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Karthick R *

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Smart Wearable Inhalers for Chronic Respiratory Care in Advanced Lung Cancer

Karthick R

Department of Computer Science and Engineering, K.L.N. College of Engineering, Pottapalyam 630 612, India; karthickkiwi@gmail.com

Abstract

Wearable smart inhalers represent a transformative approach to chronic respiratory management in advanced lung cancer, integrating sensor-based monitoring, real-time connectivity, and patient-centric feedback loops. These devices track inhalation technique, dosing frequency, and timing, then transmit encrypted data to cloud-based platforms for analysis by clinicians and AI-driven algorithms. For advanced-stage lung cancer patients, this enables continuous surveillance of bronchospasm, dyspnoea, and medication adherence outside the intensive care setting, thereby reducing uncontrolled exacerbations and unplanned hospitalizations. Smart inhalers also support tele-follow-ups and personalized adjustment of bronchodilator or palliative regimens based on individual patterns of use and symptom burden. When embedded within an end-to-end care pathway from intensive care discharge to home care these wearables facilitate seamless transitions, improve self-management, and empower multidisciplinary teams with objective, longitudinal respiratory data. This article explores design principles, clinical integration, and emerging digital-health frameworks that position wearable smart inhalers as a cornerstone of modern, technology-driven chronic respiratory support in advanced lung cancer.

Keywords: wearable smart inhalers; chronic respiratory management; digital health platforms; remote monitoring; AI-assisted adherence; home-based care

1. Introduction

Chronic respiratory symptoms in advanced lung cancer significantly impair quality of life and increase the risk of acute exacerbations, emergency visits, and hospital readmissions. Many patients experience persistent dyspnoea, wheezing, cough, and fatigue due to tumour-related airway obstruction, treatment-induced lung injury, and overlapping obstructive lung diseases. Managing these symptoms across the continuum from intensive care to home care poses substantial clinical and logistical challenges [1]. Recent advances in digital health, particularly wearable smart inhalers, offer a promising pathway to continuous, objective monitoring of inhaler technique, adherence, and symptom patterns outside the hospital setting. This paper discusses how such technologies can bridge gaps in care transitions, support individualized respiratory management, and enhance patient-centred outcomes in advanced lung cancer [2].

1.1. Burden of Chronic Respiratory Symptoms in Advanced Lung Cancer

In advanced lung cancer, chronic respiratory symptoms arise from both the primary tumour and the effects of systemic therapies, including chemotherapy, immunotherapy, and radiotherapy. Patients frequently report moderate to severe dyspnoea, which is often refractory to standard bronchodilators and correlates poorly with spirometry measures. Persistent cough, wheezing, and chest tightness further contribute to functional decline, sleep disturbance, and emotional distress [3]. These symptoms are compounded by comorbidities such as chronic obstructive pulmonary disease (COPD) or interstitial lung disease, which are common in this population.

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The subjective nature of symptom reporting and episodic clinical assessment in routine practice limit the ability to detect subtle changes or early deterioration. Consequently, acute exacerbations are often recognized at an advanced stage, when hospitalization becomes inevitable. Effective chronic respiratory management in advanced lung cancer therefore requires not only pharmacological optimization but also continuous, objective surveillance that can capture day-to-day variability and accelerate timely intervention [4].

1.2. Challenges in Transitioning from Intensive Care to Home Care

Transitioning patients with advanced lung cancer from intensive care to home care involves discontinuity of monitoring, fragmentation of information, and reduced access to specialized respiratory support. During intensive care, patients benefit from continuous physiological monitoring, frequent clinical assessments, and immediate access to invasive and non-invasive ventilatory support [5]. Once discharged, many patients rely on intermittent clinic visits and self-managed inhaler therapy, often without structured follow-up or real-time feedback. This transition period is particularly vulnerable, as residual respiratory compromise, fatigue, and weakened cough reflex may predispose individuals to recurrent infections or decompensation.

Caregivers and outpatient clinicians may lack timely, objective data on inhaler use, adherence, or symptom evolution, leading to delayed recognition of impending exacerbations [6]. Moreover, advanced-stage patients often face mobility limitations, transportation barriers, and psychosocial stressors, which further complicate adherence to complex treatment regimens. Developing a seamless, technology-enabled care pathway that extends intensive-care-grade monitoring into the home environment is therefore critical to sustaining respiratory stability, reducing unplanned admissions, and preserving functional independence [7].

1.3. Rationale for Wearable Smart Inhalers in Chronic Respiratory Management

Wearable smart inhalers provide a natural technological bridge between intensive-care-level respiratory surveillance and long-term home-based management in advanced lung cancer. These devices integrate miniaturized sensors, wireless connectivity, and embedded analytics to capture inhalation flow profiles, actuation timing, and adherence patterns, then transmit encrypted data to cloud-based platforms accessible to clinicians and caregivers [8]. By continuously monitoring how and when patients use their inhalers, smart inhalers can detect suboptimal technique, missed doses, or erratic usage that may otherwise go unnoticed during routine clinic consultations. This objective feedback can guide personalized dose adjustments, technique retraining, and targeted education, thereby enhance therapeutic effectiveness and reduce symptom burden. For patients transitioning from intensive care to home care, wearable smart inhalers can function as a remote monitoring node, enabling early detection of worsening respiratory patterns and facilitating timely tele-consultations or home-care interventions [9].

2. Pathophysiology and Clinical Need

In advanced lung cancer, respiratory dysfunction results from a combination of tumour-mediated airway obstruction, treatment-related lung injury, and intrinsic lung-tissue remodelling [10]. Chronic bronchospasm, persistent dyspnoea, and intractable cough are among the most disabling symptoms, often coexisting with systemic fatigue, cachexia, and psychological distress. These manifestations not only reduce physical performance but also compromise nutrition, sleep, and social engagement, thereby worsening overall prognosis and quality of life [11]. Conventional inhaler-based therapies, although widely used, frequently fail to address the full complexity of these symptoms, especially in the context of multimodal oncological treatment and comorbid obstructive lung diseases. Understanding the underlying pathophysiology and unmet clinical needs is therefore essential to justify the integration of more advanced, technology-enabled solutions such as wearable smart inhalers into chronic respiratory management [12].

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2.1. Chronic Bronchospasm, Dyspnoea, and Cough in Advanced Lung Cancer

Chronic bronchospasm in advanced lung cancer arises from tumour-induced airway narrowing, peri-bronchial inflammation, and mediators released by both malignant cells and the host immune response. Endobronchial lesions or perihilar masses can cause partial or intermittent obstruction, leading to dynamic airflow limitation and episodic wheezing, particularly during exertion or nocturnal periods [13]. Dyspnoea is often multifactorial, reflecting a combination of mechanical obstruction, reduced lung compliance, impaired gas exchange, and increased work of breathing.

In many patients, dyspnoea is disproportionate to spirometry decline, indicating a significant neuromechanical and affective component driven by anxiety and fear of breathlessness. Persistent cough may result from airway irritation, post-tussive bronchospasm, or the presence of mucus congestion in partially obstructed bronchi [14]. These symptoms are typically refractory to standard bronchodilators and may fluctuate unpredictably, making them difficult to manage in routine outpatient settings. Moreover, systemic therapies such as radiotherapy and certain systemic agents can further exacerbate airway hyperreactivity, leading to a vicious cycle of bronchospasm, dyspnoea, and cough that degrades functional status and increases the risk of acute decompensation [15].

2.2. Impact of Comorbid Obstructive Lung Diseases

A substantial proportion of patients with advanced lung cancer have pre-existing obstructive lung diseases, including chronic obstructive pulmonary disease (COPD) and asthma, which profoundly influence respiratory symptomatology and treatment response [16]. Smoking history, chronic inflammation, and structural remodelling characteristic of COPD coexist with tumour-related airway distortion, resulting in accelerated airflow limitation and heightened airway hyperresponsiveness [17]. Asthma-like features such as variable bronchoconstriction and reversibility may further complicate symptom attribution, as clinicians must distinguish between tumour-driven obstruction and exacerbations of underlying obstructive disease.

Comorbid conditions also increase the risk of treatment-related respiratory toxicity, including radiation-induced lung injury or immune-related pneumonitis, which can mimic or amplify obstructive symptoms [18]. The presence of obstructive lung diseases often necessitates higher-dose inhaled bronchodilators and corticosteroids, further burdening patients with complex regimens and increasing the likelihood of technique errors and non-adherence. From a clinical standpoint, overlapping pathophysiological mechanisms reduce the margin for error in inhaler use and make objective monitoring of inhaler performance crucial to prevent exacerbations and optimize long-term respiratory control [19].

2.3. Limitations of Conventional Inhaler-Based Therapy

Conventional inhaler-based therapy in advanced lung cancer relies primarily on handheld metered-dose inhalers (MDIs) or dry-powder inhalers (DPIs), which require coordinated inspiration, proper inhalation flow, and correct timing of actuation [20]. Many patients, particularly those with advanced disease, experience significant difficulty mastering these techniques due to fatigue, weakness, cognitive impairment, or fear of breathlessness [21]. Inconsistent inhaler use, suboptimal inspiratory effort, and missed doses are common, yet these factors are rarely captured in routine clinical practice, where assessment is typically based on subjective recall or intermittent spirometry. As a result, healthcare providers may overestimate adherence and incorrectly attribute persistent symptoms to disease progression rather than poor inhaler technique [22].

Dose-titration decisions are often made without objective data on real-world usage patterns, leading to either under- or over-treatment. Moreover, conventional inhalers lack integrated feedback mechanisms or connectivity, making them ill-suited for continuous monitoring across the intensive-care-to-home-care continuum. The absence of real-time data also hinders early detection of exacerbation precursors and limits opportunities for personalized, adaptive respiratory management. These limitations underscore the need for a more sophisticated, technology-enhanced

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inhaler platform that can provide objective, longitudinal insights into inhaler performance and symptom evolution in advanced lung cancer [23].

3. Evolution of Inhaler Technology

Inhaler technology has evolved from simple mechanical devices delivering fixed drug doses to intelligent, connected platforms that support data-driven, patient-centred respiratory care. This shift is particularly relevant for advanced lung cancer, where chronic respiratory symptoms and complex treatment regimens demand more precise, real-time monitoring than conventional inhalers can provide [24]. Smart connected inhalers integrate sensors, wireless communication, and analytics to capture inhaler use, technique, and related physiological or contextual data, enabling clinicians to move beyond episodic assessments toward continuous, objective management. In the context of chronic respiratory care across intensive care and home settings, this evolution supports earlier intervention, improved adherence, and personalized therapeutic strategies for patients with advanced lung cancer [25].

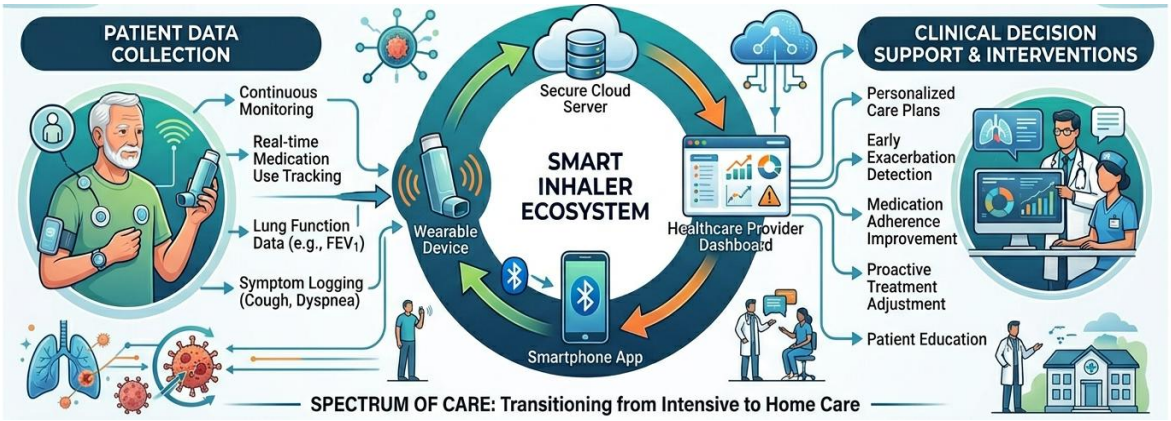

Figure 1. Acute And Chronic Respiratory Management in Advanced Lung Cancer Patients.

3.1. From Metered-Dose Inhalers to Smart Connected Devices

Metered-dose inhalers (MDIs) and dry-powder inhalers (DPIs) have long been the cornerstones of inhaled therapy for obstructive lung diseases, but they rely on manual technique and lack built-in feedback mechanisms [26]. In many patients with advanced lung cancer, factors such as fatigue, neuromuscular weakness, and anxiety further compromise the ability to achieve consistent, effective inhalation. Smart connected inhalers address these limitations by embedding miniature electronics directly on or within standard inhaler platforms, allowing automatic detection of actuation, inhalation timing, and flow profiles [27]. These devices typically communicate via Bluetooth or low-energy wireless protocols with a smartphone or central hub, transforming each inhaler use into a timestamped, structured data point that can be stored, analysed, and shared with clinicians.

A key quantitative expression of inhaler performance is the inhalation quality index Q, which can be formulated as

$$Q = \alpha \cdot v_{\max} + \beta \cdot T_{\text{in}} + \gamma \cdot D_{\text{missed}} \quad (1)$$

where $v_{\max}$ is peak inspiratory flow, T_{in} is inspiratory duration, D_{missed} is the fraction of missed doses, and α, β, γ are empirically tuned weights reflecting clinical priorities [28]. This index exemplifies how smart inhalers translate mechanical actions into a quantifiable metric for tracking inhaler technique and adherence over time, thereby supporting data-driven optimization of chronic respiratory management in advanced lung cancer.

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3.2. Role of Sensors, Connectivity, and Data Analytics

Smart inhalers leverage a suite of miniaturized sensors typically flow sensors, accelerometers, and temperature or humidity sensors to capture inhalation dynamics, device orientation, and environmental conditions during each actuation. Flow sensors characterize the shape and magnitude of the inspiratory waveform, enabling classification of acceptable versus suboptimal inhalation patterns [29]. Accelerometers help detect whether the device is properly primed and aligned, while contextual data such as time-of-day and ambient temperature can inform adherence models and trigger-based alerts. Once collected, these raw sensor readings are transmitted over Bluetooth or cellular-enabled gateways to cloud-based platforms, where they are stored in secure, interoperable databases compatible with electronic health-record systems [30].

From a data-science perspective, the observed inhaler-usage sequence can be modelled as a temporal series $X_t = \{x_1, x_2, \ldots, x_t\}$, where each x_i includes features such as dose timing, inhalation flow, and symptom annotation. A simple predictive model for adherence risk can be expressed as

$$P(\text{non-adherence} \mid X_t) = \sigma(\mathrm{w}^\top \mathrm{f}(X_t) + b) \tag{2}$$

where $\mathrm{f}(X_t)$is a feature vector extracted from the time-series inhaler data, w is a learned weight vector, $b$is a bias term, and $\sigma$is the sigmoid activation function [31]. This logistic-style formulation illustrates how smart-inhaler platforms can transform raw sensor data into clinically actionable risk scores, supporting early intervention and personalized respiratory-care pathways in advanced lung cancer.

3.3. Current Evidence from Asthma and COPD Cohorts

Clinical experience with smart inhalers largely derives from large asthma and COPD cohorts, where digital monitoring has demonstrated improvements in adherence, symptom control, and exacerbation rates [32]. Meta-analyses of electronic monitoring devices show that connected inhalers significantly increase the proportion of days with correct inhaler use and reduce gaps in dosing, particularly for maintenance therapies. In randomized trials, patients using smart inhalers with feedback apps and clinician dashboards tend to experience fewer moderate-to-severe exacerbations and report better asthma-related quality-of-life scores compared with standard care groups [33]. These findings suggest that continuous, objective inhaler monitoring can identify barriers to adherence such as poor technique, nighttime dosing errors, or fear of side effects and enable targeted education and regimen adjustments.

To express the relative benefit of smart-inhaler interventions, studies often compute the relative risk reduction (RRR) of exacerbations between intervention and control groups as

$$\mathrm{RRR} = 1 - \frac{\text{Exacerbation rate}_{\text{intervention}}}{\text{Exacerbation rate}_{\text{control}}} \tag{3}$$

where the exacerbation rate is usually defined as the number of exacerbations per patient-year of follow-up [34]. In representative trials, RRR values of 20–40% have been reported, indicating that smart-inhaler-based support can meaningfully reduce respiratory instability in obstructive lung diseases. For advanced lung cancer, these asthma and COPD data provide a methodological and clinical foundation, suggesting that similar digital platforms can enhance chronic respiratory management when adapted to the unique pathophysiology, symptom burden, and care-transition challenges of oncology patients [35].

4. Wearable Smart Inhalers, Design and Functionality

Wearable smart inhalers merge miniaturized hardware, wireless connectivity, and human-centred software into a unified platform for chronic respiratory management in advanced lung cancer [36]. These devices extend beyond simple drug delivery by embedding tensorized modules that capture inhalation dynamics, transmitting encrypted data to cloud platforms, and presenting

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actionable feedback to patients and clinicians [37]. The design must balance clinical precision, power efficiency, and ease of use, particularly for frail, elderly, or treatment-fatigued individuals. By integrating sensor-based technique analysis, secure connectivity, and intuitive interfaces, wearable smart inhalers enable continuous, objective monitoring of inhaler performance along the intensive-care-to-home care pathway [38].

Table 1. Comparison Of Inhaler Types and Features.

Feature / Device Type	Conventional MDI/DPI	Smart Inhaler (Basic)	Wearable Smart Inhaler (Advanced)
Dose delivery mechanism	Manual actuation	Manual actuation	Manual or sensor-guided actuation
Technique feedback	None	Simple LED/audio cue	Flow-based technique scoring
Connectivity	None	Bluetooth to smartphone	BLE + IoT/cloud integration
Adherence tracking	Subjective recall only	Daily usage logs	Time-stamped adherence index
Environmental/physio sensing	No	Limited (timestamp, location)	Integrated with wearables (SpO_2, RR)
AI-based decision support	No	Basic alerts	Personalized regimen suggestions
Suitable setting	Outpatient, home	Home, ambulatory care	ICU → home, chronic management

4.1. Sensor Modules for Inhalation Technique and Timing

Sensor modules in wearable smart inhalers typically include flow sensors, accelerometers, and pressure or temperature sensors to quantify inhalation effort, device orientation, and actuation timing [39]. Flow sensors characterize the inspiratory waveform, measuring peak inspiratory flow v_{peak}, inhalation duration T_{in}, and hold time T_{hold} to assess whether the patient achieves the minimum flow required for effective drug deposition [40]. Accelerometers detect whether the inhaler is shaken, primed, and held upright, while capacitive or resistive sensors can confirm proper mouthpiece sealing and detect exhalation before inhalation [41]. These measurements are time-stamped and aggregated into a per-dose inhalation profile that reflects real-world technique over days or weeks.

A compact technique-quality metric can be expressed as

$$Q_{\text{tech}} = \theta_1 \cdot \frac{v_{\text{peak}}}{v_{\text{min}}} + \theta_2 \cdot \frac{T_{\text{in}}}{T_{\text{ref}}} + \theta_3 \cdot \frac{T_{\text{hold}}}{T_{\text{hold,ref}}} \quad (4)$$

where v_{min}, T_{ref}, and $T_{\text{hold, ref}}$ are reference thresholds, and $\theta_1, \theta_2, \theta_3$ are weighting coefficients reflecting clinical priorities [42]. This formulation allows the device or backend system to classify each inhalation as "optimal," "acceptable," or "suboptimal," enabling targeted retraining and dose-regimen personalization.

4.2. Wireless Data Transmission and Cloud-Based Platforms

Once inhalation data are captured, they are transmitted via low-energy wireless protocols (e.g., Bluetooth Low Energy or BLE) to a smartphone, tablet, or dedicated gateway, which then forwards encrypted packets to cloud-based platforms. These platforms store longitudinal data in structured databases, often using RESTful APIs or FHIR-compatible interfaces to interoperate with electronic health-record (EHR) systems [43]. Cloud-hosted analytics engines preprocess raw sensor readings, extract features such as adherence rate, dosing frequency, and technique trends, and generate summary dashboards for clinicians. Role-based access control, end-to-end encryption, and audit logging ensure that sensitive respiratory data remain compliant with medical-device and privacy regulations [44].

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From a system-engineering perspective, the observed data stream can be modelled as a sequence of inhaler events $E_t = \{e_1, e_2, \ldots, e_t\}$, where each $e_i = (t_i, v_{\text{peak},i}, T_{\text{in},i}, \text{adherence}_i)$ [45]. The adherence ratio over a window $[t_0, t]$is then

$$A(t_0, t) = \frac{|\{e_i \in E_t | \text{dose}_i \text{ taken as scheduled}\}|}{\text{Total scheduled doses in } [t_0, t]} \quad (5)$$

which underpins adherence-based alerts and care-path recommendations [46]. This ratio, updated incrementally, supports real-time monitoring of chronic respiratory management in advanced lung cancer patients transitioning from intensive care to home care.

4.3. Real-Time Feedback and User-Interface Design for Patients

Effective user-interface design is critical for ensuring that wearable smart inhalers are usable by patients with advanced lung cancer, who may experience fatigue, cognitive load, and visual or manual limitations. Real-time feedback is typically delivered via smartphone apps or embedded LED/audible cues on the device itself, indicating whether an inhalation passively met target flow, duration, or timing thresholds [47]. Visual feedback may include color-coded icons (green for optimal, yellow for acceptable, red for poor), simple progress bars, or short textual prompts such as "inhale slower" or "hold breath longer." Auditory or haptic cues can further assist patients with visual impairment or low-literacy backgrounds [48].

From a usability perspective, the perceived effectiveness of the interface can be characterized by a user-experience score U, combining measures of task completion, perceived ease of use, and symptom-report reduction. A simplified composite index might be defined as

$$U = \eta_1 \cdot U_{\text{task}} + \eta_2 \cdot U_{\text{ease}} + \eta_3 \cdot \Delta S \quad (6)$$

where $U_{\text{task}}$is task-success rate, $U_{\text{ease}}$is self-reported ease-of-use, $\Delta S$is the reduction in symptom severity over time, and $\eta_1, \eta_2, \eta_3$are scaling weights [49]. Optimizing Uthrough iterative design such as larger fonts, simplified navigation, and voice-assisted guidance ensures that wearable smart inhalers remain accessible and clinically meaningful for advanced lung cancer patients managing chronic respiratory symptoms at home.

5. Application in Advanced Lung Cancer

Wearable smart inhalers can be strategically deployed within advanced lung cancer care to monitor chronic respiratory symptoms, optimize inhaler use, and support symptom-guided dose adjustments across the intensive-care-to-home continuum [50]. Their application is most impactful when targeted to patients with significant obstructive or bronchospastic components, persistent dyspnoea, or a history of inhaler-related exacerbations. By integrating objective data on adherence, technique, and symptom trajectories into existing oncological and palliative workflows, these devices enable more responsive, individualized respiratory management while preserving patient autonomy and reducing treatment burden [51].

5.1. Selection Criteria and Patient Suitability

Selection of patients for wearable smart inhalers in advanced lung cancer should balance respiratory phenotype, functional status, and digital-literacy factors. Ideal candidates typically exhibit recurrent or moderate-to-severe dyspnoea, wheezing, or cough attributable to bronchospasm or obstructive lung physiology, often with comorbid COPD or asthma [52]. Patients who have experienced frequent inhaler-related exacerbations, emergency visits, or hospitalizations due to uncontrolled respiratory symptoms are strong candidates for continuous monitoring. Conversely, individuals with profound cognitive impairment, severe upper-limb dysfunction, or inability to engage with a smartphone interface may derive limited benefit unless caregiver-mediated support is available [53].

Clinically, a simple eligibility score Ecan be defined as

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$$E = \omega_1 \cdot S_{\text{resp}} + \omega_2 \cdot H_{\text{freq}} + \omega_3 \cdot C_{\text{tech}} \quad (7)$$

where S_{resp} quantifies respiratory-symptom severity, H_{freq} reflects hospitalization or emergency-care frequency, C_{tech} indicates patient/caregiver digital-capability, and $\omega_1, \omega_2, \omega_3$ are weights representing clinical priorities [54]. A threshold on E can guide structured enrolment into smart-inhaler programs, ensuring that technology-enhanced care is directed to those most likely to benefit from continuous, objective monitoring.

5.2. Monitoring Adherence, Technique, and Symptom Patterns

Wearable smart inhalers enable granular, longitudinal monitoring of inhaler adherence, inhalation technique, and associated symptom patterns in advanced lung cancer. Each actuation is recorded as a time-stamped event, allowing the system to compute adherence rates, dose-timing regularity, and gaps in use [55]. Inhalation-flow and technique data are processed to flag suboptimal inhalations such as insufficient inspiratory flow, short inhalation duration, or missed breath-holding so that clinicians can retrain patients or adjust device type. Symptom data, ideally captured via linked patient-reported outcomes (PROs) or wearable biosensors, can be correlated with inhaler-use events to identify patterns such as nocturnal wheezing or exercise-induced breathlessness.

Mathematically, the adherence pattern over time can be represented as a binary sequence $A_t = \{a_1, a_2, \ldots, a_t\}$, where $a_i = 1$ if a dose is taken as scheduled and $a_i = 0$ otherwise. A smoothed adherence index $A_{\text{smooth}}(t)$ can then be expressed as

$$A_{\text{smooth}}(t) = \frac{1}{T_w} \sum_{i=t-T_w+1}^{t} a_i \quad (8)$$

where T_w is a rolling window (e.g., 7 days). This index supports dynamic risk stratification, sustained low values can trigger alerts for early intervention, while improving adherence trends may justify dose-reduction or regimen simplification [56]. By aligning these metrics with symptom trajectories, wearable smart inhalers provide a data-driven framework for chronic respiratory management in advanced lung cancer.

5.3. Integration with Existing Oncology and Palliative Care Regimens

For smart inhalers to be clinically meaningful, they must be integrated into existing oncology and palliative care regimens rather than treated as standalone tools. In multidisciplinary tumour boards or palliative care conferences, inhaler-use data can complement performance-status assessments, imaging findings, and treatment-related toxicity profiles to inform decisions about bronchodilator escalation, opioid-based breathlessness control, or referral to pulmonary rehabilitation [57]. Real-time dashboards can be configured to feed alerts directly into electronic health-record workflows, enabling respiratory therapists, oncologists, and palliative specialists to jointly review adherence lapses, technique errors, or emerging symptom clusters [58].

From a systems perspective, integration can be formalized as a care-path function $C(t)$ that combines inhaler-monitoring data $I(t)$, oncology status indicators $O(t)$, and palliative-symptom scores $P(t)$

$$C(t) = \phi(I(t), O(t), P(t)) \quad (9)$$

where ϕ represents a decision-logic module that maps these inputs to actions such as dose adjustment, patient education, or escalation to acute care [59]. This framework ensures that wearable smart inhalers operate as interoperable nodes within a broader oncology-palliative ecosystem, rather than isolated devices, thereby enhancing continuity and coordination of chronic respiratory management from intensive care to home care in advanced lung cancer.

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6. Transition from Intensive Care to Home Care

The transition from intensive care to home care in advanced lung cancer is a high-risk phase during which respiratory stability can rapidly deteriorate without continuous monitoring and structured follow-up. Wearable smart inhalers can bridge this gap by extending objective inhaler-use and symptom data from the ICU into the home environment, enabling seamless handover, remote surveillance, and coordinated multidisciplinary support [60]. By embedding smart-inhaler insights into discharge planning and post-ICU care pathways, healthcare teams can detect early warning signs, optimize inhaler regimens, and prevent unplanned readmissions, thereby supporting safe and sustainable respiratory management at home.

6.1. Handover Protocols Incorporating Smart Inhaler Data

Handover protocols from intensive care to home care should explicitly integrate smart inhaler data to ensure continuity of respiratory monitoring. At discharge, the ICU team can generate a structured inhaler-use summary that includes adherence rate, technique-quality index, and recent symptom trends over the preceding days. This summary, along with a clear list of inhaler-related goals (e.g., target adherence threshold, acceptable technique range), can be transmitted via secure messaging or EHR interfaces to the home-care team and primary oncologist [61]. Standardized handover checklists may include fields such as "baseline adherence over last 72 hours," "frequent time-of-day patterns," and "recent technique alerts."

Formally, a handover readiness index R can be expressed as

$$R = \rho_1 \cdot A_{\text{ICU}} + \rho_2 \cdot Q_{\text{tech}} - \rho_3 \cdot E_{\text{alarm}} \tag{10}$$

where A_{ICU} is the ICU-phase adherence ratio, Q_{tech} is the average technique quality, E_{alarm} counts unresolved inhaler-related alerts, and ρ_1, ρ_2, ρ_3 are clinically tuned weights. A threshold on R can guide whether a patient is ready for discharge with a smart inhaler or requires additional in-hospital stabilization [62]. Such a protocol-driven, data-informed approach helps ensure that transitions from intensive care to home care remain safe and evidence-based.

6.2. Remote Monitoring During Post-ICU Recovery

During post-ICU recovery at home, wearable smart inhalers enable remote monitoring of inhaler adherence, technique, and symptom progression without requiring frequent clinic visits. Encrypted inhaler-use data are transmitted periodically to cloud platforms, where they are aggregated into time-series dashboards accessible to clinicians, nurses, and respiratory therapists. Automated rule-based or AI-driven algorithms can flag concerning patterns, such as prolonged adherence lapses, sudden deterioration in technique, or clusters of nocturnal inhalers use that may indicate worsening breathlessness [63]. These alerts can trigger scheduled tele-consultations, same-day home visits, or pre-emptive medication adjustments, thereby reducing the window between symptom onset and clinical intervention.

Mathematically, a risk-of-exacerbation score $R_{\text{ex}}(t)$ can be defined over a rolling window as

$$R_{\text{ex}}(t) = \lambda_1 \cdot (1 - A(t)) + \lambda_2 \cdot (1 - Q_{\text{tech}}(t)) + \lambda_3 \cdot S_{\text{trend}}(t) \tag{11}$$

where $A(t)$ is the adherence ratio, $Q_{\text{tech}}(t)$ is the technique-quality index, $S_{\text{trend}}(t)$ reflects the slope of symptom severity over time, and $\lambda_1, \lambda_2, \lambda_3$ are weights. Rising $R_{\text{ex}}(t)$ values can prompt escalation to higher-level care or urgent home-care review, offering a quantitative, remote monitoring framework for advanced lung cancer patients recovering post-ICU [64].

6.3. Roles of Home-Care Nurses, Respiratory Therapists, and Caregivers

Home-care nurses, respiratory therapists, and family caregivers play complementary roles in interpreting and acting on smart-inhaler data within the post-ICU pathway. Home-care nurses typically perform routine visits, review inhaler-use dashboards, and correlate objective adherence

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and technique metrics with physical findings such as oxygen saturation, respiratory rate, and work-of-breathing [65]. Respiratory therapists can conduct technique-coaching sessions, reassess inhaler choice, and recommend device switches (e.g., from MDI to DPI or nebulizer) based on flow-profile data and patient strength. Family caregivers are often responsible for reminding patients about scheduled doses, assisting with device handling, and reporting subjective changes in symptom burden to the care team.

Functionally, the collaborative care loop can be described by a shared responsibility function $L(t)$

$$L(t) = \mu_{\text{nurse}} \cdot N(t) + \mu_{\text{RT}} \cdot R(t) + \mu_{\text{caregiver}} \cdot C(t) \quad (12)$$

where $N(t)$, $R(t)$, and $C(t)$represent the nurse's, respiratory therapist's, and caregiver's inputs at time t, and $\mu_{\text{nurse}}, \mu_{\text{RT}}, \mu_{\text{caregiver}}$are role-specific coefficients reflecting their relative contribution to inhaler-related decision-making [66]. When integrated with smart-inhaler data, this distributed model ensures that the transition from intensive care to home care remains coordinated, patient-centred, and responsive to evolving respiratory needs in advanced lung cancer.

7. Data-Driven Decision Support

Data-driven decision support in advanced lung cancer leverages inhaler-generated and clinical data to enable predictive analytics, personalized therapy, and secure, compliant care pathways. By applying AI and machine-learning models to longitudinal inhaler-use, symptom, and physiological data, clinicians can move from reactive symptom management to proactive, individualized respiratory support [67]. At the same time, robust privacy, security, and regulatory frameworks are essential to ensure that sensitive respiratory and oncological data are handled in accordance with medical-device standards and patient-trust requirements.

7.1. AI and Machine-Learning Models for Early Exacerbation Prediction

AI and machine-learning models can analyse time-series inhaler-use data, symptom diaries, and ancillary physiological signals (e.g., pulse oximetry, activity) to predict early exacerbations in advanced lung cancer [68]. Features such as declining adherence, suboptimal technique, increased nocturnal inhaler use, or abrupt changes in symptom-report patterns can be encoded into a feature vector $\mathbf{x}_t$at each time step t [69]. Supervised classifiers such as gradient-boosted trees or recurrent neural networks can then estimate the probability of an impending exacerbation within a defined horizon (e.g., 24–72 hours).

A simplified probabilistic model can be expressed as

$$P(\text{exacerbation} \mid \mathbf{x}_t) = \sigma(\mathbf{w}^\top \mathbf{x}_t + b) \quad (13)$$

where $\sigma$is the sigmoid function, $\mathbf{w}$ is a learned weight vector, and $b$is a bias term. This scalar output serves as a risk score that can trigger alerts for clinicians or home-care coordinators, enabling timely intervention before hospitalization becomes necessary [70]. By training on cohorts of advanced-stage patients, these models can be tailored to the specific patterns of bronchospasm, dyspnea, and nocturnal symptoms characteristic of advanced lung cancer.

7.2. Personalized Adjustment of Bronchodilator and Inhaler Regimens

Data-driven decision support also enables personalized adjustment of bronchodilator and inhaler regimens based on individual response patterns. By analysing inhaler-use data, symptom trajectories, and clinical markers, algorithms can propose dose-titration strategies that balance efficacy with side-effect risk. For instance, a patient showing frequent short-acting bronchodilator use at night may benefit from intensified long-acting bronchodilator coverage, whereas another with stable adherence but persistent dyspnoea may require adjunctive non-pharmacological interventions [71].

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Formally, a regimen-suitability index R_{reg} can be defined as

$$R_{\text{reg}} = \gamma_1 \cdot A(t) + \gamma_2 \cdot Q_{\text{tech}}(t) - \gamma_3 \cdot E_{\text{use}}(t) \quad (14)$$

where $A(t)$ is adherence, $Q_{\text{tech}}(t)$ is technique quality, $E_{\text{use}}(t)$ is excessive short-acting bronchodilator use, and $\gamma_1, \gamma_2, \gamma_3$ are weights. When R_{reg} falls below a target threshold, the system may recommend dose escalation, device switch, or adjunctive therapy, thereby translating data into actionable, patient-specific recommendations [72].

7.3. Privacy, Security, and Regulatory Considerations

Privacy, security, and regulatory compliance are central to the deployment of smart-inhaler–based decision support in oncology practice. Inhaler-generated data are typically classified as personal health information and must be encrypted both in transit (e.g., TLS/HTTPS) and at rest, with strict access controls limiting visibility to authorized clinicians, caregivers, and investigators [73]. Anonymization or pseudonymization techniques should be applied whenever data are used for research or model training. From a regulatory standpoint, smart inhalers and associated analytics platforms must comply with relevant medical-device directives (e.g., CE marking, FDA Class II/III requirements), data-protection regulations (e.g., GDPR, HIPAA), and local health-authority guidelines.

A basic security-compliance index S_{comp} can conceptually aggregate key safeguards:

$$S_{\text{comp}} = \delta_1 \cdot C_{\text{enc}} + \delta_2 \cdot C_{\text{auth}} + \delta_3 \cdot C_{\text{audit}} \quad (15)$$

where C_{enc} reflects encryption strength, C_{auth} denotes authentication-mechanism robustness, C_{audit} represents audit-logging completeness, and $\delta_1, \delta_2, \delta_3$ are weights. Sustaining high S_{comp} ensures that data-driven decision support remains trustworthy, legally sound, and aligned with patient-centred values in advanced lung cancer care [74].

8. Clinical Outcomes and Patient-Reported Benefits

The integration of wearable smart inhalers into chronic respiratory management in advanced lung cancer has the potential to improve objective clinical outcomes while simultaneously enhancing patient-reported experiences. By providing continuous, objective data on inhaler use and symptom patterns, these devices support early intervention, regimen optimization, and shared decision-making [75]. Evidence from related obstructive-lung-disease cohorts suggests that smart-inhaler platforms can reduce exacerbations and hospitalizations, improve symptom control, and positively influence quality of life, even in frail, advanced-stage populations. However, their real-world impact depends on usability, patient acceptance, and mitigation of digital-literacy or physical-access barriers.

8.1. Reduction in Exacerbations and Hospital Readmissions

Wearable smart inhalers can contribute to a measurable reduction in respiratory exacerbations and unplanned hospital readmissions in advanced lung cancer by enabling earlier detection of deteriorating patterns [76]. Continuous monitoring of adherence, technique, and nocturnal inhaler use allows clinicians and home-care teams to identify subtle shifts such as increasing short-acting bronchodilator use or declining technique quality before overt decompensation occurs. Timely interventions, including dose adjustments, caregiver education, or pre-emptive home visits, can interrupt the progression from mild symptom escalation to full-blown exacerbation [77].

Quantitatively, the impact can be accessed via the exacerbation-rate ratio R_{ex} before and after smart-inhaler implementation

$$R_{\text{ex}} = \frac{\text{Exacerbation rate}_{\text{post}}}{\text{Exacerbation rate}_{\text{pre}}} \quad (16)$$

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where the rate is expressed as exacerbations per patient-year. A reduction in R_{ex} below 1 indicates net benefit, with larger decreases reflecting stronger intervention effects [78]. In asthma and COPD studies using connected inhalers, such reductions have been associated with lower hospitalization and emergency-department utilization, similar patterns are expected in selected advanced lung cancer cohorts when smart inhalers are embedded within structured care pathways.

8.2. Improvement in Symptom Control and Quality of Life

Beyond objective clinical metrics, wearable smart inhalers can improve symptom control and overall quality of life by making inhaler use more intentional and responsive to individual needs. Real-time feedback on inhalation technique and adherence helps patients correct errors, gain confidence in self-management, and reduce anxiety related to uncontrolled breathlessness [79]. Personalized dose-adjustment suggestions, triggered by inhaler-use and symptom data, can lead to more stable bronchodilation and fewer episodes of severe dyspnoea, wheezing, or nocturnal cough.

A composite quality-of-life index Q_{QoL} can conceptually combine symptom-severity reduction ΔS, functional-status improvement ΔF, and psychological-well-being gain ΔP

$$Q_{\text{QoL}} = \xi_1 \cdot \Delta S + \xi_2 \cdot \Delta F + \xi_3 \cdot \Delta P \tag{17}$$

where ξ_1, ξ_2, ξ_3 are empirically chosen weights. When embedded within oncology and palliative-care frameworks, smart-inhaler driven symptom control can meaningfully shift Q_{QoL} in favour of patients, particularly those transitioning from intensive care to home care, by reducing symptom burden, improving sleep, and preserving social and daily activities [80].

8.3. Usability, Acceptance, and Barriers Among Advanced-Stage Patients

Despite their potential, wearable smart inhalers face several usability and acceptance barriers in advanced-stage lung cancer [81]. Factors such as visual or manual impairment, cognitive fatigue, limited digital literacy, and fear of technology can reduce comfort with smartphone-based apps, Bluetooth pairing, and data-sharing workflows. Some patients may perceive continuous monitoring as intrusive or anxiety-provoking, especially when alerts are poorly contextualized or overly frequent [82]. Additionally, cost, insurance coverage, and device-maintenance responsibilities may limit sustained engagement, particularly in low-resource or home-care–only settings.

From a human-factors perspective, overall usability can be captured by a composite score U_{use} that combines task-success rate T_s, perceived ease of use E_u, and perceived usefulness U_f

$$U_{\text{use}} = \zeta_1 \cdot T_s + \zeta_2 \cdot E_u + \zeta_3 \cdot U_f \tag{18}$$

where $\zeta_1, \zeta_2, \zeta_3$ are weighting coefficients. Optimizing U_{use} requires iterative design such as simplified interfaces, voice-assisted guidance, caregiver-mediated setup, and tailored education ensuring that wearable smart inhalers remain accessible, acceptable, and clinically meaningful for advanced-stage lung cancer patients managing chronic respiratory symptoms at home [83].

9. Implementation Challenges and Future Directions

The successful implementation of wearable smart inhalers in advanced lung cancer care requires addressing economic, organizational, and technical barriers alongside workforce readiness and evolving device capabilities [84]. While these platforms offer strong promise for continuous respiratory monitoring and personalized therapy, their widespread adoption depends on sustainable financing, seamless integration into existing health-system workflows, and robust training for clinicians and caregivers [85]. Looking ahead, next-generation smart inhalers and hybrid respiratory platforms are likely to incorporate richer sensing, multimodal feedback, and deeper integration with broader digital-health ecosystems.

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9.1. Cost, Reimbursement, and Health-System Integration

Cost, reimbursement variability, and health-system integration represent major hurdles to the routine deployment of wearable smart inhalers in advanced lung cancer. The devices themselves, along with associated connectivity infrastructure, cloud platforms, and software maintenance, can entail significant upfront and recurring expenses [86]. Reimbursement policies for digital-health tools remain fragmented, with many payers lacking clear coverage codes or outcome-based payment models for inhaler-monitoring services. Furthermore, integrating smart-inhaler data into existing electronic health-record systems, oncology information systems, and tele-health platforms requires interoperability standards, API-level connectivity, and change-management effort at the institutional level [87].

A simplified cost-effectiveness index C_{eff} can conceptually capture the balance between financial outlay and clinical benefit

$$C_{\text{eff}} = \frac{\Delta B}{\Delta C} \tag{19}$$

where ΔB represents the reduction in exacerbations, hospitalizations, or symptom-related emergency visits, and ΔC is the incremental cost per patient-year of smart-inhaler deployment [88]. Demonstrating a favorable C_{eff} through health-economic studies and pilot programs will be essential to secure long-term reimbursement and institutional support for these technologies in oncology-respiratory care pathways.

9.2. Training Clinicians and Caregivers in Digital-Device Use

Effective use of wearable smart inhalers depends heavily on training clinicians, home-care nurses, respiratory therapists, and family caregivers in digital-device workflows. Clinicians must learn to interpret inhaler-use dashboards, distinguish between technical artifacts and true clinical deterioration, and translate data-driven insights into actionable treatment adjustments [89]. Caregivers often require hands-on training in device setup, Bluetooth pairing, app navigation, and basic troubleshooting, particularly when supporting older or physically impaired patients. Without standardized education modules, simulation-based workshops, and role-specific protocols, the risk of misinterpretation, alert fatigue, or underutilization rises [90].

A training-readiness metric T_{ready} can be expressed as

$$T_{\text{ready}} = \psi_1 \cdot K_{\text{know}} + \psi_2 \cdot P_{\text{skill}} + \psi_3 \cdot C_{\text{conf}} \tag{20}$$

where K_{know} is knowledge of device functionality, P_{skill} measures practical performance in demo scenarios, C_{conf} reflects user confidence, and ψ_1, ψ_2, ψ_3 are weighting coefficients. Programs that systematically improve T_{ready} across multidisciplinary teams will be critical to ensure that smart inhalers are used safely, consistently, and effectively in the transition from intensive care to home care [91].

9.3. Next-Generation Smart Inhalers and Hybrid Respiratory Platforms

Next-generation smart inhalers are expected to evolve into hybrid respiratory platforms that combine inhaler monitoring with additional physiological and environmental sensing. Future devices may integrate pulse oximetry, respiratory-rate detection, voice-based symptom capture, or even positional sensors to provide a more holistic picture of respiratory status. These platforms could operate in a multimodal fashion, linking inhaler-use data with wearable biosensors, home-based spirometry, or tele-rehabilitation systems to support end-to-end respiratory management [92]. From an engineering perspective, a unified platform scores P_{unified} can conceptually represent the degree of system integration

$$P_{\text{unified}} = \nu_1 \cdot S_{\text{sen}} + \nu_2 \cdot C_{\text{comm}} + \nu_3 \cdot A_{\text{anal}} \tag{21}$$

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where S_{sen} reflects sensor diversity, C_{comm} denotes communication and interoperability robustness, and A_{anal} captures the sophistication of embedded analytics, with ν_1, ν_2, ν_3 as scaling weights [93]. Such hybrid platforms will likely play a central role in the future of chronic respiratory management in advanced lung cancer, enabling more responsive, patient-centred, and data-rich care from intensive care to home.

Conclusions

Wearable smart inhalers offer a clinically meaningful pathway to bridge the gap between intensive care and home-based chronic respiratory management in advanced lung cancer, enabling continuous, objective monitoring of inhaler adherence, technique, and symptom patterns while supporting early intervention and personalized bronchodilator adjustments. Evidence from related obstructive-lung-disease cohorts indicates that connected inhaler platforms can reduce exacerbations, hospital readmissions, and symptom burden when embedded within structured care pathways, and these benefits are likely transferable to selected advanced lung cancer patients with significant bronchospastic components and frequent inhaler-related exacerbations. Successful implementation will depend on addressing cost and reimbursement barriers, integrating smart-inhaler data into existing oncology and palliative-care workflows, standardizing training for clinicians and caregivers, and advancing next-generation hybrid respiratory platforms that combine richer sensing, multimodal feedback, and deeper interoperability with digital-health ecosystems.

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