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Beyond the Ball: An AI-Driven Ecosystem for Real-Time Diaphragmatic Coaching and Dual-Mode Lung Function Assessment in Asthma Management

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ABSTRACT

Background: Respiratory health management requires accessible tools for both rehabilitation and diagnostic monitoring. Traditional devices like incentive spirometers and peak flow meters are limited by user error and provide incomplete data that patients find difficult to interpret. **Objective:** This paper presents a conceptual framework for the AI-Driven Pranayama Spiroball, a proposed dual-action biofeedback system designed to integrate rehabilitative inhalation guidance using Pranayama principles with expiratory function measurement through a dedicated spirometric sensor. **Material and Methods:** The proposed system architecture comprises two functional modes: (1) rehabilitative inhalation using a standard spiroball with AI-guided diaphragmatic breathing coaching via smartphone camera-based abdominal tracking, and (2) diagnostic exhalation using a calibrated flow sensor to measure PEF, FEV1, and FVC. We propose a composite metric, the Lung Efficiency Index (LEI), combining Inspiratory Capacity Score, Expiratory Function Score, and Technique Adherence Score. This paper details the system design, technical specifications, and outlines a validation roadmap. **Results:** The conceptual framework aims to reduce user error through real-time AI feedback and simplify complex respiratory data into a single interpretable metric (LEI, 0-100 scale). Clinical validation is required to establish efficacy. **Conclusions:** This design framework addresses identified gaps in respiratory care by proposing unified rehabilitation and monitoring functions. Pilot studies with healthy volunteers and subsequent clinical trials are necessary to validate the system's effectiveness and the LEI's predictive value. A functional prototype is currently under development.

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1. INTRODUCTION

1.1 The Global Burden of Asthma and Monitoring Challenges

Asthma remains one of the most prevalent chronic respiratory diseases globally, defined by airway inflammation, bronchial hyper-responsiveness, and variable expiratory airflow limitation. Current epidemiological data indicates that asthma affects over 262 million individuals worldwide, imposing substantial economic and social burdens on healthcare systems and patient quality of life [1]. Beyond asthma, the global burden of respiratory diseases—ranging from post-operative pulmonary complications to chronic conditions like Chronic Obstructive Pulmonary Disease (COPD)—is immense and growing. Effective management of these conditions hinges on two pillars: rehabilitation and consistent monitoring. However, these are currently addressed by separate, often flawed, devices. The efficacy of traditional respiratory tools is consistently undermined by human error and data complexity. For inhalation rehabilitation, it has been established that the effects of incentive spirometry are significantly limited by the patients' inability to master correct diaphragmatic breathing techniques without professional supervision [6].

For exhalation monitoring, accurate Peak Expiratory Flow (PEF) and Forced Expiratory Volume (FEV_1) measurements require forceful, complete maneuvers that patients perform inconsistently in home settings [7]. Furthermore, even when accurate data is collected, patients face a "wall of data" consisting of multiple confusing acronyms (PEF, FEV_1, FVC) without a clear understanding of their daily health implications. This complexity creates significant barriers to effective self-management. Previous studies have demonstrated that yoga-based interventions and Pranayama can significantly improve pulmonary function tests, respiratory endurance, and muscle strength in asthma patients [3], [8]. Research into specific techniques, such as Savitri Pranayama, has shown measurable cardiorespiratory changes that benefit long-term management [4].

Additionally, yoga-based guided relaxation has been highlighted as a viable complementary therapy for managing bronchial asthma symptoms [9]. Despite these benefits, the therapeutic application of Pranayama requires precise technique to be effective [2], [5]. There is a clear need for a unified solution that merges the rehabilitation benefits of yogic breathing with the objective tracking of digital spirometry. This paper proposes an AI-guided system that integrates these functions, utilizing computer vision to correct technique in real-time while translating complex spirometric data into a single, understandable metric for the patient.

2. MATERIAL AND METHODS

2.1 Conceptual Framework Design

The AI-Driven Pranayama Spiroball addresses these problems through dual-mode functionality synthesizing data into a single meaningful score. The proposed system employs a multimodal sensing approach combining precision flow measurement with computer vision-based posture and movement tracking.

2.2 System Architecture Overview

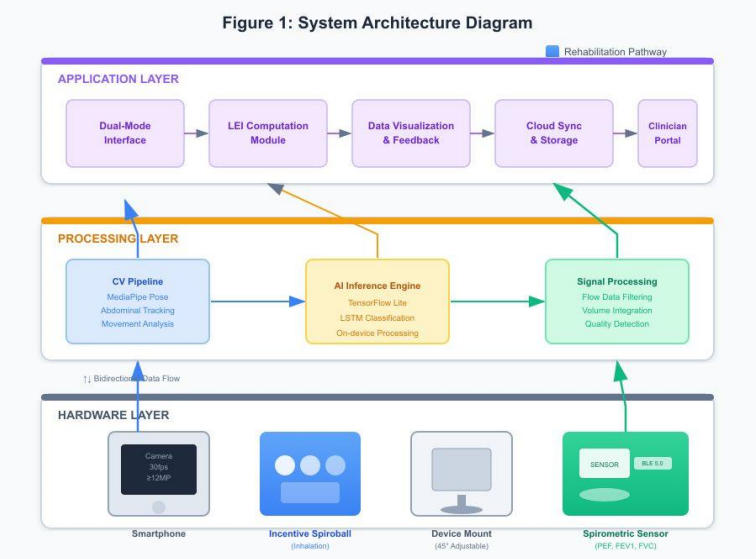

Figure 1. System Architecture Diagram

Description: Block diagram showing three main components: (1) Hardware Layer containing smartphone, spiroball, and spirometric sensor module; (2) Processing Layer showing data flow from sensors through CV pipeline and signal processing to AI inference engine; (3) Application Layer displaying dual-mode interface, LEI computation module, and cloud sync. Arrows indicate bidirectional data flow between layers. Color-coded blocks distinguish rehabilitation pathway (blue) from diagnostic pathway (green).

The system architecture comprises three integrated layers:

1. **Hardware Layer:** Physical sensing components for respiratory measurement
2. **Processing Layer:** On-device AI inference and signal processing
3. **Application Layer:** User interface, data visualization, and cloud synchronization

2.3 Hardware Specifications

Table 1. Proposed Hardware Components

Component	Specification	Function
Smartphone	Android 10+ / iOS 14+; Rear camera ≥12MP; 30fps video recording	Abdominal motion tracking, UI display, and data processing
Incentive Spiroball	Standard 3-ball or single-ball unit (e.g., Romsons Respirometer)	Provides real-time visual inhalation feedback to the user
Spirometric Sensor	Differential pressure sensor (±500 Pa range, ±2.5% accuracy); Fleisch-type pneumotachograph or turbine flowmeter	Measurement of PEF, FEV1, and FVC metrics

Component	Specification	Function
Device Mount	Adjustable phone holder with 45° tilt capability	Maintains a stable abdominal field-of-view for the camera
Bluetooth Module	BLE 5.0 (integrated with spirometric sensor)	Facilitates wireless data transmission to the smartphone

Critical Hardware Note: The standard spiroball measures inspiratory effort only and cannot measure expiratory parameters (PEF, FEV1, FVC). The proposed system therefore requires a separate calibrated spirometric sensor module for diagnostic exhalation mode. This dual-hardware approach is essential for the system's intended functionality.

Table 2. Estimated Bill of Materials (excluding smartphone)

Component	Estimated Cost (₹)	Estimated Cost (USD)
Incentive Spiroball	150 – 300	$2 – $4
Differential pressure sensor + housing	800 – 1,200	$10 – $15
BLE module (ESP32 or similar)	400 – 600	$5 – $8
Mouthpiece adapter + tubing	200 – 400	$3 – $5
Phone mount	300 – 500	$4 – $6
Total BOM	**₹1,850 – ₹3,000**	**$24 – $38**

Note: Costs are approximate and exclude manufacturing, regulatory compliance, and software development.

2.4 Software Architecture and AI Specifications

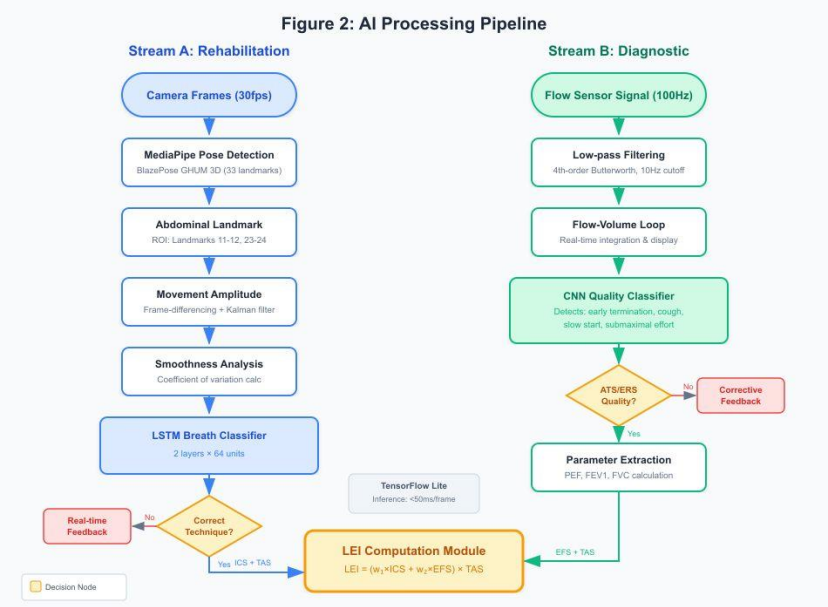

Figure 2. AI Processing Pipeline

Description: Flowchart showing parallel processing streams.

1. **Stream A (Rehabilitation):** Camera frames → MediaPipe Pose detection → Abdominal landmark extraction → Movement amplitude calculation → Smoothness analysis.
2. **Stream B (Diagnostic):** Flow sensor signal → Low-pass filtering → Flow-volume loop generation → Maneuver quality classification → Parameter extraction.
3. Both streams feed into LEI Computation Module. Decision nodes show real-time feedback triggers.

Computer Vision Pipeline:

1. **Pose Estimation:** Google MediaPipe Pose (BlazePose GHUM 3D) for 33-landmark body tracking
2. **Abdominal ROI:** Landmarks 23-24 (hips) and 11-12 (shoulders) define abdominal region
3. **Movement Quantification:** Frame-differencing of landmark positions at 30fps, Kalman filtering for noise reduction
4. **Processing Framework:** TensorFlow Lite (mobile), inference time <50ms per frame on mid-range devices.

Signal Processing (Spirometric Sensor):

1. **Sampling Rate:** 100 Hz minimum for accurate flow-volume loop capture
2. **Filtering:** 4th-order Butterworth low-pass filter, 10 Hz cutoff
3. **Calibration:** 3-point volume calibration using 3L syringe per ATS/ERS standards
4. **Quality Detection:** CNN classifier trained on flow-volume loop morphology to detect: early termination, cough artifacts, slow start, submaximal effort

AI Inference Engine:

1. Framework: TensorFlow Lite with GPU (Graphics Processing Unit) delegate for on-device inference

2. Technique Classification Model: LSTM network (2 layers, 64 units) trained on labeled breathing patterns

3. **Feedback Generation:** Rule-based system triggered by classification outputs with natural language templates

2.4.1 Environmental Calibration Module:

Given the reliance on computer vision, the application incorporates a mandatory Pre-session Calibration step. The MediaPipe pipeline performs a real-time contrast and lighting assessment to ensure the 33 body landmarks are visible against the user's background and clothing. If the signal-to-noise ratio is insufficient for accurate tracking of the ROI (Region of Interest), the system provides visual prompts to the user to adjust lighting or positioning before measurements can commence.

2.5 Functional Modes

2.5.1 Mode 1: Rehabilitative Inhalation (Pranayama Coaching)

This mode is designed to strengthen respiratory muscles and improve breathing efficiency through guided practice. The application guides users through slow, deep diaphragmatic breaths while the AI analyzes the relationship between abdominal expansion (detected via camera) and ball elevation in the spiroball. Real-time feedback provides corrective cues (e.g., "Gently push your belly out more") to help optimize technique. This approach is grounded in Pranayama principles, which Madanmohan et al. (2003, 2005) demonstrated can improve ventilatory functions in healthy individuals and asthma patients.

Technical Implementation:

- Camera captures abdominal region at 30fps during inhalation
- MediaPipe extracts torso landmarks; vertical displacement calculated frame-to-frame
- Spiroball elevation provides secondary visual confirmation (not quantified electronically in basic configuration)
- LSTM model classifies breath pattern as: correct diaphragmatic, chest-dominant, shallow, or inconsistent
- Feedback latency target: <200ms from detection to audio/visual cue

2.5.2 Mode 2: Diagnostic Exhalation (Spirometric Measurement)

This mode enables home-based lung function monitoring using a dedicated spirometric sensor (separate from the spiroball). The application provides standardized forced exhalation instructions following ATS/ERS guidelines. The AI analyzes flow-volume loop morphology in real-time to detect maneuver quality issues. Upon successful maneuvers meeting quality thresholds, the system calculates and displays PEF, FEV1, and FVC, logging timestamped data for longitudinal tracking and clinical review.

Technical Implementation:

- Spirometric sensor transmits flow data via BLE at 100Hz
- Real-time integration yields volume; flow-volume loop displayed live
- CNN classifier evaluates loop shape against quality criteria:
- Back-extrapolated volume <5% FVC or 150mL (whichever is greater)
- Plateau duration ≥1 second or volume change <25mL over 1 second
- No cough in first second
- Three acceptable maneuvers required; best values reported per ATS/ERS repeatability criteria
- Failed maneuvers trigger specific corrective feedback (e.g., "Blow out faster at the start")

2.5.3 The Lung Efficiency Index (LEI): A Proposed Composite Metric

We propose a composite score (0-100 range) designed to provide an intuitive summary of overall respiratory performance. The LEI combines three components and *requires clinical validation before adoption*:

Table 3. Component Definitions (Proposed)

Component	Abbreviation	Range	Derivation
Inspiratory Capacity Score	ICS	0–100	Weighted average: Peak abdominal displacement (40%), consistency across breaths (30%), and breath-hold duration (30%). Normalized to age/sex reference values.
Expiratory Function Score	EFS	0–100	FEV_1/FVC ratio: <0.70 maps to 0–50; 0.70–0.85 maps to 50–80; >0.85 maps to 80–100. Adjusted for age-related decline per GLI-2012 equations.
Technique Adherence Score	TAS	0–1.0	Multiplicative quality factor: Proportion of "correct" rehab breaths $\times$ proportion of spirometry maneuvers meeting ATS/ERS quality grade A or B.

Proposed Formula:

$$\mathbf{LEI = ((w_1 \times ICS) + (w_2 \times EFS)) \times TAS}$$

Where w_1 and w_2 are weighting coefficients (initially proposed as 0.5 each, requiring optimization through validation studies).

Important Caveats:

- Component weightings are preliminary and must be validated against clinical outcomes
- Reference values for ICS normalization do not yet exist and require population studies
- The LEI is intended as a patient engagement tool, not a diagnostic replacement for standard spirometry interpretation
- Sensitivity and specificity for detecting clinically meaningful changes are unknown

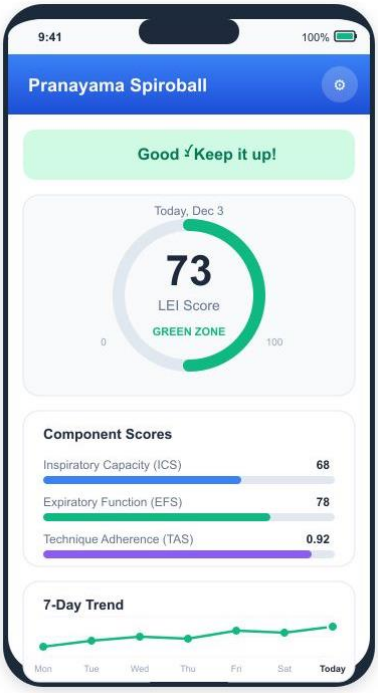

Figure 3. LEI Dashboard Mockup

Description: Mobile app screenshot showing circular LEI gauge (score 73, green zone) at center. Below: three horizontal bar charts for ICS (68), EFS (78), and TAS (0.92). Bottom section shows 7-day trend line graph with LEI scores. Header displays "Good - Keep it up!" message. Settings gear icon in corner.

2.6 Pranayama Protocol Implementation

The rehabilitative breathing protocol is based on traditional yogic Pranayama techniques adapted for clinical applications. The system guides users through three phases: Puraka (controlled inhalation), Kumbhaka (breath retention), and Rechaka (controlled exhalation). Each session begins with baseline measurements followed by graduated difficulty levels.

Table 4. Pranayama Protocol Progression

Level	**Puraka (Inhale)**	**Kumbhaka (Hold)**	**Rechaka (Exhale)**	**Sessions to Advance**
Beginner	4 seconds	2 seconds	6 seconds	7 consecutive with **TAS > 0.8**
Intermediate	6 seconds	4 seconds	8 seconds	10 consecutive with **TAS > 0.85**
Advanced	8 seconds	6 seconds	10 seconds	Maintenance

AI algorithms monitor adherence to timing, depth, and smoothness of each breath cycle, with automatic level adjustment based on sustained performance.

2.6.1 Adaptive Protocol & Patient Safety (Protocol Implementation)

Clinical Adaptation Logic:

While the protocol follows a standardized 4-6-8 second progression, the system is designed with Adaptive Leveling. If a patient demonstrates significant variation in Flow Smoothness or a drop in the Inspiratory Capacity Score (ICS) compared to their 7-day average, the AI will recommend a temporary shift to the "Beginner" level. This ensures patient safety during exacerbations and maintains high Technique Adherence without causing respiratory fatigue

2.7 Biomechanical Measurement Parameters

The computer vision module processes video streams to extract Key Performance Indicators for the rehabilitation mode:

Table 5. Biomechanical Measurement Parameters

KPI	Measurement Method	Clinical Relevance
Peak Abdominal Displacement	Maximum vertical landmark displacement (cm) from baseline	Correlates with diaphragmatic excursion and tidal volume.
Rate of Rise	Displacement velocity during first 25% of inhalation phase (cm/s)	Reflects inspiratory muscle power and efficiency.
Flow Smoothness	$1 - (\text{CV of displacement rate})$	Indicates breath control; jerky patterns suggest accessory muscle use.
Postural Stability	Standard deviation of shoulder landmark position (pixels)	Detects compensatory movement; instability reduces measurement validity.

Note: Ball elevation in the spiroball provides patient visual feedback but is not electronically quantified in the proposed basic configuration.

2.7.1 Anti-Cheating & Quality Logic (Technical Refinement)

To ensure clinical validity, the AI pipeline uses an "Inspiratory Velocity Profile" to monitor the abdominal Rate of Rise. This detects "cheating" maneuvers, such as quick suction rather than sustained diaphragmatic breathing. If the velocity exceeds thresholds calibrated to the Spiro ball's physical limits (600–1200 cc/sec), the breath is flagged as "low quality," reducing the Technique Adherence Score (TAS).

2.8 User Interface Design

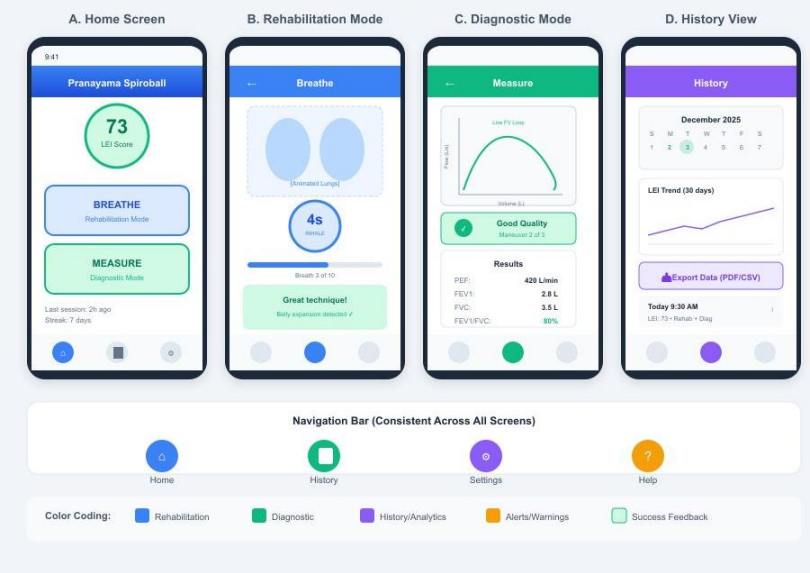

Figure 4. Application Interface Wireframes

Description: Four-panel wireframe layout.

1. Panel A: Home screen with large mode selection buttons (Breathe/Measure) and current LEI score.
2. Panel B: Rehabilitation mode showing animated lung graphic, countdown timer, and real-time feedback text area.
3. Panel C: Diagnostic mode showing live flow-volume loop graph with quality indicator traffic light.
4. Panel D: History view with calendar, trend charts, and export button. Consistent navigation bar at bottom across all panels.

The mobile application interface prioritizes simplicity and accessibility:

- **Dashboard:** LEI score with color-coded status (red: 0-40, yellow: 41-70, green: 71-100) and 7-day trend
- **Mode Selection:** Large, distinct icons for rehabilitation vs. diagnostic functions
- Real-time Feedback: Animated breathing guides with synchronized audio cues; supports eyes-free operation
- **Diagnostic Display:** Live flow-volume curves with quality traffic light and comparison to personal best
- **Education Module:** Patient-friendly explanations of metrics with video tutorials
- **Clinician Portal:** Web-based dashboard for remote patient monitoring and protocol adjustment (requires separate authentication)

2.9 Validation Roadmap

Clinical validation is essential before deployment. We propose a phased validation approach:

Phase I: Technical Feasibility (n=10-15 healthy volunteers)

- **Objective:** Verify CV-based abdominal tracking accuracy and spirometric sensor reliability
- **Methods:** Compare camera-derived displacement against gold-standard respiratory inductance plethysmography (RIP); compare sensor FEV1/FVC against laboratory spirometer (Vitalograph or equivalent)

- **Success Criteria:** Pearson r >0.85 for displacement; spirometric values within ±5% of laboratory reference
- **Duration**: 4 weeks
- **Sample Size Justification:** For detecting r=0.85 with 80% power at α=0.05, n=10 required; n=15 allows for dropouts

Phase II: Usability and Engagement (n=30 asthma patients)

- Objective: Assess patient acceptance, usability, and short-term engagement
- Methods 4-week home use; System Usability Scale (SUS); semi-structured interviews; adherence logs
- Success Criteria: SUS score >68 (above average); >70% session completion rate
- Duration:6 weeks including recruitment

Phase III: Clinical Validation (n=100 asthma patients, randomized)

- **Objective:** Establish LEI's correlation with clinical outcomes and optimize component weightings
- **Methods:** RCT comparing AI-Spiroball vs. standard peak flow monitoring over 6 months;
- **primary outcome:** asthma exacerbation rate;
- **secondary:** ACQ scores, FEV1 change, healthcare utilization
- **Sample Size Justification:** Assuming 30% reduction in exacerbation rate (from baseline 0.5 to 0.35 exacerbations per patient per 6 months, based on moderate persistent asthma rates reported in GINA 2023), 80% power, α=0.05, n=94 required; n=100 allows for 6% attrition
- **Duration:** 9-12 months including analysis

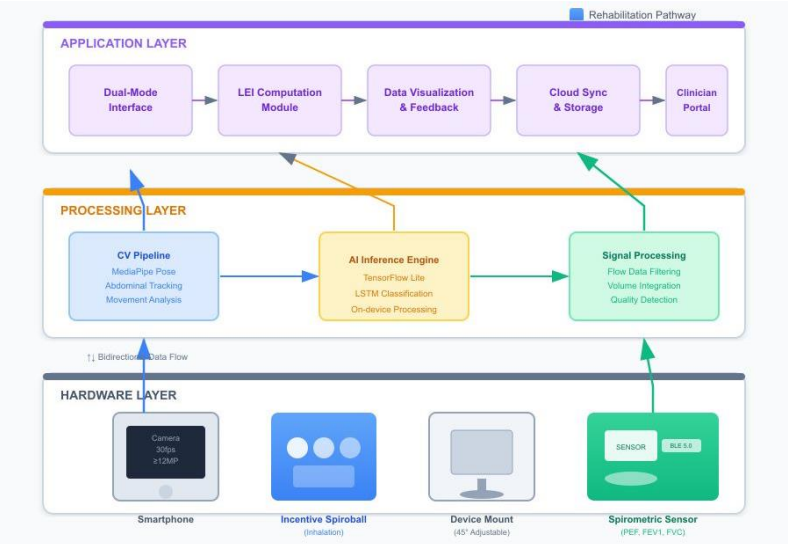

Figure 5. Validation Timeline Gantt Chart

Description: Horizontal Gantt chart showing three phases.

- Phase I (green bar): months 1-2.
- Phase II (yellow bar): months 2-4, overlapping slightly with Phase I completion.

- Phase III (blue bar): months 4-14. Milestones marked with diamonds: Ethics approval (month 0), Phase I report (month 2), Phase II report (month 4), Interim analysis (month 9), Final analysis (month 14). Critical path highlighted.

2.10 Ethical and Regulatory Considerations

Ethical Requirements:

- Institutional Review Board (IRB) / Ethics Committee approval required before any human subjects research
- Informed consent must address: video recording of abdominal region, health data storage, cloud transmission, data sharing with clinicians
- Vulnerable populations (pediatric, cognitively impaired) require additional safeguards and age-appropriate consent processes
- Data minimization: video frames processed on-device; only extracted landmarks and metrics transmitted/stored

Privacy and Data Protection:

- Compliance with applicable regulations: HIPAA (USA), GDPR (EU), DPDP Act 2023 (India)
- End-to-end encryption for data transmission
- Patient control over data sharing with healthcare providers
- Clear data retention and deletion policies

Regulatory Pathway (India):

- **Classification:** Likely Class B medical device under Medical Device Rules 2017 (diagnostic function)
- **Requirements:** CDSCO registration, clinical evidence, quality management system (ISO 13485)
- **Pathway:** Technical file submission → clinical investigation approval → marketing authorization

Regulatory Pathway (International):

- **FDA (USA):** Class II device, 510(k) pathway with predicate device comparison
- **CE Marking (EU):** MDR Class IIa, conformity assessment with Notified Body
- **TGA (Australia):** Class IIa inclusion in ARTG

3. ANTICIPATED OUTCOMES

Note: This section describes theoretical advantages of the proposed system. All claims require empirical validation through the studies outlined in Section 2.9.

3.1 Hypothesized Benefits

The conceptual framework is designed to address three identified problems in respiratory self-management:

Table 6. Problem-Solution Mapping

Current Problem	Proposed Solution	Hypothesized Benefit	Validation Required

Current Problem	Proposed Solution	Hypothesized Benefit	Validation Required
Complex Metrics (PEF, FEV_1, FVC, FEV_1/FVC)	**Single LEI Score** (0–100)	Simplified self-management and improved patient comprehension.	**Phase II:** User comprehension testing and UX surveys.
Exhalation-Only Focus (Incomplete Monitoring)	**Combined ICS + EFS**	Earlier detection of rehabilitation gaps and "silent" progression.	**Phase III:** Longitudinal correlation with exacerbation rates.
Technique Variability (Poor Data Reliability)	**Real-time AI Feedback + TAS**	Higher data quality and reduced false positives/negatives.	**Phase I:** Comparison with gold-standard supervised spirometry.

3.2 Anticipated Clinical Utility

If validation studies confirm the system's effectiveness, potential clinical applications include:

- **Self-Management:** Patients monitor a single metric rather than interpreting multiple parameters
- **Holistic Assessment:** LEI may reveal discrepancies (e.g., stable FEV1 but declining ICS) prompting investigation
- **Trend Detection:** Gradual LEI decline could provide earlier warning than threshold-based alerts
- **Clinical Efficiency:** Clinicians could use LEI trends for rapid status assessment during consultations

These potential benefits remain speculative until empirical validation.

4. DISCUSSION

4.1 Rationale and Positioning

The AI-Driven Pranayama Spiroball represents a proposed integration of rehabilitation and diagnostic monitoring within a single platform. By combining real-time technique coaching with standardized lung function measurement, the system aims to address two persistent problems: user error reducing data quality, and data complexity limiting patient comprehension.

4.2 Relationship to Existing Literature

The design rationale draws on established evidence:

- **Incentive Spirometry Limitations:** It has been documented that incentive spirometry benefits are constrained by patients' inability to master correct technique without supervision [6]. The proposed AI coaching aims to provide supervision-equivalent feedback.
- **Home Spirometry Reliability:** Studies of home PEF monitoring show significant variability due to technique inconsistency [7]. Real-time maneuver quality feedback could improve reliability.

- **Pranayama Efficacy:** Research has demonstrated that structured Pranayama training improves pulmonary function parameters [4]. The system operationalizes these techniques with objective feedback.

4.3 Design Trade-offs and Limitations

Technical Limitations:

Camera-based abdominal tracking may be affected by clothing, lighting, and body position; controlled conditions may be necessary.

Smartphone processing capabilities vary; older devices may not achieve target inference speeds.

The proposed spirometric sensor adds cost and complexity compared to standalone peak flow meters.

Methodological Limitations

LEI component weightings (w_1=w_2=0.5) are arbitrary pending optimization studies.

ICS normalization requires population reference values that do not exist.

The relationship between camera-derived abdominal displacement and actual diaphragmatic excursion requires validation.

Scope Limitations:

This paper presents a conceptual framework only; no prototype exists.

All efficacy claims are theoretical and require empirical confirmation.

Generalizability across age groups, disease severity, and cultural contexts is unknown.

4.4 Economic Considerations

Note: Economic projections below are illustrative and require validation through health economic studies.

If the system achieves its intended goals, potential cost savings in the Indian healthcare context could include:

Table 7. Illustrative Cost-Offset Analysis (Indian Healthcare Context)

Cost Category	**Current Avg. Cost (₹)**	**Potential Savings Mechanism**
ED Visit (Asthma)	8,000 – 15,000	Early trend detection allows for timely medication adjustment, preventing emergency room visits.
COPD Hospitalization	50,000 – 80,000	Real-time monitoring and high TAS (Technique Adherence) improve rehab success and reduce re-admission.
Pulmonologist Visit	800 – 1,500	Reduced need for "check-in" visits when the user's LEI (Lung Efficiency Index) remains stable and green.
Follow-up Spirometry	500 – 1,200	Substitutes frequent laboratory-grade tests with reliable, daily home monitoring.

Cost Category	Current Avg. Cost (₹)	Potential Savings Mechanism
ICU Admission	15,000 – 30,000+ per day	Prevents severe exacerbations that lead to critical care and ventilator dependency.

These projections assume the system's efficacy is validated. Actual cost-effectiveness will depend on device pricing, adoption rates, and clinical outcomes demonstrated in Phase III trials.

4.5 Future Research Directions

Beyond the validation roadmap (Section 2.9), several enhancements warrant investigation:

- **Extended Sensing:** Pulse oximetry and heart rate variability integration for cardiopulmonary assessment
- **Population Analytics:** Aggregated LEI trends for epidemiological insights and exacerbation prediction models
- **EHR Integration:** Automated data synchronization with electronic health records
- **Special Populations:** Pediatric and geriatric-specific protocols with adapted interfaces
- **Accessibility:** Voice control and multilingual support for broader reach
- **Biomarker Research:** Exhaled breath analysis for early disease detection (speculative; requires substantial additional development)

5. CONCLUSION

This paper presents a conceptual framework for the AI-Driven Pranayama Spiroball, a proposed system integrating respiratory rehabilitation with diagnostic monitoring. The key contributions are:

- Dual-Mode Architecture: A design combining Pranayama-based inhalation training (using spiroball with camera-based coaching) and spirometric exhalation measurement (using dedicated flow sensor)
- Technical Specifications: Detailed component requirements including MediaPipe-based pose estimation, BLE-connected spirometric sensor, and on-device AI inference
- Proposed LEI Metric: A composite index combining inspiratory capacity, expiratory function, and technique quality scores—presented with explicit uncertainty regarding optimal weightings and clinical validity
- Validation Roadmap: Phased approach from technical feasibility (n=15) through usability testing (n=30) to clinical validation (n=100)

Current Status: A functional prototype is currently under development. All efficacy claims remain hypothetical pending empirical validation.

Critical Next Steps:

- Completion of functional prototype
- Phase I feasibility study with healthy volunteers
- IRB approval and ethics committee review
- Iterative refinement based on pilot data

The design draws on evidence supporting Pranayama's respiratory benefits and addresses documented limitations of current home monitoring devices. However, the ultimate value of this approach depends entirely on validation outcomes.

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Conflict of Interest Statement:

The authors declare no financial or commercial conflicts of interest related to this conceptual framework. No prototype has been developed and no commercial entity is currently involved.

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