "noninvasive intracranial pressure" OR "Data Annotation" OR "rat breathing" OR "volume-based capnogram" OR "LUS competence" OR "Retracted Article")
#5	220	#4 AND Article OR Review Article (Document Types) AND Science Citation Index Expanded (SCI-EXPANDED) OR Emerging Sources Citation Index (ESCI) (Web of Science Index) AND English (Languages)

Figure 1. a) Topical search methodology and corresponding results b) Flow diagram of identification of studies c) Annual scientific production d) Average article citation per year e) Sources’ production over time.

Most local cited sources

The top 15 most cited journals in the analyzed literature are as follows. The *American Journal of Respiratory and Critical Care Medicine* had the highest number of local citations, with 304 citations. *Chest*, *Intensive Care Medicine*, and *Critical Care Medicine* were found to have 248, 225, and 201 local citations, respectively. Other journals were *Critical Care* (177 citations), *JAMA-Journal of the American Medical Association* (158 citations), *European Respiratory Journal* (156 citations), *New England Journal of Medicine* (154 citations), *PLOS One* (123 citations), *Scientific Reports* (119 citations), *Respiratory Care* (104 citations), *Sleep* (89 citations), *Lancet Respiratory Medicine* (81 citations), *Journal of Critical Care* (79 citations), and *Lancet* (79 citations). *According to the total citation index, the Annals of Emergency Medicine (190 points) had the highest local impact*. Other journals with the most local high impact were *Critical Care Medicine (121 points), Frontiers in Medicine (111 points), Respiratory Care (109 points), Sleep Medicine (84 points), Scientific Reports (80 points), Computer Methods and Programs in Biomedicine (66 points), Journal of Clinical Medicine (56 points), Respirology (53 points),* and *Journal of Medical Internet Research (42 points),* respectively. The co-citation network of sources is also demonstrated in *Figure 2a*.

Most relevant authors

Pépin JL had the most, with 2.7%, and six articles. *Bailly S* and *Chen CM* followed with 2.3% and five articles each. While *Barbé F, Chao WC, Giraldo BF, Lai CC, Yuan J*, and *Zhang G* had four articles each (%1.8%), the other 20 had three each (%1.4%). *Aliberti S* ranked last with 0.9% and two articles. The first two articles were published in 2013 and 2015 by *Giraldo BF*. *Martin-Loeches I, Reyes LF*, and *Aliberti S* followed in 2017 with one paper each. The most relevant authors' production over time is detailed in *Figure 2b*.

Additionally, *Chen CM* and *Barbé F* had the highest local impact with an H index score of 4 each. *Chao CM*, *Cheng KC*, *Chiew YS*, *Lai CC*, *Sánchez-De-La-Torre M*, *Zhang YJ*, and *Zhao QY* followed them with the local impacts, with an H index score of 4 each. A collaboration network of authors was also demonstrated in *Figure 2c*.

Most locally cited authors

Chen CM was the most cited author, with 27 citations. *Chao CM* and *Lai CC* were followed by 20 citations each. *Cheng KC* had 19 citations. While *Chao WC, Habli I, Jia Y, Kaul C, Lawton T, Murray-Smith Rhad*, and *Zhang YJ* had 16 citations each, Chan MC, Hsieh CC, Hsieh MH, Hsieh MJ, and Wu CL had 15 citations each. *Magret M* ranked 17th with 14 citations. The remaining 13 authors had 12 citations each. Densities of the co-citation network of the authors were also demonstrated in *Figure 2d*.

Most relevant affiliations

Harvard University had the most publications, with 45 articles. *Centro de Investigación Biomédica en Red*, *Université Grenoble Alpes, and the University of Michigan* followed with 38, 37, and 32 articles, respectively. Some other affiliations were *Chi Mei Hospital* (27 articles), *Taipei Medical University* (20 articles), *Chungbuk National University* (17 articles), *University of Padova* (15 articles), *Yonsei University* (14 articles), *National Chung Hsing University* (12 articles), *University of Western Ontario* (12 articles), *University of Oxford* (12 articles), *Seoul National University* (12 articles), *Institut National De La Santé Et De La Recherche Médicale* (11 articles), *University of California* (10 articles), *University of Toronto* (10 articles), *Yale University* (10 articles), *Sichuan University* (8 articles), *University of Arizona* (8 articles), and *Feng Chia University* (7 articles).

Countries

The scientific production of the countries is demonstrated in *Figure 2f*. The *People's Republic of China* and the *USA* published 262 and 190 articles, respectively. *Italy* and *Spain* followed with 89 and 77 articles, respectively. *France* and *South Korea* had 55 articles each. Some other countries were *Brazil* (46 articles), the *United Kingdom* (43 articles), *Australia* (38 articles), *Germany* (38 articles), *Canada* (36 articles), *Japan* (31 articles), *Colombia* (23 articles), *Portugal* (20 articles), and *India* (11 articles), respectively.

The corresponding authors' countries and their distribution of articles are shown in *Figure 2g*. These countries had at least two articles. The corresponding authors from the *People's Republic of China* and the *USA* contributed 58 and 39 articles, respectively. The corresponding authors in *Italy* and *South Korea* contributed 12 papers each. The corresponding authors in *Germany* and *Spain* contributed nine articles each. The corresponding authors in *France* and the *United Kingdom* contributed eight papers each. The corresponding authors in *Brazil*, *Colombia*, and *Japan* contributed seven papers each. The corresponding authors in *Australia* and *Canada* contributed five papers each. While the corresponding authors in *India* contributed four articles, the corresponding authors in *Israel* and *Malaysia* contributed three papers each.

Regarding the corresponding author's multi-country publications, the *People's Republic of China* and the *USA* published eleven and eight articles, respectively. *Germany* and *Colombia* published five articles each. *Spain* and *Brazil* published four articles each. *Italy*, the *United Kingdom*, and *Malaysia* also published three articles each. *France* and *India* published two articles each (*Figure 2g*). The collaboration network of countries were also demonstrated in *Figure 2h*.

Cited countries, total number of citations, and average number of citations are presented as follows. The most cited countries were the *USA* (577 citations), the *People's Republic of China* (385 citations), *Spain* (158 citations), *Canada* (123 citations), the *United Kingdom* (120 citations), and *France* (109 citations). The least cited countries were the *Netherlands* (1 citation), *Russia* (3 citations), *Romania* (3 citations), *Mexico* (5 citations), *Belgium* (5 citations), and *Chile* (9 citations). The highest citation average countries were *Canada* (24.60 citations), *Finland* (21.00 citations), *Iran* (19.50 citations), *Spain* (17.60 citations), *Malaysia* (17.00 citations), and the *United Kingdom* (15.00 citations). The lowest citation average countries were the *Netherlands* (0.50 citations), *Brazil* (3.00 citations), *Romania* (3.00 citations), *Russia* (3.00 citations), *Italy* (3.70 citations), *Colombia* (4.10 citations), *India* (4.50 citations), *Belgium* (5.00 citations), and *Mexico* (5.00 citations).

Most relevant documents

According to citation reports of Web of Science, the top 20 relevant documents in the analyzed literature are as follows: *(Yang et al., 2023), (Pappy et al., 2022), (Liu et al., 2021), (Cheng et al., 2024), (Krachman et al., 2021), (Heikkilä et al., 2016), (Buendía et al., 2022), (Fu et al., 2024), (Hattab et al., 2025), (Ceylan et al., 2024), (Yang et al., 2024), (Reyes et al., 2022), (Wang et al., 2024), (Hattab et al., 2024), (Matsunaga et al., 2022), (Yu et al., 2025), (Odeyemi et al., 2024), (Chang et al., 2022), (Garcia-Gutiérrez et al., 2022)*, and *(Gannon et al., 2024).*

Most cited documents

The documents were evaluated according to total citations, total citations per year, and normalized total citations, which indicate raw impact, citation rate, and relative impact to its peers from the same year, respectively. *Haimovich AD et al.* published the most globally cited article with 190 citations. *Keenan SP et al.* followed it with 96 citations. In terms of the total citations, other documents include *Poulet C et al.* (68), *Zhao QY et al.* (50), *Rodríguez A et al.* (49), *Kuo HJ et al.* (48), *Hsieh MH et al.* (46), *Jia*

Y et al. (41), *Kamran F et al.* (39), and *Thaler ER and Hanson CW* (39), respectively (*Table 1*).

Given their citation rates over total citations per year, it was observed that the most cited articles were published between 2018 and 2022. *Haimovich AD et al.* had the highest total number of citations per year (31.67). Zh*ao QY et al.* followed it with 10 total citations per year. In terms of the total citations per year, other notable documents belonged to *Kamran F et al.* (9.75 citations), *Jia Y et al.* (8.20 citations), *Fabregat A et al.* (6.60 citations), *Bendavid I et al.* (6.50 citations), *Jia Y et al.* (6.00 citations), *Hsieh MH et al.* (5.75 citations), *Pépin JL et al.* (5.67 citations), and *Gaspar LS et al.* (5.60 citations), respectively (*Table 1*).

Given their relative impacts over normalized total citations, it was observed that the most cited articles were published between 2020 and 2025. *De Jong A et al.* had relatively more impact (12 citations). *Stivi T et al.* followed it with 8.28 citations. In terms of the total citations per year, other notable documents belonged to *Farahat IS et al.* (6.62 citations), *Cohen O et al.* (5.79 citations), *Haimovich AD et al.* (5.26 citations), *Fritsch SJ et al.* (4.14 citations), *Hattab Z et al.* (4.00 citations), *Pépin JL et al.* (4.00 citations), *Bazoukis G et al.* (3.96 citations), and *Kamran F et al.* (3.72 citations), respectively (*Table 1*). Analysis revealed that none of the documents received a local citation.

Table 1. *Most globally cited documents.*

	#	First author	Year	Journal	DOI	Score
Raw impacts (TC)	1	Haimovich AD	2020	Ann Emerg Med	10.1016/j.annemergmed.2020.07.022	190
	2	Keenan SP	2000	Crit Care Med	10.1097/00003246-200006000-00072	96
	3	Poulet C	2009	Sleep Med	10.1016/j.sleep.2009.01.007	68
	4	Zhao QY	2021	Front Med	10.3389/fmed.2021.676343	50
	5	Rodríguez A	2017	Resp Care	10.4187/respcare.05481	49
	6	Kuo HJ	2015	Resp Care	10.4187/respcare.03648	48
	7	Hsieh MH	2018	J Clin Med	10.3390/jcm7090240	46
	8	Jia Y	2021	Artif Intell Med	10.1016/j.artmed.2021.102087	41
	9	Kamran F	2022	BMJ-Brit Med J	10.1136/bmj-2021-068576	39
	10	Thaler ER	2006	Am J Rhinol	10.1177/194589240602000209	39

Citation rate (TCP)	1	Haimovich AD	2020	Ann Emerg Med	10.1016/j. annemergmed.2020.07.022	31.67
	2	Zhao QY	2021	Front Med	10.3389/fmed.2021.676343	10.00
	3	Kamran F	2022	BMJ-Brit Med J	10.1136/bmj-2021-068576	9.75
	4	Jia Y	2021	Artif Intell Med	10.1016/j.artmed.2021.102087	8.20
	5	Fabregat A	2021	Comput Meth Prog Bio	10.1016/j.cmpb.2020.105869	6.60
	6	Bendavid I	2022	Sci Rep-UK	10.1038/s41598-022-14758-x	6.50
	7	Jia Y	2022	IEEE T Emerg Top Com	10.1109/TETC.2022.3171314	6.00
	8	Hsieh MH	2018	J Clin Med	10.3390/jcm7090240	5.75
	9	Pépin JL	2020	Respirology	10.1111/resp.13669	5.67
	10	Gaspar LS	2021	Ebiomedicine	10.1016/j.ebiom.2021.103248	5.60
Relative impacts (NTC)	1	De Jong A	2025	Chest	10.1016/j.chest.2024.07.171	12.00
	2	Stivi T	2024	J Clin Med	10.3390/jcm13051505	8.28
	3	Farahat IS	2024	Sci Rep-Uk	10.1038/s41598-023-51053-9	6.62
	4	Cohen O	2024	Ann Am Thorac Soc	10.1513/Annal-sATS.202309-799OC	5.79
	5	Haimovich AD	2020	Ann Emerg Med	10.1016/j. annemergmed.2020.07.022	5.26
	6	Fritsch SJ	2024	J Crit Care	10.1016/j.jcrc.2024.154795	4.14
	7	Hattab Z	2025	Value Health	10.1016/j.jval.2024.08.008	4.00
	8	Pépin JL	2025	Thorax	10.1136/thorax-2024-221422	4.00
	9	Bazoukis G	2023	J Clin Sleep Med	10.5664/jcsm.10532	3.96
	10	Kamran F	2022	BMJ-Brit Med J	10.1136/bmj-2021-068576	3.72

#: Rank / DOI: Digital Object Identifier / TC: Total citations / TCP: Total citations per year / NTC: Normalized total citations

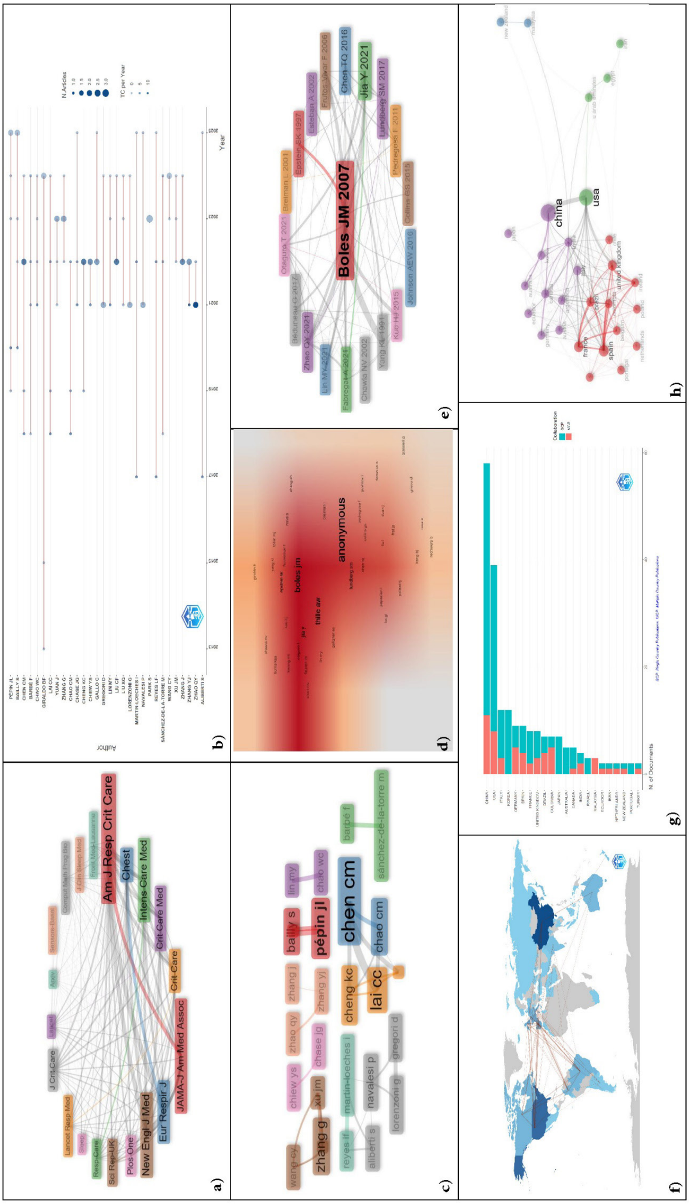


Figure 2. *a) Co-citation network of sources b) Most relevant authors' production over time c) Collaboration network of authors d) Density map of the authors' co-citation network e) Co-citation network of documents f) Scientific production and collaboration world map of countries g) Corresponding author's countries h) Collaboration network of countries.*

Most frequent words

Considering the author's keywords, titles, and abstracts, the 10 most frequent words and their total occurrences were *patients* (776), *model* (496), *ventilation* (334), *respiratory* (312), *machine learning* (302), *study* (274), *learning* (266), *machine* (265), *data* (254), and *models* (227). *Machine learning (84 articles) was the most common keyword among the author's keywords, followed by mechanical ventilation (28 articles) and artificial intelligence (19 articles)*. *Weaning* and *COVID-19* had an occurrence of 15 each. *Critical care* occurred 10 times. Other featured keywords were *continuous positive airway pressure (9 article)*, *noninvasive ventilation (9 article)*, *sleep apnea (8 article)*, *neural network (8 article)*, *intensive care unit (8 article)*, *obstructive sleep apnea (8 article)*, *prediction (7 article)*, *non-invasive ventilation (7 article)*, *artificial neural network (7 article)*, *high-flow nasal cannula (7 article)*, and *ventilator weaning (7 article)*. *Respiratory failure* was observed as a keyword in 6 articles. Word clouds are also shown in *Figure 3*. Additionally, correlations between words through the co-occurrence network are illustrated in *Figure 4*.

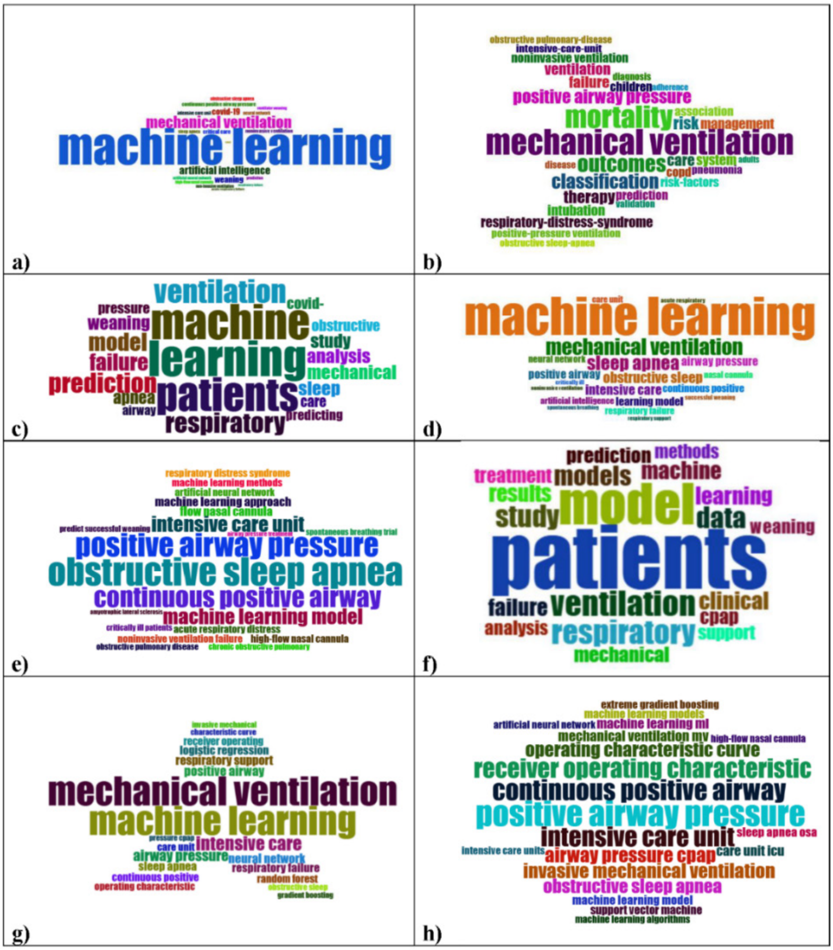


Figure 3. *Word clouds. a) The author's keywords b) Keywords plus c) Unigrams from the title d) Bigrams from the title e) Trigrams from the title f) Unigrams from the abstract g) Bigrams from the abstract h) Trigrams from the abstract.*

Trend topics

The trend topics in terms of the author's keywords over time are shown in *Figure 5a*. *Neural network* maintained its trend position from 2006 to 2021, with 2015 being the median trend year. *Artificial neural network* remained trending between 2014 and 2020, with a median trending year of 2018. *Continuous positive airway pressure* had a trend position from 2018 to 2021, with a median trend year of 2021. *Sleep apnea* became a trend in 2018 until 2023, with a median trend of 2022. *Critical care* maintained its trend from 2020 to 2025, with a median trend year of 2022. *Non-invasive ventilation* had a trend position from 2020 to 2024, with a median trend year of 2024. *Obstructive sleep apnea* had a trend position in 2021 and 2022, with a median trend year of 2022. *Machine learning*, *mechanical ventilation*, and *artificial intelligence* also maintained a trend between 2022 and 2024, with a median trend of 2023. Additionally, *COVID-19* and *respiratory failure* remained trending between 2022 and 2024, with a median trending year of 2024.

The trend topics in terms of bigram words in titles and abstracts over time are shown in *Figure 5b* and *Figure 5c*. *Artificial neural* maintained its trend from 2007 to 2018, with a median trending year of 2015. *Neural network* remained trending between 2014 and 2022, with a median trending year of 2020. *Continuous positive*, *positive airway*, and *airway pressure* were trending between 2017/18 and 2022, with a median trending year of 2021. *Obstructive sleep*, *sleep apnea*, and *intensive care* had a trend from 2021 to 2023, with a median trend of 2022. *Artificial intelligence*, *machine learning*, and *mechanical ventilation* all had a trend position between 2022 and 2024, with 2023 as the median trend year. *Acute respiratory*, *respiratory failure*, and *learning model* were trending in 2024, 2022, and 2023, respectively, and continued until 2024, with a median trending year of 2024.

The trend topics in terms of trigram words in titles and abstracts over time are shown in *Figure 5d* and *Figure 5e*. *Artificial neural network* had a trend position from 2007 to 2018, with a median year of 2015. *Continuous positive airway* and *positive airway pressure* were trending between 2017/18 and 2022, with a median trending year of 2021. *Obstructive sleep apnea*, *flow nasal cannula*, and *intensive care unit* maintained their trend from 2021 to 2022/23, with a median trending year of 2022. *Machine learning approach* was trending between 2022 and 2025, with a median trending year of 2023. *Machine learning methods* only had a trend in 2023. *Machine learning model* was trending in 2023 and 2024 (median). *Acute respiratory distress* and *high-flow nasal cannula* remained trending between 2024 and 2024/25, with a median trending year of 2024.

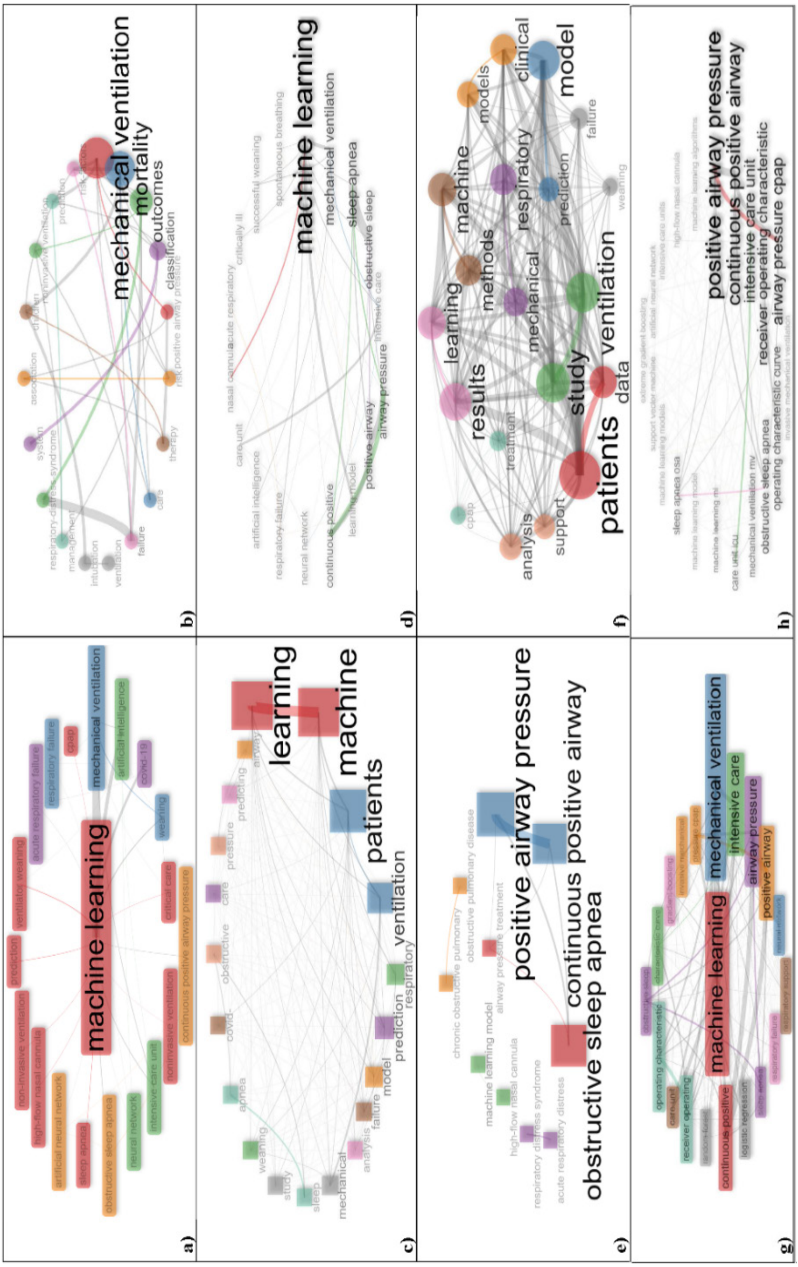


Figure 4. *Co-occurrence network of keywords. a) The author's keywords b) Keywords plus c) Unigrams from the title d) Bigrams from the title e) Trigrams from the title f) Unigrams from the abstract g) Bigrams from the abstract h) Trigrams from the abstract.*

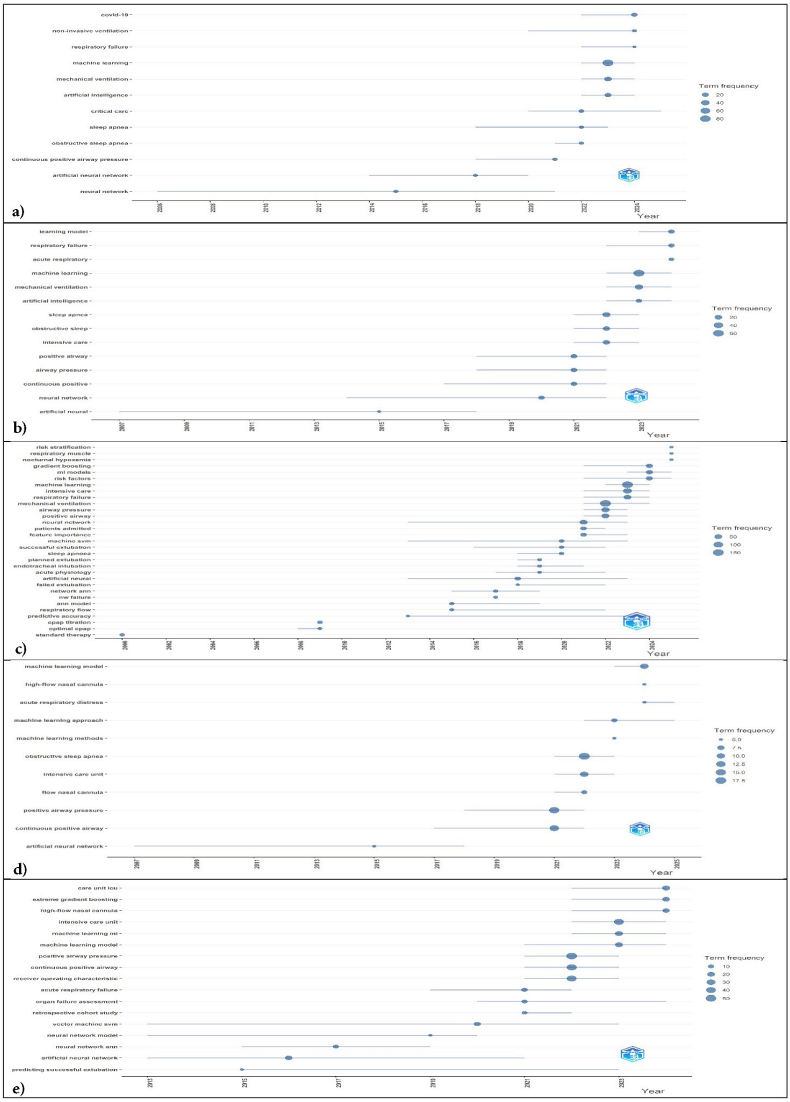


Figure 5. *The trend topics a) The author's keywords b) Bigrams from the title c) Bigrams from the abstracts d) Trigrams from the title e) Trigrams from the abstracts.*

Thematic analysis

According to the author's keywords (*Figure 6a*), the 10 most common theme clusters were *machine learning*, *artificial neural networks*, *continuous positive airway pressure*, *high-flow nasal cannula*, *mortality*, *noninvasive ventilation*, *support vector machines*, *multitask learning*, *amyotrophic lateral sclerosis*, and *extubation failure*. Niche themes were *monitoring* and *non-invasive parameters*. Motor themes were *noninvasive ventilation*, *healthcare*, *biomarkers*, and *extubation failure*. Basic themes were *machine learning*, *continuous positive airway pressure*, *high-flow nasal cannula*, *mortality*, and *amyotrophic lateral sclerosis*. *Artificial neural networks* was an emerging or declining theme. Before 2013, *neural network* was a basic theme, and *sleep apnea* and *continuous positive airway pressure* were niche themes. Between 2013 and 2022, *machine learning*, *critical care*, *continuous positive airway pressure*, *artificial neural network*, and *clustering* were basic themes. *Deep learning*, *monitoring*, *feature selection*, and *weaning* were motor themes in the same period. Also, *categorical boosting* and *cost-effectiveness* were niche themes. Additionally, *noninvasive ventilation*, *invasive mechanical ventilation*, *spontaneous breathing*, *sleep apnea*, *amyotrophic lateral sclerosis*, *neural network*, and *CPAP* were emerging or declining themes. Between 2023 and 2025, *CPAP*, *mortality*, *deep learning*, *neural network*, and *non-invasive ventilation* were basic themes. Motor themes were *machine learning* and *respiratory failure*. Niche themes were *causal forest*, *PCA*, *acute respiratory failure*, and *invasive mechanical ventilation*. *Sleep apnea*, *predictive model*, and *multitask learning* were emerging or declining themes. The multidimensional scaling factorial analysis demonstrated seven factorial themes: *machine learning*, *sleep apnea*, *biomarkers*, *predictive models*, *ventilatory parameters*, *ventilation monitoring*, and *data acquisition*.

According to the bigram words in titles, the 10 most common theme clusters were *sleep apnea*, *learning algorithm*, *acute respiratory*, *spontaneous breathing*, *machine learning*, *amyotrophic lateral*, *noninvasive ventilation*, *pilot study*, *COVID- patients*, and *network reduces*. Niche themes were *heart rate*, *amyotrophic lateral*, and *intelligence model*. Motor themes were *machine learning*, *acute respiratory*, *chronic obstructive*, *spontaneous breathing*, and *hospitalized patients*. The basic themes were *sleep apnea*, *pilot study*, *tidal volume*, *noninvasive ventilation*, and *learning algorithm*. Emerging or declining themes were *clinical data* and *COVID- patients*. Before 2020, *neural network*, *critically ill*, *airway pressure*, and *ventilator weaning* were basic, niche, motor, and emerging/declining themes, respectively. *Machine learning*, *sleep apnea*, *respiratory support*, *deep learning*, and *flow nasal* were motor themes between 2020 and 2022. During this period, *noninvasive ventilation* and *extubation failure* were basic themes. While niche themes were *convolutional neural* and *amyotrophic lateral*, emerging or declining themes were *clinical deterioration*, *clinical data*, *lung cancer*, and *COVID patients*. Between 2023 and 2025, *machine learning*, *acute respiratory*, *successful weaning*, *ICU patients*, and *neural network* were motor themes. *Artificial intelligence* was a motor or basic theme. *Sleep apnea* was a motor or niche theme. *Chronic obstructive*, *mechanically ventilated*, and *invasive mechanical* were niche themes. *Machine-learning model*, *preterm infants*, and *respiratory support* were basic themes. *COVID patients* and *deep learning* were emerging or declining themes. The multidimensional scaling factorial analysis demonstrated seven factorial themes such as *machine learning*, *clearance techniques*, *sleep apnea/airway pressure*, *diffusion speed*, *cardiovascular disease*, *airway clearance*, and *care system*.

According to the bigram words in abstracts (*Figure 6b*), the 10 most common theme clusters were *chronic obstructive*, *respiratory failure*, *airway pressure*, *disease progression*, *pressure CPAP*, *experimental results*, *machine learning*, *analysis algorithm*, *randomized controlled*, and *ventilator parameters*. The niche theme was *disease progression*. Motor themes included *machine learning*, *respiratory failure*, *chronic obstructive*, *pressure CPAP*, and *randomized controlled*. There was no basic theme. Emerging or declining themes were *ventilator parameters*, *muscle fatigue*, *breathing effort*, *ventilation based*, and *analysis algorithm*.

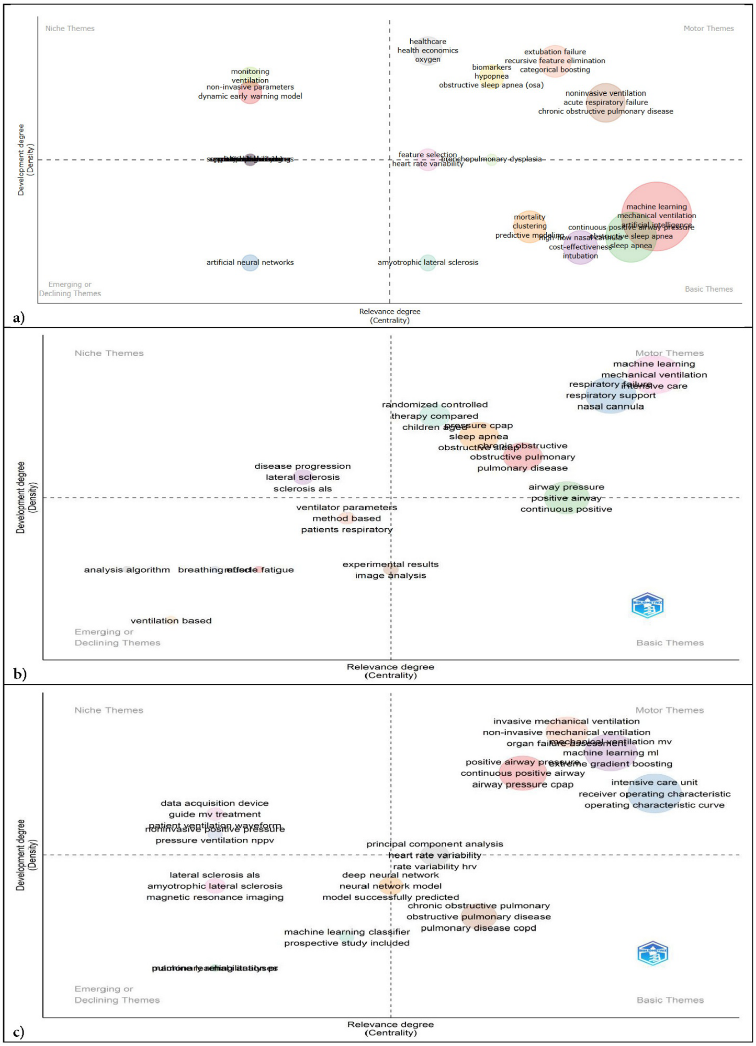


Figure 6. *Thematic maps a) The author's keywords b) The bigrams from the abstract c) The trigrams from abstract.*

Before 2017, *neural network* and *decision tree* were motor themes. *Artificial intelligence* was an emerging/declining theme. *Obstructive sleep* and *sleep apnea* were ambiguous themes. Between 2017 and 2019, *mechanical ventilation*, *risk factors*, and *planned extubation* were motor themes. *Endotracheal intubation*, *input features*, and *decision tree* were emerging or declining themes. Between 2020 and 2021, *mechanical ventilation*, *COVID patients*, *boosting XGBoost*, *airway pressure*, and *clinical data* were motor themes. *Respiratory support* and *decision tree* were ambiguous themes. *Support vector* was a niche theme. *Neural networks*, *lung condition*, *ML algorithms*, *severe acute*, and *heart rate* were emerging or declining themes. Between 2022 and 2023, *machine learning*, *deep learning*, *ill patients*, *sleep apnea*, and *AI model* were motor themes. *Chronic obstructive* and *patients undergoing* were ambiguous themes. *Airway pressure* was a basic theme. *Delayed intubation* was a niche theme. *Breathing cycles*, *lung cancer*, *CPAP adherence*, *deep learning-based*, and *index AHI* were emerging or declining themes. Between 2024 and 2025, *machine learning*, *high-flow nasal*, *decision tree*, *airway pressure*, *chronic obstructive*, *analysis identified*, and *extubation failure* were motor themes. *Blood pressure* was a basic theme. *Therapy compared* and *convolutional neural* were ambiguous themes. *Tidal volume*, *controlled trials*, *regression models*, *component analysis*, *lung volume*, *experimental results*, and *patients received* were emerging or declining themes. The multidimensional scaling factorial analysis demonstrated eight factorial themes such as *heart rate*, *hyperparameter optimization*, *laboratory variables*, *accurate machine-learning*, *predictive models*, *ICU stay*, *ventilation non-invasive*, and *multicenter cohort*.

According to the trigram words in titles, the 10 most common theme clusters were *machine learning model*, *intensive care unit*, *obstructive sleep apnea*, *spontaneous breathing trial*, am*yotrophic lateral sclerosis*, *predict successful weaning*, *neural network reduces*, *artificial intelligence model*, *deep learning model*, and *artificial neural network*. Niche themes were *predict successful weaning*, *acute respiratory distress*, *chronic obstructive pulmonary*, *spontaneous breathing trial*, and *retrospective study based*. Motor themes were *machine learning model* and *high-flow oxygen therapy*. The basic themes were *intensive care unit*, *obstructive sleep apnea*, and *machine learning prediction*. Emerging or declining themes were *noninvasive ventilation failure*, *deep learning model*, and *artificial neural network*.

Before 2022, *continuous positive airway* was a basic theme while *critically ill patients* was motor theme. In this period, *chronic obstructive pulmonary*, and *amyotrophic lateral sclerosis* were niche themes while int*ensive care unit* and *artificial neural network* were emerging or declining themes. From 2022 to 2023, *machine learning model* and *intensive care unit* were motor themes while *obstructive sleep apnea* and *noninvasive ventilation failure* were basic and emerging/declining themes, respectively. Between 2024 and 2025, *machine learning model* and *obstructive sleep apnea* were motor themes while *machine learning approach*, *acute respiratory distress*, and *spontaneous breathing trial* were basic, niche, and emerging/declining themes, respectively. The multidimensional scaling factorial analysis demonstrated five factorial themes: *obstructive sleep ap-*

nea/positive airway pressure, *intensive care unit*, *randomized controlled trial*, *airway clearance care*, and *cardiovascular disease outcomes*.

According to the trigram words in abstracts (*Figure 6c*), the 10 most common theme clusters were *positive airway pressure*, *intensive care unit*, *machine learning analyses*, *mechanical ventilation MV*, *deep neural network*, *chronic obstructive pulmonary*, *lateral sclerosis* ALS, *principal component analysis*, *machine learning classifier*, and *invasive mechanical ventilation*. Niche themes were *data acquisition device* and *noninvasive positive pressure*. Motor themes were *positive airway pressure*, *invasive mechanical ventilation*, *mechanical ventilation MV*, and *intensive care unit*. *Chronic obstructive pulmonary* was the basic theme. Emerging or declining themes were *machine learning classifier*, *lateral sclerosis ALS*, and *pulmonary rehabilitation PR*. Before 2016, *artificial neural network* and *chronic obstructive pulmonary* were motor themes. *Support vector machine* was a basic theme. *Obstructive sleep apnoea* was a niche theme. *Pressure CPAP therapy* and *maintain spontaneous breathing* were emerging or declining themes. Between 2016 and 2019, *artificial neural network* and *chronic health evaluation* were motor themes. *Intensive care unit* and *positive airway pressure* were ambiguous themes. *Positive pressure ventilation* was an emerging or declining theme. Between 2020 and 2021, *intensive care unit*, *extreme gradient boosting*, *receiver operating characteristic*, and *critically ill patients* were motor themes. *Positive airway pressure* and *feature importance analysis* were basic themes. *Chronic obstructive pulmonary* and *amyotrophic lateral sclerosis* were niche themes. *Machine learning model*, *non-invasive ventilation NIV*, *heart rate HR*, and *tidal volume TV* were emerging or declining themes. Between 2022 and 2023, *receiver operating characteristic*, *invasive mechanical ventilation*, *positive airway pressure*, *intensive care units*, *machine learning model*, and *acute respiratory failure* were motor themes. *Chronic obstructive pulmonary* and *background obstructive sleep* were basic themes. *Deep neural network* and *epic deterioration index* were niche themes. *Decision tree model*, *learning ML algorithms*, *binary logistic regression*, and *age weight height* were emerging or declining themes. *Logistic regression algorithm*, *traditional risk adjustment*, *apnea-hypopnea index* AHI, and *deep learning model* were ambiguous themes. Between 2024 and 2025, *intensive care unit/s*, *extreme gradient boosting*, *acute respiratory distress*, *positive airway pressure*, and *breathing trials sbts* were motor themes. *Random forest classifier*, *respiratory support required*, *intensive care patients*, *mechanical ventilation IMV*, and *principal component analysis* were emerging or declining themes. *Artificial neural networks* and *care unit admission* were ambiguous themes. The multidimensional scaling factorial analysis demonstrated eight factorial themes such as po*sitive airway pressure*, *intensive care units*, *non-inva-*

sive mechanical ventilation, *sequential organ failure/coronavirus disease COVID*, *recursive feature elimination*, *comorbidity index score*, *accurate machine-learning model*, and *clinical parameters results*.

DISCUSSION

Given the rapid improvements in machine learning and its use in healthcare, a comprehensive bibliometric study can illuminate the quantity of published literature and identify influential studies that have changed the field (Medić et al., 2019; Tran et al., 2019). Understanding the confluence of subjects is crucial for finding trends, gaps, and future study directions, even with significant research on each. Therefore, this study aimed to examine bibliometric data to detect research trends using machine learning in respiratory physiotherapy. As a result, we monitored the research outlook, featured key contributors, recognized influential papers, and provided insights into the research progress in this field.

General information

Annual scientific production was relatively low before 2017. It increased in the following years, reaching up to 48 articles in 2024. From 1992 to 2025, an annual growth rate of 9.5% was observed. Average citations per year showed large fluctuations. This was observed due to the low number of citations. The most citations were received in 2020; the average was 6. The most relevant sources were open-access journals with high-impact factors, such as *Scientific Reports, Frontiers in Medicine, and PLOS One*. *Scientific Reports* had the highest local impact. These journals, along with *Computer Methods and Programs in Biomedicine*, were also some of the primary sources according to Bradford's Law. In addition, three journals of *BioMed Central* were among the most relevant sources. Over time, the cumulative production of the most relevant sources was relatively low before 2022. In 2022 and later, significant production increases were observed, driven mainly by *Scientific Reports*. *The American Journal of Respiratory and Critical Care Medicine, Chest, Intensive Care Medicine, and Critical Care Medicine* were the most cited local sources with higher local citations. *The American Journal of Respiratory and Critical Care Medicine, Chest, Intensive Care Medicine, and Critical Care Medicine* were co-cited with *the JAMA- Journal of the American Medical Association, European Respiratory Journal, Respiratory Care, and Lancet Respiratory Medicine*, respectively. These journals were also co-cited with most of the journals. The authors were not significantly different from each other due to their low number of publications. However, *Pépin JL* emerged as the most relevant author and collaborated with *Bailly S*, the second most relevant author. *Chen CM* was also the most cited author and collaborated with *Chao CM*, the second most cited author. Most relevant affiliations have produced varying numbers of publications. Due to its nationwide presence, most publications originated from *Harvard University, Centro de Investigación Biomédica en Red, and Université Grenoble Alpes*, respectively. *The People's Republic of China, the USA, and Italy* were the top publishing countries, respectively, and this may be due to the number of qualified researchers or research institutions. They also had the highest number of corresponding authors, respectively. Most countries have collaborated with *the People's Republic of China and the USA*. Most *European Union* countries, *the United Kingdom, Brazil, and Chile* had collaborated to develop a network cluster. *The People's Republic of China* has established a cluster of worldwide collaborations with countries from different continents, such as *Japan, Korea, Australia, India, Argentina, Canada, Germany, and Italy*. *The USA* had established collaborations with *the United Arab Emirates, Egypt, and Iran*. Among the most cited countries, the *USA, China, and Spain* stand out in terms of total citations, while *Canada, Finland, and Iran* stand out in terms of average citations. The article with the highest raw impact and citation rate was about creating a predictive and interpretable model to detect early respiratory failure within 24 hours in COVID-19 patients admitted to the emergency room (Haimovich et al., 2020). The article with the highest relative impact evaluated extubation failure rates and risk variables within 48 hours in critically ill patients with and without obesity and found that the failure rates were similar in both groups in addition that the risk factors for extubation failure changed according to obesity status, emphasizing the significance of personalized preventive interventions (De Jong et al., 2025). The most co-cited article was a guideline from an international consensus conference that provided recommendations for managing the weaning process from mechanical ventilation, emphasizing early evaluation, use of spontaneous breathing trials, and categorizing patients by weaning difficulty (Boles et al., 2007). It recommended specialized ventilation procedures for challenging situations and caution when using noninvasive ventilation after extubation failure (Boles et al., 2007). The authors' most preferred keywords were *machine learning, mechanical ventilation, artificial intelligence, weaning, COVID-19,* and *critical care*. The authors frequently used the keywords *machine learning, prediction, weaning, mechanical ventilation, and sleep apnea* in the title. The authors also frequently used the keywords *prediction, weaning, machine learning, and mechanical ventilation* in the abstract. This study found that the most prominent and co-occurrent keywords were *machine learning, mechanical ventilation, obstructive sleep apnea, patients, and continuous positive airway pressure*.

Trends and themes

Keyword analyses reflect the shift from technology-related topics, including *neural networks*, to clinic-related topics emphasizing *respiratory care* and *COVID-19* after 2020. The last few years have emphasized *non-invasive ventilation* and *intensive care* more. The trend reflects the continuation of aligning research priorities with priority healthcare needs.

Bigram trends shift from technical terms like *artificial neural* to clinical topics such as *sleep apnea* and *respiratory failure* over time. Since 2022, interest in AI-related and respiratory terms has grown. This reflects a merging of technological and clinical research focuses.

Analysis of trigram frequency in titles focuses first on the phrase *artificial neural network*, followed by an increased emphasis on respiratory and clinical terms like *positive airway pressure* and *obstructive sleep apnea* after 2018. Starting in 2022, *machine learning applications* have increased prominence in the context of acute respiratory disease. This shift highlights the increased integration of evidence-based methodology into clinical research environments.

Thematic analysis reveals a shift from the early focus on *neural networks* and *CPAP* towards more unified themes like *machine learning and respiratory failure* in recent years. Between 2013 and 2022, clinical and computational topics coexisted as major themes. Between 2023 and 2025, *CPAP and machine learning* remained focal, while *sleep apnea*'s popularity declined. This is evidence of the integration of artificial intelligence into respiratory care research.

Thematic analysis of the titles shows movement from the early focus on *neural networks and ventilatory support* towards more general sets of themes involving *machine learning, acute respiratory disease, and intensive care* in later years. From 2020 through 2022, motor and basic themes showed increasing integration of artificial intelligence into clinical respiratory topics. Between the years from 2023 through 2025, *machine learning, neural network, and those relevant to the ICU* remained the dominant themes, *while COVID-19 and those relevant to deep learning* seemed to fall off. Overall, this thematic progression shows increasing integration of computational approaches into research in critical care.

An analysis of thematic trigrams across titles consistently emphasizes *machine learning* and *intensive care*. This is reflected through the relevance of terms like *machine learning model* and *intensive care unit* ranking among the most prominent thematic terms in recent years. On the contrary, previous thematic terms like *continuous positive airway* and *artificial neural network* follow a declining trend, while new clinical topics like *obst-*

ructive sleep apnea and *high-flow oxygen therapy* are rising. In 2024 and 2025, the application of artificial intelligence frameworks with respiratory diseases continued, with particular clinical trials and traditional practices facing either niche usage or declining trends. The findings generally indicate the ongoing integration of clinical respiratory studies with computational technology.

The thematic analysis of bigram terms from the abstracts reveals an increased focus on *machine learning, respiratory failure, and chronic obstructive disease* as major themes, especially after 2020. Contrarily, previous major themes like *neural networks and decision trees* had declining popularity over the years, while new methodologies such as *deep learning and nasal therapy with high flow* emerged with increased prominence. Notably, there was limited evidence of basic themes, with several topics being placed as either motor or in an emerging/declining phase, indicating rapid thematic changes. Overall, the findings reflect the increasing integration of computational methods into respiratory and critical care research.

The trigram thematic analysis shows that *positive airway pressure* and *intensive care unit* often occur as key thematic terms, especially between 2020 and 2025. On the other hand, *chronic obstructive pulmonary* has always been a core theme, while others, like *machine learning classifier* and *pulmonary rehabilitation*, have emerged or disappeared over time. The supremacy, in the past, of terms like a*rtificial neural networks* has gradually shifted towards more modern approaches like *extreme gradient boosting* and *deep learning models*. These findings reflect a shift in the research environment towards applying machine learning methods more and more in critical care and respiratory medicine.

CONCLUSION

This bibliometric study offers an overall picture of the changing landscape regarding the application of machine learning in respiratory physiotherapy and rehabilitation. The study demonstrates a sharp increase in academic publication after 2017, especially in leading, open-access journals, with increasing emphasis on clinical applications such as mechanical ventilation, sleep apnea, and respiratory failure. Research focus areas have shifted from technical approaches only—e.g., artificial neural networks—to more clinically oriented and integrative research themes, i.e., CPAP, ICU treatment, and predictive modeling of respiratory illness. Greater institutional collaboration worldwide, with a particular focus on institutions in China, the USA, and Europe, demonstrates international dedication to promoting the application of artificial intelligence in respiratory health care. The recognized keywords, thematic clusters, and citation network trends demonstrate an emerging research area combining machine learning technologies with pressing clinical demands. Future research must continue to foster cross-disciplinary partnerships and promote the creation of explainable and resilient models for real-world respiratory care environments.

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CHAPTER 3

EVIDENCE-BASED PRACTICES IN SURGICAL PATIENTS: EXAMPLES OF CARE BUNDLES

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1. INTRODUCTION

Approximately 234 million major surgical procedures are performed worldwide each year, making surgical care an essential part of health care. Surgical procedures are associated with significant risk of complications (e.g. infections) that negatively impact patient outcomes and increase healthcare costs (Cheng et al., 2018). Therefore, recent studies on surgical procedure outcomes have focused on length of hospital stay, morbidity and mortality, time to return to full function (work or activities of daily living), patient satisfaction, and postoperative recovery (Kehlet and Wilmore, 2008).

Evidence-based practice (EBP) is about finding evidence and using this evidence to make clinical decisions (Burns, Rohrich, & Chung, 2011). The aim of EBP is to encourage nurses to evaluate the evidence in the existing literature more comprehensively and critically when caring for their patients (Meshikhes, 2015).

Evidence-based surgery is a tool adopted by surgeons worldwide. The approach to achieving this should be standardized, as all decisions need to be up-to-date and have a scientific basis. Five important steps are required to realize evidence-based surgical practices. Transforming the need for information into a question that can be answered, finding the best information to answer that question, critical evaluation of the evidence and its validity, impact and applicability, integrating the evidence with your own experience and patients' assessment (Duran-Vega, 2015).

The surgical process requires interdisciplinary teamwork. One of the most important members of this team is the surgical nurse. The surgical nurse makes important contributions to this process both in the operating room, in the clinic and during discharge with her/his professionalism, serious education, knowledge and clinical skills. The surgical nurse should evaluate the patient's clinical condition and the conditions in which the patient is in during communication with the patient and while providing care. When planning the care to be provided, a surgical nurse should take into account the relevant resources and the evidence obtained in research results for the interventions planned. Evidence-based practices are realized by synthesizing the strongest evidence from research results with the nurse's expertise, experience and patients' values and decisions, thus facilitating clinical decision-making. The most important responsibility of the surgical nurse is to meet patient needs based on evidence-based practices, to provide evidence-based patient care, and to ensure that patients are protected or minimally affected by all complications in the perioperative process that may be frequently encountered in surgical patients. With this awareness of responsibility, it is possible for surgical nurses to ensure patient safety at the highest level only by providing patient care based on evidence-based practices (Tuna & Karaaslan, 2024).

Care bundle are mixed interventions with a high level of evidence to improve patient outcomes. The implementation results of evidence-based care Bundle are considered as quality indicators in health care institutions. Surgical nurses have an important position in the implementation of care bundle since they have a key role in patient care and therefore, they should continuously follow the literature on care bundle and be able to transfer evidence-based guidelines to practice (Yazıcı & Kayserilioğlu, 2024).

The aim of this study is to explain the care bundle, the importance of the care bundle in nursing care and the care bundle that surgical nurses can use.

2. CARE BUNDLE

2.1 Definition and History of Care Bundle

Health care service requires teamwork and is affected by the personal knowledge, motivation, equipment, experience and skills of the team. Changes in these elements may create differences in nursing care. In order to increase the quality of care and patient satisfaction, standardization in nursing care should be ensured. care bundle is a set of practices used to create standardization in nursing care and treatment (Candaş & Gürsoy, 2017).

The care bundle consists of a range of interventions that, when implemented together, significantly improve patient outcomes. Multidisciplinary teams work to deliver the best care supported by evidence-based research and practice, with the ultimate goal of improving the quality of patient care. A care bundle is a set of evidence-based care components for a specific disease that, when implemented together, can lead to better clinical outcomes than when implemented individually (Rashmi, Sunitha, Saraswati, & Mamatha, 2020).

The Institute for Healthcare Improvement (IHI) developed the concept of care bundle to help healthcare providers more reliably deliver the best care to high-risk patients receiving treatment. A care bundle is a structured approach to improving care processes and patient outcomes. A care bundle is a set of easy-to-implement, evidence-based practices consisting of three to five practices (Rashmi et al., 2020; Yazıcı & Kayserilioğlu, 2024).

Care bundle is defined as a bundle of practices that have been proven to be effective as a result of scientific studies. Although the care bundle has been mentioned in our country in recent years, it is an increasingly used practice with a higher frequency of use in the international arena. In many countries such as the USA and the UK and in international literature, the use of care bundle is recommended to prevent infections and mortality and to reduce unnecessary bed occupation (Kurutkan, 2014).

In 2001, IHI developed the concept of "care bundle" as part of a joint initiative of IHI and the Voluntary Hospital Associaton called "Ideal Design of Intensive Care Units", which was organized with the participation of 13 hospitals and aimed to improve the quality of intensive care. This was the first mention of the care bundle. The main objective of this initiative was to bring critical care processes to the highest level of reliability, leading to significant improvement in patient outcomes. The underlying theory was that improved teamwork and communication in multidisciplinary teams would create the conditions for safe and reliable care in intensive care units. The study focused on areas with potentially serious risk of harm and high costs, and areas with a strong level of evidence. Although there were many changes that the teams involved in the initiative sought to implement, the primary focus was on the care of patients on mechanical ventilators and patients with central catheters. This is because the clinical changes proposed are based on strong evidence and there is almost no debate about their effectiveness. In addition, teams have had to find new and more effective ways of working together to deliver credible change and achieve superior patient outcomes. When a small "bundle" of evidence-based interventions was implemented for a specific patient group and care setting, improvements in patient outcomes exceeded the expectations of both teams and teaching staff (Candaş & Gürsoy, 2017; Resar, Griffin, Haraden, & Nolan, 2012; Yazıcı & Kayserilioğlu, 2024).

Benefits of using a care bundle;

- Direct benefit to the patient,
- Shorter length of stay in the intensive care unit,
- Reduced cost burden,
- Improved resource utilization, which in turn benefits other patients outside the scope of the care bundle.

With the approval of the clinical team and Quality Improvement Managers, any healthcare professional in the clinical setting can implement these care bundle. Although there is a growing body of evidence that the use of these bundle to improve patient safety is associated with improved clinical outcomes, some nurses remain disinterested in the use of the care bundle and disagree with its validity (Rashmi et al., 2020).

2.2 General Characteristics of the Care Bundle

The main rationale of the care bundle is not to focus on how care should be provided, but on how to provide the best care practicable. The general characteristics of a care bundle are as follows:

- All steps in a care bundle are interventions that are supported by randomized controlled trials, consist of consistent data, and have an evidence level of I-II.
- If a change is made to the care bundle, the final modified version of the bundle needs to be re-administered to the patients in order to assess the outcomes of the bundle for an accurate assessment.
- The care bundle is tailored to the patient's current medical condition or related symptom. A patient-specific care bundle cannot be prepared.
- A care bundle is developed in line with the needs of an institution, i.e. it is institution-specific. The care bundle implemented in a different institution does not have to be replicated.
- The needs of the organization, the feasibility of the bundle and patient outcomes should be considered when developing the care bundle.
- When developing an institution-specific care bundle, issues such as accessibility, the benefits of implementing the bundle, the extent to which institutional nurses will adapt to the bundle, the extent to which the interventions included in the bundle will be implemented, and how long the bundle will be implemented by all nurses should be considered.
- Each care bundle should include 3-5 practical or preventive practices to ensure and maintain applicability.
- All of the elements that make up the care bundle must achieve the desired result.
- If any of the bundle components are not implemented, all interventions should be considered not implemented. Because of this nature, the care bundle is also described as an "all or nothing" standard and the steps are used through checklists with "yes" and "no" options.
- For effective implementation of the care bundle, a multidisciplinary approach and a compliance rate of at least 95% are required (Candaş & Gürsoy, 2017; Kurutkan, 2014; Resar et al., 2012; Se-

bastiani, Scacchetti, Cesare, Maurici, & Loiudice, 2024; Yazıcı & Kayserilioğlu, 2024).

2.3 Challenges in Implementing the Care Bundle

- Resistance to change,
- Communication breakdown within the team,
- The idea that it increases workload,
- Lack of information (Rashmi et al., 2020; Sayın, 2017; Türken Gel, Yaşacak, & Yorgun, 2020).

3. EXAMPLES OF CARE BUNDLE USED IN SURGICAL PATIENTS

3.1. Care Bundle Example for Prevention of Ventilator Associated Pneumonia

Ventilator-associated pneumonia (VAP) is one of the most common nosocomial infections in critically ill patients, defined as a lung infection that develops 48 hours or more after the initiation of mechanical ventilation. It is reported that VAP causes a significant increase in mortality and morbidity, and leads to the highest cost due to prolonged hospitalization, pharmacologic treatment, etc. If patients need intubation or ventilator support, the risk of VAP increases 7 to 21 times. Patients undergoing major operations such as cardiac surgery and hospitalized in the intensive care unit (ICU) usually require prolonged mechanical ventilation; therefore, surgical patients undergoing major operations are a high-risk group of patients in terms of VAP (He et al., 2014; Mastrogianni, Katsoulas, Galanis, Korompeli, & Myrianthefs, 2023). In addition, trauma-related injuries contribute to an increased rate of pneumonia in mechanically ventilated patients requiring treatment in the ICU (Nannapaneni et al., 2022).

Over the last two decades, many guidelines have been proposed to reduce the incidence of VAP. It has been scientifically proven that interventions must be combined to be beneficial. All of these interventions should be implemented together to achieve significantly better outcomes (Mastrogianni et al., 2023). In studies examining the effectiveness of the care bundle for the prevention of VAP, it was reported that VIP was significantly prevented in patient groups in which this care bundle was used (Karateke and Terzi, 2021; Mastrogianni et al., 2023; Nannapaneni et al., 2022).

The implementation steps of the Care Bundle for the Prevention of Ventilator Associated Pneumonia are as follows:

- Raising the head of the bed by 30-45 degrees,
- Daily assessment of the patient's readiness for extubation,
- Daily assessment of sedation,
- Peptic ulcer prophylaxis,
- Deep vein thrombosis prophylaxis (Kurutkan, 2014; Mastrogianni et al., 2023; Yazıcı and Kayserilioğlu, 2024).

3.2. Example of Care Bundle for Prevention of Catheter-Associated Urinary Tract Infections

A urinary tract infection (UTI) is defined as an infection involving any part of the urinary system, including the urethra, bladder, ureter and kidneys. Catheter-associated UTI is one of the most common types of healthcare-associated infections reported by the National Healthcare Safety Network (Gupta et al., 2023). Urinary catheters are used in 12-16% of the entire hospitalized surgical patient population. Nosocomial urinary tract infections account for 40% of healthcare-associated infections. Up to 80% of these infections are urinary catheter related**.** Especially among surgical patients, UTI rates vary between 1.8% and 4.1% depending on the type of surgery, and UTI development has been associated with increased length of hospital stay, increased incidence of surgical site infections, increased incidence of prosthesis infections, and increased mortality (Ramanathan and Duane, 2014). Prevention of catheter-associated UTI In studies examining the effectiveness of the care bundle in preventing catheter-associated UTI, it was reported that UTI was significantly prevented in patients in whom this care bundle was used (Gupta et al., 2023; Shadle et al., 2021).

The implementation steps of the Care Bundle for the Prevention of Catheter Associated Urinary Tract Infections are as follows:

- Daily assessment of urinary catheter removal,
- Catheterization using aseptic techniques,
- Keeping the drainage bag under the bladder,
- Obstruction control,
- Indication for catheterization (Gupta et al., 2023; Kurutkan, 2014; Yazici and Kayserilioglu, 2024).

3.3. Example of a Bundle for Prevention of Catheter-Associated Bloodstream Infections

Bloodstream infections (BSI) rank fourth among nosocomial infections. It has been reported in national/international studies and guidelines that 85% of these infections are catheter-related, especially central venous catheter-related (Kavak and Caner, 2020).

Catheter-associated bloodstream infections (CABIs) are diagnosed on the first day when all of the criteria for laboratory-confirmed bloodstream infection according to the Centers for Disease Control and Prevention (CDC) surveillance criteria are present in patients with venous or umbilical catheters lasting longer than two days. In a study conducted to examine the care bundle approach in the prevention of CABIs in surgical intensive care units, it was reported that the care bundle approach was effective in preventing central venous catheter-related CABIs (Akyol & Çavdar, 2019).

The implementation steps of the bundle for the Prevention of Catheter Associated Bloodstream Infections are as follows:

- Ensuring hand hygiene before the procedure,
- High level sterile barrier precautions,
- Use of chlorhexidine for skin antisepsis,
- Avoiding the use of the femoral vein area in adult patients,
- Providing daily assessment and care and removing unnecessary catheters (Akyol & Çavdar, 2019; Kavak & Caner, 2020; Kurutkan, 2014).

3.4. Care Bundle Example for Prevention of Surgical Site Infections

The type of healthcare-associated infection seen in the wound area after surgical operation is defined as surgical site infection (SSI). SSIs are among the most common and preventable complications after surgical procedures and account for approximately 20% of all hospital-acquired infections (Aygin and Yaman, 2024). According to the CDC, SSI is defined as the day of surgical intervention as the first day and infections that occur in the surgical site that may develop within 30 or 90 days following the intervention (Yazıcı and Kayserilioğlu, 2024).

In studies examining the effectiveness of the care bundle in the prevention of SSI, it was reported that SSI decreased significantly (Glenn et al., 2023; van der Slegt et al., 2013).

The application steps of the Care Bundle for the Prevention of Surgical Site Infections are as follows:

- Appropriate prophylactic antibiotic use,

  Prophylactically administered antibiotics 1 hour before surgical intervention (2 hours for vancomycin and fluoroquinolones),

  Prophylactic antibiotic selection and dose adjustment according to guidelines,

  Termination of prophylactic antibiotics within 24 hours,

- Hair/feather cleaning in accordance with the guidelines,
- Ensuring control of blood glucose level in all patients (below 200 mg/dl),
- Maintaining normothermia throughout the perioperative period,
- In patients with normal pulmonary function, 80% O_2 administration for 2 to 6 hours in the intraoperative process and immediately after extubation in the postoperative period (Kurutkan, 2014; Yazıcı and Kayserilioğlu, 2024).

3.5. Care Bundle Example for Preventing Sepsis

Sepsis is defined as a life-threatening organ dysfunction caused by an irregular host response to infection. There is still no "gold standard" sepsis screening tool. However, several screening tools are recommended for early sepsis diagnosis and treatment. Current validated screening tools include SOFA, qSOFA, National Early Warning Score and Modified Early Warning Score (Desposito and Bascara, 2024). Septic shock, the most severe form of sepsis, causes more than 200,000 deaths annually and has a hospital mortality rate close to 30% (Kalimouttou, Lerner, Cheurfa, Jannot, & Pirracchio, 2023).

Postoperative sepsis is defined as a surgical complication associated with any type of infection that can lead to sepsis, severe sepsis or septic shock that occurs in patients immediately after surgical operations. Postoperative sepsis is a major health problem estimated to occur in more than 1% of elective procedures and more than 4% of non-elective procedures (Mulita et al., 2022).

In studies examining the effectiveness of sepsis care bundle, it was reported that the mortality rate was lower in groups where bundle were applied (Daniels, Nutbeam, McNamara, & Galvin, 2011; Kalimouttou et al., 2023).

The implementation steps of the Care Bundle in Preventing Sepsis are as follows:

- Measurement of lactate level. Re-measure if initial lactate >2 mmol/L,
- Taking a blood culture before starting antibiotic treatment,
- Broad-spectrum antibiotics should be administered,
- Patients with hypotension or a lactate level >4 mmol/L should be rapidly started on 30ml/kg crystalloid,
- If the patient is hypotensive during or after fluid resuscitation, vasopressors should be administered to maintain or reach a mean blood pressure >65mmHg (Levy, Evans, & Rhodes, 2018; Yazıcı & Kayserilioğlu, 2024).

3.6. Example of a Care Bundle to Prevent Delirium

Delirium is a common but mostly preventable complication among patients in intensive care units, with an incidence as high as 70-87% (Zhang, Han, Xiao, Li, & Wu, 2021). According to the fifth edition of the American Psychiatric Association's Diagnostic and Statistical Manual of Mental Disorders (DSM-5), delirium is defined as a condition with the following five basic features impairment in attention and awareness; the impairment develops over a short period of time and tends to fluctuate in severity over the course of a day; an additional impairment in cognition; these impairments cannot be explained by other pre-existing neurocognitive disorders and do not occur at a severely reduced level of arousal, such as coma; and there is evidence that the impairment is the direct result of another medical condition (Chen, Mo, Hu, Ou, & Luo, 2021). Delirium has a significant negative impact on outcomes and costs for surgical patients. Postoperative delirium is common in elderly patients (Deeken et al., 2022).

In two meta-analyses evaluating the impact of the delirium care bundle, it was reported that the incidence of delirium decreased in patients in whom the delirium care bundle was used and supported that the bundle interventions were effective in reducing the coma patient-day ratio, length of hospital stay and 28-day mortality rate (Sosnowski et al., 2023; Zhang et al., 2021).

The implementation steps of the Care Bundle for Delirium Prevention are as follows:

- Assessment, prevention and management of pain, especially when the patient is in the prone position,

- Regular daily spontaneous awakening and spontaneous breathing trials,
- Selection of sedation and analgesia according to the patient's pain-sedation-agitation level,
- Assessment of delirium,
- Early mobilization,
- Family involvement (Yazıcı & Kayserilioğlu, 2024).

3.7. Example of Care Bundle for Fall Prevention

Falls after surgical procedures in electively hospitalized patients are a major concern. With an ageing population, this is becoming an increasingly serious public health issue. Studies show that approximately 1% to 4% of hospitalized patients experience falls after surgical intervention. Since elective surgical procedures are carefully planned and require close interaction with the healthcare system, the preoperative and postoperative periods can be ideal times to implement fall prevention interventions. Effective fall prevention practices require multicomponent interventions because fall risk is associated with many factors (Fritz et al., 2022).

In studies evaluating the effectiveness of fall prevention care bundle, it was reported that the bundle had a protective effect on patients and statistically significantly reduced the risk of falls (Di Gennaro et al., 2024; Kelley, Gutchell, & O'Neill, 2023).

The application steps of the care bundle used for fall prevention are as follows:

- Assessment of fall risk,
- Avoidance of sedative drugs,
- Providing an accessible call bell and informing patients about it,
- Ensuring that the patient wears appropriate shoes or slippers to prevent the risk of falls,
- Assessment of walking aid use and provision within 24 hours (Pop et al., 2020; Richardson, Dawson, & Henderson, 2020).

3.8. Example of Care Bundle for Preventing Pressure Sores

Despite the advances in care and treatment with the development of technology, pressure injury is still a current problem that poses a significant threat to patient safety. Exposure of patients to intense or prolonged pressure during surgical operations, increased pressure on bone protrusions due to position changes in some cases, and friction during transport and positioning on the operating table/bed in the operating room increase the risk of pressure injury in surgical patients (Kılınç, Karaman Özlü, Yayla, & Bağaçlı, 2024).

When the literature is examined, available evidence shows that care bundle are effective in preventing pressure sores and reducing the workload of nurses (Neill & Martin, 2024; Yılmazer & Tüzer, 2022).

The application steps of the care bundle used to prevent pressure sores are as follows:

- Risk assessment,
- Skin care
- Nutrition management,
- Change of position,
- Use of support surfaces,
- Education,
- Wetness/incontinence management (Orhan, 2017; Yazıcı & Kayserilioğlu, 2024).

3.9. Gastrostomy Care Bundle Example

Gastrostomy is the placement of a tube through an artificial opening in the abdominal wall into the stomach to provide long-term nutrition or gastric decompression in patients (Grant, 1998; Sezer Ceren and Talas, 2024). There are various techniques including percutaneous fluoroscopic, percutaneous endoscopic (PEG) and open surgical methods (P. Möller, 1999).

The implementation steps of the gastrostomy care bundle are as follows:

- Peristomal space maintenance;

    Dressing with appropriate frequency and aseptic techniques,

    Observation of the peristomal area for bleeding, tenderness, discharge, redness, stiffness

    When closing the dressing, leave at least 0.5 cm movement space between the external fixing button and the skin,

    In percutaneous endoscopic gastrostomy tubes only, once a week after healing of the peristomal area, the external fixation button should be released and the tube should be rotated 360 degrees left-right and pushed into the stomach and retracted at least 2 cm.

- Tube feeding;

  The product in the feeding bag is given to the patient within a maximum of 8 hours,

  Changing feeding sets every 24 hours,

  Keeping the patient in the semifowler (30-45 degrees) position for at least 1 hour during and at the end of feeding,

  Starting feeding with continuous infusion at a low rate (10-30ml/h), gradually increasing the infusion rate (10-20ml/h) and reaching the targeted amount in 3-4 days,

  Flushing the tube with at least 30 ml of water every 4 hours.

- Administration of medication through a tube;

  The drug should not be added directly into the enteral product,

  Each medicine should be administered separately using a syringe of at least 20 mL,

  The tube should be washed with at least 15 ml of water before and after administration,

  With the recommendation of the pharmacist, in cases where drug bioavailability may change, interruption of nutrition before and after drug administration as necessary (Sezer Ceren and Talas, 2024).

3.10. Cardiac Surgery Care Bundle Example

Cardiovascular diseases are the most common leading cause of death worldwide. Surgical treatment plays an important role in the treatment of heart disease, which is common in adults and elderly people. Cardiac surgery is a serious process that includes intensive care, discharge and home care. Complications can be prevented to a great extent if individualized evidence-based care is planned and implemented for the problems that may be seen in patients before and after surgical intervention (Özdemir & Yılmaz, 2024).

In a study examining the effect of the care bundle on the recovery process in patients undergoing open heart surgery, it was reported that the “Cardiac Surgery Care Bundle” reduced respiratory complications (Yılmaz and Yava, 2022).

The implementation steps of the cardiac surgery care bundle are as follows:

- Informing patients and their relatives;

  Respiratory management,

  Early mobilization,

  Providing information on pain management and encouraging the patient to perform the exercises.

- Respiratory management;

  Pre-exercise pain assessment,

  Deep breathing exercises 5-10 times every hour,

  Use of an incentive spirometer 5-10 times per hour,

  Supporting the incision site with a pillow during cough exercise,

  Controlled coughing 3-5 times every hour after spirometer use,

  Mobilization until discharge.

- Early mobilization;

  Pain assessment before mobilization,

  Assessment of vital signs,

  Checking the glucose level (should be 80-180 mg/dl) before mobilization,

  Two hours after extubation, the patient is placed in a sitting position with feet hanging down for up to 15 minutes,

  Five minutes of lower extremity exercise in the morning on the first day after extubation,

  After providing a five-minute sitting on the edge of the bed, walk 10 meters,

  Five minutes of lower extremity exercise in the evening on the first day after extubation.

  Walk 30 meters after providing five minutes sitting on the edge of the bed,

  Five minutes of lower extremity exercise in the morning on the second day after extubation, After sitting on the edge of the bed for five minutes, walk 30 meters (Yilmaz and Yava, 2022).

3.11. Care Bundle Example for Increased Intracranial Pressure Syndrome

Intracranial pressure is defined as the dynamic pressure exerted by the organs within the skull (brain tissue 83%, blood flow 9% and cerebrospinal fluid 9%) (Özkan and Arslan, 2022). Increased intracranial pressure syndrome (ICPS) may occur due to the formation of an intracranial mass (such as tumor, hematoma, abscess); increased amount of extra or intracellular fluid (cerebral edema); increased cerebral blood flow, increased amount of cerebrospinal fluid (Torun, Uysal Yazıcı, Azapağası, Özdemir, & Ceylan, 2021).

Evidence-based nursing interventions such as medical treatment, surgical operations and care bundle are included in the prevention and treatment of ICPS (Sarı & Özdemir Köken, 2023).

The implementation steps of the care bundle for ICPS are as follows:

- Ensuring adequate oxygenation,
- Maintaining vital signs within normal limits,
- Maintaining cerebral circulation,
- Neurological evaluation,
- Control of external stimuli (Sarı & Özdemir Köken, 2023).

3.12. Preoperative Care Bundle Example

Preoperative patient assessment and appropriate patient preparation are crucial to reduce morbidity and mortality in the perioperative process. This process involves assessing the patient's medical condition, functional capacity and possible risk factors (Zambouri, 2007). In order to minimize errors that may occur during the preoperative assessment process, the implementation of systems similar to checklists used in operating rooms may contribute to improving patient prognosis (Painter & Ludbrook, 2013).

Studies evaluating the ethicality of preoperative care bundle have reported a decrease in surgical complications (Fleming et al., 2016a; Ma et al., 2017).

The implementation steps of the preoperative care bundle are as follows:

- Blood glucose level <200 mg/dl,

- Body temperature >36 degrees,
- Pain management,
- Removal of patient hair with an electric shaver as close to the operation as possible,
- Shortening the fasting period,
- Information about the perioperative process (Ongün & Deniz Öztekin, 2021).

3.13. Perioperative Care Bundle Example

The perioperative period covers three main stages: preoperative, intraoperative and postoperative (Davrıeux et al., 2019). Individualized nursing care should be applied in order to meet the physiological, psychological and sociological needs of patients in the perioperative period and to ensure that they regain their health (Kızılcık Özkan, Dığın, & Dinlegör Sekmen, 2023).

The application steps of the perioperative care bundle are as follows: (This care bundle is an example of a care bundle applied to patients undergoing cardiac surgery).

Pre-op Bundle;

- Preoperative evaluation, including comprehensive patient education about anesthesia practices and pre/postoperative fluid intake protocols,
- Intake of 400-800 mL of carbohydrate solution (2-4 units of 200 mL) the night before surgery,
- The day of surgery;

    Clear fluids up to 2 hours before surgery,

    Preoperative oral administration of 600 mg gabapentin,

Postoperative Bundle;

- Termination of opioid infusion after extubation,
- Nausea and vomiting prophylaxis in the first 48 hours postoperatively,
- Analgesia after extubation: Regular paracetamol and codeine with additional oral morphine sulphate solution as needed,
- Ensuring intestinal motility,
- Early mobilization protocol (Fleming et al., 2016b).

3.14. Pain Management Care Bundle Example

Pain management is one of the most important challenges of nursing care in the perioperative period and inadequate pain management can lead to adverse clinical outcomes such as increased complications, prolonged hospitalization and risk of opioid dependence. The severity and duration of pain are influenced by patient-related risk factors, the surgical procedure and the degree of tissue damage. Pain management strategies include multimodal approaches combining pharmacological, interventional and non-pharmacological methods as part of advanced recovery programs (Eisenach & Brennan, 2018).

The implementation steps of the pain management care bundle are as follows:

- Patient education on pain and pain management,
- Pain assessment using a validated scale,
- Regular pain assessment hourly during the day and every two hours at night when the patient is awake,
- Visual documentation and sharing of the pain management plan (comfort goal and next analgesic dose time) on a board in the patient room,
- Pharmacological management,
- Recommending multiple nonpharmacologic treatment alternatives appropriate to the patient's clinical condition and preferences (Rice et al., 2019).

4. CONCLUSION

Care bundling is a quality improvement methodology based on the principle of systematic implementation of more than one evidence-based clinical practice together, which, when implemented in a holistic manner, provides more effective results than individual practices. This approach, which was developed especially for the optimization of intensive care processes, has been widely adopted in the improvement of surgical quality indicators over time. Due to the multifactorial nature of complications that may occur in surgical patients (patient factors, surgical technique, antibiotic prophylaxis, etc.), it is especially important to implement multiple interventions that are effective in this field together as a care bundle (Ching, 2024).

In this study, some examples of care Bundle that can be widely used in the care of surgical patients are included. However, there are many different and comprehensive examples of care bundle that can be applied for the needs of surgical patients in the literature, such as "Oral Care Bundle", "Constipation Prevention Bundle", "Thermal Care Bundle" and "Venous Thromboembolism Prevention Bundle".

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