Patient Preference and Adherence Dovepress

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A Review of Sensor-Based Interventions for Supporting Patient Adherence to Inhalation Therapy

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Purpose: This review aims to provide a comprehensive overview of sensor technologies employed in interventions to enhance patient adherence to inhalation therapy for chronic respiratory diseases, with a particular emphasis on human factors. Sensor-based interventions offer opportunities to improve adherence through monitoring and feedback; however, a deeper understanding of how these technologies interact with patients is essential.

Patients and Methods: We conducted a systematic review by searching online databases, including PubMed, Scopus, Web of Science, Science Direct, and ACM Digital Library, spanning the timeframe from January 2014 to December 2023. Our inclusion criteria focused on studies that employed sensor-based technologies to enhance patient adherence to inhalation therapy.

Results: The initial search yielded 1563 results. After a thorough screening process, we selected 37 relevant studies. These sensor-based interventions were organized within a comprehensive HFE framework, including data collection, data processing, system feedback, and system feasibility. The data collection phase comprised person-related, task-related, and physical environment-related data. Various approaches to data processing were employed, encompassing applications for assessing intervention effectiveness, monitoring patient behaviour, and identifying disease risks, while system feedback included reminders and alerts, data visualization, and persuasive features. System feasibility was evaluated based on patient acceptance, usability, and device cost considerations.

Conclusion: Sensor-based interventions hold significant promise for improving adherence to inhalation therapy. This review highlights the necessity of an integrated "person-task-physical environment" system to advance future sensor technologies. By capturing comprehensive data on patient health, device usage patterns, and environmental conditions, this approach enables more personalized and effective adherence support. Key recommendations include standardizing data integration protocols, employing advanced algorithms for insights generation, enhancing interactive visual features for accessibility, integrating persuasive design elements to boost engagement, exploring the advantages of conversational agents, and optimizing experience to increase patient acceptance.

Keywords: patient adherence, inhalation therapy, sensor-based technology, human factors and ergonomics

Introduction

Inhalation therapy stands as a cornerstone in the management of chronic respiratory conditions, including asthma and Chronic Obstructive Pulmonary Disease (COPD).[1] Its efficacy lies in its ability to deliver targeted pharmacological agents to the respiratory tract, providing rapid symptom relief while minimizing systemic side effects.[2] However, despite its proven benefits, patient adherence to inhalation therapy remains suboptimal, lagging behind rates observed in other chronic illnesses.[3,4] The term "adherence", often used synonymously with "compliance", denotes the extent to which patients conform to the treatment regimens prescribed by healthcare professionals (HCPs).[1] Poor adherence is associated with increased morbidity, manifesting as aggravated symptoms, diminished life quality, heightened healthcare demands, and elevated mortality rates.[1,5]

Achieving precise monitoring and timely management of patient adherence is crucial in both clinical and research settings.[6] However, this effort faces numerous global challenges, further complicated by the multifaceted nature of adherence, influenced by factors related to the patient, their condition, the treatment, and the healthcare system.[1,7,8] Moreover, the use of inhalers poses unique "patient-device interaction" challenges for patients given their characteristics

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as drug-device combination products (DDCPs).[9] The multi-step procedures involved in device preparation, medication inhalation, and device maintenance add layers of complexity not encountered in simpler oral medication regimens.[9,10] Errors in inhaler usage may arise from non-adherence to the prescribed regimen, such as missed doses, or from improper inhalation techniques, such as incorrect dose loading.[11] Addressing these issues requires an understanding and tailored intervention strategies that specifically target the obstacles associated with patient adherence and inhaler technique proficiency.

In recent decades, there has been an increase in the development of information technology-driven strategies to enhance patient adherence. Among these strategies, sensor-based technologies, associated with mobile health applications and wearable devices, have emerged as promising tools for precisely monitoring adherence to prescribed treatments.[12–14] Studies have shown that sensor technologies can improve medication adherence by providing real-time feedback, reminders, and personalized interventions.[13,15,16] For example, the use of electronic monitoring devices to track medication usage in patients with asthma and COPD has been demonstrated to significantly improve medication adherence, reduce the frequency of exacerbations, and enhance overall lung function.[17,18] Additionally, environmental sensors that monitor air quality and detect potential asthma triggers can help patients manage their exposure to pollutants and allergens, thereby reducing the likelihood of asthma attacks.[19,20] However, despite these advancements, many of these studies primarily focus on technological capabilities and often overlook the complex human factors influencing user interaction and sustained engagement with these devices.[21,22] This indicates a gap in the current research regarding the integration of human factors into the design and implementation of sensor-based adherence interventions.

Human Factors and Ergonomics (HFE) plays a crucial role in this domain, offering a multidisciplinary approach that integrates patients' capabilities, limitations, and needs into the design and utilization of these systems or devices.[23,24] Unlike oral medications, inhalation therapy involves a complex interaction between the patient and the inhalation device, requiring proper technique and coordination.[8,15,25] This patient-device interaction is critical, as improper use can lead to reduced medication efficacy and poor health outcomes. When employing sensor-based technologies to enhance adherence in inhalation therapy, it is essential to understand how patients interact not only with the inhalation devices but also with the supporting systems. By employing an HFE framework, a dual assessment can be achieved: firstly, it refines our understanding of how patients engage with sensor-based systems, thereby evaluating the efficacy of interventions; secondly, it identifies specific patient-inhaler interaction issues that may lead to non-adherence and improper inhalation technique. Addressing these issues is critical to enhance the effectiveness of sensor-based technologies as they profoundly impact patient adherence and treatment efficacy.[12,15,23]

In the healthcare sector, HFE has proven instrumental in assessing the practical application of health information technology,[23] enhancing patient safety and care quality,[26] and optimizing healthcare workflow efficiency.[27] This track record highlights the potential of applying HFE principles to sensor-based interventions in inhalation therapy, where patient-device interactions are critical. Despite the existing literature cataloging these technologies, a comprehensive HFE perspective evaluating the impact of sensor-based technologies on patient adherence to inhalation therapy remains notably underexplored. In response to this gap, we present a systematic review that not only examines the effectiveness of sensor-based interventions but also explores how HFE principles can be integrated to optimize patient adherence.

The review is structured to examine the integration of sensor technologies within the HFE framework,[23,25] encompassing the nature of data collected, the processing methods employed for extracting insights, and the mechanisms of system feedback crucial to the effectiveness of adherence interventions. We propose that such a comprehensive framework not only enhances our understanding of current practices but also sets the stage for future advancements in sensor technology and adherence enhancement.

Materials and Methods

Search Strategy

The systematic literature search was conducted across several databases, including PubMed, Scopus, Web of Science, Science Direct, and ACM Digital Library. These databases were selected for their extensive coverage of healthcare and technology-related literature, as well as their established scholarly reputation. The search strategy employed a combination of keywords:

(sensors OR electronic monitoring devices) AND (adherence OR compliance) AND (asthma OR Chronic Obstructive Pulmonary Disease) AND inhalers. This approach was designed to collate the most current research of sensor-based interventions that enhancing patient adherence to inhalation therapy, with the scope limited to peer-reviewed studies published in English from January 2014 through December 2023.

Study Selection

Eligibility Criteria

The inclusion criteria for this systematic review were as follows: (a) participants must be diagnosed with chronic respiratory diseases, specifically asthma or COPD; (b) participants must have been undergoing a regimen of inhalation therapy; (c) studies must involve the direct implementation of sensor technologies to enhance patient adherence to inhalation therapy; (d) studies must have been published in a peer-reviewed journal; and (e) studies must have been authored in English language.

The exclusion criteria comprised the following: (a) studies not centered on sensor-based interventions aimed at improving adherence to inhalation therapy; (b) studies addressing chronic diseases other than respiratory conditions; (c) studies failing to specify the use of inhalation medications among participants; (d) studies categorized as editorials, discussions, opinion pieces, or conference proceedings; (e) non-original studies, such as study protocols or reviews; and (f) studies lacking accessible full-text versions.

Selection of Studies

The initial screening involved examining the titles and abstracts, leading to the exclusion of studies that did not meet the predetermined eligibility criteria. In cases where the abstracts and titles did not provide definitive eligibility determinations or when there was disagreement between the reviewers, full-text evaluations were conducted. If the two primary reviewers could not reconcile their differences, a third evaluator, was consulted to reach a consensus.

Data Extraction

Once the definitive collection of studies was determined, a comprehensive examination and categorization were conducted based on various evaluative criteria. Specifically, regarding sensor-based interventions aimed at supporting patient adherence to inhalation therapy, a team of three researchers extracted the relevant data. This process was carried out independently by each researcher, followed by collective discussions within the research team to ensure a harmonized understanding. Any discrepancies encountered during the data extraction process were resolved through collaborative consensus. The extracted data were then organized into four main thematic categories: (1) data collection, (2) data processing, (3) system feedback, and (4) system feasibility.

Results

Search results

The search strategy employed across various databases culminated in the accrual of 1563 citations (PubMed=122, Scopus=377, Web of Science=99, Science Direct=737, ACM Digital Library=228). After removing duplicates, an initial screening of titles and abstracts was conducted on 1232 studies. This process resulted in the exclusion of 1143 studies. A more in-depth full-text assessment was conducted on the remaining 89 studies to ascertain their eligibility, leading to the exclusion of an additional 52 studies. These includes a significant subset (n=28) that was excluded on the grounds of either not employing sensor-based technologies directly or providing inadequate details concerning sensor-based applications. Another 13 studies were eliminated as they focused on participant adherence to the intervention program rather than to inhalation therapy, and the rest 11 studies did not predominate with asthma/COPD patients or did not identify participants receiving inhaled therapy. Ultimately, 37 studies that met the selection criteria and were published between January 2014 and December 2023, were included in the systematic review (Figure 1).

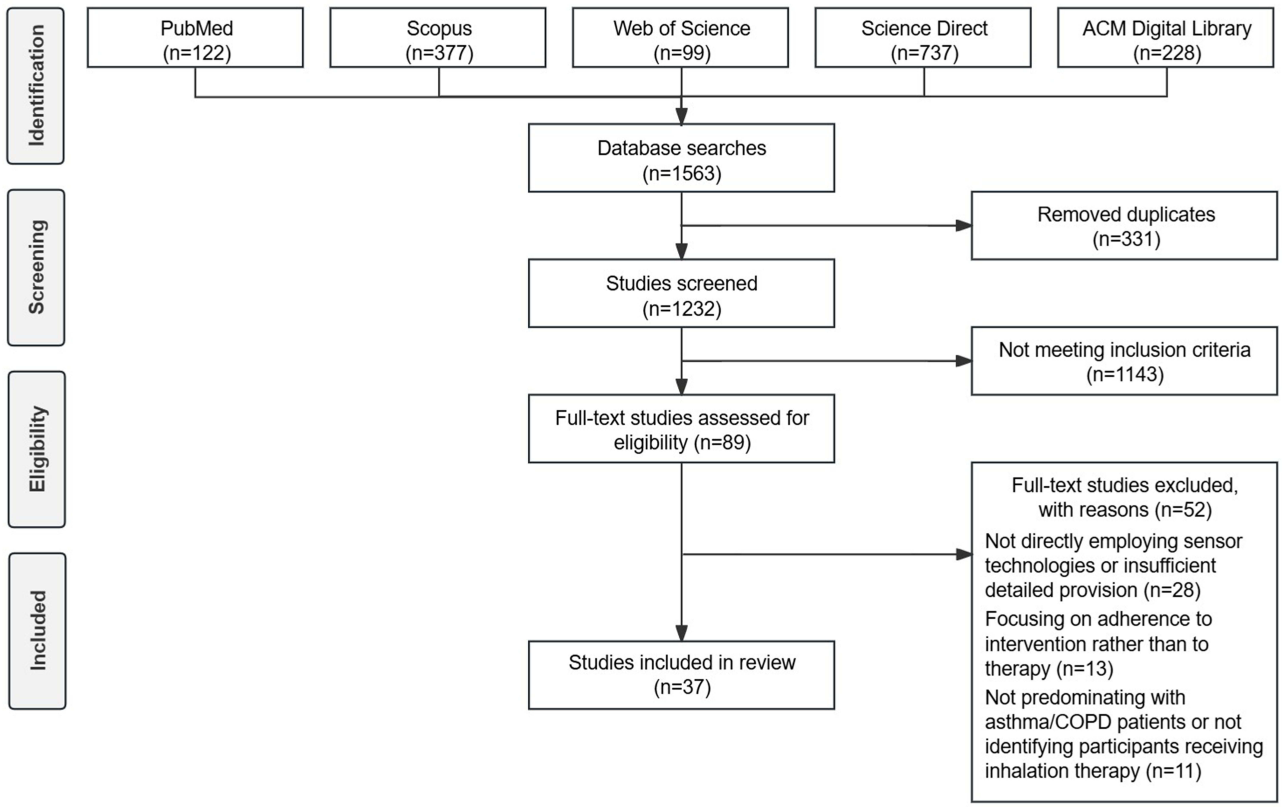

Figure 1 Flow diagram of included studies.

Study Characteristics

The literatures investigated in this study demonstrated a high level of diversity characteristic and avoided the uniformity of the data. The studies identified were conducted across 15 geopolitical regions: the United Stated (n=9),[20,28–35] the United Kingdom (n=8),[36–43] Ireland (n=7),[44–50] the Netherlands (n=2),[51,52] New Zealand,[53] England,[11] Australia,[54] Bangladesh,[19] China,[55] Greece,[56] India,[57] Japan,[58] and Switzerland (n=1 each).[59] Notably, one study included participants from Ireland and the United Kingdom,[60] while another involved a transcontinental cohort encompassing the United Kingdom, Europe, and North America.[61] The methodological heterogeneity of the studies was substantial, with 12 being randomized clinical trials, 7 being classified as experimental studies, 6 utilizing mixed-methods, 4 employing a cohort design, 4 being prospective observational in nature, 2 designated as pilot studies, one identified as a feasibility study, and a single study characterized as a prospective interventional investigation. The sample sizes of the included studies varied considerably, extending from a minimum of 11 participants to a maximum of 437 individuals. The temporal scope of the interventions also demonstrated a broad spectrum, with durations ranging from as brief as 14 days to as extended as 20 months. The demographic focus of the majority of interventions was centered on the adult and older adult populations. However, a subset of nine studies specifically targeted a younger demographic, inclusive of children and adolescents.

Thematic Categorization

The literature synthesis conducted in this study has identified three overarching themes related to the utilization of sensor-based interventions in supporting patient adherence to inhalation therapy. These themes are based on the framework proposed by Tsao et al (2019), which provides a comprehensive overview of wearable sensor applications for assessing human work and status within the context of HFE.[23] The framework consists of three fundamental components: data collection, data processing, and system feedback. It serves as a solid foundation for comprehending patient interactions with system elements and offers a structured approach to evaluating the efficacy of sensor-based intervention strategies. In response to recent insights on practical application, we have also included system feasibility as an additional theme, recognizing its importance in assessing the real-world viability of these interventions.[62–64]

In our previous research, which also adopted an HFE theoretical framework, we delved into the pivotal themes of "person", "task", and "physical environment" that significantly impact patient adherence to inhalation therapy.[25] The "person-related" factors encompass inherent patient characteristics, such as their capabilities. Task-related factors involve the specific tasks that patients must perform as integral parts of their therapy, such as the use of inhalation devices. On the other hand, "physical environment-related" factors encompass aspects of the physical surroundings that can influence patient adherence and overall health status, such as the home environment. These themes correspond to the subtopics within the data collection component of our review of sensor-based research (Figure 2).

Data Collection

The reviewed studies employed various sensors to collect person-related, task-related, and physical environment-related data. Person-related sensors monitored physiological conditions and tracked physical activities.[19,33,39–41,47,48,50,53,60] Task-related data focused on recording inhaler usage and technique to assess inhalation patterns.[11,20,28–41,43–56,58–61] Physical environment-related sensors gathered environmental parameters to identify triggers associated with respiratory symptoms.[19,42,57]

Person-Related Data

The utilization of person-related sensor data for the monitoring of physiological condition and the detection of physical activity has been the subject of investigation across a range of sensor modalities (n=10). Specifically, nine studies employed various sensor types to monitor critical physiological indicators, including lung function (n=8),[39–41,47,48,50,53,60] heart rate, oxygen saturation (n=1),[19] and body temperature (n=2).[19,39] Lung function is commonly measured with electronic spirometers or peak flow meters, which enable patients to measure and track their peak expiratory flow rate (PEFR), peak inspiratory flow rate (PIFR), forced expiratory volume in 1 second (FEV1) or forced vital capacity (FVC). One study harnessed sensor such as max30100 and ds18b20 to evaluate health data (ie heart rate, oxygen saturation and body temperature) to detect anomalous physical states.[19] The sensor-derived health monitoring data were further validated against commercial pulse oximeters and digital thermometers. In addition, two studies examined daily physical activity behaviour, with one using an accelerometer sensor to record the number of daily steps taken by patient,[33] and another utilizing a smartwatch to log sleep quality data and daily exercise pattern.[39]

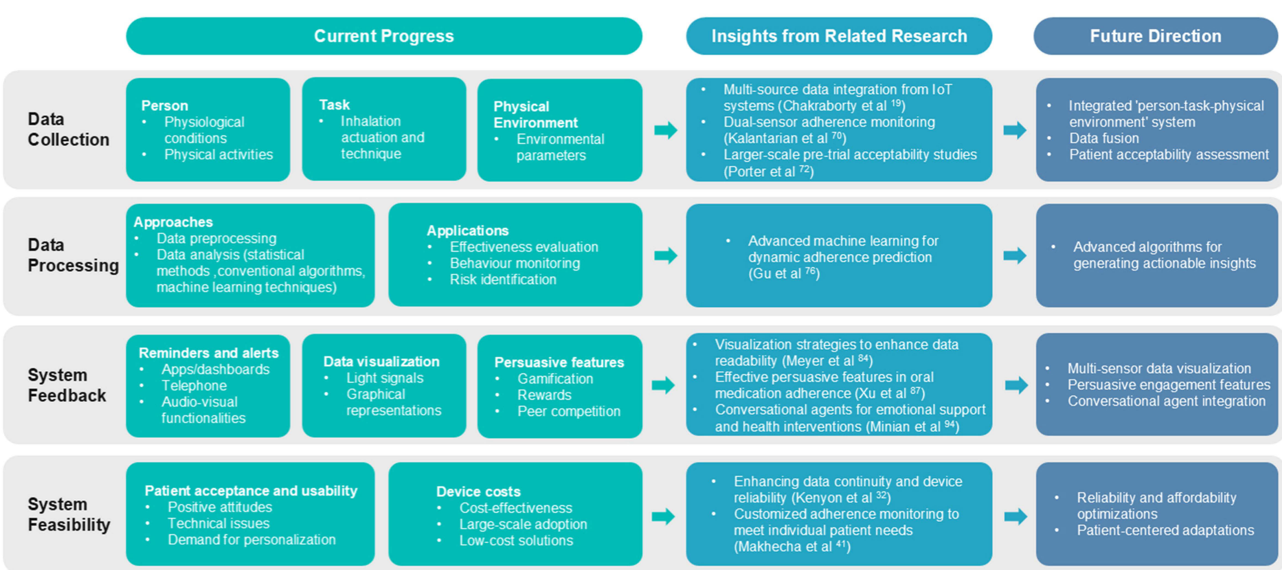

Figure 2 Framework of sensor-based interventions for supporting patient adherence in inhalation therapy: current progress, related insights, and future directions (data from Tsao et al 2019[23] and Ma et al 2023).[25]

Task-Related Data

The majority of the reviewed studies (n=34) leveraged task-related sensors to record the inhalation actuation and technique. Among these investigations, 18 studies primarily captured data related to the temporal aspects of device actuations, including date and time.[20,28–35,37,39,40,52–55,59,61] Notably, all studies seamlessly integrated commercial electronic monitoring devices, such as the Propeller Health,[20,28,34,35,61] SmartTrack,[53–55] and Smartinhaler.[37,40,59] Within this subset, two studies additionally incorporated location data to discern patient inhaler use patterns.[29,31] An additional 16 studies employed sensor-based technology to assess patient inhalation technique, utilizing acoustic sensors, motion sensors, airflow sensors, or multi-sensor configurations. The majority of these studies (n=13) explored the variability in acoustic characteristics and the consistency of the inhalation acoustic spectral profile, demonstrating a correlation between the acoustic features of inhaler inhalation and PIFR, thereby aiding in the monitoring of patient inhalation technique and adherence. Among these studies, 11 employed the INCA (INhaler Compliance Assessment) device to capture sound data during inhaler use,[11,36,38,41,44–47,49,50,60] while the remaining two studies utilized microphones.[48,56] Furthermore, one study proposed an inhalation monitoring system incorporating a motion sensor (ie, inertial measurement unit) attached to the inhaler to capture the time series of angular data during the administration of medication.[58] Another study employed a smart spacer with an integrated airflow sensor to detect errors in inhaler technique, such as multiple actuations, lack of inhalation, delayed inhalation, excessive flow, and low volume.[51] In addition, one study developed a sensor system embedded within a valved holding chamber, comprising temperature, pressure, and relative humidity sensors, to differentiate between tidal and deep breaths.[43]

Physical Environment-Related Data

Three studies were identified that employed sensors to collect environmental parameters, including physical devices (eg, temperature and humidity sensors, dust sensors, gas sensors, smartphones) as well as virtual sensors (eg, APIs). Collectively, these studies suggested that environmental indicators such as temperature, humidity, air quality, and associated GPS coordinates could reveal potential correlations with environmental triggers. Two of these studies gathered data on outdoor environmental conditions at the patient's location and the patient's physiological responses, subsequently analyzing the data to identify environmental factors associated with asthma symptoms.[42,57] One study developed an IoT-based remote health monitoring system for the surveillance of indoor environmental parameters, complete with an integrated alerting system designed to automatically issue alerts to patients and HCPs when sensor readings exceed safe thresholds.[19] Table 1 shows different sensor categories and examples.

Data Processing

The studies applied data preprocessing techniques to enhance sensor data quality by reducing noise and artifacts.[48–50,56] Analytical methods included statistical techniques to identify trends in adherence,[11,19,20,28,30–41,45–55,59–61] conventional algorithms for signal processing and pattern recognition,[43,44,58] and machine learning methods for classifying inhalation sounds and providing adaptive feedback.[42,56] These analyses were essential for evaluating the effectiveness of adherence interventions,[28–32,34–41,46,47,51–55,57,59–61] monitoring patient behavior and inhalation techniques,[11,19,33,43,44,48–50,56,58] identifying risks and predicting exacerbations.[20,42,45]

Approaches

The majority of studies included in this review employ different approaches for analyzing sensor data, with the primary objective being the extraction of valuable insights from complex datasets, particularly those related to adherence information. Since sensors are routinely affixed to inhalation devices, the normal operation and usage by patients can unintentionally generate signal artifacts and noise, potentially covering the core data elements. To enhance the precision and reliability of data analysis, a suite of data preprocessing strategies is meticulously applied prior to the application of sophisticated analytical techniques (Table 2). Such strategies encompass data normalization, notably the adjustment of DC offsets in audio recordings to cohere the signal baseline with a uniform reference point.[48–50] Concurrently, data cleaning operations are executed, deploying filtering methods to remove noise and artifacts, thereby revealing the authentic characteristics of the intrinsic respiratory signals.[50] Within the domain of feature engineering, deliberate efforts

Table 1 Sensor Categories and Examples

Category	Subcategories	Parameters	Sensor Examples
Person	Physiological condition	Lung function	Electronic spirometer or peak flow meter
		Heart rate and oxygen saturation	Pulse oximeter and heart rate sensor
		Body temperature	Skin temperature sensor
	Physical activity	Daily steps	Accelerometer
		Sleep quality and exercise pattern	Smartwatch
Task	Inhalation actuation	Date and time of actuation	EMD (eg Propeller Health, SmartTrack, Smartinhaler)
		Location of actuation	Smartphone
	Inhalation technique	Acoustic features of inhalation	INCA or microphone
		Inhalation motion	Inertial measurement unit
		Inhalation airflow characteristics	Airflow sensor
		Tidal and deep breaths	Temperature, pressure, and relative humidity sensor
Physical Environment	Environmental trigger	Temperature	Thermometer
		Humidity	Hygrometer
		Air quality	Dust sensors and gas sensors
		GPS coordinates	Smartphone

Table 2 Data Preprocessing Strategies

Preprocessing Technique	Approach Applied	Description
Data normalization	DC offsets removal	Normalizing audio data by aligning the signal baseline with a uniform reference point.
Data cleaning	Filtering	Removing noise and artifacts that may veil the intrinsic respiratory signals.
Feature engineering	Feature extraction	Extracting the most relevant audio features from raw data.

are directed towards the extraction and refinement of the most pertinent audio features from the raw data, thereby amplifying the signal's relevance for subsequent analytical pursuits.[48–50,56] These elemental preprocessing phases are meticulously delineated in four studies, establishing the foundation for an in-depth and perspicacious analysis of the data.

Following the preprocessing phase, the majority of the included studies have focused on applying various analytical strategies to the sensor data. Three primary analytical approaches have been identified: statistical methods (n=30), conventional algorithms (n=3), and machine learning techniques (n=2). A cohort of 30 studies has been identified to engage statistical methodologies (eg Descriptive Statistics, Linear Regression Model, Logistic Regression Model, etc.) to quantify and articulate the underlying trends and patterns observed within datasets pertinent to patient adherence. Notably, five of these studies have gone beyond quantitative analysis by integrating statistical methodologies with qualitative approaches, thus enriching the research with a deeper exploration into the narrative aspects of the data.[32,37–39,41] Concurrently, three studies have been recognized for their employment of conventional algorithms in data processing and analysis. Among these, one study has applied signal processing algorithms to the analysis of audio data derived from sensors.[44] One study has implemented a custom algorithm to differentiate between deep and tidal breaths,[43] while another has introduced a Dynamic Programming (DP) matching algorithm to assess individual inhaler motion by comparing patient data with pre-established reference patterns.[58] Furthermore, two studies have applied machine learning algorithms, a subset of artificial intelligence, to classify and interpret data with the aim of optimizing patient outcomes. One studies have employed an array of machine learning techniques, such as Support Vector Machines, Random Forests, and AdaBoost, etc. to autonomously classify and discern distinct sound types during inhaler utilization.[56] Another study has integrated Context-Aware Reasoning (C-AR) with Case-Based Reasoning (CBR) to analyze and learn from past cases, thereby enabling an adaptive feedback provision for current contextual information.[42]

Applications

The inclusion of adherence intervention programs has been a central focus in the studies examined, encompassing effectiveness evaluation of intervention (n=24), behaviour monitoring (n=10), and risk identification (n=3). Studies within the domain of effectiveness evaluation of intervention frequently assess clinical outcomes across diverse groups, aiming to compare the efficacy of sensor-based technologies against traditional methods or evaluate changes in adherence before and after implementing sensor technologies. Behaviour monitoring primarily focuses on the delineation and extraction of inhalation behaviour metrics, serving as a barometer for assessing patients' inhalation techniques and frequency of use (n=8).[11,43,44,48–50,56,58] Furthermore, two studies have ventured into the domain of remote health status monitoring, employing real-time analysis of data amalgamated from various sensors (eg health monitoring sensor, physical activity sensor, smart inhaler sensor and environmental monitoring sensor).[19,33] In the context of assessing the risk of asthma exacerbation, three studies have played a pivotal role. One study focused on the collection of space-time data pertaining to rescue inhaler utilization, thereby shedding light on environmental triggers associated with the deployment of inhalers.[20] Another study advocated for the integration of context dimensions with CBR to facilitate the identification of cause-effect dynamics associated with asthma triggers and symptomatic manifestations.[42] Moreover, a singular study has demonstrated the superior predictive capability of adherence data, specifically utilizing audio-based remote monitoring devices (ie, INCA), in forecasting asthma exacerbation risks. This monitoring system provides more accurate predictions than traditional dose counters by offering detailed adherence data through the analysis of audio recordings from inhaler use.[45] Table 3 presents an overview of the analytical approaches and practical applications within the domain of sensor data processing.

Table 3 Approaches and Applications Employed in Sensor Data Processing

Analysis Approach	Analysis Category	Application	Description
Statistical method	Quantitative	Effectiveness evaluation of intervention	Utilizing statistical methods to evaluate the effectiveness of interventions and compare clinical outcomes among diverse patient groups.
		Behaviour monitoring	Utilizing statistical methods to capture and convey the intrinsic characteristics of inhalation behaviour.
		Risk identification	Utilizing statistical methods to identify trends indicating the risk of asthma exacerbation.
	Quantitative and qualitative	Effectiveness evaluation of intervention	Combining statistical methods with qualitative approaches for a comprehensive evaluation of clinical outcomes.
Conventional algorithm	Quantitative	Behaviour monitoring	Employing conventional algorithms to extract key inhalation metrics through structured computational approaches.
Machine learning	Quantitative	Behaviour monitoring	Leveraging machine learning to dynamically extract and recognize patterns in inhalation behaviour.
		Risk identification	Leveraging machine learning techniques to analyze vast datasets and predict the risk of asthma exacerbation.

System Feedback

Studies implemented system feedback mechanisms to enhance patient adherence and engagement. Reminders and alerts were provided via sensors that monitored inhaler usage patterns and environmental parameters, delivering personalized notifications to prompt adherence and alert patients to unsafe conditions.[19,30,31,34,37,39,41,42,52–55,57,59,61] Data visualization used light signals and graphical representations to present data, aiding in trend identification and interventions.[19,32,41,43,44,54,56,57] Persuasive features like gamification, rewards, and peer competition enhanced engagement.[29,37,41]

Reminders and Alerts

Sensors within adherence-promoting systems actively monitor and respond to changes in inhaler usage patterns and environmental parameters, providing personalized reminders and alerts to enhance patient adherence. A total of 15 studies within the review focused on the implementation of reminders to prompt participants to adhere to their prescribed inhaler use regimens. The majority of the included studies have harnessed schedule-based medication notifications delivered through paired smartphone applications or web-based dashboards (n=12).[19,30,31,34,39,41,42,52,55,57,59,61] These reminders are aligned with prescribed care plans, and serve to prompt patients to adhere to their inhaler regimen. Notably, two studies have underscored the role of HCPs in providing additional telephone reminders when patients miss doses beyond predetermined thresholds.[34,55] Among these, three studies demonstrated the proactive alerting of users by their systems when sensor-detected environmental readings exceeded safe thresholds, such as in conditions with heightened pollen or pollution levels.[19,42,57] Additionally, three studies utilized electronic monitoring devices with audio-visual functionalities.[37,53,54] These devices provided visual feedback on the most recent usage information and employed sound alarms to notify participants, which could be silenced upon the correct administration of a dose.

Data Visualization

The design of data visualization within the studies aimed to present collected data to patients and/or HCPs. While the majority of studies indicated their systems' capability to record and review patient adherence-related data, only a subset (n=8) explicitly implemented data visualization mechanisms.[19,32,41,43,44,54,56,57] These mechanisms were categorized into two types: light signals (n=2) and graphical representations (n=6). Light signals were used to help patients understand device status, such as battery life or inhalation speed, through color-coded indicators.[32,43] In terms of graphical representations, three studies utilized bar charts,[19,41,54] and one employed scatter plots to offer feedback and assess data from sensors,[57] thereby aiding in the identification of significant trends and the facilitation of targeted interventions. Moreover, two studies provided researchers and HCPs with advanced visualization tools, such as spectrograms, cepstrograms, or Mel-frequency cepstral coefficients (MFCC) feature extraction, to discern each procedural step in inhaler use and to enhance comprehension of patients' inhaler usage patterns.[44,56]

Persuasive Features

Three studies incorporated persuasive elements, such as gamification, rewards, and peer competition, to enhance consistent inhaler use and bolster patients' self-efficacy. Two of these studies specifically targeted children or adolescents, using gamification techniques to increase engagement and interaction.[29,41] One study employed the Flo-Tone device, which attaches to an inhaler and produces an audible signal when the spacer is correctly utilized.[41] This signal triggers a game that children can play during medication inhalation, with the game's progression dependent on the detection of correct airflow by the accompanying app. Another study introduced an interactive basketball-themed system that provides immediate feedback via animations and scoring.[29] Upon correct inhaler use, patients were prompted within the app to attempt a virtual basketball shot, earning reward points and contributing to a leaderboard that displayed participants' adherence scores, incorporating a competitive element to encourage adherence. Additionally, one study offered monetary rewards tied to adherence, demonstrating the feasibility and acceptability of this intervention in improving adherence levels.[37] Table 4 delineates the mechanisms and categorizes the types of system feedback employed in the study.

Table 4 Feedback Mechanisms and Types

Feedback Mechanism	Type	Description
Reminders and alerts	Application or dashboard	Delivering scheduled medication reminders through paired smartphone applications or web dashboards.
	Audio-visual functionality	Providing visual feedback on device usage and sound alarms for timely notifications.
Data visualization	Light signal	Applying color-coded indicators to convey device status, including battery life and inhalation speed.
	Graphical representation	Utilizing graphical representations to provide feedback, assess data, and enable trend identification and targeted interventions.
Persuasive features	Gamification	Targeting children and adolescents with gamification techniques to enhance engagement and interaction.
	Rewards	Utilizing monetary incentives to encourage consistent and correct inhaler use.
	Peer competition	Leveraging a public leaderboard and reward points to introduce a competitive element, motivating adherence.

System Feasibility

The studies reviewed generally reported positive attitudes among participants regarding the acceptance and usability of sensor-based interventions.[30,32,38,39,41,42,51,52] However, technical issues, such as data synchronization delays and stability problems, were noted as factors that negatively impacted user satisfaction.[32,39,42,51,52] Additionally, the high costs associated with these devices were identified as a barrier to clinical implementation, raising concerns about their reusability.[41,53]

Patient Acceptance and Usability

Eight studies examined the acceptance and usability of sensor-based intervention programs. Seven of these used a mixed-methods approach, combining quantitative and qualitative methods,[32,38,39,41,42,51,52] while one study employed only quantitative methods.[30] Of the eight studies, six utilized the System Usability Scale (SUS) questionnaire to assess usability,[30,38,39,42,51,52] and two studies applied the Technology Acceptance Model (TAM); one study used a TAM-based questionnaire,[32] and the other conducted semi-structured interviews guided by TAM constructs.[38] Additionally, three studies incorporated patient adherence data,[30,38,41] specifically measuring inhalation frequency and correct usage, to provide an objective measure of user engagement with the interventions. The primary qualitative method used across studies was interviews, designed to capture participants' subjective experiences, preferences, and perceived barriers. Only one study used a structured observational method, examining the installation and use of the device to evaluate feasibility.[32]

Across all eight studies, participants generally expressed positive attitudes toward the acceptance and usability of the interventions. This favorable evaluation was largely attributed to the real-time data and feedback features, which significantly enhanced participants' awareness of their condition and promoted better adherence. However, six studies explicitly highlighted areas for potential improvements in usability and user experience.[32,39,41,42,51,52] Among these, five studies identified technical issues, primarily related to data synchronization delays and stability problems.[32,39,42,51,52] These issues were noted to disrupt the seamlessness of the experience, which negatively impacted participants' overall satisfaction. Additionally, four of the six studies indicated a strong demand for greater personalization, with participants expressing interest in receiving more individualized reminders and feedback tailored to their specific needs.[39,41,51,52]

Device Costs

Seven studies discussed the cost-effectiveness of device-related expenses. Two studies specifically highlighted the high costs of sensor-based electronic monitoring devices, noting the significant expense associated with their clinical implementation.[41,53] Device cost and reusability were identified as key considerations for the broader application and sustainability of such monitoring devices in clinical practice. Conversely, three studies suggested that large-scale adoption of sensor-based intervention technologies might enhance medication optimization services, potentially leading to long-term cost savings for healthcare systems.[38,46,60] Furthermore, two studies aimed to develop low-cost IoT health monitoring systems for daily asthma management, intending to create affordable options for patients and reduce overall costs for both patients and healthcare systems.[19,57]

Discussion

The present review conducted a systematic assessment of the current applications of sensor-based interventions designed to support patient adherence to inhalation therapy. The scope of this review encompassed a multidimensional examination of data collection methodologies, processing approaches, system feedback mechanisms, and system feasibility, all tailored to an HFE framework that underpins patient-device interaction and assesses practical applicability. Sensor technologies have demonstrated significant potential in the enhancement of healthcare quality and the promotion of patient adherence to inhalation therapy.[34] These interventions are capable of monitoring various data related to patient adherence, pertinent to patient adherence, including person-related, task-related, and physical environment-related factors.[25] Furthermore, they facilitate the assessment of intervention effectiveness, monitoring of patient behaviour, and prediction of disease states.[29,45,61] Notably, certain studies have provided personalized feedback on data and health counseling, effectively enhancing the effectiveness and efficiency of patient self-management and equipping HCPs with more sophisticated tools for patient oversight.[38,44,56]

Sensor-based technologies offer an objective metric for assessing adherence, which is indicative of the treatment's efficacy.[65] Clinical trials have substantiated the superior effectiveness of these technologies in tracking long-term adherence, as compared to traditional measurement techniques such as self-reporting and dose counting.[66] Within this context, this review employs an HFE framework to systematically categorize and evaluate sensor-based interventions aimed at enhancing patient adherence to inhalation therapy. The HFE framework, which accounts for the dynamic interplay among the person, device and environment, facilitates a thorough analysis of how sensor technologies may be strategically utilized to confront the multifaceted challenges inherent in adherence.[25] This review aims to underscore a significant opportunity for future research from a human factors perspective. By adopting the HFE framework, subsequent studies can develop more comprehensive interventions that address the complex nature of patient adherence, ultimately fostering improved adherence behaviors and sustainable outcomes. Despite this, a small subset of research has recognized the multidimensional aspects of non-adherence, employing Internet of Things (IoT) systems to collect data across various sensor dimensions.[19,39,57] These studies represent a nascent but important shift towards a more integrated approach to adherence monitoring. This review, therefore, advocates for a paradigm where future sensor technology design for inhalation therapy adheres to an integrated "person-task-physical environment" system. Such a system would facilitate the deployment of sensors that collect comprehensive data reflective of the patient's health status, device usage patterns, and environmental influences, thus providing a more comprehensive understanding of adherence behaviours.

Certainly, there is no single sensor that can be considered the ultimate choice, and the debate regarding the optimal sensor selection continues. For example, acoustic sensors, motion sensors, and airflow sensors each hold potential for assessing a patient's inhalation technique, yet each presents distinct advantages and challenges. Acoustic sensors, while minimally obtrusive and compatible with wearable technology, can be susceptible to interference from non-respiratory activities and ambient noise.[58] Motion sensors, useful for assessing the accuracy of the inhalation phase, may not capture the entire inhalation process.[67] Airflow sensors, known for their precision and sensitivity, require direct contact with the patient's airstream, which can be considered intrusive.[68] In light of this, a synthesis of data from multiple sensors may offer a more pragmatic solution. The fusion of data from various sensors enhances perceptual capabilities, improving system integrity, reliability, and robustness.[69] For instance, Kalantarian et al (2016) proposed a dual-step medication adherence assessment system, integrating commercial smart bottle technology with a bespoke smart necklace featuring piezoelectric sensors.[70] This integration not only detects pill bottle access but also confirms medication ingestion via analysis of lower neck skin movements during swallowing, demonstrating the potential of sensor fusion to provide a detailed and nuanced adherence profile. Future research is encouraged to exploit the collective strengths of diverse sensors and to apply data fusion methodologies, thereby overcoming the inherent limitations of individual sensors.[71] Additionally, future studies should assess the acceptability of such integrated systems from the patients' perspective before initiating larger-scale trials.[72,73] This strategy is expected to elevate the precision of adherence monitoring and enable tailored interventions for a more accurate reflection of patient behaviours.

The review also reveals a predominant reliance on conventional data analysis methods, with statistical techniques being the most commonly used. However, the applications of both standard algorithms and machine learning are notably scarce.[74] Advanced methodologies like reinforcement learning, deep learning, or ensemble learning are conspicuously absent from the surveyed literature. The paucity of deep learning applications may stem from the limited sample sizes, as deep learning thrives on extensive datasets.[75] Remarkably, Gu et al (2021) leveraged an internet-connected "smart sharps container" equipped with machine vision-based sensors to monitor adherence to injectable medications, employing ensemble and deep learning models to predict adherence.[76] Their findings indicated that Long Short-Term Memory (LSTM) networks outperformed traditional machine learning models in discerning nuanced variations under dynamic conditions. Furthermore, studies incorporating machine learning have reported high levels of patient acceptability, as the personalized, adaptive, and unbiased feedback provided by these algorithms enhances user engagement and satisfaction.[63,77] Given the proven effectiveness of advanced machine learning algorithms in enhancing adherence monitoring for DDCPs, such as injectable medications, it stands to reason that these algorithms could also significantly improve predictive and monitoring capabilities for other types of DDCPs, including inhalation devices. Therefore, it is recommended that future research should consider the application of advanced algorithms to augment the monitoring and predictive capabilities of patient adherence to inhalation therapy.

Moreover, in the majority of studies, adherence-related data is commonly presented through sensor-paired application interfaces using traditional two-dimensional chart formats, such as bar graphs. However, these conventional methods often fail to effectively convey the dynamic interplay and depth of information that can be extracted from sensor data.[78] The integration of data from multiple sensors presents unique challenges, such as harmonizing data representations from different sources, aligning and correlating data across various time scales, and condensing extensive data into visually digestible formats without sacrificing crucial details.[79,80] Unfortunately, these challenges have not been extensively explored in existing research, highlighting a gap that future studies must address.[81] To fully leverage the potential of visualizations, it is crucial to recognize that different visual representations can significantly impact user engagement and experience, even when presenting the same data.[82] Factors like color choice, layout, narrative text, interactivity, metaphorical elements, and data volume all play vital roles in enhancing information readability and perceived value.[83] For instance, Meyer et al (2016) demonstrated the use of a tree metaphor to objectively depict a patient's health status, ensuring privacy while making health data more comprehensible through metaphorical visualization.[84]

Expanding on this premise, visualizing multi-sensor data involves complexities that go beyond these considerations. The integrated presentation of data must not only be visually appealing and user-centric but also capable of revealing nuanced patterns and relationships necessary for understanding patient behaviour and adherence.[85,86] This requires a sophisticated approach to visualization that can effectively manage the intricacies of multi-sensor data, ensuring that the visualizations provide a meaningful representation of the underlying complexities. Future research should thus focus on assessing the preference and usability of diverse sensor data presentation methods, with a particular emphasis on integrating data from multiple sensors.[78,80] This research should aim to develop visualizations that are not only informative but also enhance user interaction and comprehension. Moreover, it is essential to consider the preferences and requirements of various demographic groups, including the elderly and children, as well as individuals with different levels of professional expertise, such as patients and HCPs.

In the current landscape of sensor-based interventions for inhalation therapy adherence, it is evident that only a minority of studies have incorporated persuasive design elements such as gamification, rewards, and peer competition within their systems. These elements are strategically implemented to bolster regular user engagement and deepen immersion within intervention programs.[87,88] Although persuasive strategies have been documented to enhance medication adherence in the management of chronic diseases involving oral therapies, the domain of inhalation therapy adherence lacks robust empirical evidence and standardized methodologies for evaluating the impact of these persuasive elements. Consequently, there is a pressing need for future research to substantiate the efficacy of such approaches.

The majority of studies reviewed here have utilized mobile applications or web dashboards in conjunction with sensor technology to monitor patient adherence to inhalation therapy. However, it is noteworthy that only two studies have incorporated a conversational agent approach for data interaction. Conversational agents, such as virtual assistants or chatbots, offer a more contemporary approach within healthcare settings.[89,90] The benefits of conversational agents are underscored by their ability to provide personalized feedback and suggestions through the application of natural language processing (NLP) and machine learning algorithms.[91] Furthermore, conversational agents can provide emotional support and motivational encouragement through simulated interpersonal communication,[92] which is particularly important for long-term adherence to treatment regimens.[93] For instance, Minian and colleagues (2023) developed a patient-centered healthbot to help people adhere to varenicline.[94] This healthbot agent not only delivers personalized support but also effectively boosts patient engagement. The results indicated that this approach had positive effects on improving patient adherence and quality of life. Given these advantages, future interventions could explore the integration of conversational agent and sensor-based technology, with the aim of providing a more comprehensive and effective patient support system.

Beyond the data-centric themes, this review underscores important insights into the acceptance and usability of sensor-based interventions. Patient acceptance and usability were generally high, with real-time feedback and self-monitoring features significantly enhancing patients' awareness and willingness to use the intervention system.[38,39] These factors contributed to enhanced adherence through sustained engagement and satisfaction.[41,51] However, several studies identified technical issues, including data synchronization delays and device stability problems, which negatively affected user satisfaction.[32,39,42,52] Additionally, there was a strong demand for more personalized features, such as individualized reminders and tailored feedback, to better meet patient needs and improve convenience.[41,51] These findings suggest that future research should focus on enhancing technical reliability and developing customized engagement strategies to optimize both user experience and adherence, thereby facilitating the scalability of these interventions.

Besides, the included studies exhibited considerable methodological diversity and a broad range of intervention durations, reflecting differing objectives and developmental stages of sensor-based technologies in inhalation therapy. For instance, short-term studies primarily assessed the validity, usability, and acceptability of new sensor technologies over brief periods to demonstrate technical feasibility and collect initial user feedback.[38,52] In contrast, long-term studies, often structured as clinical trials, aimed to evaluate the sustained impact of sensor-based interventions on patient adherence and clinical outcomes, necessitating extended observation periods to capture long-term effects and behavioral changes.[34,47,60] Despite these methodological and temporal differences, the review identified consistent themes related to data collection, processing, and system feedback mechanisms within the HFE framework. This uniformity notes the robustness of the HFE framework in categorizing and synthesizing diverse study outcomes, demonstrating that fundamental principles of patient-device interaction remain central to improving adherence regardless of study design or duration. However, the methodological heterogeneity and varying study durations do pose challenges for direct comparability and generalizability of adherence measurements.[3,95] Future research should strive for more standardized methodologies and consistent adherence definitions to enhance the comparability of findings, while continuing to leverage the HFE framework to uncover enduring insights across diverse intervention strategies.

Limitations

This review acknowledges several limitations that may impact the comprehensiveness of our findings. One of the primary limitations of this systematic review is the methodological heterogeneity among the included studies. This heterogeneity reflects the diverse objectives and developmental stages of sensor-based technologies in inhalation therapy. Such differences may affect the comparability of adherence outcomes across studies and limit the ability to draw definitive conclusions regarding the overall effectiveness of sensor-based interventions. Additionally, as with any review, our database selection and search strategies might not have been sufficiently extensive to capture all published literature. Although the trial search was performed in the major digital libraries related to computer science and medicine, relevant studies that investigate sensor-driven interventions for supporting patient adherence to inhalation therapy may have been missed. Moreover, our review's focus on sensor technologies for inhalation adherence improvement suggests that the assessment criteria and findings may not be directly generalizable to other forms of oral medication adherence.

Conclusion

The paper presents the findings of a systematic literature review, which consolidates current research on the utilization of sensor technologies to support patient adherence to inhalation therapy. Employing an HFE framework, the review has systematically characterized the spectrum of sensor-based interventions, detailing their respective data collection strategies, methodologies for data processing, mechanisms for system feedback, and considerations of system feasibility. The review advocates for the adoption of an integrated "person-task-physical environment" system as a foundational framework for the development of future sensor technologies. This system is essential for the deployment of sensors that can comprehensively capture data on patient health status, device usage patterns, and environmental contexts, thereby enabling a detailed understanding of adherence behaviours.

It is recommended that future research should focus on integrating sensors across multiple dimensions of measurement, employing advanced algorithms for data analysis and investigating strategies to visualize the data and provide effective feedback to users. For future research, it is highly recommended to prioritize the integration of sensors across multiple dimensions of measurement. This would entail incorporating a wide range of sensor technologies to capture and analyze data from various sources, enabling a more comprehensive understanding of the adherence under investigation. Additionally, the development of advanced algorithms for data analysis should be explored, as this can enhance the accuracy and efficiency of data processing, leading to more robust findings.

Furthermore, investigating strategies to effectively visualize the collected data and provide meaningful feedback to users is of utmost importance. This would involve developing innovative approaches to present complex data in a user-friendly and easily interpretable manner, facilitating better comprehension and engagement with the research outcomes. Future research should also focus on improving usability, reducing technical issues, and enhancing user experience, as these factors are essential for increasing patient acceptance and engagement. There is a pressing need to further substantiate the efficacy of these intervention strategies and develop a robust scientific evaluation framework. Taking a comprehensive approach will facilitate a more exhaustive and effective intervention, ultimately aimed at enhancing patient adherence to inhalation therapy.

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