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Deployable 5G Respiratory Units in Enhancing Acute Care for Lung Cancer Patients

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Abstract

5G-connected mobile respiratory units introduce a paradigm shift in acute crisis management for lung cancer patients by merging portable ventilatory support with ultra-low-latency, high-bandwidth connectivity. These units integrate on-board ventilators, non-invasive and invasive respiratory interfaces, vital-sign monitors, and 5G modems to enable real-time transmission of flows, pressures, oxygen saturation, and high-definition video to remote critical-care hubs. During transport or in-field deployment, intensivists and respiratory specialists can guide airway management, titrate ventilator settings, and override parameters via cloud-based control interfaces, effectively extending ICU-grade care into ambulances, rural clinics, and home-based acute episodes. For lung cancer patients experiencing sudden respiratory failure due to tumour-related airway obstruction, pleural effusion, or post-procedure complications, such units reduce time-to-intervention and improve stabilization before hospital arrival. This article discusses the system architecture, 5G-enabled tele-ICU connectivity, safety protocols, and clinical workflows that position 5G-connected mobile respiratory units as a scalable, technology-driven solution for managing acute respiratory crises along the lung cancer care continuum.

Keywords: 5G-connected respiratory units; mobile ventilatory support; lung cancer emergencies; Tele-ICU integration; real-time remote monitoring; ambulance-based critical care

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1. Introduction

Acute respiratory crises are frequent and life-threatening complications in advanced lung cancer, arising from tumour-related airway obstruction, pleural effusion, post-procedure complications, or systemic disease progression. These events often require immediate ventilatory support and rapid escalation to intensive care, yet conventional pre-hospital and emergency-transport systems are frequently ill-equipped to deliver ICU-grade respiratory management on the move [1]. Delayed or suboptimal ventilatory intervention during transit can worsen hypoxemia, increase the risk of cardiac arrest, and compromise long-term outcomes. 5G-connected mobile respiratory units offer a transformative solution by integrating portable ventilators, real-time vital-sign monitoring, and ultra-low-latency 5G connectivity to enable continuous, remote-guided respiratory support from the site of crisis to the hospital. This article explores how such platforms can bridge critical care gaps, improve stabilization, and enhance the safety and efficiency of acute respiratory management in lung cancer patients across the intensive-care-to-home continuum [2].

1.1. Acute Respiratory Crises in Advanced Lung Cancer

Acute respiratory crises in advanced lung cancer encompass a spectrum of rapidly progressive events including partial or complete airway obstruction by endobronchial tumours, malignant pleural effusion with lung compression, post-radiation or post-surgical pulmonary oedema, and acute pulmonary embolism [3]. These conditions often manifest with sudden onset of severe dyspnoea, tachypnoea, hypoxemia, and respiratory distress, sometimes without preceding warning

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signs. In mechanically ventilated or pre-intubated patients, airway-related crises may involve tube obstruction, dislodgement, or secretions-induced bronchospasm, further complicating management [4].

The clinical urgency of these events is amplified by the underlying frailty, reduced respiratory reserve, and multimodal treatment burden characteristic of advanced lung cancer. Conventional emergency responses rely on rapid transfer to hospital, but during transport patients may experience worsening hypoxemia or hypercapnia due to inadequate ventilatory support or delayed recognition of deterioration [5]. Effective management therefore hinges not only on timely hospital arrival but also on early, high-fidelity ventilatory and monitoring interventions delivered at the point of crisis whether at home, in a clinic, or enroute to an ICU. 5G-connected mobile respiratory units can address this need by offering real-time, ICU-like respiratory support that is both portable and remotely supervised [6].

1.2. Limitations of Conventional Emergency Transport and Pre-Hospital Care

Conventional ambulance-based emergency transport for lung cancer patients with respiratory crises typically emphasizes rapid relocation rather than sophisticated ventilatory management. Basic life support ambulances may provide oxygen therapy or non-invasive ventilation, but often lack advanced ventilators, real-time waveform monitoring, or continuous capnography, limiting the ability to safely titrate respiratory support during transit [7]. Even in advanced life support units, real-time decision-making is constrained by the absence of low-latency connectivity to critical-care specialists, forcing paramedics and on-board clinicians to rely on intuition and protocol-driven interventions.

Furthermore, communication gaps between pre-hospital teams and hospital-based intensive care units hinder coordinated handover and early preparation for arrival. Vital-sign trends, ventilator settings, and imaging findings are often conveyed verbally or via delayed documentation, increasing the risk of misinterpretation or treatment delays [8]. In patients with complex comorbidities or ongoing oncological therapies, these limitations can result in suboptimal ventilator settings, unsafe transport, and poor ICU preparedness. 5G-connected mobile respiratory units overcome these constraints by embedding high-fidelity monitoring and ultra-reliable connectivity, enabling remote intensivists to guide ventilator management, adjust support strategies, and prepare the receiving ICU in real time [9].

1.3. Rationale for 5G-Connected Mobile Respiratory Units

5G-connected mobile respiratory units are conceptually designed to extend intensive-care-grade respiratory support into any location where lung cancer patients experience acute respiratory crises [10]. By integrating portable ventilators, non-invasive and invasive respiratory interfaces, pulse oximeters, capnographs, and high-definition audio-visual feeds with 5G-enabled modems, these units can transmit physiological data, waveforms, and clinician-to-clinician interaction in near real time. Remote intensivists and respiratory specialists can then view high-resolution ventilator screens, adjust tidal volume, pressure support, and oxygenation targets, and provide step-by-step guidance to on-scene providers [11].

From an engineering and clinical perspective, the rationale for these units lies in their ability to reduce latency-sensitive decision-delays, maintain continuous respiratory monitoring, and standardize ventilatory support during critical phases of transport [12]. The 5G network's ultra-low latency, high bandwidth, and massive device connectivity ensure that lifesaving adjustments occur within seconds rather than minutes, even in high-mobility environments such as ambulances or rural roads [13]. For lung cancer patients, this technology significantly narrows the gap between crisis onset and optimal ventilatory intervention, improving stabilization, reducing complications, and enhancing the continuity of care from home or community settings to intensive care.

2. Pathophysiology and Clinical Need

Acute respiratory failure in advanced lung cancer arises from both tumour-driven mechanical compromise and treatment-related physiological derangements, creating a high-risk clinical scenario that demands rapid recognition and prompt intervention [14]. Unlike chronic respiratory insufficiency, acute episodes often occur suddenly, driven by airway obstruction, pleural space pathology, or circulatory-pulmonary mismatch, and can rapidly progress to hypoxemic or hypercapnic respiratory failure [15]. The clinical need for early, high-fidelity ventilatory support is particularly acute in this population, where baseline respiratory reserve is already diminished by chemotherapy, radiotherapy, or underlying obstructive lung diseases. Integrating time-sensitive pathophysiological understanding with advanced mobile respiratory platforms such as 5G-connected units enables more effective, pre-emptive management of respiratory crises in lung cancer patients [16].

2.1. Mechanisms of Acute Respiratory Failure in Lung Cancer

Acute respiratory failure in lung cancer can be broadly classified into hypoxemic, hypercapnic, or mixed types, driven by overlapping mechanisms and multimodal insults. Tumour-related airway obstruction such as endobronchial masses or vocal-cord paralysis can cause sudden drops in ventilation and uneven distribution of airflow, leading to V/Q mismatch and hypoxemia [17]. Radiation-induced or chemotherapy-associated pneumonitis can trigger diffuse alveolar injury, reduce gas exchange surface area and cause non-cardiogenic pulmonary oedema. In post-surgical or post-biopsy settings, acute atelectasis, bronchopleural fistula, or aspiration pneumonia can further compromise respiratory function, especially in patients with limited pulmonary reserve [18].

Systemic complications such as sepsis, cardiac dysfunction, or fluid overload can exacerbate pre-existing respiratory compromise, turning marginal compensation into overt failure [19]. Additionally, treatments including immune-checkpoint inhibitors may precipitate rapid-onset immune-related pneumonitis, which mimics acute respiratory distress syndrome (ARDS) and requires immediate ventilatory support. In many cases, these diverse mechanisms coexist, making early differentiation and targeted intervention essential. Understanding these pathophysiological pathways underscores the need for portable, real-time ventilatory platforms that can adapt to rapidly evolving respiratory physiology in lung cancer patients experiencing acute crises [20].

2.2. Tumour-Related Airway Obstruction, Pleural Effusion, and Pulmonary Embolism

Three cardinal tumour-related pathologies airway obstruction, malignant pleural effusion, and pulmonary embolism play a central role in acute respiratory failure among lung cancer patients. Endobronchial tumour growth or necrotic debris can partially or completely occlude central or segmental airways, resulting in dynamic collapse, mucus plugging, and acute atelectasis [21]. These lesions often present with sudden onset of severe dyspnoea, wheezing, or cough, sometimes accompanied by unilateral lung collapse on imaging. In mechanically ventilated patients, tube-related obstruction or secretions-induced bronchospasm can mimic tumour-related obstruction, complicating differential diagnosis and management [22].

Malignant pleural effusion is another frequent cause of acute respiratory decompensation, as fluid accumulation compresses lung parenchyma and reduces lung compliance, leading to restrictive respiratory failure [23]. Large effusions can rapidly impair oxygenation and increase work of breathing, particularly in patients with pre-existing lung disease. Ultrasound-guided or immediate drainage may be required to relieve compression, but ventilatory support is often needed before and during the procedure [24]. Pulmonary embolism, frequently secondary to cancer-associated hypercoagulability, can cause acute right-ventricular strain and sudden hypoxemia, often presenting as a rapidly progressive respiratory crisis. In lung cancer, these entities may coexist or sequentially occur, necessitating versatile, mobile ventilatory platforms capable of adapting to shifting hemodynamic and ventilatory demands [25].

2.3. Time-Sensitivity and Outcome Impact of Early Ventilatory Support

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The time-sensitivity of acute respiratory failure in lung cancer cannot be overstated, minutes of inadequate oxygenation or ventilation can lead to cardiac arrest, multi-organ failure, or prolonged ICU stay [26]. Early ventilatory support not only in the ICU but also at the point of crisis can mitigate progressive hypoxemia, stabilize respiratory mechanics, and reduce the risk of secondary complications such as aspiration or arrhythmias. In patients with limited pulmonary reserve, delayed intubation or suboptimal non-invasive ventilation may result in irreversible decompensation before hospital arrival [27].

From an outcome perspective, early ventilatory support has been associated with reduced mortality, shorter ICU lengths of stay, and lower rates of intubation-related complications such as ventilator-associated pneumonia [28]. In lung cancer cohorts, prompt initiation of appropriately titrated ventilation guided by waveform analysis, blood-gas trends, and hemodynamic monitoring can improve gas exchange, facilitate secretion clearance, and support ongoing oncological or interventional procedures [29]. Mobile, 5G-connected respiratory units enhance this timeliness by enabling real-time parameter adjustment, remote supervision by intensivists, and seamless integration with hospital-based care systems, thereby ensuring that time-sensitive respiratory support is delivered as early and effectively as possible [30].

3. Evolution of Pre-Hospital and Mobile Respiratory Care

The evolution of pre-hospital and mobile respiratory care has transformed simple transport vehicles into sophisticated, ventilator-equipped platforms that support ICU-grade respiratory management outside the hospital. This trajectory from basic ambulances to ICU-equipped mobile units, augmented by tele-medicine and 5G connectivity enables real-time, expert-guided care for lung cancer patients experiencing acute respiratory crises [31].

3.1. From Basic Ambulances to ICU-Equipped Mobile Units

A useful metric for tracking the functional maturity of pre-hospital units is the intensive-care capability index C_{ICU}, which reflects how closely ambulance hardware matches ICU standards

$$C_{\mathrm{ICU}} = \frac{N_{\mathrm{vent}}+N_{\mathrm{mon}}+N_{\mathrm{inv}}}{N_{\mathrm{ref}}} \quad (1)$$

where N_{vent} is the number of advanced ventilator functions supported, N_{mon} is the number of integrated monitoring parameters (e.g., SpO_2, $EtCO_2$, ECG), N_{inv} counts invasive-care capabilities (e.g., IO access, advanced airway tools), and N_{ref} is the reference count of full-ICU-equivalent features [32]. Higher values of C_{ICU} indicate a transition toward a true mobile ICU, particularly relevant for lung cancer patients needing on-the-move ventilatory support.

3.2. Role of Tele-Medicine and Remote Monitoring in Emergency Settings

To quantify the impact of remote supervision, a tele-medicine oversight index T_{ov} can express the degree of real-time expert involvement in pre-hospital care

$$T_{\mathrm{ov}} = \frac{t_{\mathrm{remote}}}{t_{\mathrm{total}}} \quad (2)$$

where t_{remote} is the time during which a remote intensivist or pulmonologist is actively engaged via video, waveform review, or parameter adjustment, and t_{total} is the total duration of the emergency-care episode from crisis onset to hospital handover. Increasing T_{ov} reflects greater integration of tele-medicine into emergency workflows, improving quality and safety in managing acute respiratory failure in lung cancer [33].

3.3. Integration of 5G Networks Into Mobile Critical-Care Platforms

The communication effectiveness of 5G-integrated mobile units can be captured by a network-readiness index N_{ready}

$$N_{\text{ready}} = \lambda_{\text{lat}} \cdot L_{\text{norm}} + \lambda_{\text{bw}} \cdot B_{\text{norm}} + \lambda_{\text{sec}} \cdot S_{\text{sec}} \quad (3)$$

where $L_{\text{norm}}$is normalized end-to-end latency (inverted so lower latency gives higher score), $B_{\text{norm}}$is normalized bandwidth utilization for ventilatory and physiological data, S_{sec}reflects security and reliability metrics (e.g., encryption coverage, packet-loss rate), and $\lambda_{\text{lat}}, \lambda_{\text{bw}}, \lambda_{\text{sec}}$ are empirically chosen weights [34]. A high N_{ready}indicates that 5G connectivity is sufficiently robust and low-latency to support real-time remote ventilator control and continuous monitoring in mobile critical-care platforms for lung cancer emergencies.

4. System Architecture of 5G-Connected Mobile Respiratory Units

The system architecture of a 5G-connected mobile respiratory unit integrates portable, ICU-grade respiratory hardware with a multi-layer communication and computing infrastructure to support real-time, remote-supervised ventilation during acute respiratory crises in lung cancer [35]. At the core lies on-board ventilators and monitors these feed data into a 5G-enabled communication stack, edge-computing nodes, and a cloud-based tele-ICU layer that hosts dashboards and control interfaces for remote clinicians. This architecture ensures continuous, secure, and low-latency respiratory support from the point of crisis through to hospital admission [36].

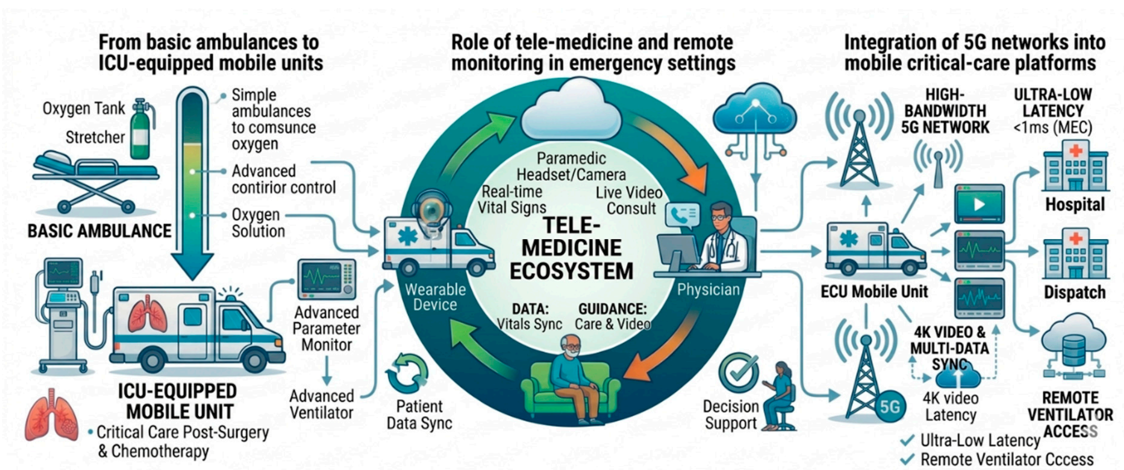

Figure 1. Evolution of Mobile Respiratory Care.

4.1. On-Board Respiratory Hardware: Ventilators, Interfaces, and Monitors

The on-board hardware includes a compact, multi-mode ventilator supporting invasive and non-invasive ventilation, along with endotracheal tubes, mask interfaces, high-flow nasal cannula, and integrated suction systems [37]. Vital-sign monitors capture SpO_2, $EtCO_2$, respiratory rate, airway pressures, flow-volume loops, and ECG, while backup oxygen and battery packs ensure uninterrupted operation. In lung cancer patients, this hardware must support rapid mode switching and precise parameter tuning (PEEP, tidal volume, FiO_2) to respond to dynamic airway and pleural pathology [38]. A hardware-capability index can be expressed as

$$H_{\text{cap}} = \frac{N_{\text{mode}} + N_{\text{param}} + N_{\text{safe}}}{N_{\text{ref}}} \quad (4)$$

where $N_{\text{mode}}$is supported ventilation modes, N_{param}counts adjustable parameters, $N_{\text{safe}}$is safety-critical features (alarms, auto-PEEP control, backup-ventilation), and N_{ref} is a reference ICU-ventilator baseline [39]. Higher H_{cap}indicates greater on-board flexibility for managing acute crises in advanced lung cancer.

4.2. 5G-Enabled Communication Stack and Edge-Computing Nodes

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The communication stack comprises a 5G modem, protocol converters, and an edge-computing node that preprocesses ventilator and physiological data before transmission [40]. The modem connects to 5G NR, using network slicing and QoS policies to prioritize low-latency ventilatory traffic over less critical data. The edge node compresses streams, filters artifacts, and executes lightweight AI models while maintaining local buffers for gap-tolerant operation when connectivity degrades [41]. A communication-efficiency metric can be formulated as

$$C_{\mathrm{eff}} = \xi_{\mathrm{lat}} \cdot L_{\mathrm{inv}} + \xi_{\mathrm{rel}} \cdot R_{\mathrm{rel}} + \xi_{\mathrm{sec}} \cdot S_{\mathrm{sec}} \quad (5)$$

where $L_{\mathrm{inv}}$is the inverse of end-to-end latency, R_{rel}reflects packet-delivery reliability, S_{sec} captures security strength (encryption, authentication), and $\xi_{\mathrm{lat}}, \xi_{\mathrm{rel}}, \xi_{\mathrm{sec}}$are empirically tuned weights. High C_{eff}values indicate that the communication stack can sustain real-time remote supervision even under high-mobility conditions [42].

4.3. Cloud-Based tele-ICU Dashboards and Control Interfaces

The cloud layer hosts tele-ICU dashboards that aggregate ventilator waveforms, physiological trends, and patient status from multiple mobile units and hospital ICUs. Remote clinicians use role-based control interfaces to adjust tidal volume, PEEP, FiO_2, or pressure support, with every command logged for audit and safety [43]. The cloud also supports retrospective analysis and machine-learning models for early-exacerbation prediction. An interoperability-and-usability score for the tele-ICU system can be defined as

$$I_{\mathrm{UI}} = \mu_{\mathrm{vis}} \cdot V_{\mathrm{vis}} + \mu_{\mathrm{resp}} \cdot R_{\mathrm{resp}} + \mu_{\mathrm{audit}} \cdot A_{\mathrm{audit}} \quad (6)$$

where V_{vis}measures dashboard clarity and visualization quality, R_{resp}reflects interface response time to user actions, A_{audit} is completeness of audit-log recording, and $\mu_{\mathrm{vis}}, \mu_{\mathrm{resp}}, \mu_{\mathrm{audit}}$ are empirical weights. By optimizing I_{UI}, the cloud-based tele-ICU layer ensures that remote intensivists can manage lung cancer patients safely and efficiently despite physical distance from the mobile unit [44].

5. 5G-Enabled Connectivity and Real-Time Monitoring

5G-enabled connectivity is the backbone of real-time monitoring in mobile respiratory units, ensuring that ventilatory data, physiological signals, and video feeds reach remote clinicians with minimal delay and maximum reliability. This layer supports continuous, low-latency interaction between the mobile unit and the tele-ICU, enabling timely parameter adjustments and rapid response to acute respiratory deterioration in lung cancer patients [45].

5.1. Ultra-Low-Latency and High-Bandwidth Requirements for Ventilatory Data

To characterize the suitability of the network for ventilatory control, a latency-bandwidth readiness index L_{BR}can be defined as

$$L_{\mathrm{BR}} = \frac{1}{\tau} \cdot \min\left(\frac{B}{B_{\mathrm{min}}}, 1\right) \quad (7)$$

where $\tau$is end-to-end latency (lower is better), $B$is available bandwidth, and $B_{\mathrm{min}}$is the minimum bandwidth required to stream ventilator waveforms and vital signs without degradation [46]. A higher L_{BR}indicates that 5G connectivity can support real-time ventilator control and waveform-based decision-making during acute respiratory crises in lung cancer.

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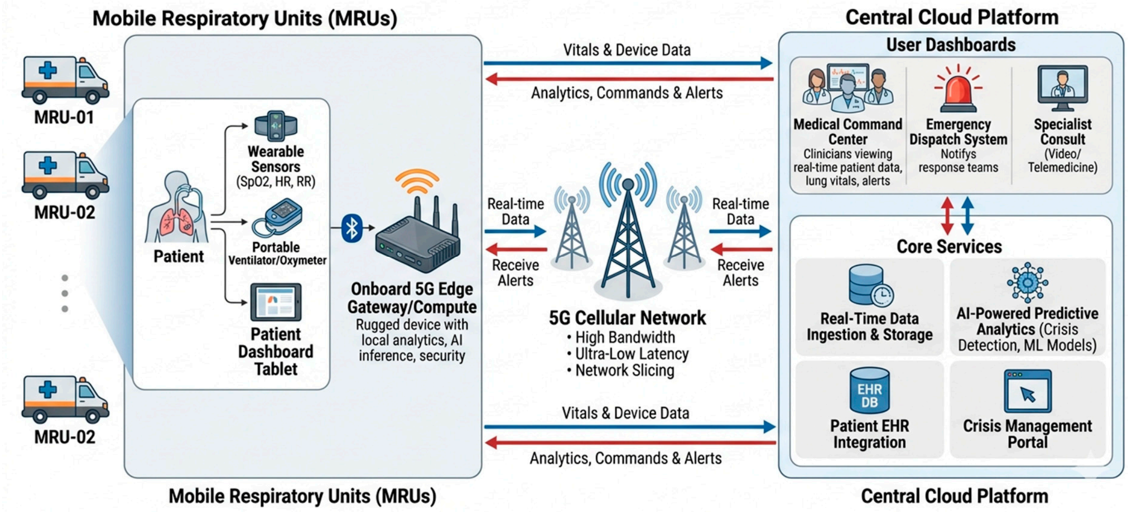

Figure 2. 5G Connected MRUs for Acute Crisis Management in Lung Cancer Patients.

5.2. Streaming of Physiological Signals, Waveforms, and Video Feeds

The quality of multimodal streaming can be captured by a streaming fidelity index F_{stream}, which balances temporal resolution, compression distortion, and synchronization across channels

$$F_{\text{stream}} = \omega_{\text{res}} \cdot R_{\text{res}} + \omega_{\text{lat}} \cdot L_{\text{sync}} + \omega_{\text{drop}} \cdot (1 - D_{\text{drop}}) \quad (8)$$

where R_{res} is temporal resolution of sampled signals, L_{sync} reflects synchronization error between ventilator waveforms and physiological data, D_{drop} is the packet-loss rate, and $\omega_{\text{res}}, \omega_{\text{lat}}, \omega_{\text{drop}}$ are empirically tuned weights [47]. A high F_{stream} ensures that remote clinicians perceive accurate, temporally aligned physiological and ventilatory information for lung cancer patients during transport.

5.3. Redundancy, Failover, and Network-Security Mechanisms

Network resilience and security can be summarized by a reliability-security index R_{sec}

$$R_{\text{sec}} = \nu_{\text{red}} \cdot R_{\text{red}} + \nu_{\text{fail}} \cdot F_{\text{fail}} + \nu_{\text{crypt}} \cdot C_{\text{crypt}} \quad (9)$$

where R_{red} is the degree of redundant network paths (e.g., 5G/4G/Wi-Fi), F_{fail} measures the effectiveness of automatic failover without data loss, C_{crypt} captures encryption and access-control strength, and $\nu_{\text{red}}, \nu_{\text{fail}}, \nu_{\text{crypt}}$ are weighting coefficients [48]. A high R_{sec} indicates that the 5G-enabled system remains dependable and secure even under network disruptions or cybersecurity threats during acute respiratory management in lung cancer.

6. Clinical Workflow in Acute Crisis Management

The clinical workflow of 5G-connected mobile respiratory units spans from early crisis detection through in-transit ventilatory support to structured handover in the in-hospital ICU. This end-to-end pathway is designed to compress the time-to-intervention, maintain respiratory stability, and preserve continuity of care for lung cancer patients experiencing acute respiratory failure [49].

6.1. Triggering Deployment: Remote Triage and Early Warning from Home or Clinic

To express the responsiveness of early-warning systems, a deployment readiness index D_{ready} can be defined as

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$$D_{\text{ready}} = \frac{T_{\text{early}} - T_{\text{delay}}}{T_{\text{early}}} \quad (10)$$

where T_{early} is the time window between the first detectable sign of deterioration (e.g., falling SpO_2, rising dyspnoea score) and clinical crisis, and T_{delay} is the time taken to trigger and dispatch the mobile unit after the alert is generated [50]. A higher D_{ready} indicates that remote-triage and early-warning mechanisms can initiate timely deployment before irreversible decompensation occurs in lung cancer patients.

6.2. In-Transit Interventions and Remote Ventilator Parameter Adjustment

The effectiveness of in-transit care can be captured by an intervention-quality index Q_{int}, which reflects how well remote-adjusted ventilator settings align with physiological targets:

$$Q_{\text{int}} = \eta_{\text{stab}} \cdot S_{\text{stab}} + \eta_{\text{resp}} \cdot R_{\text{resp}} - \eta_{\text{risk}} \cdot V_{\text{risk}} \quad (11)$$

where S_{stab} is the degree of respiratory-parameter stability (e.g., constant SpO_2, controlled airway pressures), R_{resp} is the responsiveness of remote clinicians to adverse trends, V_{risk} is the incidence of high-risk ventilator configurations, and $\eta_{\text{stab}}, \eta_{\text{resp}}, \eta_{\text{risk}}$ are empirically chosen weights. A high Q_{int} indicates that real-time remote ventilator adjustment during transport safely optimizes gas exchange and minimizes lung-injury risk in lung cancer crises [51].

6.3. Handover Protocols from Mobile Unit to In-Hospital ICU

The quality of handover can be summarized by a handover-continuity index H_{cont}, which measures how consistently critical information is preserved across the transition

$$H_{\text{cont}} = \frac{I_{\text{shared}} + M_{\text{matched}}}{I_{\text{total}}} \quad (12)$$

where I_{shared} is the number of ventilator and physiological parameters successfully transmitted to the ICU EHR before arrival, M_{matched} counts the number of key parameters that are correctly interpreted and retained in ICU settings, and I_{total} is the total number of critical parameters recorded in the mobile unit [52]. A high H_{cont} indicates that handover protocols ensure minimal information loss and support smooth transition of respiratory care for lung cancer patients from the mobile unit into the in-hospital ICU.

7. Safety, Usability, and Interoperability

Ensuring safety, usability, and interoperability in 5G-connected mobile respiratory units is essential for reliable acute respiratory crisis management in lung cancer. These attributes must be explicitly modelled and optimized to guarantee that ventilatory hardware remains fail-safe, interfaces are intuitive for diverse users, and data can flow seamlessly into hospital information systems [53].

7.1. Safety-Critical Design and Fail-Safe Modes for Ventilatory Hardware

A safety-integrity index S_{int} can express how robust the ventilatory hardware is in a safety-critical context

$$S_{\text{int}} = \frac{N_{\text{safe}} + N_{\text{fail}}}{N_{\text{haz}}} \quad (13)$$

where N_{safe} is the number of built-in safety features (e.g., high-pressure alarms, auto-PEEP control, low-tidal-volume defaults), N_{fail} counts the number of tested fail-safe modes (e.g., backup ventilation, pressure-limiting algorithms), and N_{haz} is the total number of identified hazard scenarios in lung-cancer-related respiratory failure [54]. A higher S_{int} indicates stronger safety-critical design, reducing the likelihood of harm during acute crises.

7.2. Usability for Paramedics, Respiratory Therapists, and Remote Clinicians

A clinical-usability index U_{clin} can quantify how well the system supports users across roles

$$U_{\text{clin}} = \alpha_{\text{task}} \cdot T_{\text{success}} + \alpha_{\text{load}} \cdot (1 - C_{\text{load}}) + \alpha_{\text{error}} \cdot (1 - E_{\text{rate}}) \quad (14)$$

where T_{success} is the proportion of critical tasks completed correctly, C_{load} reflects perceived cognitive load, E_{rate} is the operator-error rate, and $\alpha_{\text{task}}, \alpha_{\text{load}}, \alpha_{\text{error}}$ are empirically tuned weights. A high U_{clin} indicates that paramedics, respiratory therapists, and remote clinicians can operate the unit efficiently and safely under time-pressured emergency conditions [55].

7.3. Interoperability with Hospital EHRs, PACS, and Clinical-Decision Systems

An **interoperability coverage index** I_{cov} can express how comprehensively the mobile unit integrates with hospital systems

$$I_{\text{cov}} = \frac{C_{\text{EHR}} + C_{\text{PACS}} + C_{\text{CDS}}}{C_{\max}} \quad (15)$$

where C_{EHR} is the fraction of ventilatory and physiological data successfully mapped into the electronic health record, C_{PACS} is the fraction of imaging-related metadata consistently shared with the picture-archiving system, C_{CDS} is the degree of integration with clinical-decision support tools (e.g., risk-prediction models), and $C_{\max}$ is the maximum achievable coverage score [56]. A high I_{cov} indicates that 5G-connected mobile respiratory units function as tightly coupled nodes within the broader lung-cancer care ecosystem, from pre-hospital crisis management to in-hospital ICU care [57].

8. Clinical Outcomes and Patient-Reported Experience

5G-connected mobile respiratory units have the potential to improve both objective clinical outcomes and subjective patient-reported experiences in lung cancer patients experiencing acute respiratory crises [58]. By enabling earlier, expert-guided ventilatory support during transport or in-field deployment, these platforms can reduce delays in intubation and ventilatory initiation, lower complication rates, and shorten ICU stays. At the same time, patients and caregivers may perceive enhanced safety and confidence when they know that intensive-care-level monitoring and remote-specialist oversight accompany the mobile unit. Quantitative metrics and subjective feedback together can be used to evaluate the real-world impact of these systems [59].

8.1. Reduction in Time-To-Intubation and Time-To-Ventilatory Support

Early ventilatory support is a key determinant of outcome in acute respiratory failure, and 5G-connected mobile units can significantly reduce the time from crisis recognition to effective ventilation [60]. A time-to-intervention index T_{interv} can express this improvement

$$T_{\text{interv}} = \frac{T_{\text{conventional}} - T_{\text{5G}}}{T_{\text{conventional}}} \quad (16)$$

where $T_{\text{conventional}}$ is the average time-to-intubation or time-to-ventilatory-support using standard ambulances, and T_{5G} is the corresponding time when a 5G-connected mobile unit is deployed. A higher positive value of T_{interv} indicates greater time saving, which correlates with better oxygenation, reduced secondary organ injury, and improved overall prognosis in lung cancer patients [61].

8.2. Impact on Mortality, Intubation-Related Complications, and ICU Length of Stay

The clinical benefit of 5G-connected units can also be captured through a composite outcome index O_{comp} that reflects changes in mortality, complications, and resource utilization

$$O_{\text{comp}} = \omega_{\text{mort}} \cdot (1 - R_{\text{mortality}}) + \omega_{\text{comp}} \cdot (1 - R_{\text{comp}}) + \omega_{\text{LOS}} \cdot \left(1 - \frac{L_{\text{5G}}}{L_{\text{base}}}\right) \quad (17)$$

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where $R_{\text{mortality}}$ is the relative mortality rate, R_{comp} is the relative rate of intubation-related complications (e.g., ventilator-associated pneumonia, barotrauma), $L_{\text{5G}}$is the average ICU length of stay with 5G-support, $L_{\text{base}}$is the baseline length of stay, and $\omega_{\text{mort}}, \omega_{\text{comp}}, \omega_{\text{LOS}}$are empirically chosen weights. A higher O_{comp}value indicates that 5G-connected mobile units not only save lives but also reduce complications and optimize ICU resource use in lung cancer cohorts [62].

8.3. Perceived Safety and Confidence Among Patients and Caregivers

Patient- and caregiver-perceived safety and confidence are critical components of the overall value of 5G-connected mobile units [63]. A perceived-safety score P_{safety}can be derived from survey-based responses and qualitative feedback

$$P_{\text{safety}} = \frac{1}{N}\sum_{i=1}^{N} \left(\frac{S_i + C_i}{2}\right) \quad (18)$$

where S_i and C_i are the safety and confidence scores (e.g., on a 5-point Likert scale) reported by the i-th patient or caregiver, and $N$is the total number of respondents [64]. A higher P_{safety} indicates that patients and caregivers feel more secure knowing that remote intensivists are monitoring ventilator settings and that the unit is equipped with advanced safety features, enhancing trust and adherence to the care pathway [65].

9. Implementation Challenges and Health-System Integration

Deploying 5G-connected mobile respiratory units into routine lung-cancer care requires overcoming economic, educational, and organizational barriers while embedding these platforms into existing emergency and oncology pathways [66]. Cost, reimbursement uncertainty, and workforce readiness are key constraints, but structured deployment models, standardized training, and deliberate integration into regional care networks can mitigate these challenges and support sustainable adoption [67].

9.1. Cost, Reimbursement, and Deployment Models for 5G-Mobile Units

A central challenge is the capital and operational cost of 5G-mobile units, including ventilators, sensors, 5G modems, cloud infrastructure, and maintenance [68]. A cost-effectiveness readiness index C_{ready}can express the financial viability of deployment

$$C_{\text{ready}} = \frac{B_{\text{saved}} - C_{\text{unit}}}{C_{\text{unit}}} \quad (19)$$

where $B_{\text{saved}}$is the estimated annual benefit from reduced ICU days, fewer complications, and lower readmission rates, and $C_{\text{unit}}$is the total annualized cost per mobile unit [69]. A positive C_{ready}suggests that investment in 5G-units can be justified, especially when integrated with targeted reimbursement models that reward early intervention and outcome-improvement in acute respiratory crises [70].

Table 1. Stakeholder roles in 5G-mobile respiratory-care pathways.

Stakeholder group	Primary responsibilities
Paramedics and EMTs	Rapid deployment, basic life support, initial ventilation setup
On-board respiratory therapists	Advanced airway management, ventilator optimization
Remote intensivists (tele-ICU)	Real-time parameter adjustment, escalation guidance
Hospital ICU teams	Handover, definitive care, integration with oncology treatment

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5G-network and IT engineers	Ensure connectivity, security, edge-cloud integration
Health-policy and reimbursement bodies	Establish coverage models, regulatory and data-privacy standards

9.2. Training for Paramedics, Respiratory Staff, and tele-ICU Teams

Widespread deployment depends on consistent, high-quality training for paramedics, respiratory therapists, and tele-ICU clinicians [71]. A training-proficiency index T_{prof} can capture how well teams master mobile-unit workflows

$$T_{\text{prof}} = \frac{1}{N}\sum_{i=1}^{N}\left(P_{\text{sim},i} + P_{\text{real},i}\right) \quad (20)$$

where $P_{\text{sim},i}$ is the performance score in simulation-based drills (e.g., correct ventilator setup and parameter adjustment) and $P_{\text{real},i}$ is the performance in real-world deployments, averaged over N trainees [72]. Higher T_{prof} indicates that structured education, scenario-based modules, and repetitive practice have successfully prepared multi-disciplinary teams to use 5G-connected units safely and confidently in lung cancer emergencies [73].

9.3. Integration Into Regional Emergency-Care Networks and Lung-Cancer Pathways

For these units to have maximum impact, they must be formally integrated into regional emergency-care networks and lung-cancer-specific clinical pathways [74]. A pathway-integration index P_{integ} can quantify the degree of alignment with existing systems

$$P_{\text{integ}} = \frac{M_{\text{dispatch}} + M_{\text{handover}} + M_{\text{onc}}}{M_{\text{max}}} \quad (21)$$

where M_{dispatch} measures how well early-warning alerts trigger mobile-unit deployment, M_{handover} reflects the smoothness of handover into ICU and oncology workflows, M_{onc} captures the degree to which 5G-unit data are used in lung-cancer treatment planning, and M_{max} is the maximum possible integration score [75]. A high P_{integ} indicates that 5G-connected mobile respiratory units function as a coordinated element of regional emergency response and comprehensive lung-cancer care rather than an isolated technology.

10. Future Directions and Policy Implications

The integration of 5G-connected mobile respiratory units into lung-cancer care is poised to evolve further with smarter algorithms, broader deployment, and stronger governance frameworks [76]. Next-generation units will likely incorporate AI-driven decision support, extend care to rural and low-resource regions, and operate within robust regulatory and privacy-protection ecosystems [77]. Together, these directions will shape how acute respiratory crises are managed along the intensive-care-to-home continuum, ensuring equitable, safe, and scalable 5G-enabled respiratory care [78].

10.1. Next-Generation Mobile Units with AI-driven Decision Support

Future mobile units will increasingly embed AI models that analyse ventilator-derived data, physiological signals, and patient-history profiles to anticipate respiratory deterioration, recommend parameter adjustments, and personalize ventilatory strategies in real time [79]. These systems may combine supervised learning for early-exacerbation detection with reinforcement-learning-based controllers that adapt to changing lung-compliance and airway-resistance patterns [80]. A decision-support quality index D_{DS} can express how well these AI components assist clinicians

$$D_{\text{DS}} = \frac{A_{\text{pred}} + R_{\text{corr}}}{2} \quad (22)$$

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where A_{pred} is the area-under-curve (AUC-style) accuracy of early-deterioration prediction and R_{corr} is the proportion of AI-recommended ventilator adjustments that are clinically appropriate and actually adopted by remote intensivists [81]. Higher D_{DS} indicates that AI-driven support enhances safety and efficiency without undermining clinician autonomy in lung cancer emergencies [82].

10.2. Expansion to Rural, Underserved, and Low-Resource Settings

Widespread deployment of 5G-connected mobile units will depend on their adaptability to rural, underserved, and low-resource environments. Future strategies may include modular, lower-cost ventilator modules, energy-efficient edge-computing hardware, and satellite-augmented 5G-type links to compensate for patchy terrestrial coverage [83]. A coverage-equity index E_{cov} can capture the degree to which these platforms reach vulnerable populations

$$E_{\text{cov}} = \frac{C_{\text{rural}} + C_{\text{urban}}}{C_{\text{total}}} \quad (23)$$

where C_{rural} is the share of acute-crisis responses covered in rural areas, C_{urban} is the share in urban centres, and C_{total} is the total number of eligible events [84]. A high E_{cov} reflects equitable geographic distribution, ensuring that lung-cancer patients in remote or resource-limited areas benefit from the same level of 5G-enabled respiratory support as those in well-equipped urban hospitals [85].

10.3. Regulatory, Privacy, and Policy Frameworks for 5G-Enabled Respiratory Care

Regulatory, privacy, and policy frameworks will be critical to ensuring the safe, ethical, and interoperable use of 5G-connected mobile respiratory units [86]. These frameworks must address medical-device classification, data-privacy compliance (e.g., HIPAA, GDPR), cybersecurity standards, and liability in remote-ventilation scenarios [87]. A policy-compliance index P_{comp} can summarize alignment with key requirements

$$P_{\text{comp}} = \frac{L_{\text{med}} + L_{\text{privacy}} + L_{\text{sec}}}{L_{\text{max}}} \quad (24)$$

where L_{med} is the degree of adherence to medical-device regulations, L_{privacy} reflects compliance with data-protection laws, L_{sec} captures cybersecurity and risk-management maturity, and L_{max} is the maximum possible score [88]. A high P_{comp} signals that 5G-enabled respiratory platforms operate within a robust governance structure, fostering stakeholder trust and enabling sustainable, large-scale adoption in lung-cancer care ecosystems [89].

5G-connected mobile respiratory units represent a transformative step in acute respiratory crisis management for lung cancer patients, extending intensive-care-grade ventilatory support from the point of crisis through to hospital admission [90]. By integrating portable ventilators, real-time physiological monitoring, and ultra-low-latency 5G connectivity, these units enable remote intensivists to guide ventilator parameter adjustments, detect early deterioration, and coordinate interventions while the patient is in transit or in-field. Evidence suggests that such platforms can reduce time-to-ventilatory support, lower mortality and complication rates, and shorten ICU length of stay, while also improving perceived safety and confidence among patients and caregivers [91].

However, successful implementation requires overcoming challenges related to cost, reimbursement, workforce training, and seamless integration into regional emergency networks and lung-cancer care pathways [92]. Future directions will likely involve AI-driven decision support, expansion into rural and low-resource settings, and robust regulatory and privacy frameworks that ensure secure, interoperable, and equitable use of 5G-enabled respiratory care [93]. As these technologies mature, 5G-connected mobile respiratory units are poised to become a cornerstone of integrated, data-driven acute and chronic respiratory management in advanced lung cancer, bridging the gap between intensive care and home-based care with unprecedented speed, precision, and patient-centred outcomes.

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11. Conclusions

5G-connected mobile respiratory units represent a transformative step in acute respiratory crisis management for lung cancer patients, extending intensive-care-grade ventilatory support from the point of crisis through to hospital admission. By integrating portable ventilators, real-time physiological monitoring, and ultra-low-latency 5G connectivity, these units enable remote intensivists to guide ventilator parameter adjustments, detect early deterioration, and coordinate interventions while the patient is in transit or in-field. Evidence suggests that such platforms can reduce time-to-ventilatory support, lower mortality and complication rates, and shorten ICU length of stay, while also improving perceived safety and confidence among patients and caregivers.

However, successful implementation requires overcoming challenges related to cost, reimbursement, workforce training, and seamless integration into regional emergency networks and lung-cancer care pathways. Future directions will likely involve AI-driven decision support, expansion into rural and low-resource settings, and robust regulatory and privacy frameworks that ensure secure, interoperable, and equitable use of 5G-enabled respiratory care. As these technologies mature, 5G-connected mobile respiratory units are poised to become a cornerstone of integrated, data-driven acute and chronic respiratory management in advanced lung cancer, bridging the gap between intensive care and home-based care with unprecedented speed, precision, and patient-centred outcomes.

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