Investigating Sensor-based Interventions to Support Patient Adherence to Inhalation Therapy

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Abstract

Patient adherence to inhalation therapy for chronic respiratory conditions, specifically asthma and Chronic Obstructive Pulmonary Disease (COPD) remains a persistent challenge in healthcare, undermining treatment efficacy and leading to worsened health outcomes and increased costs. This thesis investigates the potential of sensor-based interventions, guided by Human Factors Engineering (HFE) principles, to improve patient adherence in these specific chronic respiratory conditions. By integrating real-time monitoring technologies and personalized feedback mechanisms, the research aims to design and evaluate systems that better support asthma and COPD patients in managing their inhalation therapy.

The thesis begins by establishing the theoretical foundations of patient adherence, sensor technologies, and the HFE framework (Chapter 2). It also outlines the research methodologies, with an emphasis on user-centered design approaches tailored to inhalation therapy for asthma and COPD (Chapter 3). As part of this structured, multi-phase approach, key factors influencing adherence—such as emotional experiences, environmental conditions, and cultural beliefs—are identified through semi-structured interviews within the HFE framework (Chapter 4). These insights inform the design of the XIAOXI system through participatory workshops (Chapter 5), and its development, which integrates multiple sensors to monitor patients' physiological conditions, inhaler usage, and environmental factors in real time (Chapter 6). The system's usability and effectiveness are evaluated, and machine learning models are applied to classify adherence behaviors based on the collected data (Chapter 7).

A comprehensive discussion of the key findings (Chapter 8) showcases the successful application and validation of the Patient Adherence to Inhalation Therapy Work System Model, demonstrating how the integration of HFE principles into the design significantly enhanced patient adherence in asthma and COPD. The research highlights the XIAOXI system as an innovative, sensor-based intervention that effectively combined user-centric design with personalized feedback, improving patient adherence and management of inhalation therapy in these patients. The assessment of data-driven approaches revealed that machine learning models were highly effective in classifying adherence behaviors, with emotional and environmental factors playing a crucial role. The final chapter (Chapter 9) concludes by summarizing the thesis' primary contributions and identifying avenues for future research to further improve patient adherence and outcomes in inhalation therapy for asthma and COPD.

Keywords: Patient Adherence, Inhalation Therapy, Asthma and COPD, Human Factors Engineering, Sensor-based Technology, Health Interventions

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Publications

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Abbreviations

ABS Acrylonitrile Butadiene Styrene

Accu Accuracy

ACT Asthma Control Test

API Application Programming Interface

ATU Attitude Toward Use

AUC Area Under the Receiver Operating Characteristic Curve

BI Behavioral Intention

BMQ Beliefs about Medicines Questionnaire

BPM Beats Per Minute

CAT COPD Assessment Test

CHI Consumer Health Informatics

CIS Connected Inhaler System

COPD Chronic Obstructive Pulmonary Disease

COPD-Q Chronic Obstructive Pulmonary Disease Knowledge Questionnaire

CQ Consumer Asthma Knowledge Questionnaire

DDCPs Drug-Device Combination Products

DHIs Digital Health Interventions

DP Dynamic Programming

DPI Dry Powder Inhaler

EEG Electroencephalogram

EMD Electronic Monitoring Device

F F-measure

FDA U.S. Food and Drug Administration

FEV1 Forced Expiratory Volume in 1 second

FP False Positive

GINA Global Initiative for Asthma

GOLD Global Initiative for Chronic Obstructive Lung Disease

GPS Global Positioning System

GSE General Self-Efficacy Scale

HBM Health Belief Model

HCPs Healthcare Providers

HFE Human Factors Engineering

INCA INhaler Compliance Assessment

IBI Inter Beat Interval

IMU Inertial Measurement Unit

IoT Internet of Things

IQR Interquartile Range

IRR Inter-rater Reliability

LMICs Low- and Middle-Income Countries

LR Logistic Regression

MAM Multidimensional Adherence Model

MARS Medication Adherence Rating Scale

MFCC Mel-Frequency Cepstral Coefficients

MHRA Medicines and Healthcare Products Regulatory Agency

ML Machine Learning

MLP Multiple Layer Perceptron

MMAS Morisky Medication Adherence Scale

MQTT Message Queuing Telemetry Transport

NB Naive Bayes

NEMDs Novel Electronic Adherence Monitoring Devices

NLP Natural Language Processing

PEFR Peak Expiratory Flow Rate

PEOU Perceived Ease of Use

PMC Particle Mass Concentration

pMDI pressurized Metered Dose Inhalers

PNC Particle Number Concentration

PPV Precision

PU Perceived Usefulness

QoL Quality of Life

RCTs Randomized Controlled Trials

RF Random Forest

RH Relative Humidity

RT Random Tree

SABA Short—Acting Beta 2 Agonists

SCT Social Cognitive Theory

SDK Software Development Kit

SEIPS Systems Engineering Initiative for Patient Safety

SMI Soft Mist Inhaler

SMOTE Synthetic Minority Over-sampling Technique

SMS Short Message Service

SUS System Usability Scale

SVM Support Vector Machine

TAI Test of the Adherence to Inhalers

TAM Technology Acceptance Model

TCM Traditional Chinese Medicine

TP True Positive

TPB Theory of Planned Behavior

TTM Transtheoretical Model

UPSQ Usability, Preference and Satisfaction Questionnaire

WHO World Health Organization

Chapter 1 Introduction

1.1 Introduction and Aims

Chronic respiratory diseases, notably asthma and chronic obstructive pulmonary disease (COPD), represent significant global health challenges due to their chronic inflammatory nature and progressive airflow limitation(Sabaté, 2003; Soriano et al., 2017). These conditions impose substantial burdens, given their persistent symptoms, frequent exacerbations, and the intensive management they require(Quaderi & Hurst, 2018; Soriano et al., 2017). According to World Health Organization (WHO), COPD is projected to be the third leading cause of death globally by 2030, highlighting the severity and urgency of addressing these diseases(C.-T. Wu et al., 2021). Similarly, asthma affects millions worldwide, significantly contributing to healthcare costs associated with frequent hospitalizations and emergency treatments(Nurmagambetov et al., 2018). While inhalation therapy is applicable to various respiratory conditions, this thesis specifically focuses on asthma and COPD due to their high prevalence globally, substantial impact on patient quality of life, and significant economic burden on healthcare systems. Effective and accessible treatment strategies are therefore essential for managing these chronic conditions.

Inhalation therapy has become a primary treatment modality for chronic respiratory diseases due to its ability to deliver medication directly to the lungs(Bhattacharyya & S Sogali, 2018; Borghardt et al., 2018). This method facilitates rapid symptom relief and reduces systemic side effects compared to oral medications(Cochrane et al., 2000; Dalby & Suman, 2003). The widespread prescription of inhaler devices worldwide underscores their critical role in disease management(S. Anderson et al., 2022; Y. Liang & Mak, 2021). However, the effectiveness of inhalation therapy is critically dependent on patient adherence, which remains problematic due to the complexity involved in inhaler usage(DiMatteo, 2004; Mäkelä et al., 2013).

Adherence is defined as the extent to which patients follow their prescribed treatment regimens(Sabaté, 2003). Compared to oral medications, inhalers—classified as drug-device combination products (DDCPs)—pose unique “patient-device interaction” challenges(Leiner et al., 2015). DDCPs are therapeutic products that integrate a pharmacological component (the drug) with a device component (such as an inhaler device), and effective medication delivery relies on the correct use of the device(Leiner et al., 2015; Y. Wang & Burgess, 2010). Inhalers require multiple procedural steps, including medication preparation, inhaler usage, and device maintenance, increasing the likelihood of errors and non-adherence(Gregoriano et al., 2018). Poor adherence can lead to ineffective treatment, persistent symptoms, frequent disease exacerbations, and increased healthcare costs(Osterberg & Blaschke, 2005; Sabaté, 2003). These limitations highlight the necessity of exploring new methods to support patient adherence.

There have been recent advancements in sensor-based technologies, which promise to bring solutions to these adherence challenges(Aldeer et al., 2018; Bhatia et al., 2020; Himes et al., 2019). Sensors integrated with inhalers can monitor inhaler usage patterns in real time, enabling healthcare providers (HCPs) to identify adherence issues promptly and offer personalized interventions, such as reminders or corrective feedback(Himes et al., 2019; G. Mosnaim et al., 2021; G. S. Mosnaim et al., 2022). By targeting individual adherence barriers, sensor-based technologies can potentially enhance patient engagement and improve clinical outcomes(Al-kahtani et al., 2022; Blakey et al., 2018; Chrystyn et al., 2019).

However, the successful implementation of sensor-based interventions demands a thorough understanding of patient-device interactions, making the application of Human Factors Engineering (HFE) essential. HFE is a discipline focused on optimizing interactions between people, technology, and systems by considering human capabilities, limitations, and characteristics(Meister, 2018; Tsao et al., 2019). In healthcare, HFE principles have effectively improved patient safety, usability, and care quality by tailoring technology and systems to patient needs(Carayon et al., 2006; Holden et al., 2013; Salwei et al., 2021). Nevertheless, integrating HFE into sensor-based inhaler interventions remains challenging, requiring detailed insights into specific adherence barriers, such as improper inhaler technique, which directly affect therapeutic effectiveness(J. Anderson et al., 2010; Carayon & Wooldridge, 2020; Hegde, 2013; Holden et al., 2013).

Despite the recognized importance of sensor technologies and inhalation therapy in managing chronic respiratory diseases, significant research gaps remain. Current studies often overlook critical patient-device interaction factors unique to inhalers, limiting their effectiveness in addressing adherence challenges comprehensively(Leiner et al., 2015). Additionally, systematic integration of HFE frameworks into the design and evaluation of sensor-based interventions in inhalation therapy is still emerging, and comprehensive empirical studies are scarce(Tsao et al., 2019). Addressing these gaps requires focused research to identify patient adherence barriers more precisely and to leverage HFE approaches effectively, facilitating the design of targeted, patient-centered interventions.

The objective of this PhD thesis is therefore to design and evaluate sensor-based interventions aimed at improving patient adherence to inhalation therapy for asthma and COPD patients by integrating HFE principles.

Specifically, this research examines factors influencing patient adherence, develops a sensor-based system tailored to patient needs, and assesses the practical effectiveness of sensor-driven interventions. Ultimately, this work seeks to enhance treatment outcomes and optimize inhalation therapy management for patients with chronic respiratory diseases.

1.2 The Call for Research on Sensor-based Interventions through an HFE Theoretical Framework

This research highlights the urgent need for sensor-based interventions, framed through the lens of HFE, by analyzing the intricacies of disease characteristics, inhalation adherence, and existing literature.

Related Studies: The use of sensor technology in healthcare has become increasingly popular, improving diagnostic procedures and offering individualized patient approaches(Al-kahtani et al., 2022; Awad et al., 2021). Innovations often focus on enhancing sensor sensitivity, optimizing algorithms, and improving data analysis. Examples of these advancements can be seen in applications like remote care and wearable health devices(Conway & Kelechi, 2017; Kaplan et al., 2023; G. Mosnaim et al., 2021). However, many of these developments prioritize technological improvements over the patients' experiences in real-world use(Tsao et al., 2019), especially in the context of managing chronic respiratory conditions such as asthma and COPD(Chrystyn et al., 2019).

HFE has been effectively implemented in healthcare to improve safety, usability, and patient outcomes. For example, HFE-based designs have improved surgical equipment arrangement to minimize mistakes and enhance teamwork(Hignett et al., 2013). Similarly, redesigning medication dispensing systems with HFE principles has reduced errors, and educational tools based on HFE have enhanced patient comprehension and engagement(Rousek & Hallbeck, 2011; Vaughn-Cooke et al., 2015). Despite these successes, HFE is rarely applied to sensor-based interventions in DDCPs such as inhalers. Existing research often focuses on device functionality and data accuracy, overlooking critical aspects like user interaction and adherence behaviors(Leiner et al., 2015; Tsao et al., 2019). This gap highlights the need to integrate HFE principles to better align sensor-based technologies with patient needs.

Characteristics of Diseases and Adherence Complexity: Asthma and COPD, as chronic respiratory diseases, present unique challenges due to their long-term and variable nature. Patients' responses to treatment often differ significantly, necessitating personalized monitoring and continuous management(George, 2018; Y. Liang & Mak, 2021; Quaderi & Hurst, 2018). Given the chronic course of these conditions, adherence to prescribed therapy is critical. However, non-adherence not only disrupts disease control but also undermines the effectiveness of continuous interventions(Bryant et al., 2013; George, 2018).

Adherence to inhalation therapy is particularly complex compared to oral medications. It involves intricate interactions between the patient and the inhaler device, requiring correct execution of multiple steps—including device preparation, device usage, and device maintenance(Cochrane et al., 2000; Rogliani, Calzetta, et al., 2017). These technical demands increase the likelihood of errors and make adherence more difficult. Furthermore, common barriers to oral medication adherence—such as forgetfulness, lack of understanding, and low motivation—are often intensified in inhalation therapy due to its procedural complexity(Monteiro et al., 2021; Skrabal Ross et al., 2020). Therefore, improving adherence requires addressing both behavioral challenges and technical demands of inhaler use(Chrystyn et al., 2019; Melani, 2021). This is especially critical for asthma and COPD patients, whose health outcomes rely heavily on consistent and correct use of inhalers(Barjaktarevic & Milstone, 2020; Bhattacharyya & S Sogali, 2018).

Sensor-Based Intervention Needs: Sensor-based technologies offer promising solutions to the challenges of inhalation therapy adherence by enabling objective, real-time monitoring of inhaler use(Aldeer et al., 2018; A. H. Y. Chan et al., 2021). These sensors can capture crucial data on inhalation timing, frequency, and technique, revealing adherence patterns and identifying specific errors such as missed doses or incorrect usage(Foster, Smith, Usherwood, et al., 2012; Nousias et al., 2018; Pradeesh et al., 2022). Real-time data also allows HCPs to deliver timely and personalized interventions based on actual patient behavior. In addition, proactive reminders and feedback mechanisms can help patients stay on track with their prescribed regimen, improving both engagement and clinical outcomes(J. Chen et al., 2020; De Simoni et al., 2021; Foster et al., 2014).

Despite these advancements, most existing sensor-based systems remain limited to passive monitoring and fall short in transforming data into meaningful, actionable feedback. Many studies fail to conduct real-world evaluations from multiple perspectives—such as usability, acceptance, and clinical effectiveness—which are essential to assess the true impact of these technologies on adherence(L. J. Anderson et al., 2020; Blakey et al., 2018; Farzandipour et al., 2017; Merchant et al., 2018). Moreover, while machine learning and data analytics have become prevalent in broader healthcare applications, their use in inhalation therapy adherence remains scarce(C.-T. Wu et al., 2021; Xiong et al., 2023). Few studies utilize these methods to classify adherence behaviors or extract insights from sensor-generated data.

Therefore, it is crucial that sensor-based interventions move beyond data collection to become more proactive, engaging patients directly through tailored feedback mechanisms. Current systems are often effective at acquiring data but fail to close the loop with users, offering little in the way of dynamic, real-time interaction(Kelders et al., 2012; A. Xu et al., 2014). There is a growing need for responsive systems that not only monitor patient behavior but also adapt feedback based on individual actions and preferences(Minian et al., 2023; Silva & Canedo, 2024). Tailoring such systems to the specific needs of asthma and COPD patients could significantly enhance adherence by supporting correct and consistent inhaler use(Basheti et al., 2014; Chorão et al., 2014; Eikholt et al., 2023).

Application of HFE Theoretical Framework: HFE offers a systematic approach to analyzing and improving the interactions between patients and inhaler devices, particularly in the context of chronic respiratory diseases such as asthma and COPD. These conditions often require complex and sustained self-management, where improper inhaler use is a common barrier to adherence(Bourbeau & Bartlett, 2008; Mäkelä et al., 2013). HFE provides tools to examine patient-device interactions, identify points of failure—such as incorrect technique, device handling issues, and misunderstandings—and guide the design of interventions that improve both usability and adherence(Leiner et al., 2015; Powell-Cope et al., 2008). These insights are crucial for developing interventions that improve adherence by addressing real-world patient-device interactions. In the context of asthma and COPD, such tailored interventions can directly target the specific challenges these patients face.

HFE emphasizes understanding the user experience, enabling the development of tailored interventions such as personalized training, enhanced instructional materials, or feedback systems that directly address the specific challenges patients face(J. Anderson et al., 2010; Carayon & Wooldridge, 2020; Holden et al., 2013). By integrating the perspectives of patients and HCPs, it becomes possible to design systems that provide more personalized feedback and support, improving both patient satisfaction and adherence(Jayaratne et al., 2019; Tsao et al., 2019). Incorporating HFE principles ensures that sensor-based interventions account for patient behavior, adherence patterns, and device interaction, ultimately enhancing patient care.

1.3 Research Aims

The primary objective of this thesis is to investigate the effectiveness and underlying mechanisms through which sensor-based interventions enhance patient adherence to inhalation therapy for asthma and COPD. This study aims to contribute both theoretically and practically by developing a framework for understanding adherence behaviors and evaluating the impact of sensor-supported systems in real-world settings. The specific goals are as follows:

1. To develop and apply an HFE framework to systematically analyse the factors influencing patient adherence to inhalation therapy in asthma and COPD.

2. To investigate the design and implementation of sensor-based interventions tailored to asthma and COPD patients, with the aim of enhancing adherence to inhalation therapy.

3. To evaluate the effectiveness of these interventions in improving adherence within the context of asthma and COPD management.

1.4 Research Questions

This study investigates how sensor-based interventions can support patient adherence to inhalation therapy for asthma and COPD, with the following specific aims:

1. Identify the key factors influencing patient adherence through the lens of the HFE theoretical framework.

2. Examine the scope and effectiveness of support offered by sensor-based interventions.

3. Evaluate the impact of these interventions on improving adherence to inhalation therapy.

Additionally, the study explores the design considerations of these interventions, including data collection methods, feedback delivery strategies, and integration approaches to ensure contextual relevance and practical effectiveness.

The primary research question is:

How can sensor-based interventions, informed by Human Factors Engineering principles, improve patient adherence to inhalation therapy for asthma and COPD?

This primary question is further divided into three groups of sub-questions:

RQ1. What are the key factors influencing patient adherence to inhalation therapy in the context of asthma and COPD?

- What is the current state of patient adherence to inhalation therapy?

- How can the HFE framework help identify specific factors influencing adherence?

The first group of questions focuses on identifying the factors that influence patient adherence to inhalation therapy within the HFE context, with a particular focus on asthma and COPD patients. This approach aims to deepen the understanding of patient behaviors—whether adherent or non-adherent—and to identify determinants that affect adherence to prescribed inhalation therapy.

RQ2. How can sensor-based interventions be designed to support patient adherence to inhalation therapy for asthma and COPD?

- How can sensor-based interventions collect data on patient adherence to inhalation therapy?
- How can they facilitate timely and personalized feedback based on adherence data?
- How can sensor-based approaches be effectively integrated into adherence support interventions?

The second set of questions explores the design and implementation of sensor-based interventions. Building on the findings from RQ1, it focuses on the technical and methodological elements necessary for developing effective adherence-support interventions for asthma and COPD.

RQ3. How can sensor-based interventions impact patient adherence to inhalation therapy for asthma and COPD?

- How can the effectiveness of sensor-based interventions in improving patient adherence be evaluated?
- How can data from sensor-based interventions be utilized to

monitor and classify patient adherence behaviors?

The third group of questions investigates the impact of sensor-based interventions on patient adherence. It includes both the evaluation of effectiveness and the use of sensor data, supported by machine learning techniques, to monitor and classify adherence behaviors, thereby contributing to a deeper understanding of patient engagement and treatment response.

1.5 Research Scope, Theoretical Basis, and Contributions

This thesis adopts an HFE perspective, specifically applying and extending the SEIPS 2.0 model to address patient adherence to inhalation therapy in asthma and COPD populations. Rather than focusing solely on technological development, this research systematically explores how HFE principles and systems thinking can guide the design, development, and evaluation of sensor-based interventions. The resulting system, XIAOXI, serves both as a practical intervention and as a validation platform for the proposed theoretical framework and identified adherence factors.

The research delivers integrated contributions across four domains: theoretical, methodological, technological, and practical. Central to these is the advancement of theoretical understanding through the adaptation of SEIPS 2.0 into a context-specific framework for inhalation therapy adherence.

Theoretical Contributions: This thesis extends the SEIPS 2.0

framework by developing the Patient Adherence to Inhalation Therapy Work System Model, which systematically defines and operationalizes five critical dimensions: Person, Task, Tool, Physical Environment, and Cultural & Social factors. This adapted model addresses a key theoretical gap by offering a structured understanding of multifactorial influences on adherence behavior within inhalation therapy. Moreover, since inhalers are representative DDCPs, this framework provides a transferable foundation for supporting patient adherence in other DDCP-based treatment contexts, broadening its theoretical relevance beyond respiratory care.

Methodological Contributions: A structured, HFE-driven mixed-methods approach was designed and applied across four sequential studies: qualitative exploration, participatory design workshops, sensor-based intervention system development, and an integrated evaluation of usability, effectiveness, and adherence behavior classification using machine learning. This structured approach not only facilitated the identification of key adherence factors but also demonstrated how these factors could be operationalized and validated through a sensor-based intervention. The methodology showcases how theoretical models can be effectively translated into real-world digital health solutions, providing a replicable process for future research in similar healthcare contexts.

Technological Contributions: The development of the XIAOXI system embodies the practical application of the theoretical and methodological frameworks. Guided by HFE and SEIPS principles, the system integrates adherence-related factors through a structured sensor deployment strategy developed in this study, based on the ‘Person–Task–Physical Environment’ framework. XIAOXI features real-time monitoring of inhaler usage, physiological conditions, and environmental factors, alongside interactive support components such as self-assessment tools, educational resources, and personalized feedback. This comprehensive design not only addresses behavioral challenges and context-specific barriers to adherence, but also serves as a prototype for scalable solutions in both respiratory care and broader DDCP applications.

Practical Contributions: This thesis offers actionable recommendations for HCPs and researchers regarding the design, implementation, and evaluation of sensor-based adherence interventions. The data-driven approach facilitates early identification of non-adherence risks, enabling HCPs to tailor treatment strategies. Simultaneously, patients benefit from enhanced self-management through real-time feedback, personalized reminders, and educational support. The demonstrated improvements in adherence outcomes among asthma and COPD patients highlight the system's practical value and its potential for broader clinical adoption in chronic disease management.

1.6 Mapping of Research Questions, Research Gaps, and Research Methods

To address the need for a clearer articulation of the relationship between research questions, identified gaps, and methodological choices, this section presents a structured mapping that clarifies the overall research logic and coherence. It explicitly links the primary research question and sub-questions to their corresponding research gaps and methodological approaches. Table 1.1 provides an overview demonstrating how each research question systematically responds to specific gaps identified in the literature through appropriate qualitative, quantitative, or mixed-methods approaches. Sampling strategies and methodological choices were carefully aligned with the nature of each research question to ensure that participant selection and research design directly addressed the identified gaps. Detailed rationale for sampling, methodological procedures, and a study-by-study mapping of objectives and methods are provided in Chapter 3.

Table 1. 1: Mapping of research questions, research gaps, and research methods.

Research Questions	**Research Gaps Addressed**	**Type of Research Approach**	**Specific Methods (Detailed in Chapter 3)**
Primary Research Question: How can sensor-based interventions, informed by Human Factors Engineering principles, improve patient adherence to inhalation therapy for asthma and COPD?	Integrative question addressing all identified gaps	Mixed-methods research	Semi-structured interviews, participatory workshops, system development, system evaluation, machine learning analyses
RQ1: What are the key factors influencing patient adherence to inhalation therapy in the context of asthma and COPD?	Limited exploration of patient engagement with inhalation therapy; Scarcity of studies applying HFE principles to identify adherence factors	Qualitative exploratory research	Semi-structured interviews
RQ2: How can sensor-based interventions be designed to support patient adherence to inhalation therapy for asthma and COPD?	Limited application of HFE principles in designing adherence support systems; Insufficient use of multidimensional sensor technologies; Need for intuitive and effective feedback systems	Qualitative design, participatory research, and system development	Persona development, scenario design, participatory design workshops, sensor-based system prototyping and implementation

RQ3: How can sensor-based interventions impact patient adherence to inhalation therapy for asthma and COPD?	Insufficient multi-perspective evaluation of intervention systems; Limited use of advanced data analytics for classification and evaluation of adherence data	Qualitative and quantitative evaluation & classification analysis	Multi-perspective system evaluation; machine-learning-based classification

1.7 Overview of Thesis

The structure of this thesis follows a traditional research format (Figure 1.1). It begins with a literature review, followed by a methods chapter detailing all the research activities. Next, there are four chapters, each describing one of the main research activities. The discussion and conclusion chapters complete the thesis. A more detailed overview of each chapter is provided below.

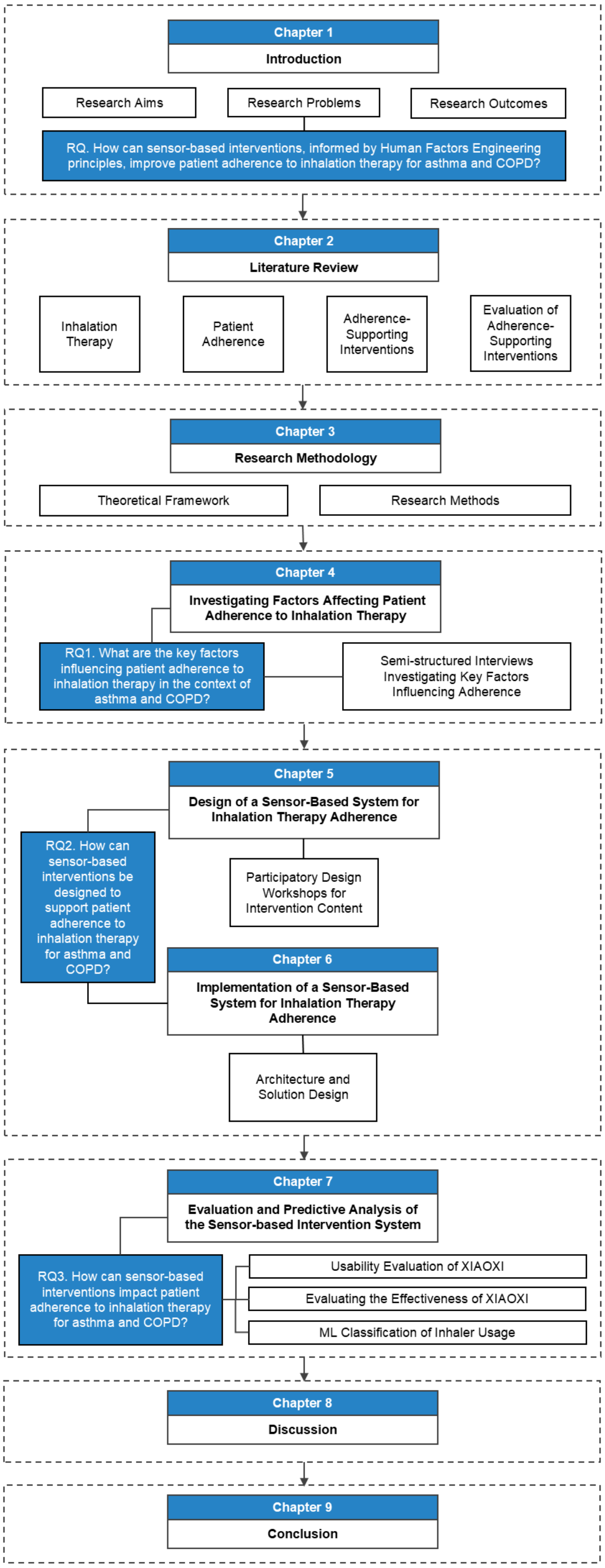


Figure 1. 1: Thesis structure.

Chapter 1 – Introduction: This chapter introduces the background, context, and motivation for investigating patient adherence to inhalation therapy in chronic respiratory diseases such as asthma and COPD. It highlights the need for sensor-based interventions through an HFE theoretical framework, defines the research aims and questions, and outlines the theoretical basis, contributions, and scope of the study. It also maps the relationships between the research questions, research gaps, and the methods used to address them, and concludes with an overview of the thesis structure.

Chapter 2 - Literature Review: This chapter reviews the existing literature to establish the foundational knowledge for this research. Section 2.1 introduces the aims of the literature review. Section 2.2 focuses on inhalation therapy, including its evolution, device types, usage processes, and the rationale for focusing on asthma and COPD. Section 2.3 examines patient adherence as a multifaceted concept, reviewing related theories, the SEIPS model and HFE, and adherence measurement methods. Section 2.4 reviews adherence-supporting interventions, with a focus on assistive technologies and sensor-based components. Section 2.5 outlines evaluation approaches and key assessment dimensions. Finally, Section 2.6 discusses key themes and gaps in the literature, highlighting this study's contribution in integrating HFE and sensor-based interventions to improve adherence in asthma and COPD.

Chapter 3 - Research Methodology: This chapter outlines the research methodology adopted in this study, which is grounded in the HFE framework and the SEIPS 2.0 model. Section 3.1 introduces the methodological aims and overall approach. Section 3.2 presents the theoretical framework, explaining the core concepts of SEIPS 2.0 and its relevance to the context of inhalation therapy for asthma and COPD. Section 3.3 describes the research methods, including data collection, design and prototyping, and evaluation strategies. Section 3.4 addresses methodological challenges encountered during the research and the strategies used to address them. Finally, Section 3.5 details the specific methods applied in each of the four studies, mapping them to research questions and discussing reliability and validity considerations.

Chapter 4 - Investigating Factors Affecting Patient Adherence to Inhalation Therapy: This chapter describes the semi-structured interviews conducted with patients and HCPs to understand the key factors influencing adherence to inhalation therapy in the context of asthma and COPD. The analysis, guided by the SEIPS 2.0 model, revealed a complex interplay of person, task, tool, physical environment, and cultural & social factors that shape patient adherence behaviors.

Chapter 5 - Design of a Sensor-Based System for Inhalation Therapy Adherence: This chapter focuses on the participatory design process of the XIAOXI system. Participatory workshops with patients and HCPs guided the conceptual design, helping to determine the system's core functionalities and components targeted for asthma and COPD patients. This chapter also compares different visualization strategies based on patient and HCP preferences, directing the user-centered design approach.

Chapter 6 - Implementation of a Sensor-Based System for Inhalation Therapy Adherence: This chapter details the technical implementation of the XIAOXI system, including sensor selection and integration for real-time monitoring of patient behavior. The final system design was informed by user requirements identified during the design phase, enabling the provision of personalized feedback and enhanced support for adherence to inhalation therapy in asthma and COPD.

Chapter 7 - Evaluation and Classification Analysis of the

Sensor-based Intervention System: This chapter presents a field study evaluating the XIAOXI system from both patient and HCP perspectives. The study uses quantitative data and qualitative feedback to assess system usability and effectiveness. It also introduces the application of machine learning models to classify daily inhaler adherence behaviors based on sensor and questionnaire data.

Chapter 8 - Discussion: This chapter discusses the main findings of the thesis. These findings primarily pertain to the application and evaluation of the patient adherence to inhalation therapy work system model, the role of HFE in enhancing adherence, and the strengths and challenges of data-driven approaches in supporting patient adherence specifically within the context of asthma and COPD.

Chapter 9 - Conclusion: The final chapter summarizes the primary contributions of this research, emphasizing the novel integration of HFE and sensor-based technologies to support patient adherence to inhalation therapy for asthma and COPD. The chapter also outlines potential avenues for further research that can be derived from this thesis.

Chapter 2 Literature Review

2.1 Introduction and Aims

This chapter establishes the theoretical foundation for understanding patient adherence to inhalation therapy. It begins with an overview of inhalation therapy, including its evolution, device types, usage processes, and the rationale for focusing on asthma and COPD (Section 2.2). Section 2.3 discusses patient adherence as a multifaceted concept, covering both dosage and technique adherence, and introduces theoretical models such as the SEIPS framework and HFE for analyzing patient adherence. Section 2.4 reviews adherence-supporting interventions, highlighting the role of assistive technologies and sensor-driven mechanisms in enhancing inhaler usage and monitoring.

In Section 2.5, evaluation methods and dimensions are examined to understand how adherence-supporting interventions are evaluated through field studies and real-world applications. Finally, Section 2.6 synthesizes global trends, challenges, and innovations in inhalation therapy, and discusses the novelty of this research in integrating HFE principles with sensor-based technologies under the SEIPS framework. The overall aim of this chapter is to provide a relevant theoretical perspective that can inform the research process in the context of inhalation therapy for asthma and COPD.

The specific objectives are:

1. To understand key concepts related to patient adherence and inhalation therapy.
2. To explore assistive technologies and sensor-driven mechanisms for adherence support.
3. To investigate theoretical and technical approaches for designing and evaluating adherence interventions.

2.2 Inhalation Therapy

2.2.1 The Evolution and Significance of Inhalation Therapy

Inhalation therapy has been known for many centuries, and the first records of its application can be traced back to ancient civilizations that used herbal smoke in the treatment of respiratory diseases (see Figure 2.1)(Lavorini, Buttini, et al., 2019; Rogliani, Calzetta, et al., 2017). A major breakthrough in modern inhalation therapy came with the introduction of the pressurized metered-dose inhaler (pMDI) in the 1950s, providing an efficient and portable method for delivering medication directly to the lungs. This advancement was followed by the development of the dry powder inhaler (DPI) and the soft mist inhaler (SMI), further enhancing the precision and convenience of drug delivery(Brocklebank et al., 2001; Sorino et al., 2020).

Significant technological advancements have established inhalation therapy as a cornerstone in the management of respiratory diseases(Bhattacharyya & S Sogali, 2018; Borghardt et al., 2018; Y. Liang & Mak, 2021). Its primary advantage lies in delivering medication directly to the lungs, resulting in fewer systemic side effects and faster drug action(Borghardt et al., 2018; Sorino et al., 2020). The evolution of inhaler devices has not only improved treatment efficiency but also expanded their role in clinical practice(George, 2018; Quaderi & Hurst, 2018; Rogliani, Calzetta, et al., 2017). Despite these advancements, respiratory diseases remain a major global health concern, underscoring the need for continuous innovation in inhaler design and technology to enhance treatment outcomes and patient quality of life(Bhattacharyya & S Sogali, 2018; Chrystyn et al., 2019; Steiropoulos et al., 2021).

(a) (b)

Figure 2. 1: A drawing (a) and photo (b) of the Mudge Inhaler.

2.2.2 Types of Inhalers

Inhalation devices are categorized primarily into four types (see Figure 2.2): pMDIs, DPIs, SMIs and Nebulizers (Bhattacharyya & S Sogali, 2018; Chrystyn et al., 2019; Garcia-Contreras et al., 2015; Usmani, 2019). Each type varies in their action and application and have different efficacy and indications for use with different patients.

(a) pMDI (b) DPI. (c) SMI. (c) Nebulizer.

Figure 2. 2: Types of inhalers.

pMDIs: pMDIs are designed to release a specific amount of medication in aerosol form through gas pressure. However, proper hand-breath synchronization is crucial for effective inhalation, which can be challenging for some patients, particularly the elderly and those with limited hand mobility. To improve drug deposition and reduce the need for precise synchronization, spacers are often recommended(Dhand et al., 2018; Steiropoulos et al., 2021; Usmani, 2019).

DPIs: DPIs deliver medication in powdered form and are breath-activated, meaning the medication is released when the patient inhales. This eliminates the need for hand-breath coordination, making DPIs especially suitable for patients who have difficulty using pMDIs. Due to their convenience and efficacy, DPIs are currently among the most commonly used inhalation devices worldwide(Islam & Gladki, 2008). However, effective use of DPIs requires a strong and consistent inspiratory flow rate, which may be challenging for certain populations, such as children, the elderly, and individuals with severe respiratory impairments(Altman et al., 2018; Clark et al., 2020).

SMIs: SMIs are a relatively newer device for drug delivery which is developed to overcome certain disadvantages of pMDIs and DPIs.

They produce a slow moving, fine droplets which take longer before they settle, this gives the patient enough time to take in the drug deep into the lungs(Komalla et al., 2023). SMIs require minimal inspiratory effort, making them suitable for patients with reduced lung capacity. However, they tend to be more complex to operate and are generally more expensive than pMDIs and DPIs, which may limit their accessibility(Nelson, 2016).

Nebulizers: Nebulizers convert liquid medication into a mist or aerosol, which is inhaled over an extended period using a mask or mouthpiece. They are particularly beneficial for patients who cannot effectively use other inhalation devices, such as infants, the elderly, or those with severe respiratory conditions(Barjaktarevic & Milstone, 2020). Nebulizers are widely used in hospitals for the management of severe and acute asthma and COPD, as well as in patients requiring high or long-term dosages. However, their larger size and limited portability often restrict their use to home or hospital settings, compared to the more portable pMDIs, DPIs, and SMIs(Tashkin, 2016).

2.2.3 Usage Process of Inhalers

Success of inhalation therapy is dependent on performing a precise series of interdependent steps(Basheti et al., 2014; Bosnic-Anticevich et al., 2018; Chorão et al., 2014). A thorough understanding of these steps is crucial for identifying potential adherence challenges and developing effective intervention strategies. The inhaler usage process can be broadly divided into three key phases: Device Preparation, Device Use, and Device Maintenance(Price et al., 2013; Sanchis et al., 2016; Usmani et al., 2018).

2.2.3.1 Device Preparation

Device preparation is a crucial phase consisting of two key aspects:

Usage Training: Before using an inhaler, patients need proper training on its operation. This training is typically provided by HCPs during clinical consultations or through clear instructions in the device's user manual(Bosnic-Anticevich et al., 2018; Dabrowska et al., 2019). Effective training ensures that patients understand the proper techniques and can perform the necessary steps accurately.

Preparation of the Inhaler: Once trained, patients must physically prepare the device for use. This involves several steps(Sanchis et al., 2016):

1. Uncapping: Removing the cap or cover from the inhaler.

2. Dose Loading: Loading the medication into the inhaler. This process varies by device type. For example, pMDIs require shaking the device to mix the medication and propellant, while DPIs often require twisting the cover/base to load a dose.

3. Holding the Inhaler: Positioning the device correctly to maximize medication delivery.

Common Errors in Device Preparation: Common errors during device preparation include insufficient training, where patients may misinterpret proper setup instructions, leading to mistakes. Improper uncapping can block medication delivery, while inadequate dose loading—such as forgetting to shake a pMDI or not fully twisting a DPI—reduces the effective dosage. Furthermore, incorrect handling, such as holding the inhaler in the wrong orientation, can significantly decrease lung deposition of the medication(Bosnic-Anticevich et al., 2018; Dabrowska et al., 2019; Sanchis et al., 2016; Usmani et al., 2018).

2.2.3.2 Device Use

Usage of the Inhaler: The effective use of an inhaler requires patients to perform the following steps correctly(Sanchis et al., 2016):

1. Exhalation: Fully exhale to clear the lungs before inhaling the medication.

2. Sealing: Place the lips firmly around the mouthpiece to form an airtight seal.

3. Inhalation: Breathe in deeply and steadily to allow the medication to reach the lungs.

4. Breath-Holding: Hold the breath for several seconds to allow the medication to efficiently reach the airways.

Common Errors in Device Use: Errors during device use often arise from improper exhalation, which limits the depth of inhalation. Inadequate sealing of the mouthpiece may result in medication leakage, reducing the amount of medication delivered to the lungs. Additionally, irregular or shallow inhalation patterns prevent the medication from reaching the lower respiratory tract, thereby diminishing its therapeutic effectiveness(Azouz et al., 2015; Basheti et al., 2014; Bosnic-Anticevich et al., 2018; Sanchis et al., 2016).

2.2.3.3 Device Maintenance

Maintenance of the Inhaler: Proper maintenance is crucial to ensure the effectiveness and longevity of the inhaler(Lavorini, Janson, et al., 2019; Ma et al., 2023; Rajan & Gogtay, 2014). Key maintenance steps include:

1. Cleaning: Wipe the device mouthpiece with a clean dry cloth when it needs cleaning.

2. Closing: Put the cap back on the mouthpiece and make sure it is firmly closed.

3. Storage: Store the device in a clean, dry place, away from direct sunlight and humidity.

4. Medication Update: Regularly check the medication level and expiration date, and replace it as needed.

Common Errors in Device Maintenance: The most frequent errors in device maintenance include forgetting to clean the mouthpiece, which can lead to blockages, and failing to properly close the cap, increasing the risk of contamination. Improper storage, such as leaving the device in humid or excessively hot environments, may degrade the medication. Additionally, patients sometimes continue to use inhalers that are expired or empty, which compromises treatment effectiveness(Price et al., 2013; Rajan & Gogtay, 2014, 2014; Sanchis et al., 2016).

2.2.4 Rationale for Focusing on Asthma and COPD

While inhalation therapy is applied to various respiratory conditions, this research specifically focuses on asthma and COPD, two of the most prevalent and impactful chronic respiratory diseases where adherence challenges are particularly pronounced and clinically significant(Bateman et al., 2008; Bousquet & Weltgesundheitsorganisation, 2007; Sabaté, 2003). Concentrating on these diseases allows for an in-depth analysis of adherence issues while providing insights that may be adapted to other inhalation-based therapies.

Prevalence and Global Health Impact: Asthma and COPD are among the most common chronic respiratory diseases worldwide, significantly affecting patient quality of life, morbidity, and healthcare resource utilization. Asthma currently affects approximately 300 million people globally and remains a major chronic condition across all age groups, with an estimated 100 million additional individuals projected to be at risk(Levy et al., 2023; Nurmagambetov et al., 2018; Q. Y. A. Wong et al., 2023). Meanwhile, COPD is projected by the WHO to become the third leading cause of death worldwide by 2030, reflecting its growing impact on public health(Mathers & Loncar, 2006; Nurmagambetov et al., 2018).

Complexity of Disease Management: Both asthma and COPD require sustained long-term management strategies, making patient adherence especially critical(Sabaté, 2003). Patients with these diseases typically need ongoing medication delivered via inhalers, and adherence challenges frequently arise not just from medication-taking frequency but also from the complexity of correctly using inhalation devices(Chorão et al., 2014; Chrystyn et al., 2019; Leiner et al., 2015). This complexity offers a valuable context for investigating adherence-related factors, positioning asthma and COPD as ideal case studies for intervention development.

Need for Personalized Intervention: Asthma and COPD have highly individualized treatment responses, requiring tailored patient monitoring and personalized interventions(George, 2018; Y. Liang & Mak, 2021). This heterogeneity underscores the importance of technology-enhanced, patient-centered approaches to adherence support—an area that is central to this research(Blakey et al., 2018; A. Chan et al., 2022; Kaplan et al., 2023; Van De Hei et al., 2023).

Socioeconomic and Regional Variability: The management of asthma and COPD is also heavily influenced by socioeconomic factors and healthcare accessibility, with marked disparities observed across different regions(Beran et al., 2015; Jansen et al., 2021; Mortimer et al., 2022; Soriano et al., 2017). In high-income countries, patients often benefit from advanced inhaler devices and robust healthcare support, contributing to better disease outcomes. Conversely, in low- and middle-income countries, inadequate disease management is common due to limited healthcare resources, high medication costs, and insufficient patient education, exacerbating health inequalities(Ait-Khaled et al., 2001; Mortimer et al., 2022). In China, asthma and COPD are major public health concerns due to the large patient population and persistently low adherence rates, highlighting the urgent need for targeted interventions(Kurmi et al., 2018; Q. Y. A. Wong et al., 2023).

By focusing on asthma and COPD, this research targets the most critical adherence challenges in inhalation therapy, establishing a framework to guide future interventions across similar therapeutic contexts.

2.2.5 Global Trends in Inhalation Therapy

The most recent development in inhalation therapy is the integration of technology in the design of digital inhalers(Al-kahtani et al., 2022; Blakey et al., 2018; A. Chan et al., 2022; A. H. Y. Chan et al., 2021). These innovative devices incorporate sensors and wireless communication technologies to track inhaler usage and monitor patient adherence to prescribed dosages(A. H. Y. Chan, Harrison, et al., 2015; Eikholt et al., 2023). By providing real-time feedback to both patients and HCPs, digital inhalers enhance compliance and improve treatment outcomes, holding significant promise for improving inhalation therapy adherence among asthma and COPD patients(A. Chan et al., 2022; G. S. Mosnaim et al., 2022; Rumi et al., 2022). Below are some of the most commonly used digital inhalers (see Table 2.1).

Table 2. 1: Different types of digital inhalers.

Device Name	**Mechanism/Function**	**Device Image**
CapMedic	An attachable sensor for pMDIs that provides real-time feedback on critical errors, measures inhalation flow, and records inhaler usage.	
Digihaler	Built-in inhalation flow sensor that monitors inhaler use and measures inhalation technique, including inspiratory flow rate.	
Hailie	Monitors inhaler shaking, orientation, and inspiratory flow; connects via Bluetooth to a patient's smartphone app.	
INhaler Compliance Assessment (INCA)	Audio recording sensor for Diskus inhalers; detects inhalation errors like incorrect priming and inadequate inspiratory flow.	
Respiro	Vibration sensor for various inhalers; provides feedback on inhalation steps and monitors inhaler usage.	
Smart AeroChamber	A digital spacer with an inhalation flow sensor that detects inhaler technique errors; currently available as a research prototype.	

Smart inhalers are increasingly recognized as essential tools for enhancing treatment outcomes due to their capacity to minimize human errors associated with inhaler use(Blakey et al., 2018; A. H. Y. Chan et al., 2021). These devices facilitate better communication between patients and HCPs, enabling more accurate tracking of inhaler technique and medication adherence(Chrystyn et al., 2019). As technology advances, it is anticipated that digital inhalers will become the gold standard for managing chronic respiratory diseases(Blakey et al., 2018; Chrystyn et al., 2019; Himes et al., 2019).

Recent trends indicate a growing demand for advanced inhalation devices that are both effective and user-friendly. The integration of digital health technologies into inhalers reflects a shift towards personalized medicine and data-driven healthcare, marking a new era in respiratory disease management(Greene & Costello, 2019; Kikidis et al., 2016; Xiroudaki et al., 2021). For asthma and COPD patients, these advancements enable more precise monitoring and tailored interventions, addressing the inherent complexity and variability of these conditions. With the rising global prevalence of respiratory disorders, inhalation therapy remains a rapidly evolving field. The development of tailored, technology-driven interventions will be critical in meeting the global challenges of chronic respiratory diseases(Bosnic-Anticevich et al., 2023; G. Mosnaim et al., 2021).

2.2.6 Efficacy of Inhalation Therapy

DDCPs are defined as systems comprising a pharmaceutical active substance and a delivery device that work together to achieve therapeutic effects(Y. Wang & Burgess, 2010). Inhalation therapy, where inhalers are employed to administer respiratory medications, is a classic example of a DDCP. For optimal therapeutic efficacy, three core dimensions must be addressed: safety, effectiveness, and usability (see Figure 2.3)(Hegde, 2013; Leiner et al., 2015; Pirozynski & Sosnowski, 2016; Skoner, 2002).

Safety: The safety of inhalation therapy is contingent upon both the medication and the device itself. Medications must be effective with minimal side effects, while the device should be designed to prevent misuse and avoid causing harm to the user(Alshammari, 2016; Donaldson et al., 2017). Proper design considerations can significantly reduce risks associated with incorrect handling or accidental exposure.

Effectiveness: The effectiveness of inhalation therapy is determined by the ability of the device to deliver the prescribed medication accurately to the targeted regions of the lungs(Borghardt et al., 2018; Patton & Byron, 2007). Achieving optimal therapeutic outcomes is heavily reliant on the formulation quality of the medication and the delivery precision of the inhaler. Devices such as pMDIs and DPIs are specifically engineered to ensure controlled and precise drug release, minimizing the risk of formulation degradation during the delivery process(Sorino et al., 2020). The reliability of these devices in maintaining dosage accuracy is critical for consistent treatment outcomes.

Usability: Usability refers to the ease with which patients can operate their inhalers correctly and consistently(Hegde, 2013; Leiner et al., 2015). Unlike oral medications, inhalers require users to learn specific handling techniques, such as positioning the device and synchronizing breathing. This complexity often leads to misuse and administration errors, thereby reducing treatment efficacy(Dabrowska et al., 2019; Hesso et al., 2020; Melani, 2021). HFE plays a crucial role in optimizing inhaler design to align with user needs, enhancing intuitiveness and reducing the cognitive and physical demands on patients(Carayon & Wooldridge, 2020; Hignett et al., 2013; Leiner et al., 2015). By applying HFE principles, developers can systematically evaluate how patients interact with inhalers, identify common usage errors, and refine device designs to improve usability.

Global Regulatory Landscape and Challenges: Regulatory bodies like the FDA and MHRA have incorporated HFE into their guidelines for DDCPs, emphasizing real-world usability testing to address patient variability and device complexity(Lauritsen & Nguyen, 2009; R. Patel et al., 2019). However, global adoption of these standards remains uneven. In developing countries like China, awareness of HFE's role in DDCP design is growing, yet the regulatory framework remains underdeveloped(Singh et al., 2023; Tian et al., 2022). Current Chinese guidelines predominantly focus on drug safety and effectiveness, with limited emphasis on device usability and human factors. This regulatory gap means that critical factors such as individual differences, device usability, and environmental conditions are often neglected in the design and evaluation of inhalers and other DDCPs(Carayon & Wooldridge, 2020; Hegde, 2013; Holden & Abebe, 2021; Leiner et al., 2015).

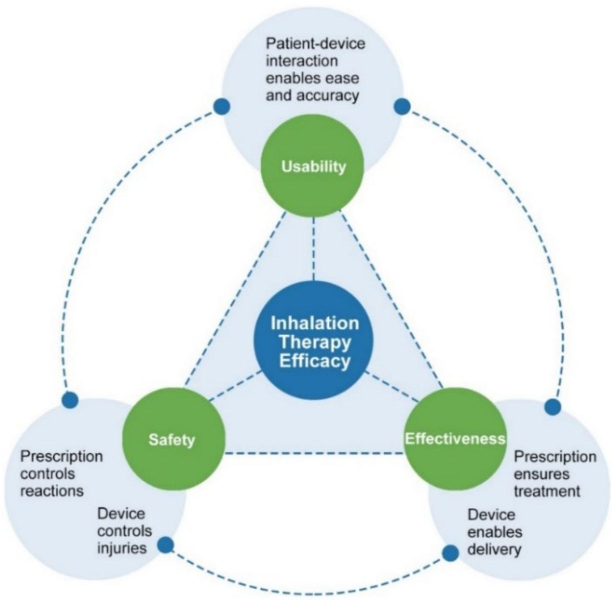


Figure 2. 3: Efficacy of inhalation therapy.

2.3 Patient Adherence to Inhalation Therapy

2.3.1 Defining Adherence: A Multifaceted Concept in Inhalation Therapy

2.3.1.1 Definition of Adherence

Patient adherence is a complex concept with varied interpretations across medical literature. The WHO defines adherence as “the extent to which a person’s behavior – taking medication, following a diet, and/or executing lifestyle changes – corresponds with agreed recommendations from a health care provider”(Sabaté, 2003). While this definition is widely accepted, it primarily emphasizes the patient's alignment with prescribed medical guidance, without fully addressing the unique demands of inhalation therapy. Balkrishnan (2005) further refines the definition by describing medication adherence as the degree to which a patient follows a treatment regimen after providing informed consent. Although both definitions underscore the importance of patient cooperation, they do not account for the specific procedural complexities associated with inhaler-based treatments.

To address the complexity of adherence, Vrijens et al. (2012) introduced the ABC taxonomy, categorizing adherence into three distinct phases: initiation, implementation, and persistence. “Initiation” refers to the first use of the prescribed medication, “implementation” describes how well the patient maintains correct dosing, and “persistence” measures the duration of therapy. While the ABC taxonomy provides a structured framework for assessing adherence, it falls short in capturing the precise handling and correct inhalation techniques required for optimal inhalation therapy. This gap is particularly significant for conditions like asthma and COPD, where effective delivery depends heavily on patient technique.

In the context of inhalation therapy, adherence extends beyond merely following dosage schedules; it also includes correct inhaler technique. Nikander et al. (2014) emphasize that true adherence encompasses both prescription adherence (taking medication as prescribed) and inhaler technique adherence (correctly using the inhaler device). Pritchard and Nicholls (2015) further quantify this dual-component perspective, suggesting that “adherence equals the percentage of adherence to the prescribed regimen multiplied by the percentage of correct inhaler technique.” This dual-layered definition highlights the need for interventions that not only encourage consistent use but also ensure proper technique to maximize clinical efficacy.

An additional perspective in understanding non-adherence is the application of Human Error Theory(Barber et al., 2005; R. Patel et al., 2021; Vaughn-Cooke et al., 2015). Barber et al. (2005) suggest that non-adherence can be analyzed similarly to human errors observed in high-risk industries, such as aviation or nuclear energy. From this viewpoint, non-adherence is not always a matter of deliberate choice; it can result from memory failures, misunderstandings, or environmental distractions. Applying Human Error Theory to inhalation therapy allows healthcare systems and device manufacturers to identify common usage errors and design interventions that minimize these mistakes. This perspective is aligned with HFE principles, which aim to optimize system design by accounting for human limitations and enhancing user experience(Vaughn-Cooke et al., 2015).

2.3.1.2 Forms of Non-adherence

Adherence in inhalation therapy is not a binary concept but occurs along a spectrum, with several forms of non-adherence often overlapping(Rand & Wise, 1994; Van Dulmen et al., 2007):

Non-Fulfillment: This includes "failure to start", when patients do not commence therapy after filling the prescription.

Non-Persistence: This occurs when patients discontinue therapy on their own, often without consulting a physician, typically within two to three months. Non-persistence is particularly problematic in chronic conditions where long-term adherence is crucial.

Unintentional Non-Adherence: This form is often due to cognitive factors such as lack of concentration, forgetfulness, or dementia. Patients may unintentionally make errors in inhaler technique, significantly compromising the effectiveness of the treatment.

Intentional Non-Adherence: Derived from the patients' beliefs and attitudes, this type involves a deliberate decision not to adhere strictly to the prescribed regimen. Some of the reasons include: fear of side effects, doubt in the effectiveness of the medication or a particular stigma of using the inhaler among other factors.

Non-Conforming Behaviors: Includes overuse, underuse, or unauthorized modifications to the dosage regimen. This type of non-adherence reveals that it can be difficult to manage treatments when the patient's behavior and preferences differ significantly.

2.3.1.3 Adherence Thresholds

Measuring adherence in inhalation therapy is inherently complex due to the multitude of influencing factors(Aldan et al., 2022; Khdour et al., 2012; Monteiro et al., 2021). Researchers have proposed various thresholds to define "good" adherence, which often vary based on clinical context and patient populations.

In inhalation therapy, adherence is typically quantified by the percentage of prescribed doses taken by the patient. Some studies consider adherence rates of 80% or higher as indicative of good adherence(Baumgartner et al., 2018; Murphy et al., 2012). However, recent research suggests that an adherence level of 75% is generally sufficient for maintaining clinical stability, particularly for patients with asthma or COPD(Asamoah-Boaheng et al., 2021; Huurne et al., 2015; Jansen et al., 2021). Deviations below this threshold have been associated with significant health deterioration, emphasizing the importance of maintaining this minimum adherence level. In terms of classification, adherence rates between 50% and 75% are often regarded as partial adherence, while rates below 50% are classified as poor adherence, reflecting a substantial gap in medication intake that could compromise disease control(Gutiérrez et al., 2017; J. Lee et al., 2018). Additionally, excessive medication usage, defined as more than 125% of the prescribed dosage, is associated with adverse effects and may paradoxically worsen disease outcomes(Baumgartner et al., 2018; Huurne et al., 2015; Rogliani, Ora, et al., 2017). This highlights the need not only to maintain the required dosage for therapeutic effectiveness but also to avoid overuse, which could contribute to medical complications and reduced therapeutic efficacy.

Beyond simple dosage adherence, proper inhalation technique is equally vital for effective therapy. The success of inhalation therapy is not solely dependent on the quantity of medication administered but also on the patient's ability to use the inhaler correctly(Melani, 2021; Nikander et al., 2014; Pritchard & Nicholls, 2015). Research indicates that patients frequently exhibit poor inhaler technique, such as incorrect device preparation, suboptimal inhalation flow rates, insufficient inhalation duration, and inadequate breath-hold after inhalation(Dabrowska et al., 2019; Eikholt et al., 2023; Hesso et al., 2020). These errors can substantially reduce drug deposition in the lungs, directly affecting treatment outcomes. Therefore, a comprehensive evaluation of adherence in inhalation therapy must consider not only the frequency of use but also the quality of inhalation technique, as both are crucial for optimizing patient outcomes in asthma and COPD management(Melani, 2021; Nelson, 2016).

2.3.2 Related Theories in Understanding Adherence

Understanding the factors influencing adherence in inhalation therapy requires an exploration of multiple theoretical models that address the psychological, environmental, systemic, physiological, and contextual dimensions of patient behavior. Below are the key models widely utilized in adherence research.

Health Belief Model (HBM): The HBM is widely applied to explain and analyze health behaviors by considering constructs such as perceived susceptibility, perceived severity, perceived benefits, and perceived barriers(Janz & Becker, 1984). In the context of patient adherence, HBM has been particularly effective in illustrating how patients' perceptions of their health conditions and treatment efficacy influence their medication-taking behaviors(C. J. Jones et al., 2014). For example, Khdour et al. (2012) utilized the HBM to examine how psychosocial factors affect medication adherence among COPD patients in secondary care settings. Their findings indicated that adherence in COPD patients is predominantly influenced by their perceptions of health status and medication effectiveness, rather than demographic factors or disease severity. Further supporting this perspective, Zhao et al. (2022)

identified that perceived risk and perceived benefits significantly impact health information-seeking behaviors among patients with chronic conditions.

Social Cognitive Theory (SCT): The SCT emphasizes the role of beliefs, self-efficacy, and social influences in shaping health behaviors(Conner & Norman, 2015). This model posits that individuals' confidence in their ability to perform a behavior (self-efficacy), along with environmental factors, significantly affect adherence outcomes. Bennett et al. (2018) applied SCT to analyze medication adherence among patients with depression, revealing that self-control, expectations about medication use, age, and race are significant determinants of adherence. Similarly, Heidari-Soureshjani et al. (2018) conducted a cross-sectional study exploring the relationship between adherence to health behaviors and SCT constructs among women with diabetes. Their findings demonstrated that outcome expectations, self-efficacy, and self-regulation were directly correlated with adherence levels.

Transtheoretical Model (TTM): The TTM proposes that individuals progress through six stages of change: precontemplation, contemplation, preparation, action, maintenance, and termination(Hashemzadeh et al., 2019). This model is frequently used to guide interventions by identifying a patient's readiness to change and tailoring support accordingly(Bridle et al., 2005; Prochaska et al., 2008). Johnson et al. (2006) applied TTM-based expert systems to enhance adherence to antihypertensive medications, demonstrating that stage-specific interventions can positively influence adherence irrespective of the patient's initial readiness. However, Ficke and Farris (2005) noted that TTM remains underutilized in medication adherence research, despite its capacity to segment patient populations based on readiness for behavioral change.

Theory of Planned Behavior (TPB): The TPB links health-related behaviors to attitude, perceived control, and subjective norms(Godin & Kok, 1996). According to TPB, an individual's intention to adhere to therapy is influenced by these three constructs, which in turn predict actual adherence behavior. Lin et al. (2016) utilized TPB in combination with action planning and coping planning to assess medication adherence among adults with epilepsy, finding that these factors collectively explained over 50% of adherence variance. Additionally, Ho and Lee (2014) conducted a cross-sectional analysis indicating that attitude, subjective norms, and perceived behavioral control significantly influenced hypertensive patients' intentions to adhere to medication, ultimately impacting their actual behavior.

WHO's Multidimensional Adherence Model (MAM): The MAM developed by the WHO classifies adherence determinants into five dimensions: patient-related, therapy-related, condition-related, healthcare system-related, and social/economical(Sabaté, 2003). This comprehensive framework addresses the multifaceted nature of adherence by examining both patient behaviors and systemic influences. For example, Aldan et al. (2022) found that medication adherence in COPD patients was primarily influenced by factors related to the patient, the treatment, and the condition itself. They recommended that HCPs implement tailored training and counseling programs for newly diagnosed patients, those with multiple medications, and individuals with comorbidities. Furthermore, Wu et al. (2008) demonstrated that patient education, perceived health benefits, and access to healthcare significantly impact adherence rates in heart failure patients, underscoring the relevance of MAM in understanding complex adherence behaviors.

While these models effectively capture various determinants of patient adherence, they largely overlook the critical role of device-related interactions specific to inhalation therapy. Factors such as device handling, user confidence, technical complexity, and comfort of use substantially influence adherence but are inadequately represented in these theoretical frameworks. This gap suggests a need for models that integrate patient-device interaction to more accurately predict and support adherence behaviors in asthma and COPD patients (see Table 2.2).

Table 2. 2: Related theories in understanding adherence.

Theory	Core Factors	Strengths	Limitations in the Context of Inhalation Therapy
HBM	Perceived susceptibility, severity, benefits, barriers, and stigma	Explains motivation and health beliefs	Primarily focuses on individual beliefs and does not fully address practical challenges of device use
SCT	Self-efficacy, interaction between behavior, personal factors, and environment	Highlights self-efficacy and social support	Does not fully account for the impact of device design and usability on adherence
TTM	Stages of change: precontemplation, contemplation, preparation, action, maintenance, termination	Supports stage-based interventions	Focuses mainly on behavior change and does not consider device-related barriers or external factors impacting adherence
TPB	Attitude, perceived control, subjective norms	Analyzes intention and motivation	Lacks a comprehensive approach that accounts for device intricacy or external conditions
MAM	Patient-related, therapy-related, condition-related, healthcare system-related, and socioeconomic factors	Considers multiple dimensions	May require more granular insights into device-specific barriers

2.3.3 SEIPS Model and HFE in Adherence

2.3.3.1 The Role of HFE in Patient Adherence

HFE provides a structured approach to optimizing patient interactions with healthcare systems, emphasizing safety, efficiency, and usability(J. Anderson et al., 2010; Carayon & Wooldridge, 2020; Hignett et al., 2013). In the context of DDCPs like inhalers, HFE addresses critical barriers such as device complexity, cognitive overload, and inadequate user training that can impair proper usage(Leiner et al., 2015; Saidi et al., 2019). By focusing on user-centered design and ergonomic principles, HFE enhances both patient experience and adherence, leading to improved treatment outcomes(Sheehan et al., 2022; Tsao et al., 2019).

HFE is instrumental in analyzing patient-device interactions by identifying how design flaws, poor user interfaces, and operational complexity impact effective use(Hegde, 2013; Leiner et al., 2015; R. Patel et al., 2019; Privitera et al., 2017). For example, Grant et al. (2015) demonstrated the design optimization of the ELLIPTA DPI, focusing on user-friendly features to enhance medication delivery and task compliance. Their study applied HFE principles to evaluate in vitro dosing performance and real-world usability, showcasing how well-structured design reduces patient errors. Similarly, Leiner et al. (2015) highlighted that integrating HFE into inhaler design minimizes user errors and optimizes therapeutic outcomes by prioritizing patient needs and regulatory standards.

Beyond patient-device interactions, HFE also considers the broader context of patient-healthcare system interactions. This perspective includes understanding how patients manage their treatment regimens outside clinical settings, where environmental factors and real-world challenges often disrupt optimal usage(Albahri et al., 2018; Carayon & Wooldridge, 2020; Merchant et al., 2018; Negoescu et al., 2023). Fortuna et al. (2019) proposed a theoretical model emphasizing peer support as a critical human factor in digital health interventions for individuals with serious mental illness. Their findings suggest that community-driven engagement significantly improves adherence. Similarly, O’Connor et al. (2016) underscored the importance of human factors in digital health recruitment, highlighting how motivation, personal agency, and life context influence participation. They argue that user-centered digital health interventions (DHIs) must align with patient values and daily routines to ensure long-term engagement.

2.3.3.2 SEIPS Applications in Patient Adherence

The Systems Engineering Initiative for Patient Safety (SEIPS) model, grounded in HFE, provides a structured framework to analyze healthcare systems by examining the interactions between Person, Tasks, Tools, Organization, and Environment. SEIPS 1.0 primarily focused on enhancing patient safety and healthcare outcomes through systematic design improvements(Carayon et al., 2006). Building on this foundation, SEIPS 2.0 expanded the framework to include patient-centered considerations, emphasizing how patient engagement and environmental factors contribute to successful healthcare interventions(Holden et al., 2013).

The SEIPS model has been widely applied across various healthcare domains, demonstrating its effectiveness in optimizing system design, enhancing patient education, improving device usability, and streamlining healthcare workflows(Berman et al., 2021; Frith, 2013; Strauven et al., 2020; Wooldridge et al., 2017). Although not always explicitly targeting adherence, these applications often result in improved patient compliance as a secondary benefit.

Patient Education and Training: The SEIPS model has been instrumental in tailoring educational interventions by identifying system-level and patient-specific barriers. For example, Brick et al. (2023) utilized SEIPS to examine patient education among hospitalized older cancer survivors, revealing that hospital size, illness severity, and cancer type significantly impact educational delivery. Their findings suggest that a system-based approach is essential to address these contextual factors. Similarly, Papautsky

(2019) applied SEIPS to breastfeeding education in hospitals, highlighting how patient-specific elements like environmental settings and personal goals can optimize educational outcomes. These examples underscore SEIPS's ability to design patient-centered education that aligns with individual needs, ultimately supporting better adherence.

Device Design and Usability Optimization: SEIPS has proven effective in optimizing the usability of medical devices, thereby indirectly enhancing patient adherence. Keller et al. (2017) employed the SEIPS framework to evaluate the use of home medical devices by older adults during transitions from hospitals to home settings. The study identified barriers like complex device interfaces and insufficient support during discharge, emphasizing the need for coordinated system-level solutions. Likewise, Santos et al. (2013) used SEIPS to identify performance obstacles related to medical devices in emergency settings, highlighting the importance of human factors and user-centered design to reduce errors during critical moments. These findings reflect SEIPS's capacity to bridge the gap between device complexity and user capability, leading to improved safety and adherence.

Process and Workflow Improvements: SEIPS is also effective in optimizing healthcare processes and workflows to enhance treatment delivery and patient safety. Martinez et al. (2017) applied SEIPS 2.0 to the CONDUIT-HID intervention, which aimed to manage hypertension in diabetic patients through consumer health informatics (CHI). Their findings showed that simplifying workflows and enhancing usability were crucial to program success, particularly in supporting patient self-management. Steele et al. (2018) also utilized SEIPS to evaluate medication safety in mental health settings, identifying critical vulnerabilities such as interruptions during medication administration and insufficient pharmacological training for nurses. These studies illustrate how SEIPS-driven process optimization can minimize risks and improve patient adherence.

Through its patient-centered, systems-based approach, SEIPS not only optimizes education, device usability, and care processes but also inherently addresses many adherence challenges. By considering the holistic interactions within healthcare systems, SEIPS creates opportunities for interventions that align with patient needs, thereby supporting consistent and effective medication use.

2.3.4 Measuring Adherence

Assessing patient adherence in real life and clinical trials presents significant challenges due to its multifaceted nature. Assessment methods can be broadly categorized into subjective and objective measures, or a combination of both(Cowen et al., 2007; Rand & Wise, 1994; Vitolins et al., 2000). Each method has distinct strengths and limitations, as outlined below.

2.3.4.1 Subjective Measures

Subjective measures rely on patient self-reporting and include questionnaires, diaries, and interviews. These methods are widely used due to their cost-effectiveness, simplicity, and non-intrusive nature. However, they are often criticized for their susceptibility to recall bias and overestimation of adherence(Anghel et al., 2019; W. Y. Lam & Fresco, 2015; Quirke-McFarlane et al., 2023).

Questionnaires: Standardized self-reported measures like the Morisky Medication Adherence Scale (MMAS-4), Medication Adherence Rating Scale (MARS-5), and Test of Adherence to Inhalers (TAI) are commonly used(Kwan et al., 2020; Plaza et al., 2016; Quirke-McFarlane et al., 2023). The TAI is particularly effective for assessing inhaler adherence and can distinguish between different types of non-adherence(Plaza et al., 2016). Studies by Muneswarao et al. (2021) and Ayele and Tegegn (2017) have validated its reliability and sensitivity in various populations, demonstrating its capacity to identify barriers such as polypharmacy and comorbidities.

Diaries: Diaries allow patients to log their medication usage over time, providing insights into daily patterns and potential adherence gaps(Svensson et al., 2021). Despite offering temporal context, their accuracy is often questioned due to potential fabrication and inconsistent entries(Wood-Baker et al., 2012).

Interviews: Structured or semi-structured interviews provide in-depth insights into patient behavior, perceived barriers, and attitudes towards inhalation therapy(Anghel et al., 2019; Garber et al., 2004). They are especially valuable for exploring patient-specific challenges but remain limited by recall bias and the reliability of self-reported data.

2.3.4.2 Objective Measures

Objective measures provide quantifiable data on medication usage, offering a more reliable assessment of adherence(Jensen et al., 2021; Jiang et al., 2009; W. Y. Lam & Fresco, 2015).

Canister Weight/Dose Counter: In inhaler-based therapies, measuring the canister weight or using dose counters helps track the number of actuations(Bender et al., 2000; O'Connor et al., 2004). This method is straightforward but does not account for proper inhalation technique.

Pharmacy Refill Records: Monitoring pharmacy refill data is an indirect method to estimate adherence, assuming that refilled medications are used as prescribed(C. Jones et al., 2003; Sherman et al., 2000). However, it cannot verify whether the medication was consumed correctly or consistently(Jensen et al., 2021; W. Y. Lam & Fresco, 2015).

Electronic Monitors: Considered the gold standard for inhalation therapy adherence, electronic monitors record precise data on inhaler usage, including timing, frequency, and inhalation quality (Blakey et al., 2018; Chrystyn et al., 2019). Despite their accuracy, challenges remain, such as high costs, technical reliability, and patient acceptance(A. H. Y. Chan, Harrison, et al., 2015). Recent studies have demonstrated their value not only in tracking adherence but also in improving technique and reducing long-term costs for patients with asthma(Pleasants et al., 2022; Van De Hei et al., 2023).

2.3.4.3 Biochemical Measures

While less common in inhalation therapy studies, biochemical assays provide direct evidence of medication intake by measuring drug levels in blood, saliva, or exhaled breath condensate(Chmelik & Kao, 1996; George, 2018; Rand & Wise, 1994). Exhaled breath analysis, in particular, offers a non-invasive approach to detect drug markers, confirming correct administration. However, high costs and the invasive nature of some tests limit their use to clinical trials rather than routine practice.

2.3.4.4 Mixed-Methods Approaches

To achieve a more comprehensive assessment of adherence, many studies employ mixed-methods approaches that integrate both subjective and objective measures. This method captures both quantitative usage data and qualitative patient insights, addressing the limitations of singular approaches. For example, Zeller et al. (2008) demonstrated significant discrepancies between self-reported adherence and electronic monitoring, emphasizing the need for triangulation of data. Similarly, Wagner (2002) found that combining electronic monitoring with self-reported diaries not only identified key adherence barriers but also enhanced the validity of overall adherence measurements.

2.4 Adherence-Supporting Interventions

2.4.1 The Role of Assistive Technologies in Adherence Support

2.4.1.1 Sensor-Integrated Devices

Sensor-integrated devices have become pivotal in enhancing patient adherence by enabling continuous monitoring and delivering personalized, actionable feedback. These technologies—encompassing electronic monitors, wearable devices, and IoT systems—collect comprehensive adherence-related data, supporting timely interventions and promoting sustained treatment engagement(Albahri et al., 2018; Aldeer et al., 2018; A. H. Y. Chan et al., 2021; Kalantarian et al., 2016; Kaplan et al., 2023).

Electronic Monitors: Primarily represented by smart inhalers, electronic monitors track medication usage by recording actuation patterns, timing, and frequency. Integrated feedback mechanisms alert patients to missed doses or incorrect use, improving adherence and clinical outcomes(Blakey et al., 2018; A. Chan et al., 2022; A. H. Y. Chan et al., 2021). Jansen et al. (2021) found that these devices significantly enhance adherence in asthma and COPD management by providing objective usage data. Furthermore, Rumi et al. (2022) demonstrated that combining digital coaching with smart inhaler technology in community-based asthma programs resulted in improved self-management and adherence rates. These findings underscore the dual role of smart inhalers in monitoring behavior and facilitating timely interventions.

Wearable Devices: Wearables equipped with sensors for continuous physiological monitoring (e.g., heart rate, activity levels) offer real-time health tracking and medication reminders(Kalantarian et al., 2016; C.-T. Wu et al., 2021). Kamei et al. (2022) found that integrating wearable devices with educational support significantly improved adherence in chronic disease management, such as diabetes and cardiovascular conditions. However, their application in respiratory care, particularly for asthma and COPD, remains limited, suggesting substantial potential for future research(Chrystyn et al., 2019).

IoT Systems: IoT-based platforms provide a holistic solution by integrating data from electronic monitors, wearables, and environmental sensors(Al-kahtani et al., 2022; Blakey et al., 2018; Chakraborty et al., 2023; Pradeesh et al., 2022). These systems automate data collection, deliver real-time feedback, and enable remote monitoring, reducing the need for frequent in-person consultations. For example, Serdaroglu et al. (2015) leveraged continuous activity recognition to address medication adherence challenges, while Hui et al. (2021) demonstrated that IoT-enabled real-time guidance improved asthma self-management. Moreover, IoT solutions frequently incorporate environmental monitoring of air quality and humidity—factors crucial for managing respiratory conditions(Bamashmoos et al., 2018; Chakraborty et al., 2023).

Opportunities and Challenges of Sensor-Integrated Technologies in Adherence Support: Sensor-integrated technologies, including electronic monitors, wearables, and IoT-based systems, share common features that enhance their effectiveness in supporting patient adherence. These devices facilitate real-time monitoring of patient status, medication usage, and environmental conditions, providing a comprehensive foundation for intervention strategies. Their passive data collection reduces disruption to daily routines while continuously capturing critical information. A key strength of these systems lies in their capacity to deliver personalized and actionable feedback, fostering proactive self-management and encouraging sustained treatment engagement(Aardoom et al., 2020; Al-Durra et al., 2015). Moreover, their seamless integration within broader healthcare ecosystems enables effective remote monitoring and tailored intervention delivery(Chakraborty et al., 2023; Davis et al., 2018).

Despite these advantages, several challenges persist, including ensuring sensor accuracy, addressing data privacy concerns, maintaining long-term user engagement, and overcoming technical limitations such as battery life and connectivity issues(Hui et al., 2022; Kenyon et al., 2016; Kuipers et al., 2019; Quinde, 2020). Furthermore, many existing sensor-based interventions remain heavily focused on data acquisition, often neglecting critical aspects of dynamic patient interaction and adaptive feedback mechanisms(S.-H. Kim, 2022; Rodriguez & Déry-Pinna, 2012). This highlights a significant need for future developments to better align technological capabilities with human-centered design principles, ensuring that sensor-integrated solutions not only monitor adherence but also actively promote behavioral change and patient empowerment.

2.4.1.2 Digital Health Tools

Digital health tools, including mobile applications and conversational agents (chatbots), offer scalable solutions for monitoring and supporting patient adherence. These technologies provide reminders, educational content, and direct communication channels between patients and HCPs, facilitating real-time intervention and personalized support (Axelsson et al., 2022; C.-C. Lin et al., 2023; Milne-Ives et al., 2020).

Mobile Health Applications: Mobile health applications have become integral components in patient self-management, particularly for adherence monitoring(Farzandipour et al., 2017; Jácome et al., 2021; Kosse et al., 2019). These apps typically feature medication reminders, health tracking capabilities, and personalized health information to enhance patient engagement. Liu et al. (2020) demonstrated that mobile applications with these functionalities significantly improve adherence among patients with chronic conditions. Similarly, Agarwal et al. (2019) found that continuous engagement through app-based interventions maintains long-term adherence by providing timely feedback and ongoing support. These studies highlight the potential of mobile applications to not only track medication use but also foster sustained behavioral change through interactive health management.

Chatbots for Patient Engagement: Chatbots simulate human-like conversation and provide real-time, personalized interactions, making them effective tools for enhancing patient engagement and adherence(Axelsson et al., 2022; Laranjo et al., 2018; H. Li et al., 2023; Milne-Ives et al., 2020). Kadariya et al. (2019) demonstrated that chatbots integrated with mobile health platforms could deliver tailored medication reminders and educational content, significantly improving adherence rates among users. Furthermore, Suehs et al. (2023) compared traditional face-to-face therapeutic education with a chatbot-guided program (Vik-Asthme) for asthma patients. Their findings indicated that the chatbot effectively improved adherence, enhanced asthma control, and reduced the burden on medical staff, emphasizing the potential of chatbot-based interventions to complement traditional healthcare delivery.

2.4.1.3 Telehealth Services

Telehealth platforms play a pivotal role in extending healthcare access and enabling continuous monitoring—both of which are critical for adherence in chronic disease management(Du Toit et al., 2019; Janjua et al., 2021). These technologies support remote consultations, real-time data sharing, and timely adjustments to treatment plans, making them indispensable for managing conditions that require ongoing adherence and personalized care. One of the primary benefits of telehealth is its ability to support remote monitoring services. When combined with real-time feedback mechanisms, telehealth allows for continuous supervision and prompt interventions, significantly enhancing adherence and clinical outcomes(Haddad et al., 2023). Video consultations further complement this model by providing direct, personalized interactions between patients and HCPs. These virtual visits enable immediate adjustments to care plans and address adherence barriers as they arise(Dhunnoo et al., 2024). This direct communication not only reinforces patient engagement but also improves the quality of care through timely intervention.

2.4.2 Sensor-Driven Components and Mechanisms in

Adherence-Supporting Interventions

2.4.2.1 Sensor-Driven Data Collection

This subsection reviews sensor technologies used in adherence-supporting interventions, focusing on their roles in monitoring person-related, task-related, and physical environment-related behaviors and conditions. In adherence-supporting interventions, the quality and comprehensiveness of data collection are crucial. Effective interventions collect data across multiple dimensions, capturing person-related, task-related, and environment-related information. Below is a more detailed overview (see Table 2.3).

Person-Related Data: Physiological parameters are central to understanding the health context in which adherence occurs. Commonly collected metrics include:

1. Heart Rate and Blood Oxygen Levels: The study by Chakraborty et al. (2023) developed an IoT-enabled asthma monitoring system that uses sensors like the MAX30100 to collect heart rate and blood oxygen data, providing real-time feedback and enhancing remote health management for asthma patients. Another study by Kadariya et al. (2019) focused on the development of kBot, a knowledge-enabled personalized chatbot designed for the self-management of asthma in pediatric patients. The system integrated real-time heart rate and blood oxygen data collection through wearable sensors, helping to monitor patients' adherence to their asthma care plans and providing timely feedback to improve health outcomes.

2. Lung Function Metrics: Lung function is routinely monitored using spirometers and peak flow meters to assess respiratory health. For example, Hui et al. (2022) assessed the feasibility of

a connected-for-asthma (C4A) system that integrates multiple smart devices, including smart peak flow meters, to provide accurate, real-time lung function data, supporting asthma self-management for both patients and clinicians. Similarly, Jochmann et al. (2017) evaluated the use of electronic monitoring devices for assessing adherence to inhaled corticosteroids in children with asthma, including the measurement of lung function parameters. The findings highlighted the critical role of precise monitoring in optimizing asthma management, particularly in pediatric patients.

Task-Related Data: Task-related data focuses on the proper use of inhalers, including dosage accuracy and technique. Key data points include:

1. Medication Actuation and Timing: Devices record each actuation, capturing timestamps and frequency. Gupta et al. (2021) focused on the use of sensor-based electronic monitoring devices to measure inhalation time and frequency among children with asthma. These sensors captured data on medication use, including the precise timing and number of inhalations, providing real-time feedback to improve adherence and asthma management. Kenyon et al. (2016) utilized electronic monitoring devices to measure inhalation timing and frequency in pediatric asthma patients. These devices captured detailed data on each inhalation event, including the exact time and number of inhalations, offering insights into medication use patterns and adherence, which are critical for managing asthma in high-risk populations.

2. Inhalation Technique: Smart inhalers equipped with sensors monitor key inhalation parameters, including speed and depth, to enhance medication adherence. Dierick et al. (2022) utilized a digital smart spacer that detects inhalation metrics such as

flow rate, inhalation timing, actuation coordination, and inhalation duration. These data are analyzed in real-time to identify common errors like insufficient flow, incorrect timing, and inadequate breath-hold, providing feedback to help patients correct their technique. Similarly, Chan et al. (2015) employed an electronic monitoring device with sensors that captured detailed data on inhalation technique, including timing, coordination, and flow rate. The device delivered real-time audiovisual feedback, alerting patients to inhalation errors and guiding them to improve their technique, thereby enhancing the overall effectiveness of asthma medications. Hasegawa et al. (2023) developed a method using an inertial measurement unit (IMU) sensor attached to an inhaler to measure inhalation technique by capturing data on the angular velocity and angle of the device during use. This data was analyzed using a dynamic programming (DP) matching algorithm to evaluate the correctness of inhaler movements, such as the timing and coordination of inhalation steps, providing a precise assessment of inhalation technique without the need for direct supervision by HCPs.

Physical Environment-Related Data: Environmental factors may also influence patient adherence and management strategies, with commonly monitored metrics including temperature, humidity, and air quality. For instance, Su et al. (2017) utilized inhaler sensors to capture real-time data on these environmental conditions during inhaler use, helping to identify triggers that could worsen asthma symptoms and supporting personalized management strategies. Similarly, Pradeesh et al. (2022) explored an IoT-based smart E-Inhaler equipped with sensors to monitor air quality, temperature, and humidity, providing patients with immediate feedback on environmental conditions. These smart systems enhance asthma management by alerting patients to unfavorable conditions, thereby supporting better adherence and symptom control.

Table 2. 3 : Sensor types, monitored parameters, and examples in adherence-supporting interventions.

Category	Subcategories	Parameters	Sensor examples
Person	Physiological condition	Lung function	Electronic spirometer or peak flow meter
		Heart rate/ oxygen saturation	Pulse oximeter and heart rate sensor
Task	Inhalation actuation	Date and time of actuation	Electronic monitoring devices
		Location of actuation	Smartphone
	Inhalation technique	Acoustic features of inhalation	INCA or microphone
		Inhalation motion	Inertial measurement unit
		Inhalation airflow characteristics	Airflow sensor
Physical Environment	Environmental trigger	Temperature	Thermometer
		Humidity	Hygrometer
		Air quality	Dust sensors and gas sensors

2.4.2.2 Processing Sensor-Generated Data

The data collected from these systems requires robust processing to yield actionable insights, which can be categorized into three key stages: data preprocessing, data analysis, and data application.

Data Preprocessing: Ensuring data quality through preprocessing is essential for accurate analysis in adherence monitoring. Common techniques include:

1. Normalization: Aligning sensor data to a consistent scale improves comparability across metrics. Taylor et al. (2016) highlighted the importance of normalization in preprocessing

sensor data from inhalation monitoring devices, which adjusts sensor readings for reliable comparisons across various inhalation events, enhancing overall assessment accuracy.

2. Filtering: Signal filtering techniques remove noise and artifacts, resulting in cleaner data for analysis. Taylor et al. (2018) emphasized the use of filtering in preprocessing audio signals from inhaler compliance assessments, which is crucial for isolating relevant inhalation events and improving the accuracy of inhaler technique analysis.

3. Feature Engineering: Extracting relevant features from raw data enhances the accuracy of adherence classification. Nousias et al. (2018) utilized feature engineering techniques such as Mel-Frequency Cepstral Coefficients (MFCC), Spectrogram, and Cepstrogram for audio classification, which help distinguish between inhalation, exhalation, and other sound events, significantly improving adherence monitoring in respiratory conditions.

Data Analysis: In adherence interventions, data analysis typically combines statistical methods, traditional algorithms, and machine learning models. Statistical methods are the most prevalent, used for summarizing data and drawing inferences, while traditional algorithms are applied less frequently, and advanced machine learning models are relatively rare but growing in use.

1. Statistical Method: Foster et al. (2012) used descriptive statistics to evaluate the reliability and patient acceptability of the SmartTrack device for monitoring inhaler use. Descriptive statistics were employed to summarize patient demographics, device accuracy, and usability scores, providing a clear overview of the device's performance and patient experience. Hesso et al. (2023) utilized various statistical methods,

including descriptive and inferential statistics, to analyze data from the use of the INCA™ device. Descriptive statistics were used to summarize patient characteristics, inhaler usage errors, and questionnaire responses, while inferential statistics, including the Wilcoxon signed-rank test and McNemar test, were applied to compare adherence and inhaler technique measures before and after the intervention.

2. Algorithmic Approaches: Traditional algorithms are employed for specific data analysis tasks in respiratory management. Zhao et al. (2021) developed a novel adherence sensor system for valved holding chambers, utilizing customized algorithms to ensure correct usage is recorded and incorrect use is flagged. These algorithms distinguish between deep breaths and tidal breaths, classifying the technique as good or poor, directly enhancing adherence monitoring and feedback. D'Arcy et al. (2014) employed algorithms for processing acoustic recordings of inhaler use to assess adherence, developing an automated signal processing method that accurately detects inhalation and exhalation events, enabling objective assessment of timing and technique adherence. Hasegawa et al. (2023) utilized Dynamic Programming (DP) matching algorithms to evaluate inhalation motion using data from an inertial measurement unit (IMU) sensor attached to an inhaler, allowing automated evaluation without the need for direct supervision.

3. Machine Learning: The use of machine learning in adherence monitoring is still developing but offers significant potential for personalized intervention. Quinde (2020) employed machine learning to develop personalized asthma management solutions. These methods allow the system to adaptively learn from past cases and context, enhancing its ability to provide tailored recommendations based on current environmental and health data. Nousias et al.

(2018) employed Gaussian Mixture Models (GMM) for classifying inhaler usage events based on audio features extracted from sound recordings, demonstrating the potential of machine learning in monitoring adherence in respiratory conditions.

Data Application: Processed data on patient adherence can be applied in various ways to enhance asthma and COPD management, particularly in evaluating effectiveness, monitoring behavior, and identifying risk factors.

1. Effectiveness Evaluation: Evaluating the effectiveness of adherence interventions involves comparing health outcomes across different groups. Moore et al. (2021) assessed a connected inhaler system (CIS) for improving medication adherence in patients with uncontrolled asthma. The study found that CIS significantly increased adherence to maintenance therapy compared to the control group, demonstrating its potential to enhance asthma management through real-time feedback on medication use and extended rescue-free periods. Similarly, Hesso et al. (2020) used an electronic monitoring device (EMD) to assess adherence and inhalation technique in patients with COPD and asthma. The EMD revealed significantly lower actual adherence rates compared to traditional methods such as dose counters and self-reports, highlighting the effectiveness of electronic monitoring in providing accurate adherence data and identifying inhalation errors.

2. Behavior Monitoring: Real-time monitoring of patient behavior helps reduce inhaler errors and supports long-term adherence. Taylor et al. (2018) utilized audio-based methods to estimate inhalation flow profiles, using acoustic sensors to capture inhalation sounds and assess inhaler technique and adherence.

This non-invasive, objective approach provides valuable insights into patient behavior during inhaler use. In another study, Chen et al. (2020) used electronic monitoring devices combined with weekly feedback and reminders to monitor inhaled corticosteroid adherence in pediatric asthma patients. The monitoring system recorded inhalation frequency and timing, significantly improving adherence compared to the control group.

3. Risk Identification: Combining behavioral and environmental data can effectively identify high-risk scenarios associated with non-adherence, supporting timely classification of patient behaviors and enabling early intervention. Su et al. (2017) used electronic inhaler sensors to monitor patient behavior by capturing real-time data on rescue inhaler use, including the time and location of each event. Killane et al. (2016) employed a remote monitoring device to predict asthma exacerbations based on adherence patterns, identifying patients with poor adherence who were at higher risk of exacerbations.

2.4.2.3 Feedback Provision Based on Sensor Data

Providing timely and personalized feedback is crucial for supporting adherence (see Table 2.4). Effective feedback interventions can be categorized into three main areas: Reminders and Alerts, Data Visualization, and Persuasive Features.

Reminders and Alerts: Reminders based on patient behavior and environmental conditions have been proven to significantly enhance adherence. Chakraborty et al. (2023) developed an IoT-enabled asthma patient monitoring system that integrates an alerting mechanism, sending email and SMS alerts to patients and physicians when sensor readings exceed safe levels. This real-time feedback enhances the system's ability to monitor patient conditions and respond promptly to emergencies. Quinde et al. (2020) implemented a context-aware reasoning system, featuring a mobile app that delivers reminders and alerts based on contextual data such as environmental triggers and medication schedules. These timely notifications help patients manage their condition more effectively and improve adherence.

Data Visualization: Simplifying complex data through visual/audio feedback tools is essential for engaging patients and supporting self-management.

1. Audiovisual Indicators: Simple audiovisual indicators provide quick, intuitive feedback on adherence status. For example, Chan et al. (2015) evaluated an electronic monitoring device with audiovisual reminders for children with asthma, using a color-coded light system and sound alerts to signal adherence status: green for correct usage, yellow for missed doses, and red for prolonged non-adherence. This immediate, easy-to-understand feedback helped significantly improve adherence rates.

2. Graphical Representations: Visual tools such as graphs and charts help patients track their adherence over time, making complex data more accessible and understandable. These data visualizations enable patients and HCPs to easily identify patterns, recognize missed doses, and adjust treatment plans as needed. For example, Foster et al. (2014) described how the SmartTrack device uses bar charts on a secure website to display inhaler use, allowing patients and HCPs to easily identify missed doses and adjust treatment plans. Pradeesh et al. (2022) utilized scatter plots in their IoT-based smart E-Inhaler system to correlate inhaler usage patterns with environmental factors like air quality and temperature, helping patients

understand the relationship between environmental triggers and their symptoms for more personalized management. Additionally, infographic interfaces, as discussed by Meyer et al. (2016), employed metaphor-based elements (e.g., shoe or tree) to simplify the display of complex health data on mobile devices, making real-time feedback and historical data review both intuitive and visually appealing. Furthermore, Kim (2022) highlighted that well-designed visualizations for self-generated health data, such as bar charts and infographics, can improve users' understanding and promote better self-management by making the data more actionable and personalized.

Persuasive Features: Integrating persuasive elements such as gamification, rewards, and peer competition can motivate consistent inhaler use and strengthen patients' self-efficacy. Grossman et al. (2017) incorporated gamification and rewards into an asthma management app, featuring a basketball-themed game where participants could earn rewards for proper inhaler use. This engaging and interactive approach, combined with peer competition, significantly boosted adherence among adolescents. De Simoni et al. (2021) implemented financial incentives to enhance adherence in adolescents, using electronic reminders paired with electronic monitoring devices. Participants received rewards, such as gift cards, for consistent inhaler use, demonstrating the effectiveness of financial incentives in promoting adherence and motivating younger patients.

Table 2. 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.

Persuasive features	Graphical representation	Utilizing graphical representations to provide feedback.
	Gamification	Targeting children/adolescents with gamification techniques to enhance engagement and interaction.
	Rewards	Utilizing incentives to encourage consistent use.
	Peer competition	Leveraging a public leaderboard and reward points to introduce a competitive element, motivating adherence.

2.5 Evaluation of Adherence-Supporting Interventions

2.5.1 Evaluation Methods

2.5.1.1 Quantitative Methods

Quantitative methods provide objective and statistically robust measures, which are crucial for assessing the direct impact of adherence interventions.

1. Randomized controlled trials (RCTs): RCTs are considered the gold standard for evaluating intervention effectiveness(P. Agarwal et al., 2019; Fedele et al., 2018; Gupta et al., 2021). They compare outcomes between intervention and control groups, allowing for causal inferences about the impact of adherence strategies such as electronic monitoring devices, reminders, and educational programs. For instance, Hollenbach et al. (2021) conducted a pilot RCT to evaluate the effectiveness of an EMD in improving adherence levels among children with asthma. The study demonstrated that the EMD, which recorded inhaler use and sent daily reminders, significantly improved adherence

rates and asthma control compared to standard care. Similarly, Chen et al. (2020) used an RCT to assess electronic monitoring combined with feedback and reminders, showing substantial improvements in adherence among infants and younger children with asthma compared to the control group.

2. Observational Studies: Observational studies, such as cohort, case-control, and cross-sectional designs, are valuable for evaluating real-life adherence behaviors(Dima et al., 2015; Hesso et al., 2020; Hillyer et al., 2011; Melvin et al., 2017). Kenyon et al. (2016) used an observational cohort design to assess the acceptability of electronic adherence monitoring in high-usage pediatric asthma patients and identified different adherence profiles along with better control of asthma symptoms. Melvin et al. (2017) performed an observational study of the BreatheSmart mobile application, which is a device that counts the number of inhalations and the FEV1 parameter. The effectiveness of this technology in increasing adherence among adults with asthma in real life was confirmed.

3. Pre-Post Intervention Studies: These studies compare adherence levels at baseline and after an intervention has been implemented and can be very useful when RCTs are not feasible(Newman-Casey et al., 2018). Leader et al. (2018) applied a pre-post design to investigate adherence interventions for CML patients on tyrosine kinase inhibitors, showing important improvements in adherence, with particular significance among patients with initially low adherence. Muneswarao et al. (2021) used a combination of reminders and motivational interviewing to achieve significant increases in medication adherence after the intervention.

4. Surveys and Questionnaires: Standardized tools like the Morisky Medication Adherence Scale (MMAS) and the Test of

Adherence to Inhalers (TAI) are used to measure self-reported adherence and the perceived impact of interventions(Foster, Smith, Bosnic-Anticevich, et al., 2012; Kwan et al., 2020; Muneswarao et al., 2021). For example, Vitolins et al. (2000) highlighted the extensive use of self-reported questionnaires, marking their ease of use and the importance of careful interpretation due to potential inaccuracies.

5. Data Analytics and Machine Learning: As technology advances, data analytics and machine learning techniques are increasingly applied to examine large volumes of data from electronic monitoring devices, providing insights into patterns of adherence and supporting both the evaluation of intervention outcomes and the identification of adherence-related risks(Jourdan et al., 2021; Milne-Ives et al., 2020; C.-T. Wu et al., 2021). By systematically assessing machine learning models, including logistic regression and random forest, Xiong et al. (2023) demonstrated the viability of these methods for classifying adherence behaviors and evaluating interventions related to asthma exacerbations. Similarly, Alazzam et al. (2021) used machine learning algorithms within a smart healthcare monitoring system to analyze adherence-related physiological patterns, highlighting the utility of ML techniques in monitoring and managing adherence.

2.5.1.2 Qualitative Methods

Qualitative methods, such as interviews and focus groups, provide in-depth insights into patient and provider perspectives on adherence interventions, exploring barriers and facilitators to success(Abdolkhani et al., 2020; S. A. Adams et al., 2017; Heijsters et al., 2022; Minian et al., 2023). For example, Kenyon et al. (2016) utilized semi-structured interviews and focus groups to assess the feasibility of electronic monitoring in pediatric asthma patients, gathering valuable feedback on the intervention's acceptability and areas for improvement. Hui et al. (2022) also applied qualitative methods, conducting interviews with patients and HCPs to evaluate the connected-for-asthma (C4A) system. Their analysis employed thematic analysis to study the system's impact on usability and adherence.

2.5.1.3 Mixed Methods

Mixed methods combine quantitative and qualitative approaches, offering a comprehensive evaluation of adherence interventions by integrating statistical data with contextual insights(R. A. Calvo et al., 2023; Hamine et al., 2015; Jácome et al., 2021). Makhecha et al. (2020) undertook a mixed-methods analysis to evaluate the viability of novel electronic adherence monitoring devices (NEMDs) for children with asthma. This assessment combined both quantitative data related to adherence and qualitative insights gathered from interviews and focus groups with patients, parents, and HCPs, providing a rich understanding of the devices' usability, acceptability, and their role in asthma management in real-world settings. Similarly, De Simoni et al. (2021) combined data obtained from electronic monitoring devices with qualitative information collected from both adolescents and their parents through thematic analysis, in order to better understand the facilitators and barriers to adherence and ultimately enhance the evaluation of the intervention's effectiveness.

2.5.2 Evaluation Dimensions

It is necessary to consider different dimensions when evaluating interventions that support patient adherence, as these dimensions fully represent the comprehensive impact of these interventions. Evaluation dimensions help in understanding not just whether the intervention works, but how and why it works by assessing outcomes across various domains:

Clinical Outcomes: The direct effect of adherence interventions on patient health is measured through clinical indicators, such as lung function quantities (e.g., FEV1, PEFR), the frequency of exacerbations, and the management of symptoms(M. A. Barrett et al., 2017; Boddy et al., 2021; A. H. Y. Chan, Stewart, et al., 2015; M. Patel et al., 2013). Barrett et al. (2017) evaluated a mobile health platform that integrated sensors for asthma management, assessing clinical outcomes such as reduced SABA use, improved symptom-free days, and better overall asthma control to determine how self-management impacts health outcomes. Similarly, Boddy et al. (2021) investigated the INCA electronic monitoring apparatus's effect on clinical outcomes, including better lung function and reduced blood eosinophil counts, emphasizing that monitoring adherence could prevent unnecessary therapy escalation.

Behavioral Adherence: Behavioral strategies focus on whether patients comply with prescribed treatments in terms of dosage, timing, and inhalation technique(Dierick et al., 2022; Hesso et al., 2020; Mokoka et al., 2017; O'Dwyer et al., 2016; Taylor et al., 2016; Taylor, Zigel, et al., 2018). Moore et al. (2021) measured adherence using a connected inhaler system (CIS) that recorded all actuations electronically in real-time, providing precise adherence rates and confirming the usefulness of digital monitoring in improving medication adherence. Anderson et al. (2020) reviewed various adherence measurement methods, including electronic monitoring, pill counts, and self-reports, finding that evidence quality varied considerably, with electronic monitoring proving more reliable than self-reports.

Patient Experience and Satisfaction: Achieving both the success and sustainability of adherence interventions requires attention to patient satisfaction and experience(Ali Alkhoshaiban et al., 2019; Basheti et al., 2008; Davis et al., 2018; Jácome et al., 2021). According to Hirsch et al. (2021), the use of personalized interventions led to substantial improvements in patient satisfaction over time, which in turn supported adherence through enhanced communication between patients and their providers. Another study involving elderly diabetic patients employed the Diabetes Medication Satisfaction (DiabMedSat) questionnaire to assess satisfaction, revealing significant improvements following intervention. These findings highlight the positive effect of personalized pharmacist counseling on patient satisfaction(Ali Alkhoshaiban et al., 2019).

Quality of Life and Long-term Sustainability: Chronic disease management places great importance on quality of life (QoL), and the sustainability of behavioral changes demonstrates whether there are lasting benefits over time(Abdulmalek et al., 2022; Anghel et al., 2019; Butt et al., 2016; Selzler et al., 2020; Wahyuni et al., 2018). Butt et al. (2016) evaluated a pharmacist-initiated intervention for type 2 diabetes patients, reporting significant improvements in blood sugar control and adherence. However, they acknowledged that QoL outcomes remained uncertain, emphasizing the challenges of achieving long-term QoL improvements. In another study, McGillicuddy et al. (2015) demonstrated that adherence interventions had persistently positive effects on blood pressure management, documenting sustainable reductions in systolic blood pressure 12 months after the intervention. This underscores the lasting benefits of patient-centered interventions for health outcomes.

2.6 Discussion of Literature

This section integrates key insights from sections 2.2 to 2.5, synthesizing the findings to frame the research within the broader literature. Each subsection addresses the core elements of the respective sections, offering a balanced discussion that connects foundational concepts with the novel contributions of this study.

2.6.1 Global Trends in Inhalation Therapy: Challenges, Innovations, and Device Usability

Section 2.2 provided a comprehensive overview of inhalation therapy, emphasizing its global significance in managing chronic respiratory diseases like asthma and COPD(Barjaktarevic & Milstone, 2020; Borghardt et al., 2018; Y. Liang & Mak, 2021). Despite its critical role, adherence remains a major challenge, leading to suboptimal patient outcomes(Aldan et al., 2022; Bourbeau & Bartlett, 2008; Chrystyn et al., 2019; George, 2018). Additionally, disparities in healthcare systems, socioeconomic barriers, and uneven access to advanced inhaler technologies hinder the consistent adoption of effective inhalation therapies, particularly in low- and middle-income countries(Ait-Khaled et al., 2001).

Technological advancements, particularly the introduction of sensor-integrated smart inhalers, have demonstrated significant improvements in monitoring patient usage patterns, correcting inhaler techniques, and providing personalized feedback(Blakey et al., 2018; A. Chan et al., 2022; Merchant et al., 2018). For asthma and COPD patients, such advancements offer the promise of more precise monitoring and tailored interventions that address the unique challenges of managing these conditions. However, the uneven distribution of such technologies remains a concern, highlighting the need for greater global access and cost-effective implementation strategies(Ait-Khaled et al., 2001; Bender et al., 2000; Lycett et al., 2018; Pleasants et al., 2022).

Furthermore, patient preferences and satisfaction are heavily influenced by the type of inhaler device used, given that each type has distinct advantages and limitations(P. Anderson, 2005; Chorão et al., 2014). For example, while DPIs mitigate coordination issues commonly associated with pMDIs, they demand adequate inspiratory flow from the patient. Studies indicate that proper matching of inhaler type with patient capability significantly improves adherence and clinical outcomes(Kaplan & Price, 2018; Mancuso & Rincon, 2006). This underlines the importance of personalized device selection in enhancing adherence rates.

The success of inhalation therapy extends beyond pharmacological effectiveness to include device usability, safety, and patient engagement (Hegde, 2013; Leiner et al., 2015; Pirozynski & Sosnowski, 2016; Skoner, 2002). Issues with improper handling, incorrect inhalation technique, and inconsistent usage have been well-documented as barriers to optimal therapeutic outcomes(Biswas et al., 2016; Dabrowska et al., 2019; Miravitlles et al., 2016; Newman, 2014). By focusing on usability and intuitive design, these issues can be mitigated, enabling patients to use inhalers more effectively and consistently.

In developed regions such as the US and Europe, regulatory bodies like the FDA and MHRA have established guidelines to ensure that DDCPs are user-friendly and optimized for real-world use(Lauritsen & Nguyen, 2009; R. Patel et al., 2019; Stephenson, 2014). In contrast, regulatory frameworks in developing countries like China remain focused primarily on safety and efficacy, with less emphasis on usability and human factors(G. Su & Deng, 2023; Yu et al., 2010). Bridging this gap is critical to ensuring that patients worldwide benefit equally from advanced inhalation therapies. Efforts to align global regulatory standards and integrate usability considerations into device design are essential for achieving better adherence and clinical outcomes.

2.6.2 Inhalation Therapy Adherence: A Multifaceted Approach

Inhalation therapy adherence is a multifaceted concept that involves not only following the prescribed dosage but also ensuring the correct use of the inhalation device. Both prescription adherence (adhering to the dosage regimen) and inhaler technique adherence (ensuring correct inhalation technique during use) are crucial for achieving optimal therapeutic outcomes(Eikholt et al., 2023; Pritchard & Nicholls, 2015). Errors in inhaler technique can significantly reduce the medication's effectiveness, which is why adherence in inhalation therapy must be viewed through these two critical lenses(Chorão et al., 2014; Gregoriano et al., 2018; Hesso et al., 2020).

A range of factors contribute to patient adherence, including cognitive, physical, and environmental conditions, along with the complexity of the inhaler device itself(Aldan et al., 2022; Ayele & Tegegn, 2017; George & Bender, 2019; Leiner et al., 2015). Non-adherence is not a binary concept; it exists along a spectrum, manifesting in various forms, such as unintentional errors due to forgetfulness or poor understanding, and intentional deviations driven by patient beliefs or concerns about medication(Rand & Wise, 1994; Van Dulmen et al., 2007). In the context of inhalation therapy, the interaction between patients and their inhalers is crucial for adherence. Even when patients follow their prescribed dosage, improper use of the inhaler can undermine the effectiveness of the treatment(Chorão et al., 2014; Nelson, 2016; Usmani, 2019).

The evaluation of adherence in inhalation therapy typically employs either subjective or objective strategies, each with its specific pros and cons(Anghel et al., 2019; Bender et al., 2000; A. H. Y. Chan, Harrison, et al., 2015; Chmelik & Kao, 1996). Subjective measures, such as questionnaires, interviews, and patient diaries, provide valuable insights into patient behavior and perceptions but are prone to recall bias and inaccuracies, as they rely heavily on self-reporting. On the other hand, objective measures such as dose counters, weight measurements from canisters, and pharmacy refill data provide more reliable information on medication ingestion frequency but do not indicate whether the inhaler was used correctly. The most advanced objective method involves electronic monitors, which track not only inhaler usage but also provide detailed insights into inhalation technique(Blakey et al., 2018; Kikidis et al., 2016). However, these devices tend to be expensive and may encounter technical challenges, including battery failures and device malfunctions. Given the limitations of both subjective and objective methods, mixed-methods approaches, which combine both types of measures, are increasingly regarded as the most comprehensive approach. Integrating patient self-reports with objective monitoring data allows mixed methods to provide a holistic view of adherence, capturing both behavioral intentions and real-world actions(L. J. Anderson et al., 2020; Bender et al., 2000; Chrystyn et al., 2019).

Although several behavioral models have been developed to explain patient adherence, they each have limitations when applied to inhalation therapy(Aldan et al., 2022; Cassidy, 1999; Horne &

Weinman, 2020; Stepnowsky et al., 2006; Y. Zhang & Zhao, 2021). For example, HBM focuses on patient perceptions of risks and benefits but overlooks the technical challenges of inhaler use. SCT emphasizes self-efficacy but overlooks the cognitive and physical demands of correct inhaler usage. Similarly, while TTM accounts for stages of behavioral change, it fails to address device-specific barriers. TPB links intention to behavior but lacks consideration of external factors that influence inhaler use. MAM provides a broad framework for understanding adherence but does not account for how the complexity or usability of different inhaler designs can impact patient adherence outcomes. These models are useful for understanding patient behavior but do not fully address the interaction between patients and their inhalation devices, highlighting the need for a more comprehensive framework that integrates both behavioral and technical aspects of adherence(Drotar & Bonner, 2009; Gray et al., 2018; Schaffer & Tian, 2004).

To address this gap, this research adopts the SEIPS 2.0 model, which offers a holistic approach grounded in HFE(Holden et al., 2013). SEIPS not only considers patient behavior but also focuses on optimizing the interaction between the patient and the inhaler, as well as the broader environmental and organizational factors that influence adherence. Unlike traditional behavioral models, SEIPS incorporates both technical usability aspects and behavioral dimensions, offering a more comprehensive framework for enhancing inhalation therapy outcomes(Carayon et al., 2006; Negoescu et al., 2023; M. L. Steele et al., 2018). By addressing these dimensions concurrently, SEIPS helps identify specific barriers in patient-inhaler interactions, including cognitive load, physical challenges, and environmental distractions that may impede correct use. Additionally, SEIPS emphasizes the importance of designing interventions that are adaptable to diverse patient needs and contexts, making it a powerful tool for enhancing patient engagement, improving device usability, and ultimately optimizing treatment outcomes in inhalation therapy(Berman et al., 2021; Strauven et al., 2020; Wooldridge et al., 2017).

2.6.3 Interventions in Patient Adherence

Section 2.4 reviewed the role of digital health interventions in improving adherence, emphasizing how these technologies provide continuous, objective data on patient behavior and inhaler usage(A. Chan et al., 2022; Kaplan et al., 2023; Lycett et al., 2018). Among these tools, sensor-enabled inhalers are increasingly viewed as key components for enhancing the effectiveness of inhalation therapy. These devices function by tracking inhaler use and integrating with broader health information systems, delivering real-time monitoring and intervention opportunities(Foster, Smith, Usherwood, et al., 2012; Hale et al., 2023; O'Dwyer et al., 2016). The integration of sensor data with healthcare systems aligns with the trend toward more personalized, data-driven healthcare, enabling tailored interventions that adapt to the specific needs of individual patients(Blakey et al., 2018; Kikidis et al., 2016; G. Mosnaim et al., 2021).

However, beyond sensor-enabled technologies, the role of digital tools is becoming increasingly relevant. While conventional app-based interventions are effective, they often require users to expend considerable effort in mastering and interacting with the software. In contrast, chatbots offer a more conversational and intuitive interface, reducing the learning curve and increasing engagement (Milne-Ives et al., 2020; Minian et al., 2023; Suehs et al., 2023). Unlike conventional apps, chatbots can mimic natural conversation, providing instructions, reminders, and feedback that are intuitive and accessible to a broader group of users, especially those with limited technical literacy. The ability of chatbots to adaptively interact in real time allows the system to personalize its responses according to patient behavior, health data, or preferences. This flexibility makes chatbots an ideal companion for sensor-enabled interventions. By integrating chatbot functionalities with sensor data, patients can receive instantaneous, personalized feedback on their inhaler use, dosage adherence, and overall health status(Beck et al., 2021; Pereira & Díaz, 2019). For example, a chatbot could remind patients to use their inhaler when sensors detect missed doses, provide step-by-step guidance on proper technique, or offer encouragement based on the patient's current health status(Kadariya et al., 2019). This interactive, responsive approach enhances patient adherence by delivering a more engaging and supportive user experience.

Despite the growing adoption of digital health interventions, significant gaps remain in their implementation and design. Many existing systems focus primarily on dosage adherence without considering the broader "Person-Task-Physical Environment" framework, which this research proposes to capture the complexities of patient adherence. This framework consists of three key dimensions:

1. Person: Refers to the patient's physical, psychological, and cognitive characteristics. This includes factors such as health literacy, cognitive abilities, and emotional state, all of which influence how patients interact with their inhalers. It also extends to HCPs and caregivers who support the patient.

2. Task: Encompasses the specific tasks related to completing inhalation therapy, such as correct device handling, coordination, and timing. The complexity of these tasks can greatly affect adherence, especially when patients struggle with the multi-step processes involved in using inhalers correctly.

3. Physical Environment: Refers to the surrounding environmental conditions that may influence a patient's ability to adhere to inhalation therapy. This includes factors such as air quality, noise, and other external stressors that can impact both the effectiveness of the therapy and the patient’s overall health.

Additionally, current data processing methods often rely on basic analytical techniques, limiting their ability to uncover deeper patterns in adherence behavior((Jourdan et al., 2021; Xiong et al., 2023). While conventional algorithms can detect general trends, they often miss subtle variations in patient behavior that may indicate emerging adherence issues. Advanced machine learning models, such as deep learning and support vector machines, remain underexplored. These sophisticated algorithms have the potential to provide more personalized feedback and proactive intervention strategies by offering a deeper understanding of complex adherence patterns and supporting tailored, data-driven classifications(Bae et al., 2021; Bhat et al., 2021; Gu et al., 2021).

Moreover, current feedback mechanisms rarely prioritize patient-centered design principles, which are essential for improving engagement and effectiveness(Bamashmoos et al., 2018; Benke et al., 2020; Choi et al., 2017; Tsao et al., 2019). User interfaces are often developed with limited attention to the diverse needs of different patient groups, hindering both engagement and long-term adherence. Incorporating persuasive features into digital health tools can significantly enhance patient interaction and motivation. These features, such as reminders, rewards, and personalized messages, can create a more engaging user experience by encouraging patients to take an active role in their healthcare(S. A. Adams et al., 2017; Blakey et al., 2018; A. H. Y. Chan, Stewart, et al., 2015). For instance, visualizing adherence data through intuitive charts or incorporating gamification elements—like challenges or achievements—can make the process more enjoyable and rewarding for patients(S. Kim et al., 2021; Miller et al., 2016; Sardi et al., 2017). By enhancing sensor-based feedback systems with such persuasive elements, these technologies can provide personalized, user-friendly feedback that adapts to patient needs in real-time(Grossman et al., 2017; Kelders et al., 2012). However, despite the potential of these approaches, they remain underutilized in current interventions, indicating a clear opportunity for innovation in patient interaction and feedback delivery.

While digital health interventions are becoming integral to managing inhalation therapy adherence, there is a clear need for more comprehensive systems that incorporate the full spectrum of patient, task, and environmental factors. Future research should focus on addressing these gaps by developing interventions that integrate multi-dimensional data collection, advanced data processing techniques, and patient-centered feedback design—specifically leveraging chatbots as interactive tools that support and enhance adherence in sensor-enabled interventions. By doing so, this research aims to create a more holistic and effective framework for supporting patient adherence in inhalation therapy.

2.6.4 Evaluation Methods and Dimensions

Section 2.5 provided an overview of the quantitative and qualitative methods used to evaluate adherence-supporting interventions, highlighting that no single measure is sufficient to capture all aspects of effectiveness. The review emphasized the importance of evaluating multiple dimensions, such as clinical outcomes, behavioral adherence, and patient-reported experiences. These dimensions provide a holistic view of how interventions impact patient adherence and overall well-being, ensuring that they are not only clinically effective but also practical in real-world settings(Aardoom et al., 2020; Adejumo et al., 2022; Al-Durra et al., 2015; L. J. Anderson et al., 2020).

The literature supports this multi-dimensional evaluation framework, with studies indicating the need to integrate clinical measures, behavioral data, and subjective patient feedback. Although RCTs are widely regarded as the most reliable method for demonstrating the efficacy of interventions, other quantitative study designs, such as cohort studies and cross-sectional studies, also contribute to understanding adherence patterns and outcomes(Altman et al., 2018; R. A. Calvo et al., 2023; Fedele et al., 2018; Gregoriano et al., 2017). These methods are often complemented by qualitative approaches, including interviews and focus groups, which are crucial for gaining deeper insights into patient experiences, perceived barriers to adherence, and the everyday challenges they face(Adejumo et al., 2022; J. L. Cohen et al., 2009; Davies et al., 2020). Such qualitative findings help researchers and HCPs to develop more patient-centered and effective interventions that align with patients' needs and preferences. By employing both quantitative and qualitative methods, researchers can assess not only the clinical efficacy of the intervention but also its usability and feasibility in real-world contexts(R. A. Calvo et al., 2023; De Simoni et al., 2021; Garin et al., 2023).

Evaluating adherence interventions in non-clinical settings, such as the home or workplace, is particularly important, given that patients often use their inhalers in these environments(Ammari et al., 2019; Chrystyn et al., 2019). Studies have shown that adherence can fluctuate significantly based on environmental factors, time of day, and daily routines. Understanding how interventions perform in real-world contexts, where external factors can significantly impact behavior, is critical for ensuring practical application during the intervention period(Ammari et al., 2019; Calvillo-Arbizu et al., 2021; Wooldridge et al., 2017). Therefore, a balanced and comprehensive evaluation strategy that combines objective measures with patient perspectives across diverse real-life scenarios is essential. Such an approach ensures that interventions are not only effective in improving clinical outcomes but also in enhancing quality of life over both short and long-term periods, contributing to sustainable adherence.

2.6.5 HFE and Inhalation Adherence: From Device Design to Intervention Strategies

This section focuses on the critical role of HFE principles in both the development of inhalation devices and the design of adherence interventions. The literature emphasizes that effectively incorporating HFE throughout the entire design and development process is essential for creating user-friendly and patient-centered devices

For inhalers to be truly effective and intuitive, HFE principles must be integrated at every stage of the design process, from concept development to clinical evaluation(Carayon & Wooldridge, 2020; Hegde, 2013; Leiner et al., 2015). This involves moving beyond traditional lab-based evaluations and engaging directly with end-users—patients—early and continuously throughout the development cycle. However, current design practices often fall short, prioritizing laboratory settings and clinical trials over real-world patient experiences(Dalby et al., 2004; Faisal et al., 2023; Leiner et al., 2015). Consequently, many inhalers are designed based on assumptions rather than empirical evidence of how patients interact with the devices in daily life. HFE provides methodological tools—such as usability testing, task analysis, and ergonomic assessment—to systematically incorporate patient feedback and cognitive considerations, ensuring that devices are intuitive and reduce cognitive load(Bitkina et al., 2020; Dal Negro et al., 2019; Rajan & Gogtay, 2014).

HFE is particularly valuable in understanding two critical interactions in the context of inhalation therapy:

1. Patient-Inhaler Interaction: This encompasses how well patients understand and execute the correct technique when using an inhaler. HFE principles help identify common points of failure, such as difficulties in coordinating breath and actuation with pMDIs or challenges in generating sufficient inspiratory force with DPIs. Through task analysis and usability testing, designers can refine devices to align with patient capabilities, thus enhancing adherence(Association for the Advancement of Medical Instrumentation, 2018; Leiner et al., 2015; Rau, 2005).

2. Patient-Intervention System Interaction: Beyond the device itself, HFE plays a crucial role in designing adherence support systems. By leveraging HFE principles, key factors influencing patient adherence can be identified, including understanding of treatment protocols, motivation, cognitive load, and external barriers like environmental or social challenges(Barber et al., 2005; Carayon et al., 2006; Werner et al., 2020; Wooldridge et al., 2017). These factors provide a comprehensive understanding of the specific challenges patients face in maintaining their treatment routines. Once these factors are identified, HFE guides the systematic design of intervention strategies that specifically optimize Patient-Intervention System Interaction. HFE's contribution lies in understanding how patients engage with adherence support systems in real-world contexts, which provides valuable insights for designing systems that are not

only user-friendly but also tailored to patient needs(J. Anderson et al., 2010; Carayon & Wooldridge, 2020; Fortuna et al., 2019; Tsao et al., 2019).

These insights underscore the importance of a structured framework to understand how interactions between patients, devices, intervention systems, and their environment influence adherence. The SEIPS model provides a structured framework for understanding how the interactions between patients, devices, and their environment influence adherence(Carayon et al., 2006; Holden et al., 2013; Strauven et al., 2020). In the context of Patient-Inhaler Interaction, SEIPS helps identify ergonomic and cognitive factors that may enhance or hinder proper inhaler use. For Patient-Intervention System Interaction, SEIPS guides the design of adherence systems that are responsive to patient needs and adaptable to varied usage contexts. By integrating the SEIPS components—person(s), tasks, tools & technology, internal environment, and organization—the model ensures that both inhaler design and adherence support systems are optimized for real-world conditions. This holistic perspective supports a more patient-centered approach, ensuring that devices are easy to use, intuitive, and adaptive to patient-specific needs and contexts.

Thus, the comprehensive application of HFE principles, supported by the SEIPS model, is crucial for identifying and addressing the complex factors influencing patient adherence in inhalation therapy. By focusing on usability, cognitive load reduction, and real-world adaptability, this research aims to develop more effective, patient-centered strategies that enhance adherence and improve health outcomes.

2.6.6 Novel Part of This Research

The literature reveals several key gaps in the field of inhalation therapy adherence and related interventions:

Gap in the Definition of Inhalation Adherence: Current studies predominantly focus on prescription adherence, with only a limited number recognizing technique adherence as a critical component of overall adherence(Chrystyn et al., 2019; Eikholt et al., 2023; Hesso et al., 2020; Nikander et al., 2011; Pritchard & Nicholls, 2015). This narrow focus leaves a gap in understanding the full scope of how patients engage with inhalation therapy. This research addresses this gap by clarifying the dual aspects of adherence, emphasizing both prescription adherence and technique adherence. By doing so, it provides a more comprehensive framework for understanding patient behavior and interactions with inhalation therapy. This dual focus enables the development of targeted interventions that better address the specific challenges patients face, thereby optimizing treatment outcomes.

Integration of HFE Principles in Adherence Strategies: While the importance of HFE has been recognized in device design, few studies apply HFE principles to the development of patient-centered adherence and self-management support systems (Abdolkhani et al., 2020; J. Anderson et al., 2010; Davies et al., 2020; Davis et al., 2018; Frith, 2013; Papautsky, 2019; Rau, 2005). This research fills this gap by focusing on the key factors that influence adherence, such as patient capabilities, environmental conditions, and treatment routines. It applies HFE principles to develop systems that are ergonomically appropriate, cognitively supportive, and seamlessly integrated into patients' daily lives. This integration not only enhances usability but also improves the overall effectiveness of adherence interventions by addressing both physical and cognitive demands placed on patients.

Limited Use of Multi-dimensional Sensor Technology: Although sensor technology is increasingly used in healthcare, its application in adherence interventions is largely confined to single-dimensional data, such as monitoring inhaler usage alone(Abdulmalek et al., 2022; S. A. Adams et al., 2017; Akhoundi & Valavi, 2010; M. A. Barrett et al., 2017). This research extends existing approaches by leveraging multi-dimensional sensor technology within the adherence support system. These sensors capture real-time, multi-faceted data on patient usage patterns, environmental conditions, and physiological factors, enabling more timely and individualized interventions. By applying this multi-dimensional data within the Person-Task-Physical Environment framework, the research bridges the gap between traditional adherence strategies and modern healthcare demands, providing more dynamic and personalized feedback loops.

Limited Use of Machine Learning for Classification Analysis in Adherence Interventions: Although machine learning applications have been widely reported across various healthcare sectors, their utilization for classifying patient adherence behaviors, particularly in inhalation therapy, remains limited(Jourdan et al., 2021; Najafabadi et al., 2015; Xiong et al., 2023). Most current interventions rely on static models, which hinder the ability to provide timely and adaptive support(Bae et al., 2021; Janssoone et al., 2018). This research addresses this gap by incorporating advanced machine learning algorithms to classify adherence behaviors based on sensor-based intervention system data. This approach not only promotes patient adherence by identifying patterns of non-adherence but also establishes a robust data collection framework for capturing detailed insights into patient behavior. While this study focuses on classification using retrospective data, it lays a solid foundation for developing future predictive capabilities that could enable real-time, personalized adherence support, thereby enhancing both the effectiveness of intervention systems and patient outcomes.

Need for More Intuitive Feedback Systems: Current adherence support systems often rely on traditional apps, which may not provide the most intuitive user experience(Beck et al., 2021; Belfin et al., 2019; Bharti et al., 2020; Chowdhury & Haque, 2023; Kadariya et al., 2019). This research addresses this gap by introducing a chatbot interface as a key feedback mechanism. Unlike traditional apps, chatbots offer a conversational and user-friendly way for patients to receive real-time feedback, reminders, and guidance based on sensor data. This conversational interface reduces cognitive load and enhances patient engagement by providing a more natural and intuitive interaction with the adherence support system. Moreover, the interactive nature of chatbots allows them to adapt dynamically to patient behavior, ensuring that feedback is contextualized and timely, which significantly improves the patient experience.

2.7 Conclusion

This chapter provided a comprehensive review of the literature on inhalation therapy, patient adherence, and sensor-based interventions, establishing the foundation for the conceptual framework of this research. Key insights from the literature underscored that adherence in inhalation therapy is a multidimensional concept. It encompasses both prescription adherence and technique adherence, while also being influenced by physiological, psychological, and environmental factors. Effective management thus requires a holistic understanding of these dimensions to optimize patient-device interactions and improve therapeutic outcomes.

Technological advancements, particularly sensor-based interventions, have enhanced real-time monitoring and personalized feedback, addressing critical gaps in traditional adherence support. These innovations facilitate continuous observation of physiological status, patient behavior, and environmental conditions, paving the way for proactive, data-driven intervention strategies that are better aligned with patient needs.

The literature further highlighted the importance of HFE principles and the SEIPS model in optimizing adherence interventions. This structured framework provides deeper insights into how patients interact with inhalers and digital health tools in real-world settings. Integrating sensor technology with HFE principles not only improves usability but also enhances the overall effectiveness of adherence strategies by ensuring that interventions are patient-centered and context-aware.

Finally, combining advanced analytics with personalized feedback mechanisms presents a promising pathway to overcoming existing barriers in inhalation therapy. This research contributes to addressing gaps in understanding adherence as a multifaceted phenomenon, offering innovative strategies to optimize patient engagement, device usability, and treatment outcomes in everyday contexts.

Chapter 3 Methodology

3.1 Introduction and Aims

The overall aim of this thesis is to explore how sensor-based interventions can be designed to enhance patient adherence to inhalation therapy. The previous chapter presented a detailed literature review and the theoretical underpinnings of the study; this chapter highlights the conceptual framework and the methodology of the study.

The study of patient adherence to inhalation therapy is complex because patient adherence to inhalation therapy is a multifaceted process that depends on cognitive, behavioral, and environmental factors in addition to a dynamic relationship between patient, device, and context(Aldan et al., 2022; George & Bender, 2019; Gray et al., 2018). To comprehensively guide the design, development, and evaluation of the intervention, this study adopts the SEIPS 2.0 model as the central theoretical framework(Holden et al., 2013). This chapter will outline the mixed-methods approach employed, integrating both qualitative and quantitative research methods to understand and support patient adherence to inhalation therapy.

The overall aim of this chapter is to provide a methodological framework for this research, and the specific objectives are:

1. To introduce the SEIPS 2.0 model as the guiding framework.

2. To provide an overview of the research methods used across the studies.

3. To describe strategies for ensuring reliability and validity.

3.2 Theoretical Framework

3.2.1 SEIPS 2.0 Model: Core Concepts

SEIPS 2.0 model serves as the primary theoretical framework guiding this research (Figure 3.1). This model was originally developed by Carayon et al. (2006) and further elaborated upon in SEIPS 2.0 by Holden et al. (2013). Its holistic approach focuses on how work systems engage processes in order to impact patient outcomes. Thus, the SEIPS 2.0 model, which was initially designed to examine complex healthcare interactions, is well-suited for investigating patient adherence to inhalation therapy.

The SEIPS model emphasizes the interplay between five key components: Person(s), Tasks, Tools & Technologies, Internal Environment, and Organization(Carayon et al., 2006). SEIPS 2.0 extends the original framework by incorporating concepts like configuration, engagement, and adaptation, emphasizing the dynamic and interactive nature of healthcare work systems(Holden et al., 2013). These components facilitate the systematic identification of factors affecting patient adherence, from device usage to environmental influences.

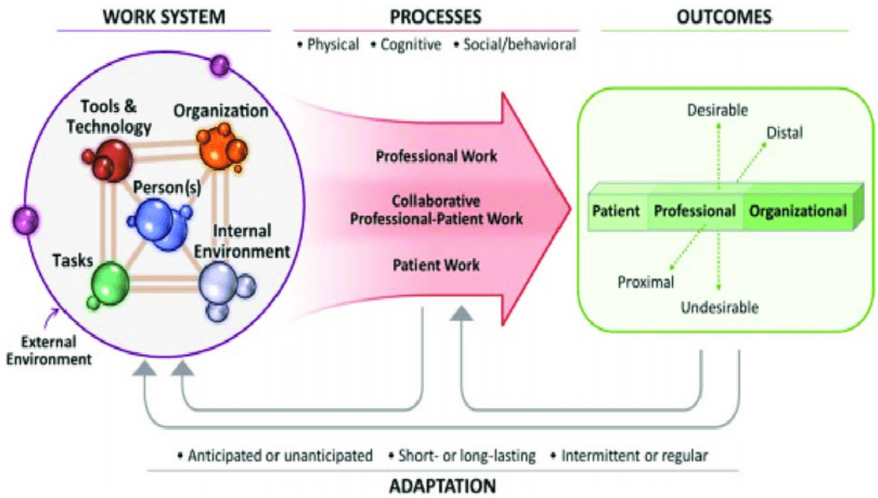


Figure 3. 1: The SEIPS 2.0 model.

In the following sections, each component of the SEIPS framework is explored to understand how it impacts patient adherence to inhalation therapy within the context of this study:

Person(s): In this context, the primary focus is on the patient using the inhalation device. The patient's physical status, their mental capacity and their health literacy are the key factors that define the likelihood of the patient's compliance with the recommended therapy(Aldan et al., 2022; Berman et al., 2021; Bourbeau & Bartlett, 2008; Gray et al., 2018). Although the patient is the main subject, the HCPs who prescribe the treatment and monitor the patient also influence the patient's adherence to the therapy.

Tasks: These include several specific activities that are required for proper inhalation therapy, such as setting up the device, performing the inhalation correctly, and maintaining the inhaler as needed(Chorão et al., 2014; Chrystyn et al., 2019; Dabrowska et al., 2019). To achieve optimal treatment outcomes, all these tasks need to be done accurately and at the right time, forming part of the patient's schedule.

Tools and Technologies: This category focuses on the inhalation device and its associated features, which may include technologies such as sensors or integration with other applications(Eikholt et al., 2023; Jácome et al., 2021; Merchant et al., 2018). Such tools are important because their design and usability are directly linked to the patient's willingness and ability to follow prescribed treatment protocols.

Internal Environment: The internal environment refers to the physical conditions and surroundings of the patient when they use the therapy in daily life. Conditions such as appropriate temperature and humidity levels, as well as good air quality, are crucial for patients with respiratory conditions(Abdulmalek et al., 2022; Bae et al., 2022; Bamashmoos et al., 2018).

Organization: The organization includes the healthcare system and the social context associated with the patient. These encompass the availability of health facilities, educational support, and the assistance of family and other caregivers(Hui et al., 2021; López-Campos et al., 2019; Margolis et al., 2019).

3.2.2 SEIPS 2.0 in This Research

While various behavioral theories (e.g., the Health Belief Model, Theory of Planned Behavior) emphasize individual beliefs and motivations(C.-Y. Lin et al., 2016; Y. Zhang & Zhao, 2021), the SEIPS 2.0 model provides a systems-oriented perspective that captures dynamic interactions among persons, tasks, tools, environments, and organizational factors(Carayon et al., 2006; Holden et al., 2013). Given that adherence to inhalation therapy is influenced not only by patient intention but also by device complexity, contextual constraints, emotional states, and socio-cultural factors, SEIPS 2.0 offers a comprehensive and holistic framework that is particularly well-suited to this research. Its integrative nature facilitates the systematic identification of adherence barriers and informs the development of context-aware, multifactorial interventions.

In this thesis, SEIPS 2.0 serves as the core theoretical foundation for examining patient adherence to inhalation therapy in asthma and COPD populations. Based on empirical findings from Study 1, the original SEIPS dimensions were refined to develop the Patient Adherence to Inhalation Therapy Work System Model, which is specifically tailored to the context of inhaler use. This adaptation redefined the "Internal Environment" as "Physical Environment" and separated cultural and social aspects from the original "Organizational Factors," forming a distinct "Culture & Social" dimension. This customized model provided consistent theoretical guidance throughout the design, development, and evaluation phases in Studies 2 to 4.

3.2.2.1 Application in Study 1: Exploring Adherence Factors

In Study 1, the original SEIPS 2.0 framework was applied to systematically explore key factors affecting patient adherence. Its five core dimensions—Person(s), Tasks, Tools and Technologies, Internal Environment, and Organization Factors—structured the development of a semi-structured interview protocol, ensuring comprehensive coverage of cognitive, behavioral, environmental, and systemic influences. Participants, including patients and HCPs, were introduced to the SEIPS 2.0 model to establish a shared conceptual foundation. Thematic coding of interview data according to these dimensions enabled the identification of both established and underexplored adherence factors. These insights informed the refinement of SEIPS 2.0, leading to the development of the Patient Adherence to Inhalation Therapy Work System

Model, which guided subsequent studies.

This foundational exploration provided a theoretical basis for understanding patient interactions with inhalers and shaped the design considerations for the intervention system in later studies.

3.2.2.2 Application in Study 2: Translating Insights into Design

Building upon the findings from Study 1, Study 2 translated the identified adherence challenges into actionable design requirements for the sensor-based intervention system. This transition from exploration to design was structured in three steps:

Step 1: Conceptualizing Core System Functions: Participants mapped identified barriers and facilitators to the five dimensions of the model (Person, Task, Tool, Physical Environment, Culture & Social), prioritizing system functions that addressed specific challenges.

Step 2: Designing System Components and Sensor Deployment: Technical requirements and essential data types—such as physiological metrics, inhaler usage patterns, and environmental conditions—were defined to ensure alignment with the model's structure.

Step 3: Exploring User Interface Design Preferences: While not explicitly mapped to the model, this step adhered to user-centered principles by incorporating feedback on usability and data presentation.

The structured application of the Patient Adherence to Inhalation Therapy Work System Model in Study 2 ensured that the intervention system was designed with a clear theoretical foundation and real-world applicability, setting the stage for system development.

3.2.2.3 Application in Study 3: System Development

Following the design phase in Study 2, Study 3 focused on transforming the conceptual framework into a fully operational sensor-based intervention system. Guided by the Patient Adherence to Inhalation Therapy Work System Model, the system's architecture, sensor deployment, and feedback mechanisms were designed to align with the five dimensions and nine key factors identified earlier. This ensured that theoretical insights were effectively embedded within practical solutions to address adherence challenges faced by asthma and COPD patients.

The successful translation of theoretical concepts into system components demonstrated the practical utility of the SEIPS-guided framework, supporting the hypothesis that a structured model can enhance real-world adherence outcomes.

3.2.2.4 Application in Study 4: System Evaluation and Classification

Study 4 applied the Patient Adherence to Inhalation Therapy Work System Model to evaluate the usability and effectiveness of the XIAOXI system. Both quantitative and qualitative findings were guided by the model, ensuring that critical adherence challenges were addressed. Additionally, machine learning analysis of sensor and emotional data provided objective insights into adherence behavior patterns.

This final phase validated the model's capacity to both guide intervention design and support comprehensive evaluation, establishing its relevance for future adherence-focused digital health solutions.

3.3 Research Methods

This research adopts a sequential exploratory mixed-methods design, in which qualitative research serves as the primary strategy, followed by quantitative and mixed-method validation. This approach was selected to first explore key influencing factors of inhalation therapy adherence (Study 1), and then use the qualitative insights to inform the design (Study 2), implementation (Study 3), and evaluation (Study 4) of a sensor-based intervention system.

The research methods are categorized into three primary areas: data collection methods, design and prototyping methods, and evaluation and validation methods. Together, they reflect a user-centered and iterative research process, integrating qualitative depth with quantitative rigor.

3.3.1 Data Collection Methods

The study employs a range of data collection methods, including interviews, questionnaires, participatory design workshops, and sensor technologies. Each method contributes uniquely to providing a comprehensive understanding of patient adherence to inhalation therapy by capturing different facets of patient behavior, decision-making processes, and real-world experiences. This holistic approach not only enables in-depth insights but also facilitates data triangulation, thereby enhancing the robustness and validity of the research findings(Biswas et al., 2016; Gray et al., 2018; Jeminiwa et al., 2019).

Interviews: Interviews are a qualitative research method used to gather detailed insights into participants' experiences, beliefs, and behaviors(Hennink et al., 2020; Mack, 2005). Semi-structured interviews are particularly valuable in healthcare research as they allow for a flexible yet guided exploration of key themes(E. Adams, 2010; Low, 2019; Whichello et al., 2019). Through open-ended questions and probing, interviews uncover cognitive and behavioral determinants of adherence, as well as external factors like environmental facilitators and barriers. However, it is essential to acknowledge potential limitations, such as interviewer bias and the challenges of generalizing findings from small, qualitative samples(E. Adams, 2010; Alshenqeeti, 2014; Lamont & Swidler, 2014). Despite these limitations, interviews remain indispensable for capturing nuanced patient experiences and contextual influences on adherence.

Questionnaires: Questionnaires serve as a quantitative data collection tool to measure or assess knowledge, attitudes, and behaviors related to inhalation therapy(Dal Negro et al., 2019; Holmes et al., 2019; Maples et al., 2010; Muneswarao et al., 2021). By utilizing validated scales, this method enhances reliability and generalizability, allowing for broader application of findings across different patient populations. Although questionnaires offer a structured and easily replicable approach, they are prone to respondent bias and may oversimplify complex behaviors and attitudes. To mitigate these limitations, questionnaires are often used in conjunction with qualitative methods to triangulate findings and provide a richer understanding of patient experiences(Anghel et al., 2019; Shi et al., 2010).

Participatory Design Workshops: Participatory design workshops represent an innovative, patient-centered approach that actively involves stakeholders in the design process(Ozkaynak et al., 2021; Schmitt & Yarosh, 2018). These workshops facilitate collaborative activities aimed at co-creating solutions to adherence challenges. Through interactive sessions, patients and other stakeholders identify real-world behaviors, usage patterns, and decision-making processes. This user-centered approach ensures that the designed interventions are not only theoretically sound but also practical and responsive to the needs of patients in their daily lives(Abdolkhani et al., 2020; Bordier et al., 2021; Houben et al., 2023). However, the success of participatory design workshops depends heavily on participant engagement and the representativeness of the sample. Thus, careful attention to participant selection and diversity is critical(Danielsson et al., 2008; Spinuzzi, 2005).

Sensor Technology: Sensor technology provides an advanced and reliable means of monitoring patient behaviors, including inhaler usage, timing, and patterns of use(Abdulmalek et al., 2022; Albahri et al., 2018; Al-kahtani et al., 2022). These technologies enable real-time, objective assessment of patient adherence under real-world conditions(Chakraborty et al., 2023; D'Arcy et al., 2014; Dierick et al., 2022; Gregoriano et al., 2017; Gupta et al., 2021). Unlike self-reported measures, sensor-generated data offers objective, verifiable indicators of patient behavior, enriching qualitative data collected through interviews and observations. However, the dependence on technology also introduces challenges, such as ensuring sensor accuracy, data reliability, and addressing potential data privacy concerns(H. Chan & Perrig, 2003; Yi et al., 2015). Despite these limitations, sensor technology remains a cornerstone of modern adherence monitoring, offering high-resolution data that informs personalized intervention strategies.

3.3.2 Design and Prototyping Methods

Design and prototyping are essential components in realizing the iterative, user-centered approach required to meet the needs identified during data collection.

Persona and Scenario: Personas are representative user archetypes derived from research data that help inform design decisions(Pruitt & Adlin, 2010; Salminen et al., 2020). They capture key characteristics, motivations, and potential challenges faced by users in real-world scenarios. Scenarios, on the other hand, are text-based narratives that illustrate how users interact with a system in specific contexts, enabling designers to anticipate user needs and potential problems(Alexander & Maiden, 2005; Brauer et al., 2009; van der Bijl-Brouwer & van der Voort, 2013). In healthcare settings, personas and scenarios are particularly valuable as they help designers understand diverse patient requirements and create solutions that are both inclusive and practical(A. M. Turner et al., 2013; Valaitis et al., 2019). However, their abstraction of user behaviors can sometimes oversimplify complex real-world interactions, potentially leading to design gaps(Gudjonsdottir & Lindquist, 2008; Lopez-Lorca et al., 2014).

Prototyping: Prototyping is an iterative process of developing, testing, and refining early versions of a system or interface(Bischofberger & Pomberger, 2012; Camburn et al., 2017). For sensor-based systems, prototyping involves constructing functional sensor modules to test data accuracy, signal processing, and system integration(Ayaz et al., 2017). This process facilitates early-stage testing and refinement of sensor placement, connectivity, and data acquisition methods before final deployment.

1. Low-Fidelity Prototypes: Low-fidelity prototypes employ basic sensor setups connected to microcontrollers for rapid data capture and processing. This configuration enables quick prototyping and testing of sensors in various positions, orientations, and environmental conditions(Bird et al., 2009). These prototypes may also include simple software interfaces that visualize raw sensor data in real time, providing early feedback from users and stakeholders(Fay et al., 1990). While adaptable and cost-effective, low-fidelity prototypes may lack the complexity needed to capture real-world data interactions, potentially affecting the accuracy of early-stage evaluations

2. High-Fidelity Prototypes: High-fidelity prototypes integrate comprehensive processing units and advanced software (e.g., embedded systems and data analysis platforms) to simulate real-world deployment conditions. These prototypes often include full sensor arrays capable of capturing multiple variables and real-time feedback algorithms for user interaction (Alazzam et al., 2021; Mathivanan et al., 2024). Although high-fidelity prototypes provide deeper insights into system performance, they are resource-intensive, requiring custom circuitry, enhanced connectivity, and sophisticated data processing frameworks(Tiong et al., 2019).

The main limitation of prototyping in sensor-based systems lies in the trade-off between fidelity and resource investment. High-fidelity prototypes offer realistic performance insights but demand substantial development costs and time. In contrast, low-fidelity prototypes allow for rapid iteration but may fail to account for the complexities of real-world conditions(Camburn et al., 2017; Walker et al., 2002).

3.3.3 Evaluation and Validation Approaches

Evaluation and validation methods are crucial for assessing the usability, efficacy, and practicality of the designed intervention. These methods ensure that the system not only benefits users but also functions effectively under real-world conditions.

Lab-based Experiments: Lab-based experiments are conducted in controlled settings to evaluate the technical characteristics of the system, such as sensor accuracy and interface effectiveness(Dutta et al., 2018; Pansiot et al., 2007). These experiments enable researchers to isolate specific variables, allowing for a clearer understanding of how the system performs under ideal conditions. For instance, sensor sensitivity and data transmission reliability can be thoroughly assessed without the unpredictability of real-world environments. However, the controlled nature of lab-based experiments may limit their capacity to capture the complexities of real-world use, where multiple interacting factors are present(Diamond, 1986; Pincus & Sokka, 2009). This gap highlights the importance of complementary field-based evaluations to understand the system's practical implications.

Field-based Experiments: Field-based experiments are conducted in real-world settings, providing insights into the system's performance during actual usage(Card et al., 2011; Sun & May, 2013). These experiments capture a holistic view of usability and effectiveness, accounting for the everyday complexities and environmental variability that patients experience. Through the collection of sensor data, questionnaire responses, and interview feedback over extended periods, field-based studies reveal interaction patterns and identify adherence barriers that may not be evident in controlled environments. Despite their strength in ecological validity, field-based experiments introduce variability due to external factors that are harder to control, such as weather conditions, patient lifestyle changes, and unexpected environmental shifts(Blumenschein et al., 2001; Diamond, 1986; Ghose et al., 2021).

3.4 Concerns and Challenges

While the methods employed in this research provided valuable insights, several challenges emerged that required strategic management. This section discusses the key concerns and the strategies implemented to address them:

Participant Bias and Subjectivity: Semi-structured interviews and participatory design workshops rely heavily on participant feedback, which is susceptible to recall bias, social desirability bias, and individual perceptions(E. Adams, 2010; Alshenqeeti, 2014; Lamont & Swidler, 2014). To mitigate these risks, data collection was conducted through multiple sources, including interviews, sensors, and questionnaires, employing triangulation to cross-validate findings. This approach helped to enhance the reliability and robustness of the collected data.

Translation and Language Barriers: Since the interview and questionnaire materials were originally designed in English, translating these materials into Chinese while maintaining their semantic integrity presented a significant challenge. Special attention was given to ensure that the translations accurately captured the original content, thereby minimizing any loss of meaning or misinterpretation. This careful translation process ensured that participants fully understood the questions and tasks, enhancing the overall quality and validity of the data collected.

Participant Engagement and Fatigue: Maintaining participant engagement and preventing fatigue during participatory workshops posed another challenge(Bertella et al., 2021; Spinuzzi, 2005). To address this, structured activities were designed to balance interactive discussions with designated rest periods, ensuring sustained participant involvement throughout the sessions. These strategies were particularly critical in managing longer workshops, which sometimes extended for several hours.

Ethical and Privacy Considerations: Data collection—particularly sensitive health information obtained through sensor monitoring and interviews—raised ethical concerns(H. Chan & Perrig, 2003; Yi et al., 2015). To address these issues, several protective measures were implemented:

1. Informed Consent: All participants provided informed consent, ensuring they understood the study's purpose and their involvement.

2. Anonymization: Participant data were anonymized to prevent identification, protecting personal privacy.

3. Data Protection Compliance: All data collection and processing activities adhered strictly to data protection policies.

4. Ethical Approval: All experiments were conducted with the approval of the Ethical Committee of the University of Nottingham Ningbo China.

These measures were crucial in safeguarding participant rights and maintaining the ethical integrity of the research.

3.5 Research Methods in This Research

This section provides a comprehensive overview of the research design, detailing the alignment of research questions with each study phase, the rationale for participant selection, data collection procedures, and analysis methods. All studies were conducted with participants recruited from the respiratory department of a major hospital in Ningbo, China. Ethical approval was obtained from the Ethics Committee of the University of Nottingham Ningbo China, ensuring compliance with ethical research standards.

3.5.1 Mapping of Research Questions to Studies

To ensure a clear alignment between the research objectives and the empirical studies, Table 3.1 presents the focus of each study and its corresponding research questions. This mapping explicitly links each research phase to the overarching research aims outlined in Chapter 1, Section 1.6. This structured approach facilitates a systematic exploration of the research questions, ensuring that each study phase directly contributes to the overall understanding of adherence in inhalation therapy.

Table 3. 1: Mapping of research questions to studies.

Study	Focus	RQs Addressed
Study 1 (Chapter 4) Investigating Factors Affecting Patient Adherence to Inhalation Therapy	Explore factors affecting adherence	RQ1
Study 2 (Chapter 5) Participatory Design of a Sensor-Based Intervention System	Translate insights into system design	RQ2
Study 3 (Chapter 6) Implementation of a Sensor-Based System for Inhalation Therapy Adherence	Implement and deploy the intervention system	RQ2
Study 4 (Chapter 7) Evaluation and Classification Analysis of the Sensor-Based Intervention System	Evaluate usability, effectiveness, and classification	RQ3

3.5.2 Methods Applied in Study 1

Study 1 aimed to explore the key factors influencing patient adherence to inhalation therapy. Guided by findings from a literature review and informed by the SEIPS 2.0 framework (Holden et al., 2013), a semi-structured interview protocol with open-ended questions systematically examined cognitive, behavioral, and environmental challenges associated with inhaler use. Interview questions were structured around the five SEIPS 2.0 components: Person(s), Tasks, Tools and Technologies, Internal Environment, and Organization, enabling an in-depth exploration of patient capabilities, inhaler usage, and the influence of environmental and healthcare system factors on adherence.

Participant Recruitment and Setting: Participants for this study were recruited from the respiratory outpatient clinic through a structured selection process:

1. Physician Screening: Patients attending outpatient appointments were identified by respiratory physicians based

on the following criteria: (a) a physician-confirmed diagnosis of asthma or COPD, (b) regular use of inhalation therapy for at least three months, and (c) a stable condition without acute exacerbations.

2. Patient Invitation: After their medical consultations, eligible patients were introduced to the researcher, who explained the study objectives and procedures.

3. Consent Process: Patients who agreed to participate received detailed information about the study, had the opportunity to ask questions, and subsequently signed informed consent forms.

HCPs were recruited through convenience sampling:

1. Initial Approach: Respiratory specialists were approached in their offices or consultation rooms during their available hours.

2. Voluntary Participation: The study's purpose, time commitment, and voluntary nature were introduced to the HCPs. Those interested signed informed consent forms to participate.

Procedure and Data Collection: Each interview commenced with the signing of a consent form, followed by a brief explanation of the study background. Participants were asked to share their perceptions and experiences regarding inhalation therapy and inhaler use. All interviews were conducted face-to-face in a semi-private hospital setting (see Figure 3.2), lasting up to one hour, and were audio-recorded with participant consent.

Data Analysis: Interview recordings were transcribed in Chinese by the interviewers and subsequently translated into English by a bilingual translator. The research team performed a line-by-line review of the transcripts to ensure accuracy and consistency. Both patient and HCP transcripts were coded separately using NVivo 14, guided by a SEIPS-based codebook. Thematic analysis was conducted independently by two researchers, following the principles of Charmaz (2006) and Strauss (1987) The analysis continued until thematic saturation was achieved, which occurred after interviewing 35 patients and 15 HCPs. Inter-rater reliability was assessed using Cohen's Kappa (κ = 0.783), indicating substantial agreement. Discrepancies in coding were resolved collaboratively through consensus discussions.

Figure 3. 2: Face-to-face interviews.

3.5.3 Methods Applied in Study 2

Study 2 involved two participatory design workshops with 10 patients, 10 HCPs, and 2 researchers to co-design a sensor-based intervention. Personas and scenarios derived from Study 1 guided the discussions, ensuring a user-centered design approach that reflected the real-world experiences and challenges of both patients and HCPs.

Participant Recruitment and Setting: Participants were recruited through a structured process designed to ensure both eligibility and diversity:

Recruitment Process:

1. Public Advertisement: Posters outlining the study objectives, procedures, and eligibility criteria were displayed in waiting areas and consultation rooms.

2. Voluntary Registration: Interested patients and HCPs registered their interest via the contact information provided on the advertisements.

3. Screening: Patients were required to meet the following inclusion criteria: (a) a physician-confirmed diagnosis of asthma or COPD, (b) regular use of inhalers for at least three months, and (c) a stable condition without recent exacerbations. HCPs were required to have a minimum of three years of clinical experience in respiratory care to ensure familiarity with inhalation therapy protocols.

4. Confirmation and Consent: Selected participants were contacted to confirm their availability, and written informed consent was obtained before their participation in the workshops.

Workshop Procedure and Data Collection: The workshop process was organized into three main stages:

- Step 1: Conceptualizing the core system functions.
- Step 2: Designing system components and sensor deployment.
- Step 3: Exploring user interface design preferences.

The first two steps were completed during the first workshop (lasting approximately 2 hours), while the third step was conducted in the second workshop (30 minutes). All discussions were held in Mandarin, audio-recorded with participant consent, and transcribed verbatim for analysis. Additionally, participants evaluated two interface prototypes using the TAM questionnaire, which assessed four key constructs: Perceived Usefulness, Perceived Ease of Use, Attitude Toward Using, and Behavioral Intention to Use(Holden & Karsh, 2010; Pai & Huang, 2011).

Data Analysis: Data analysis was conducted in two phases:

1. Qualitative Analysis: Two researchers collaboratively performed thematic analysis using NVivo 14 to extract key design requirements and identify common themes(Charmaz, 2006; Strauss, 1987).

2. Quantitative Analysis: Quantitative data from TAM responses were analyzed using SPSS v25. Subgroup analysis was performed to compare interface preferences between patients and HCPs, providing insights into differing expectations and usability perceptions.

The results of the workshops, including detailed personas, scenarios, and design outcomes, are further elaborated in Chapter 5.

3.5.4 Methods Applied in Study 3

Study 3 focused on the technical development and implementation of the XIAOXI sensor-based intervention system, translating insights from the participatory design workshops into a functional, real-world solution.

System Architecture and Components: The XIAOXI system was designed with a modular architecture composed of three core components: Monitoring, Knowledge & Awareness, and Feedback. Multi-sensor modules were integrated to continuously monitor inhaler usage, physiological indicators, and environmental conditions. To facilitate seamless connectivity, real-time data processing, and user engagement, the system was built within the Tencent ecosystem, leveraging platforms such as WeChat for efficient data transmission and accessible user interaction.

Sensor Integration and Chatbot Development: Custom-designed housings included an add-on module attached to the inhaler for monitoring inhaler usage and heart rate, and a standalone unit for home-based monitoring of air quality, temperature, and humidity. This dual-module setup enabled comprehensive, real-time data collection without disrupting daily routines.

A chatbot was developed within the Tencent ecosystem, offering personalized feedback, usage reminders, and health education. The interface design was guided by user preferences identified during Study 2, ensuring both intuitive interaction and effective presentation of adherence data. Additionally, the chatbot incorporated self-assessment tools and educational resources to support dynamic adherence management, enabling users to track their progress, understand proper inhaler use, and receive timely alerts.

Prototype Testing: Laboratory testing was conducted to validate the XIAOXI system's hardware accuracy, durability, and software reliability. Specific tests focused on the precision of sensor measurements, the stability of data transmission, platform synchronization, and the responsiveness of chatbot interactions. Iterative refinements were made based on performance outcomes to optimize sensor integration, user interface design, and real-time feedback mechanisms. These adjustments ensured that the system functioned seamlessly across various environmental conditions and user scenarios. Detailed technical development and testing outcomes are presented in Chapter 6.

3.5.5 Methods Applied in Study 4

Study 4 evaluated the XIAOXI system's usability, its effectiveness in improving adherence, and the classification of adherence behaviors through machine learning techniques during a 28-day real-world deployment with both experimental and control groups.

3.5.5.1 Usability Evaluation

Participants and Recruitment: Fifteen participants (10 patients, 5 HCPs) were recruited following the same procedures as Study 1. Patients were selected based on physician recommendations if they (a) had a confirmed diagnosis of asthma or COPD, (b) regularly used Symbicort Turbuhaler for at least one month, and (c) were in a stable respiratory condition. The choice of Symbicort Turbuhaler was informed by local clinicians due to its widespread use and compatibility with the XIAOXI sensor system. After physician approval, researchers provided detailed study information and obtained written informed consent. HCPs were recruited through direct invitation, requiring a minimum of three years' experience managing asthma or COPD patients.

Procedure: HCPs engaged in simulated usage scenarios and persona-based exercises with XIAOXI after receiving a detailed introduction to its functionalities. They interacted with the system based on predefined patient cases and completed structured evaluations on performance, usability, and clinical relevance. Patients used XIAOXI daily over a 28-day period and subsequently completed standardized questionnaires and semi-structured interviews to share their experiences.

Data Collection and Analysis: Quantitative data were collected using two validated instruments: the System Usability Scale (SUS) and a System Quality Questionnaire. The SUS evaluated overall system usability, while the System Quality Questionnaire, adapted from Kadariya et al. (2019), assessed chatbot performance—including naturalness, information delivery, interpretability—and technology acceptance based on the TAM.

Data analysis was conducted using SPSS v25 to summarize responses and compare perceptions between patients and HCPs. Following the quantitative assessment, semi-structured interviews captured qualitative insights into user experience and system interaction. All interviews were audio-recorded, transcribed verbatim, and analyzed using thematic analysis with NVivo 14, enabling the identification of key themes related to usability, satisfaction, and clinical applicability.

3.5.5.2 Effectiveness Evaluation

Participants and Recruitment: A total of 20 patients (10 in the experimental group and 10 in the control group) were recruited following the same criteria as Study 1. Eligible patients were identified by attending physicians based on the following criteria: (a) diagnosed with asthma or COPD, (b) undergoing inhalation therapy for at least one month, and (c) maintaining a stable respiratory condition without recent exacerbations.

Patients were then assigned to two groups:

- Experimental Group: Patients enrolled in the Usability Evaluation who regularly used the Symbicort Turbuhaler, compatible with the XIAOXI system’s sensor attachments.
- Control Group: Patients using prescribed inhalers, continuing standard inhalation therapy without technological intervention.

Upon physician approval, researchers approached eligible patients after their clinical consultations, providing detailed study information and obtaining written informed consent.

Procedure: The study employed a 28-day controlled experimental design. The experimental group used the XIAOXI system alongside their inhalation therapy, while the control group maintained standard care. Baseline assessments, including demographic data and adherence questionnaires, were collected before the intervention. Throughout the study period, XIAOXI continuously monitored sensor data from the experimental group, tracking inhaler usage patterns, environmental conditions, and physiological indicators. At the end of 28 days, both groups completed follow-up assessments to evaluate changes in adherence and health-related behaviors.

Data Collection and Analysis: Adherence outcomes were primarily evaluated using the Test of Adherence to Inhalers (TAI), administered to both groups before and after the intervention(Muneswarao et al., 2021; Plaza et al., 2016). Statistical analyses were conducted using SPSS v25 to examine changes in adherence scores.

For the experimental group, additional self-assessment tools were integrated within the XIAOXI system, including:

- **Consumer Asthma Knowledge Questionnaire (CQ) and Chronic Obstructive Pulmonary Disease Knowledge Questionnaire (COPD-Q):** Assessed patient knowledge regarding asthma or COPD(Kritikos et al., 2005; Maples et al., 2010).
- **Asthma Control Test (ACT) and COPD Assessment Test (CAT):** Evaluated disease control status(Gregoriano et al., 2018;

Țîrcă et al., 2022).

- **Usability, Preference and Satisfaction Questionnaire (UPSQ):** Reviewed device usability, patient preferences, and overall satisfaction(Rajan & Gogtay, 2014).

- **The Beliefs about Medicines Questionnaire (BMQ):** Explored perceptions of medication necessity and concerns(Nie et al., 2019).

- **General Self-Efficacy Scale (GSE):** Assessed confidence in managing health behaviors(Dahlberg et al., 2022; Luszczynska et al., 2005).

- **Emotional Experience (Emocard):** Administered daily to capture real-time emotional fluctuations and support personalized feedback(Reijneveld et al., 2003; Zenk et al., 2008). Figure 3.3 illustrates the structure of the Emocard and its emotional categories.

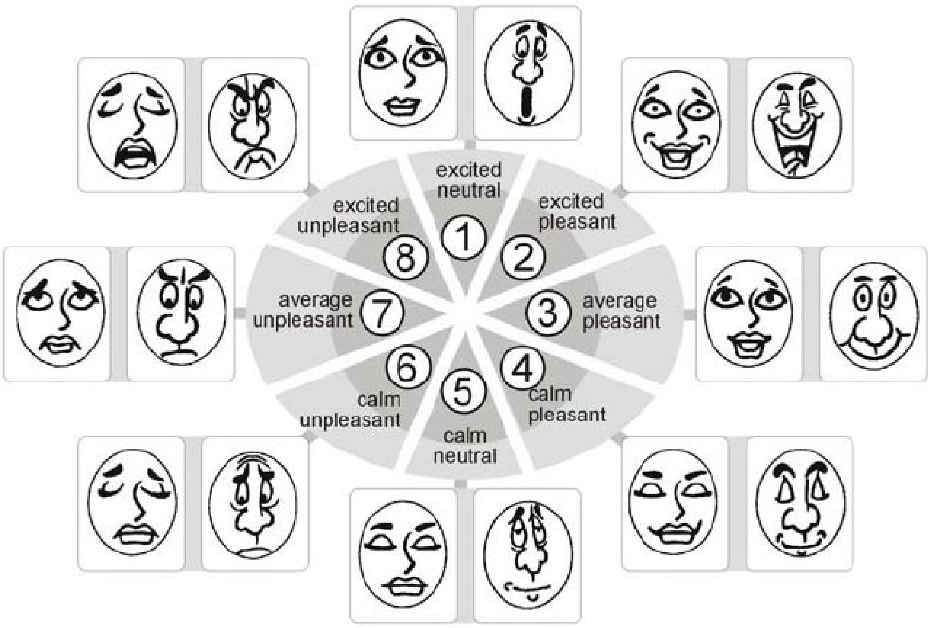


Figure 3. 3: Emocard.

Except for the Emocard, participation in these embedded questionnaires was voluntary and flexible, enabling patients to engage with the tools based on individual needs, thereby enhancing personalized disease management. These instruments formed an integral part of the XIAOXI intervention, designed to foster patient awareness, motivation, and adherence behavior.

Additionally, semi-structured interviews were conducted post-intervention with participants from both groups to explore patient experiences, adherence barriers, and perceptions of inhalation therapy. All interviews were transcribed verbatim and analyzed using thematic analysis in NVivo 14. Key themes were compared across groups to identify differences in adherence behaviors and patient perceptions resulting from the XIAOXI intervention.

3.5.5.3 Classification Analysis

The classification analysis aimed to identify patterns of patient adherence behaviors by analyzing data collected from the experimental group during the 28-day intervention with the XIAOXI system. The primary objective was to classify daily inhaler usage into adherent (completed prescribed usage) and non-adherent (missed or incomplete usage) behaviors.

Data Sources and Preprocessing: The dataset included daily sensor readings—heart rate, temperature, humidity, PM2.5 levels, and inhaler usage frequency—alongside patient-reported emotional experiences captured via the Emocard. Data cleaning was performed using the Interquartile Range (IQR) method to identify and remove outliers, thereby ensuring data integrity. Subsequently, sensor data were aggregated by calculating daily median values, while emotional data were categorized into four quadrants based on valence and arousal levels to facilitate structured analysis.

Classification Task: A binary classification framework was established, where each day was labeled as adherent (1) if the prescribed inhaler usage was completed, and non-adherent (0) otherwise. To achieve this, seven different machine learning algorithms were employed, covering a range of linear, non-linear, and ensemble-based methods. The detailed descriptions of the algorithms, parameter settings, and performance metrics are presented in Chapter 7. This comprehensive evaluation enabled the identification of key predictors and adherence patterns, contributing to a deeper understanding of inhalation therapy behaviors in real-world settings.

3.5.6 Reliability and Validity

Establishing reliability and validity is crucial in a mixed-methods study of this nature. Potential threats to reliability include participant error, participant bias, and observer bias(L. Cohen et al., 2017; Franklin & Ballan, 2001). To enhance reliability, the study employed triangulation through the integration of multiple data sources: objective sensor data, subjective self-reported questionnaires, and qualitative interviews. For example, adherence behaviors captured through sensor logs were cross-verified with self-reported data from the TAI questionnaire, ensuring consistency and reducing the influence of biases associated with any single method. This multi-faceted approach provided a more balanced and reliable assessment of patient adherence.

To ensure construct validity, only standardized and validated tools—such as the SUS, TAM, and TAI—were employed, aligning with established theoretical constructs(Holden & Karsh, 2010;

Kadariya et al., 2019; Plaza et al., 2016). External validity was strengthened by recruiting participants from a diverse demographic range, reflective of the broader population affected by chronic respiratory diseases. This diversity enhances the generalizability of findings across different patient populations. Furthermore, all protocols were applied consistently across participants to minimize procedural discrepancies, ensuring that observed differences in adherence behavior were genuinely reflective of individual variations rather than inconsistencies in data collection or intervention delivery.

3.6 Conclusion

This chapter presented a comprehensive overview of the research methodology employed in this study, detailing the theoretical foundations, methods, and procedures applied across the four studies. The SEIPS 2.0 model served as a critical framework for understanding the multifaceted factors influencing patient adherence to inhalation therapy and guided both the design and evaluation of the sensor-based intervention system.

Key methodological considerations, including reliability and validity, were thoroughly addressed. The integration of standardized procedures, validated tools, and a combination of qualitative and quantitative data ensured methodological rigor, enhancing the reliability of the findings. This structured approach bridges the gap between theoretical concepts and practical application by thoroughly examining patient behaviors and the effectiveness of the intervention system in real-world settings.

The subsequent chapters will present the findings from each study, demonstrating how the methodological strategies outlined here contributed to a deeper understanding of patient behavior, intervention efficacy, and the role of technology in enhancing adherence to inhalation therapy.

Chapter 4 Investigating Factors Affecting Patient Adherence to Inhalation Therapy

4.1 Introduction and Aims

Asthma and COPD are chronic respiratory conditions with significant implications for global public health. Inhalation therapy, recognized for its rapid onset of action and targeted delivery, remains one of the primary treatment approaches for these diseases (Bhattacharyya & S Sogali, 2018; Borghardt et al., 2018). However, while existing research has identified various factors influencing patient adherence, specific challenges remain, particularly in developing regions like China—where limited healthcare resources, varying levels of health literacy, and cultural beliefs pose significant barriers to effective treatment(Ait-Khaled et al., 2001; C. Huang et al., 2016; C. Wang et al., 2023). Notably, the interaction between patients and inhalation devices in this context is underexplored, suggesting a need for deeper investigation into the specific factors affecting patient adherence.

Building on the framework introduced in previous chapters, this chapter applies the SEIPS 2.0 model, a foundational framework in HFE, to systematically explore the complex interactions among Person(s), Tasks, Tools and Technologies, Internal Environment, and Organization within the context of inhalation therapy. A primary focus of this exploration is understanding how patients engage with inhalation devices, accounting for both cognitive and behavioral challenges that may arise during use. Semi-structured interviews are utilized to reveal insights into these interactions and other contextual factors that shape patient adherence. These findings contribute to the construction of a theoretical framework that informs the design of individualized interventions aimed at enhancing adherence. The primary aim of this chapter is to identify the factors that influence patient adherence to inhalation therapy and to explore how these findings can guide the design of interventions tailored to the specific needs of patients. Understanding the challenges and barriers that patients currently face, alongside their characteristics, behaviors, and preferences, is critical for designing effective solutions.

The objectives of this chapter are:

1. To investigate the characteristics and needs of asthma and COPD patients in the context of inhalation therapy.

2. To examine the current challenges and barriers affecting patient adherence.

3. To explore the implications of these findings for designing personalized interventions that support improved adherence and better patient outcomes.

4.2 Methods

This study employed semi-structured interviews to explore the multifaceted factors influencing patient adherence to inhalation therapy, guided by the SEIPS 2.0 framework for structured analysis. The interview protocol is provided in Appendix 4A. Methodological details, including participant recruitment strategies, interview protocols, and data analysis procedures, are comprehensively described in Chapter 3, Section 3.5.2. This section presents the demographic characteristics of the participants and outlines the thematic structure derived from the analysis, setting the context for the findings presented in the following sections. The demographic profiles of both patients and HCPs involved in this study are summarized below.

Table 4. 1: Participant demographics (patients).

Demographic	**Count (n=35)**	**Percentage**
Gender		
Male	16	45.70%
Female	19	54.30%
Age Range		
18-35	10	28.60%
36-50	18	51.40%
51-65	7	20.00%
Educational Level		
Primary	8	22.90%
Secondary	15	42.90%
Tertiary	12	34.30%
Type of Disease		
Asthma	20	57.10%
COPD	15	42.90%
Disease Severity		
Mild	21	60.00%
Moderate	14	40.00%
Severe	0	0.00%
Number of Inhaled Medications (Inhalers)		
1	19	54.30%
2	12	34.30%
>2	4	11.40%
Number of Comorbidities		
0	15	42.90%
1	13	37.10%
2 or more	7	20.00%
Type of Patient		
Outpatient	23	65.70%
Inpatient	12	34.30%
Experience with Inhaler Device (Years)		
<1	13	37.10%
1-3	15	42.90%

>3	7	20.00%

Table 4. 2: Participant demographics (HCPs).

Demographic	Count (n=15)	Percentage
Gender		
Male	7	46.7%
Female	8	53.3%
Age Range		
18-35	7	46.7%
36-50	6	40.0%
51-65	2	13.3%
Work Experience		
3-6	4	26.7%
7-10	7	46.7%
>10	4	26.7%

The thematic analysis resulted in five key categories aligned with the adapted SEIPS framework: (1) person, (2) task, (3) tool, (4) physical environment, and (5) culture and social factors. These thematic categories form the basis for the presentation and discussion of findings in the subsequent sections.

4.3 Results

4.3.1 Person-related Factors

4.3.1.1 Patient Ability

Participants highlighted the significance of patient abilities, both physical characteristics and cognitive ability, that hinder self-efficacy during inhalation therapy.

Physical Characteristics: Two primary aspects were identified: lung function decline and manual dexterity issues. Patients with reduced lung capacity, common in respiratory diseases, struggle to achieve the necessary inhalation flow rate. *"I know that during inhalation treatment I ought to take a deep breath, however, due to my lung disease I sometimes get barely able to draw normal breaths."* Additionally, many elderly patients reported difficulties in securely gripping the inhaler due to tremors or weakened hands. *"I try to hold it tightly, but my hands are trembling which makes it difficult to use the inhaler."*

HCPs observed that patients with physical impairments often face challenges using inhalers effectively, potentially reducing treatment efficacy. They suggested selecting devices tailored to patients' physical capabilities to optimize outcomes. *"When prescribing, I consider the patient's physical abilities. For instance, the use of SMI shall be preferred for elderly patients because it provides the benefit of less inspiratory flow rate."*

Cognitive Ability: Cognitive limitations, including disease knowledge gaps and communication barriers, were frequently linked to poor adherence. HCPs noted that misunderstandings about the chronic nature of conditions like asthma often led to inconsistent inhaler use. *"Some patients mistakenly believe that the absence of symptoms means they are cured. Chronic conditions like asthma require long-term management, even when symptoms are not apparent."*

HCPs emphasized the need for effective education to ensure patients understand their condition and the necessity of consistent inhaler use. However, patients expressed frustration with medical jargon, feeling overwhelmed and often leaving consultations without clear understanding. *"In fact, I didn't understand the medical terms the doctor used, so all I could do was to pay the money and take the medicine that I had no clue about. It would be nice if they could explain it more."*

Some patients even questioned the credibility of their doctors due to vague explanations: *"I found that my doctor often uses words like perhaps, probably, and maybe. How can I trust him when his diagnosis is so uncertain?"* In response, HCPs acknowledged the difficulty of providing definitive answers due to medical uncertainties and individual differences.

Furthermore, memory issues were noted as a barrier, with some patients forgetting to use their inhalers or struggling with dosage instructions. To mitigate this, some patients set phone alarms as reminders. *"With my tendency for forgetfulness I put an alarm on my phone to serve as a reminder for using my inhaler daily."*

4.3.1.2 Emotional Experience

Negative interactions with inhaler devices were reported to significantly affect patients' emotional experiences, leading to burnout and resistance. The noise generated during inhaler use was cited as a source of stress: *"While using the inhaler, there is probability of hearing the sound of internal mechanism, which raises my stress and hesitance to use it again."* Additionally, the repetitive nature of inhaler use contributed to feelings of frustration and fatigue: *"For over a year now I've been using the same device and I have to repeat the same operation every single day as if I am a robot and this feels very boring and annoying."*

While some HCPs acknowledged this emotional burden, they stressed that the effectiveness of the medication remains their primary concern, often placing less emphasis on emotional discomfort: *"As doctors, our priority is the patient's health, so the effectiveness of the inhaled medication is more important than the patient's feelings about the inhaler."* Figure 4.1 illustrates the person-related factors.

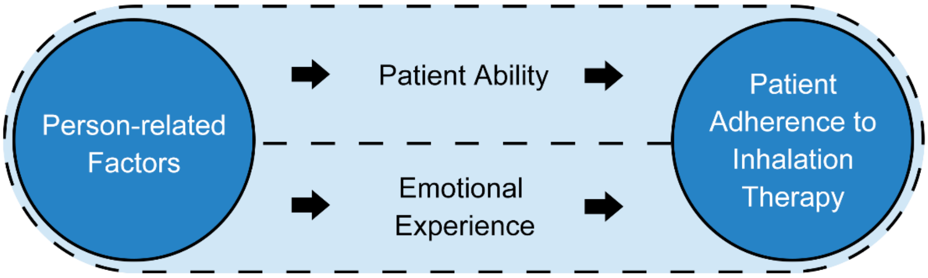


Figure 4. 1: Person-related factors.

4.3.2 Task-related Factors

4.3.2.1 Task Type

Collaborative Task: Inhalation therapy often requires effective cooperation between HCPs and patients. Proper inhaler technique training and regular assessments are critical for ensuring effective usage. However, many patients reported that the training they receive is insufficient for developing a consistently correct technique. Interviews revealed that 4 out of 5 patients received less than 10 minutes of inhaler technique training, and only 1 in 7 had a follow-up check on their usage. *"The entire visit took just 10 minutes with the doctor discussing how to use the inhaler for less than 1 or 2 minutes."* HCPs acknowledged that heavy workloads and time constraints often prevent them from providing comprehensive training or conducting regular assessments. *"Many patients come to me every day and I lack time to review all details regarding its use."* Some HCPs noted that patients often turn to self-education, such as reading instructions or watching online tutorials, to improve their inhaler techniques. To enhance patient understanding, several HCPs suggested incorporating visual aids during consultations as a way to demonstrate proper inhaler use more effectively, even within limited timeframes. *"I present a used inhaler to demonstrate how to operate it so the patient can learn quickly."*

Independent Task: Tasks that patients carry out independently, such as administering inhalation therapy at home, are classified as independent tasks. Many patients reported that insufficient guidance on proper inhalation techniques made self-administration more challenging. Patients with chronic respiratory conditions, like asthma, are often prescribed both relievers and maintenance therapies, which can lead to inhaler mixing (using multiple inhalers with different techniques). Several patients expressed frustration over managing different devices: *"The task of mastering one technique is challenging enough; attempting two simultaneously is even more difficult, and I get these two different techniques mixed up all the time."* Additionally, patients described difficulties with inhaler switching—transitioning from one device to another—especially when adequate time or guidance was not provided. This often resulted in incorrect usage and reduced treatment effectiveness. *"It appears that though this new device looks like the old one, it works differently; initially, I used the old way, but the operation was always unsuccessful."*

4.3.2.2 Frequency and Flexibility

The findings reveal that both the frequency of inhaler use and the lack of flexibility in treatment schedules can significantly impact patient adherence. Many patients reported that the more frequently they are required to use their inhaler, the greater the likelihood of missed doses. *"Even if I set an alarm for using my inhaler in the morning and evening, sometimes I forget to use it, that is why it* *would be so much easier if I needed to use the inhaler just once a day."* Additionally, some patients expressed frustration with the rigid schedules associated with inhalation therapy, citing difficulties in maintaining regular use due to work obligations or travel. *"I frequently work overtime or have to travel for business, which makes it hard to stick to my inhaler schedule. Additionally, since an asthma attack can happen at any time, I always try to keep the device with me—like a pet on a leash."* HCPs acknowledged the inconvenience of strict inhalation routines but emphasized that patients must often endure these challenges for the sake of effective disease management. *"Suffering is also therapy, perhaps, that is the cost of waging war on the disease, patients must endure it for the sake of their health."* Figure 4.2 shows the task-related factors.

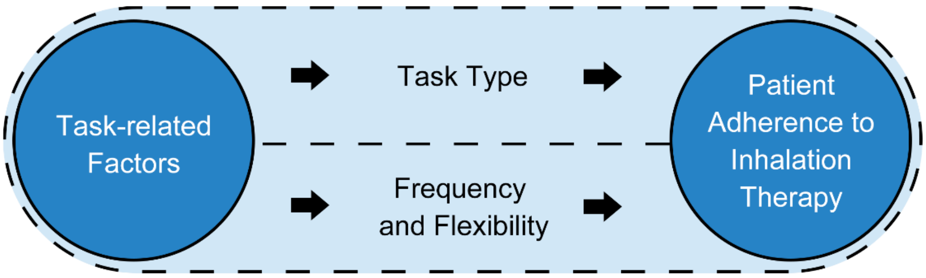


Figure 4. 2: Task-related factors.

4.3.3 Tool-related Factors

4.3.3.1 Type of Inhalers

There are four main types of inhalers commonly used in clinical settings: pMDIs, DPIs, SMIs, and Nebulizers. According to our interviews, each type presents distinct advantages and drawbacks, and no single device meets the needs of all patients. For instance, 71.4% of patients aged 51 and above expressed frustration with pMDIs, citing the need for coordinated timing between pressing the inhaler and inhaling, which they found challenging compared to other devices. *"Sometimes I remember to push the button but ignore the need to breathe and at other times I find myself breathing but failing to press the button."*

In contrast, male patients voiced more concerns about DPIs, particularly issues with drug powder clumping due to improper cleaning. If the device is not properly maintained, powder residue remains in the mouthpiece, leading to clumping. We observed that female patients tended to be more diligent in maintaining and cleaning their inhalers, while male patients were more likely to overlook these "details." Some HCPs noted that a patient's clinical outcomes may depend on the type of inhaler they use, as patients often respond differently to various devices. They emphasized that the same patient might exhibit different adherence behaviors depending on the device selected. *"He was initially a non-compliant patient, but after switching to a different inhaler, he began using it correctly every time."*

Additionally, several HCPs mentioned a newer category of inhalers—the digital inhaler—which includes built-in or add-on sensors capable of detecting inhaler use and measuring inspiratory flow. Although these devices are not yet widely promoted in China, HCPs believe that this technology could offer significant benefits to patients. However, when discussing the potential future adoption of digital inhalers, many patients expressed concern about increased costs. *"As the inhalers become digital, does the price go up? If so, I do not know whether it is worthwhile."*

4.3.3.2 Usability of Inhalers

Participants emphasized the importance of inhaler usability, noting that it plays a crucial role in promoting patient adherence to inhalation therapy. Many patients suggested that instead of more advanced devices, they primarily require inhalers that are user-friendly and capable of providing feedback.

Providing Feedback: In this study, nearly two-thirds of the patients expressed a desire for immediate feedback on their inhaler usage during treatment, while about three out of seven preferred receiving overall feedback after a period of use, such as weekly or monthly. During the interviews, approximately 88.6% of patients voiced concerns about whether the medication was truly being inhaled. Patients reported that their only indicators were "*a change in the counter display*" and "*the bitter taste of the medication*". Some participants suggested that inhalers should offer more real-time information, such as feedback on how the device is being operated and the speed of inhalation, to ensure proper usage. *"I doubt I am on the correct path. I want the device to provide more clues and details at that time."*

Additionally, some patients mentioned that receiving regular reports on their inhaler usage might help them better track their progress and take control of their treatment. *"I mark my calendar after each inhalation so I know how am I doing. When I realise I skipped some doses last week, I will take extra precautions this week."*

HCPs also acknowledged the potential benefits of feedback mechanisms, particularly in helping patients establish better routines and refine their inhalation techniques. However, about four-fifths of HCPs reported feeling overwhelmed by the volume of information they already manage during clinical visits. While receiving overall feedback could assist HCPs in monitoring a patient's condition and adjusting treatment plans accordingly, they indicated that real-time feedback is likely more valuable to patients than to themselves.

Intuitive to use: A key feature that patients desired was ease of use, which they noted would significantly reduce their cognitive burden and allow them to focus more effectively on their treatment. Patients explained that an intuitively designed inhaler would be easy to understand and operate without requiring much effort or instruction. One patient shared her vision of what an "intuitive inhaler" would look like: *"One does not have to consider how to operate the device; simply open it up and take a breath."* HCPs also expressed their preference for intuitive inhalers, which would minimize the need for extended training sessions with patients. *"It is less time-consuming when patients do not require additional explanation on how to use the device, allowing us to attend to more patients."* Figure 4.3 illustrates the task-related factors.

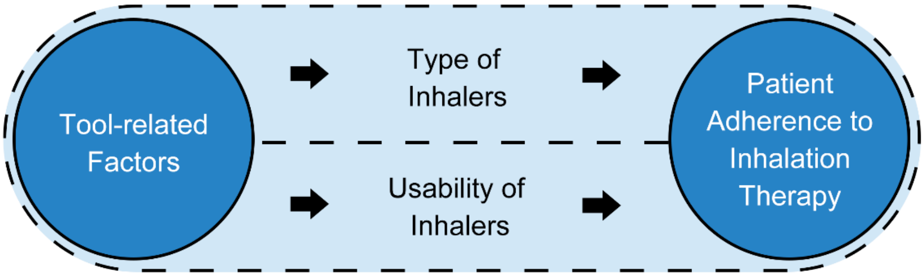


Figure 4. 3: Tool-related factors.

4.3.4 Physical Environment-related Factors

4.3.4.1 Daily Environment

All patients reported that they most often use their inhalers within their daily environment, with home settings being the primary location (see Figure 4.5). Several participants noted the influence of factors such as temperature, humidity, and storage location on how their inhalers are maintained. One patient shared her experience with drug deterioration caused by improper storage conditions at home: *"Because I rinse my mouth after every use, I leave the inhaler on the bathroom washstand for convenience; but the humidity and heat in the bathroom make the powder clump and deteriorate quickly."*

Similarly, another patient described accidentally using the wrong inhaler after storing different types together: *"By my bedside, there were both the reliever and the maintenance inhalers. One day, I used the reliever inhaler instead of the maintenance one. It was bad."* Some HCPs pointed out that managing patients' health-related behaviors in their daily environments is challenging, as it falls outside their direct control and expertise. They emphasized the need for better patient education on proper storage practices and the importance of differentiating between different types of inhalers to avoid mistakes.

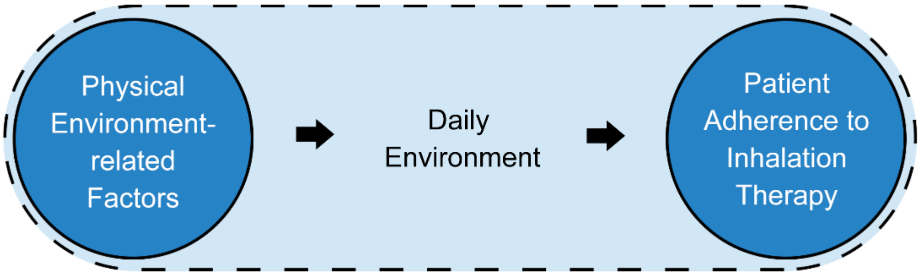


Figure 4. 4: Physical environment-related factor.

4.3.5 Culture and Social-related Factors

4.3.5.1 Cultural Beliefs

Cultural beliefs, defined as "a set of behavioral patterns encompassing thoughts, manners, and actions shared by members of a society and passed down through generations," can significantly influence patients' decisions regarding inhaler use(Md Hatah et al., 2015). In our study, we found that more than two-thirds of the participants held strong convictions in the effectiveness of Traditional Chinese Medicine (TCM) and traditional Chinese health beliefs. As a result, many of these patients had either reduced or entirely discontinued their inhaler use. One patient explained, *“There’s an old Chinese saying, 'All medicine has du (toxicity) to some degree,' so once the symptoms are gone, there’s no need to keep using an inhaler.”* HCPs noted that changing patients' cultural beliefs is particularly challenging, especially among older individuals whose beliefs are deeply ingrained. However, they also observed that younger patients tend to be more receptive to ongoing counseling and education.

4.3.5.2 Social Stigma

Social stigma refers to the negative judgment or discrimination directed at individuals or groups based on visible traits that set them apart from the rest of society(Latalova et al., 2014). In our study, approximately one in seven patients reported experiencing feelings of stigmatization due to their inhaler use during treatment. One patient shared feelings of social shame and devaluation when using her inhaler in public settings: *“I feel embarrassed to use the inhaler around my family or colleagues. It's my fault for being the one who’s unwell when everyone else is healthy, and I need inhaled medications to get better.”* Another patient described feeling discriminated against during interactions with HCPs: *“When I was in the hospital, the nurses kept telling me I was doing the steps wrong and complained that I couldn’t learn them, which made her frustrated. I could tell she preferred dealing with 'smart patients' over 'dumb patients' like me.”* Figure 4.5 illustrates the culture and social-related factors.

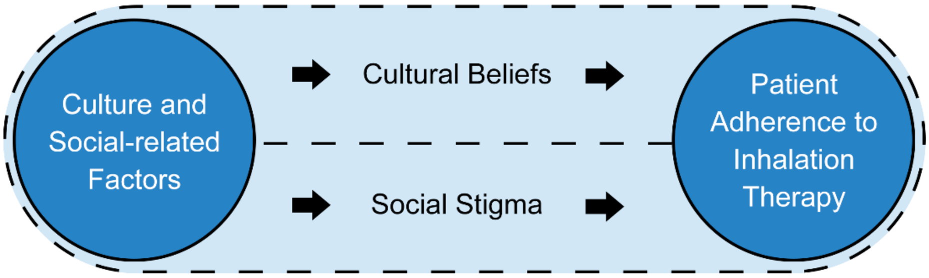


Figure 4. 5: Culture and social-related factors.

4.4 Discussion

This study, which analyzed interviews with 35 patients and 15 HCPs, identified nine key factors influencing patient adherence to inhalation therapy, as outlined by the SEIPS 2.0 framework. The study revealed a broad range of factors—including person, task, tool, physical environment, culture and social influences—that shape adherence behaviors and outcomes in patients with asthma or COPD. By centering the participants' perspectives, the research highlighted that adherence to inhalation therapy is a dynamic process, influenced by the interplay of various elements such as patient abilities, emotional experiences, task type, frequency and flexibility of use, inhaler type and usability, daily environment, cultural beliefs, social stigma, and imperfect medical encounters. Figure 4.6 presents a comprehensive model consolidating these HFE influences.

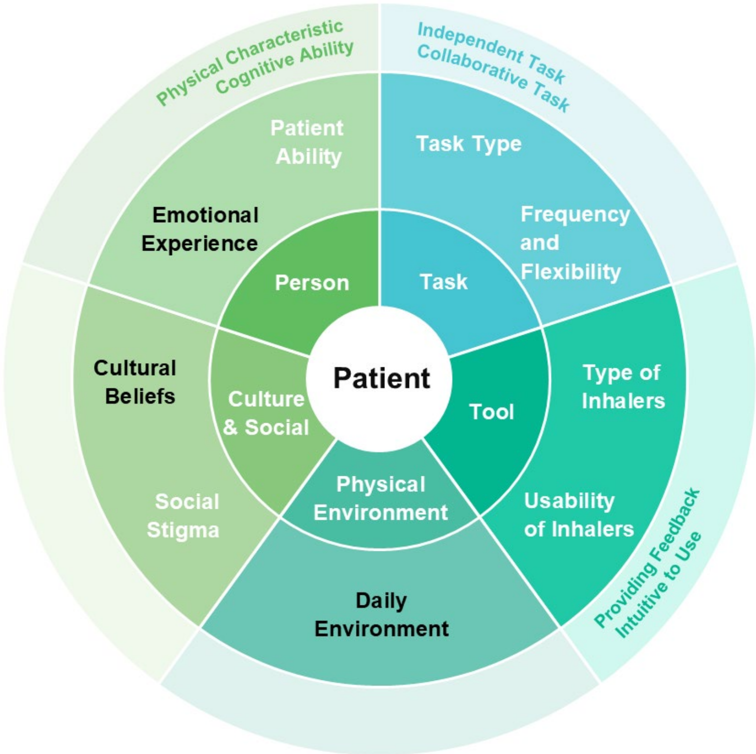


Figure 4. 6: Patient adherence to inhalation therapy work system model.

While several of these factors have been discussed in previous studies(Bourbeau & Bartlett, 2008; Brandstetter et al., 2017; Leventhal et al., 1992; Restrepo, 2008), this research reveals new dimensions affecting adherence behaviors. These newly identified factors include the challenges patients face in using inhaler devices due to negative emotional experiences, the influence of physical environmental conditions (such as the home setting), and the role of traditional cultural beliefs in shaping patients' decisions to use their inhalers.

Emotional experiences related to patient-device interactions emerged as a critical factor influencing adherence, which is less explored in current literature. Most studies on chronic illness have primarily focused on emotional states at the individual level (e.g., depression) or within interpersonal contexts (e.g., social support). Few studies have emphasized the emotional dimension of patient-device interactions, even though it can significantly impact adherence. Previous research has illustrated that conditions like depression or anxiety increase the likelihood of patients discontinuing treatment and reduce the number of days they adhere to medication(Restrepo, 2008; Sanduzzi et al., 2014). Additionally, support from families or HCPs has been shown to improve patient adherence and enhance their quality of life(Bonito et al., 2013; DiMatteo, 2004). However, emotional consequences of human-device interactions and their effect on adherence are rarely examined. One study found that emotional barriers negatively impacted patients' confidence and satisfaction with self-injection devices, ultimately reducing their willingness to adhere to treatment—a pattern consistent with the findings of our study(Rekaya et al., 2020). This suggests that emotional design theories, such as Norman's Emotional Design Theory and Kansei Engineering, could be leveraged to improve patient engagement and foster positive experiences during inhaler use(Nagamachi, 1995, 2002; Norman, 2007). For example, emotional design principles have been successfully applied in the development of prosthetic devices, enhancing user acceptance and satisfaction(Sansoni et al., 2016).

Environmental influences were also found to be significant, particularly the impact of temperature, humidity, and storage conditions on inhaler effectiveness. While clinical settings provide optimal conditions for drug storage and inhalation therapy, home environments often do not(Juliá Nehme et al., 2021; National Research Council et al., 2011). Patients reported improper storage practices, such as leaving inhalers in humid or overheated areas, which can degrade medication quality. This finding underscores the importance of simulating real-world environments during inhaler training to prepare patients for everyday usage scenarios.

Cultural beliefs were found to be another influential factor, particularly the traditional Chinese concept that "*All medicine has du (toxicity) to some degree*." This belief often led patients to reduce or discontinue inhaler use after symptom relief, despite medical advice to maintain treatment. Historically, in ancient China, "du" was perceived as an inherent attribute of medicine, symbolizing both its therapeutic potency and its risks(Y. Liu, 2021). This understanding has evolved, with many patients now interpreting "du" simply as "poison," influencing their willingness to adhere to inhaled medications. Although cultural beliefs are known to affect medication adherence, relatively few studies have examined their impact within the context of inhaler adherence. This underscores the need for culturally sensitive intervention strategies that respect traditional beliefs while promoting effective treatment practices(Shahin et al., 2019).

The study also highlighted the mismatch between patient and HCP priorities. While HCPs tend to focus on treatment effectiveness and clinical outcomes, patients often prioritize comfort, usability, and their daily experiences with inhaler devices. Research suggests that involving patients in treatment decisions improves satisfaction and adherence(Cvengros et al., 2007; Pollard et al., 2017; Wilson et al., 2010). However, patients are frequently excluded from device selection and treatment planning, which may reduce their engagement and adherence. Time constraints, heavy workloads, and limited resources were cited by HCPs as barriers to providing comprehensive inhaler training and addressing patient concerns, consistent with previous findings(Fink & Rubin, 2005).

Finally, the emergence of digital inhalers presents new possibilities for real-time monitoring and adaptive feedback. Digital inhalers can objectively track inhaler usage, monitor inspiratory flow, and capture environmental data, offering HCPs and patients deeper insights into adherence behaviors(Pritchard & Nicholls, 2015). While cost and data management challenges remain, the integration of sensor technologies and digital interfaces could transform adherence monitoring, enabling more personalized and data-driven interventions(Chrystyn et al., 2019; Ghozali, 2023). Future research should focus on demonstrating the clinical and economic benefits of digital inhalers to justify their broader adoption.

4.5 Conclusion

This research identified nine key HFE elements that impact patient adherence to inhalation therapy. By developing a conceptual framework grounded in the SEIPS 2.0 model, the study highlighted previously underexplored factors, including emotional experiences, physical environment conditions, and traditional cultural beliefs, as crucial components for understanding patient adherence behaviors. These findings suggest that future interventions should place greater emphasis on patients' perceptions and experiences with their inhaler devices in real-world settings.

Additionally, the study points to the potential of digital inhalers as promising tools for improving adherence. However, the effectiveness of such technologies hinges on their accessibility, ease of use, and alignment with patient-specific needs. This research offers practical insights for enhancing the patient experience in inhalation therapy, with implications that may extend to other DDCPs.

Chapter 5 Design of a Sensor-Based System for Inhalation Therapy Adherence

5.1 Introduction and Aims

Poor adherence to inhalation therapy is influenced by various factors, including the complexity of inhaler use, challenges in environmental control, and differences in patient ability(Aldan et al., 2022; Price et al., 2015). These challenges highlight the limitations of one-size-fits-all approaches and underscore the need for personalized interventions that account for the unique characteristics, behaviors, and environments of different patient groups.

The theoretical background was discussed in Chapters 2 and 3; the factors that affect patient adherence to inhalation therapy were identified in Study 1 (Chapter 4), thus setting the stage for the user-centered approach to intervention development. Drawing from these findings, this chapter is dedicated to the design of a sensor-based intervention system named XIAOXI. The name XIAOXI (小溪), which translates to "Little Stream," symbolizes the aspiration for smooth, uninterrupted breathing akin to the gentle flow of a stream. This metaphor reflects the system's goal of enhancing patient comfort and consistency in inhalation therapy, promoting a sense of ease and natural rhythm in each breath.

The objectives of this chapter are:

1. To explain participatory design and its role in gathering user insights to guide the design process.
2. To detail how workshop findings influenced the system's functions, interface, and design features.
3. To illustrate how personalized intervention strategies were incorporated to address diverse patient needs and behaviors.

5.2 Methods

This study adopted a participatory design approach to collaboratively develop a sensor-based intervention system, actively involving both patients and HCPs to ensure the design was firmly grounded in real user needs and clinical practices. The methodological framework—including participant recruitment, workshop procedures, and data analysis—is comprehensively detailed in Chapter 3, Section 3.5.3. To contextualize the participatory design process, this section presents the demographic characteristics of the participants involved. The demographic profiles of the participating patients and HCPs are summarized in Tables 5.1 and 5.2.

Table 5. 1: Participant demographics (patients).

Demographic	Count (n=10)	Percentage
Gender		
Male	6	60.00%
Female	4	40.00%
Age Range		
18-35	4	40.00%
36-50	4	40.00%
51-65	2	20.00%
Educational Level		
Primary	1	10.00%
Secondary	5	50.00%
Tertiary	4	40.00%
Type of Disease		
Asthma	8	80.00%
COPD	2	20.00%
Disease Severity		
Mild	9	90.00%
Moderate	1	10.00%
Severe	0	0.00%
Number of Inhaled Medications (Inhalers)		
1	8	80.00%
2	2	20.00%
>2	0	0.00%
Number of Comorbidities		
0	7	70.00%
1	2	20.00%
2 or more	1	10.00%
Experience with Inhaler Device (Years)		
<1	2	20.00%
1-3	6	60.00%
>3	2	20.00%

Table 5. 2: Participant demographics (HCPs).

Demographic	Count (n=10)	Percentage
Gender		
Male	3	30.0%
Female	7	70.0%
Age Range		
18-35	6	60.0%
36-50	4	40.0%
51-65	0	0.0%
Work Experience		
3-6	2	20.0%

7-10	5	50.0%
>10	3	30.0%

5.3 Personas and Scenarios

To ensure a patient-centered design approach, two personas were developed based on insights derived from semi-structured interviews, guided by the SEIPS 2.0 framework and the nine key factors influencing adherence identified in Study 1. These factors, categorized across five dimensions—Person, Task, Tool, Physical Environment, and Culture & Social—served as a structured reference for persona development, ensuring comprehensive coverage of adherence challenges.

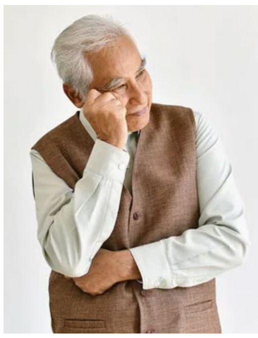
The nine key factors were systematically reviewed during the persona development process to ensure that each persona embodied distinct barriers and needs across these dimensions. For example, the Busy Professional primarily reflects challenges related to Task Type, Frequency and Flexibility, Emotional Experience, and aspects of Tool Usability, highlighting issues such as managing independent tasks within a busy schedule, emotional stress, and the need for intuitive inhaler use. In contrast, the Retired Senior emphasizes factors such as Patient Ability (physical and cognitive aspects), sensitivity to the Daily Environment, reliance on Effective Feedback Mechanisms, and the influence of Cultural Beliefs on self-management behaviors.

The decision to focus on these two personas—Busy Professional and Retired Senior—was made to balance comprehensive user representation with analytical depth. This approach aligns with best practices in persona development, which recommend limiting the number of personas to those most reflective of core user challenges to maintain design focus and effectiveness(Chang et al., 2008; Pruitt & Grudin, 2003). Scenarios were developed alongside these personas to contextualize the identified factors within realistic daily experiences, enabling workshop participants to engage with tangible adherence challenges grounded in the theoretical model(Gudjonsdottir & Lindquist, 2008; Lopez-Lorca et al., 2014).

Persona 1: Busy Professional (Asthma, 1 years)

- Background: A 30-year-old working adult managing daily tasks while adapting to a recent asthma diagnosis. This persona highlights challenges related to balancing professional responsibilities with consistent inhalation therapy adherence.
- Pain Points: Frequent forgetfulness due to a demanding work schedule, anxiety over potential asthma attacks, and difficulties maintaining a standard treatment routine. These factors contribute to poor symptom control and inconsistent medication use.
- Goals: Seeks an unobtrusive system that provides gentle reminders, monitors inhaler usage seamlessly, and offers proactive recommendations to avoid asthma triggers—without disrupting daily workflows.

Persona 2: Retired Senior (COPD, >10 years)



- Background: A 70-year-old male living with COPD for over a decade, representing elderly patients facing physical frailty and complex self-management needs.

- Pain Points: Requires educational support for proper breathing techniques, assistance in monitoring environmental and physiological conditions, and struggles with distinguishing normal symptoms from warning signs.
- Goals: Needs a simple, intuitive system that offers clear educational guidance, environmental monitoring, and health status feedback to support informed self-management without cognitive overload.

Scenario 1: A Typical Day for the Busy Professional

The Busy Professional, a working woman managing both her career and asthma, rushes through her morning routine, trying to fit everything in before heading out the door. In the midst of preparing for a busy day, she quickly grabs her inhaler and uses it in a hurry, not paying much attention to whether she’s using it correctly. With no time to spare, she reassures herself that using it, even hastily, is better than not using it at all, hoping it will provide some relief for the day ahead.

By midday, she may experience shortness of breath after climbing stairs or walking quickly to meetings, but she tends to brush it off, telling herself there’s no time for a break. As the workday continues, fatigue sets in. By evening, after long hours at the office or managing projects from home, she feels completely drained. Despite knowing she should use her inhaler before bed, exhaustion often leads her to forget, leaving the inhaler untouched on her nightstand as she drifts off to sleep.

Scenario 2: A Day at Home for the Retired Senior

The Retired Senior spends most of his day at home. After waking, he follows his prescribed treatment by using the inhaler to ensure stable breathing for the day ahead. Breathing exercises are incorporated into his routine, helping to manage symptoms and instill a sense of control. Household chores, such as tidying up or preparing meals, are completed in short, manageable intervals to prevent overexertion.

As the day progresses, he moves from room to room, occasionally needing to stop and rest due to shortness of breath. This discomfort leads him to wonder if it signals a worsening of his condition or if it's simply due to environmental factors, like changes in temperature or humidity. In the evening, as he uses the inhaler once more, he feels uncertain whether his unease is caused by an impending flare-up or just normal seasonal changes.

These personas and scenarios provided a practical foundation for structuring the participatory design workshops, ensuring that user insights were effectively translated into actionable system design requirements.

5.4 Workshop Structure and Procedures

The overall structure of the participatory workshops—including recruitment procedures and the three-step framework—is detailed in Chapter 3, Section 3.5.3. For clarity, Figure 5.1 illustrates the structured workflow adopted during the workshops.

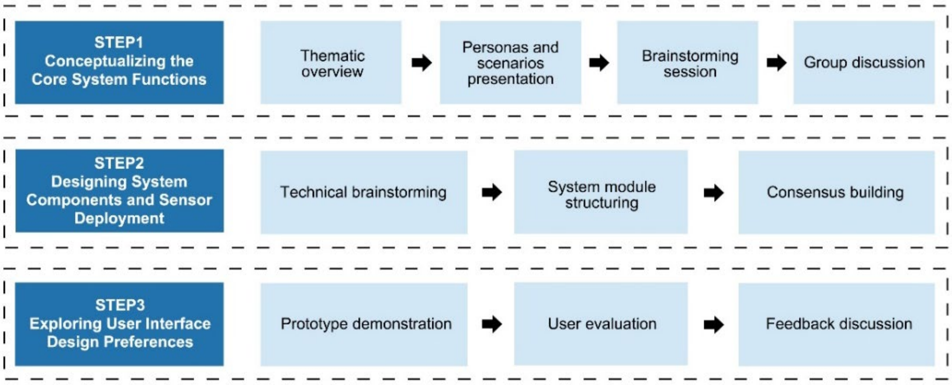


Figure 5. 1: Workshop structure and procedures.

This section elaborates on the specific activities conducted within each step, highlighting how stakeholder engagement informed the functional design, technical architecture, and user interface of the sensor-based intervention system.

5.4.1 Step1: Conceptualizing the Core System Functions

This step began with a presentation of the theoretical model developed from Study 1, which summarized five main themes and nine sub-themes related to adherence challenges. To contextualize the discussions, personas and scenarios were introduced to ground participant insights in realistic patient experiences(Gudjonsdottir & Lindquist, 2008; Lopez-Lorca et al., 2014; Marshall et al., 2015).

Key activities in this step included:

1. Thematic Overview: Researchers introduced the conceptual model to frame discussions around adherence determinants.

2. Personas and Scenarios Presentation: Two personas and their daily-life scenarios were presented to contextualize challenges faced by typical users(Gudjonsdottir & Lindquist, 2008).

3. Brainstorming Session: Participants identified adherence barriers and proposed potential system functions based on personal experiences and clinical practice(LaNoue et al., 2019).

4. Group Discussion: Ideas were collaboratively reviewed to assess feasibility and prioritize core functionalities aligned with user needs(Bohnsack, 2004).

5.4.2 Step 2: Designing System Components and Sensor Deployment

Building on the functional insights from Step 1, this step focused on translating user-identified needs into technical requirements and sensor deployment strategies.

Key activities in this step included:

1. Technical Brainstorming: Participants discussed appropriate sensor types and data collection priorities to address identified adherence challenges.

2. System Module Structuring: Group discussions organized core functions into preliminary system modules, considering usability and technical feasibility.

3. Consensus Building: Collaborative alignment was reached on system architecture and sensor integration strategies, ensuring the design reflected both user needs and technological capabilities.

5.4.3 Step 3: Exploring User Interface Design Preferences

The final step centered on evaluating user interface options to ensure intuitive interaction and user acceptance.

Key activities in this step included:

1. Prototype Demonstration: Researchers explained two distinct interface designs, emphasizing usability features.
2. User Evaluation: Participants completed the TAM questionnaire to assess Perceived Usefulness, Perceived Ease of Use, Attitude Toward Using, and Behavioral Intention to Use(Pai & Huang, 2011).
3. Feedback Discussion: Group discussions allowed participants to elaborate on preferences and suggest improvements for interface refinement.

5.5 Results

5.5.1 Step 1: Conceptualizing the Core System Functions

In this phase, participants collaborated to define the core needs and functionalities that the sensor-based intervention system should support. Below are the identified functions within each theme (see Table 5.3):

Table 5. 3: Core functionalities of the sensor-based intervention system.

Theme	**Sub-theme**	**System function**	**Feature description**
Person	Patient ability	Physiological condition monitoring	Help users understand their current physiological state
		Disease control	Allow users to know

		assessment	how the current disease is being controlled
		Disease-related knowledge	Help users to know what to do to prevent an attack/exacerbation
		Pulmonary rehabilitation knowledge	Help users to know the symptoms and signs of a worsening/exacerbation
	Emotional experience	Supportive and positive messaging	Provide users with supportive, positive response messages
		Inhalation emotional assessment	Allow users to know their feeling about inhalation treatment
Task	Task type	Inhalation technique instruction	Help users understand their inhalation techniques
		Inhaler usage monitoring and reminder	Remind users to use inhalers on time
	Frequency and flexibility	Adherence reports	Help users daily review their adherence-related data
Tool	Type of inhalers	Inhaler preference assessment	Allow users to know the usability, satisfaction, and preference of their inhalers
	Usability of inhalers	Inhaler usability and satisfaction assessment	Allow users to know the usability, satisfaction, and preference of their inhalers
Physical Environment	Usage environment	Inhaler storage knowledge	Help users store inhaled drugs correctly
		Environmental factor monitoring	Help users understand their environment information
Culture and Social	Cultural beliefs	Medication misconception clarification	Clear up users' misunderstanding to "All Medicine Have Toxicity to Some Degree"
		Beliefs assessment about medications	Access user's views about medication
	Social stigma	Self-efficacy evaluation	Understand the user's general self-efficacy
		Achievement acknowledgment and peer competition	Provide users with information about affirming their achievements; Leverage peer-influences to motivate users' usage willingness

1. Person

Patient Ability:

- Physiological Condition Monitoring: Participants emphasized the importance of tracking physiological indicators. This feature enables patients to monitor their current health status, supporting informed decision-making in their therapy.

- Disease Control Assessment: Participants reported uncertainty regarding their current disease control status. They expressed the need for ongoing assessments that clearly indicate how well their condition is being managed, allowing for timely adjustments to their treatment plans.

- Disease-related Knowledge: Participants indicated a need for educational content, including preventive measures, symptom management, and specific actions to take during exacerbations.

- Pulmonary Rehabilitation Knowledge: Suggestions were made to provide materials that support pulmonary rehabilitation, such as exercise guidelines and lifestyle adjustments to improve lung function.

Emotional Experience:

- Supportive and Positive Messaging: This feature sends encouraging messages to patients, reinforcing the importance of adhering to their treatment plans. Participants noted that such motivational content could enhance their commitment and overall experience.

- Emotional Assessment: Participants recommended that the system offer insights into emotional responses toward their inhalation routine, helping to identify triggers of stress or anxiety.

2. Task

Task Type:

- Inhalation Technique Instruction: Participants highlighted the need for clear, accessible instructions on correct inhaler usage. Suggestions included visual aids, tutorials, and guided instructions to improve inhaler technique and patient confidence.

- Inhaler Usage Monitoring and Reminders: This function monitors inhaler usage and its effectiveness while providing reminders to ensure proper use.

Frequency and Flexibility:

- Adherence Report: A daily adherence report was considered essential for monitoring real-time inhaler usage. Participants also expressed interest in receiving daily or weekly summaries to reflect on progress, review overall trends, and make necessary adjustments to their treatment.

3. Tool

Type of Inhalers:

- Inhaler Preference Assessment: This feature allows patients to compare different inhaler types based on ease of use and effectiveness, supporting informed decision-making.

Usability of Inhalers:

- Inhaler Usability and Satisfaction Assessment: Participants stressed the importance of assessing inhaler usability and user experience regularly, highlighting its impact on adherence.

4. Physical Environment

Daily Environment:

- Inhaler Storage Knowledge: This feature provides guidance on proper storage conditions for inhaled medications to maintain their effectiveness.

- Environmental Factor Monitoring: Participants suggested continuous monitoring of environmental conditions—such as temperature, humidity, and air quality. This feature aims to alert patients to environmental triggers that may worsen their conditions, offering timely recommendations for avoidance.

5. Culture and Social

Cultural Beliefs:

- Medication Misconception Clarification: Participants identified the need to address common misconceptions about medications, such as the belief that "*All medicine has toxicity to some degree.*" This feature would provide scientifically accurate information to dispel myths and support informed decision-making.

- Beliefs Assessment about Medications: This function would help evaluate patient attitudes toward medications, enabling HCPs to understand concerns that may influence adherence.

Social Stigma:

- Self-efficacy Evaluation: This feature assists patients in assessing their confidence levels in managing their condition, supporting strategies for enhanced self-management and autonomy.

- Achievement Acknowledgment and Peer Competition: Participants suggested the inclusion of persuasive elements, such as acknowledgment of personal milestones and friendly competition. They believed these features would boost motivation, foster accountability, and encourage consistent adherence.

5.5.2 Step 2: Designing System Components and Sensor Deployment

The second step involved specifying the necessary components to support the identified functions and designing the system architecture. The system was organized into three primary domains: Monitoring, Knowledge & Awareness, and Feedback (see Figure 5.2). Drawing from the "Person-Task-Physical Environment" framework introduced in Chapter 2, sensor technologies were strategically deployed to ensure comprehensive monitoring and support across all relevant aspects of patient care.

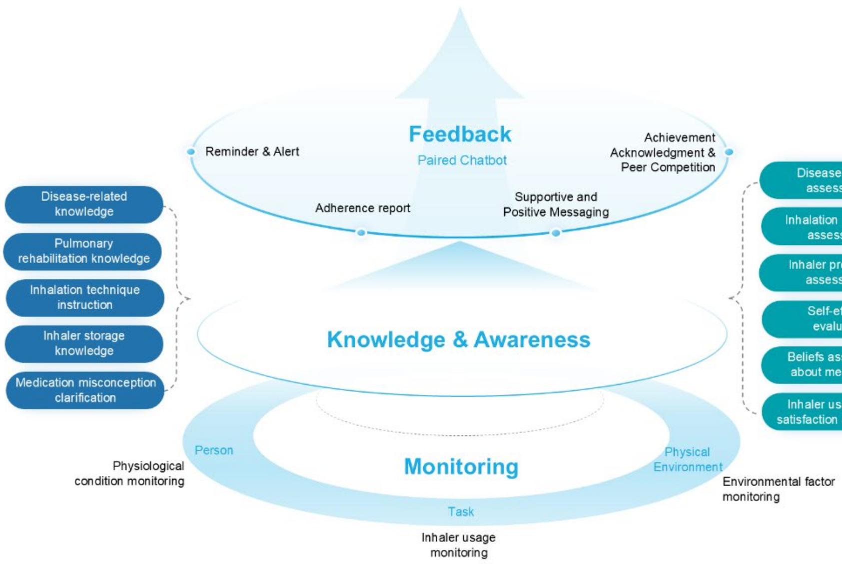


Figure 5. 2: The components of sensor-based intervention system.

1. Monitoring

In the Monitoring component, participants emphasized the integration of sensor technologies and targeted metrics to collect data across three key areas: Person, Task, and Physical Environment. This holistic approach enables real-time data collection, which is critical for enhancing patient adherence to inhalation therapy.

Physiological condition (Person): Continuous monitoring of physiological indicators, such as heart rate, was deemed crucial for assessing a patient's overall health status.

Inhaler usage (Task): Accurate tracking of the timing, frequency, and technique of inhaler use was prioritized. These metrics are vital for evaluating adherence and ensuring proper inhalation therapy.

Environmental factors (Physical Environment): Given the significant impact of environmental conditions on respiratory health, participants unanimously agreed on the importance of monitoring temperature, humidity, and air quality. This data helps to ensure optimal medication storage and supports patients in managing their daily living environments.

2. Knowledge and Awareness

Participants emphasized the importance of providing patient-specific educational materials and self-assessment tools. The system should deliver tailored information on disease management, medication storage, inhaler usage techniques, and pulmonary rehabilitation exercises. Additionally, self-assessment tools should enable patients to regularly monitor various health aspects, including: self-efficacy, disease control, emotional experience, medication beliefs, preference and satisfaction, and adherence to inhalation therapy. These tools empower patients with real-time insights into their health status, enabling them to take proactive measures for effective disease management.

3. Feedback

The Feedback component was designed to deliver timely, personalized information that supports patient engagement and adherence. It is structured around four main features:

Paired Application (Chatbot): The paired application serves as the primary interface for delivering real-time data, adherence reports, and motivational content. Participants were presented with both conventional health apps and chatbot-based health assistants during workshops. Most participants favored the chatbot interface due to its direct and conversational nature, which felt more personalized and less formal than traditional apps. Importantly, participants suggested that the chatbot should be integrated into familiar platforms, like popular messaging apps, to blend seamlessly into their daily routines.

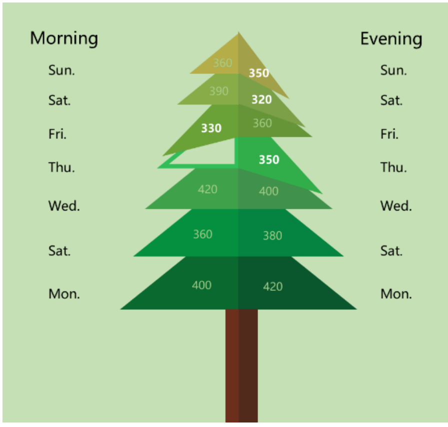
Reminder and Alert: Participants stressed the importance of effective reminders and alerts. The system should provide timely reminders for inhaler usage and real-time alerts when sensor data indicates abnormal health patterns, prompting immediate action.

Adherence Report: Beyond immediate alerts, participants advocated for regular adherence reports that consolidate key adherence information. These reports would highlight both progress and areas for improvement, offering patients a clear view of their treatment journey and enhancing their motivation to maintain therapy.

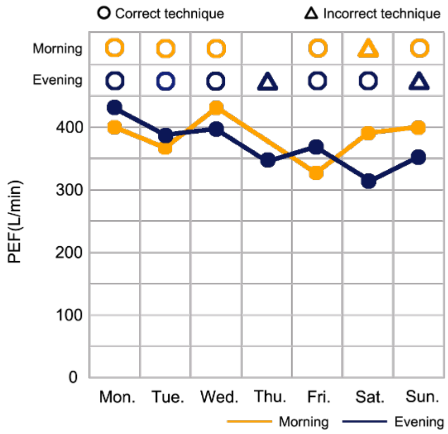
Persuasive Features: Participants emphasized the need to integrate persuasive features that effectively influence patient behavior and adherence. Many users expressed enthusiasm for elements that foster friendly competition, allowing them to compare their adherence progress with peers. Personalized motivational messages were also highlighted as essential, with participants valuing messages that recognize milestones and provide encouragement during difficult periods.

5.5.3 Step 3: Exploring Interface Design Preferences

This phase of the study focused on evaluating user preferences for two distinct interface designs (see Figure 5.3): Infographic (Tree Metaphor) and Data Visualization (Line Chart). The evaluation was grounded in the Technology Acceptance Model (TAM), assessing four key criteria: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Toward Using (ATU), and Behavioral Intention to Use (BI). The questionnaire is presented in Appendix 5A. Participants rated each interface using an 11-point Likert scale, ranging from 0 (strong disagreement) to 10 (strong agreement). Both descriptive and inferential analyses were conducted to capture user feedback and statistically validate differences.



(a) Infographic.



(b) Data visualization.

Figure 5. 3: Interface design prototypes.

Prototype 1: Infographic Interface

Patient Feedback: Patients rated the infographic interface highly across all four dimensions, with an average score of 9.3 for PU (SD = 0.48), 9.5 for PEOU (SD = 0.71), 9.4 for ATU (SD = 0.70), and 9.1 for BI (SD = 0.88). The evolving tree metaphor was particularly well-received, as it provided a visually engaging and intuitive representation of their inhaler adherence. Patients expressed strong interest in incorporating this visually appealing design into their daily inhaler routines, noting its ease of understanding and motivational impact.

HCP Feedback: HCPs provided more moderate ratings, with an average score of 7.5 for PU (SD = 0.71), 7.3 for PEOU (SD = 0.82), 7.0 for ATU (SD = 0.67), and 7.6 for BI (SD = 0.52). While they acknowledged the interface's potential to engage and motivate patients, they noted that its lack of detailed data representation limited its utility for clinical assessments. HCPs suggested that while it is effective for patient engagement, it may not be robust enough for critical medical evaluations.

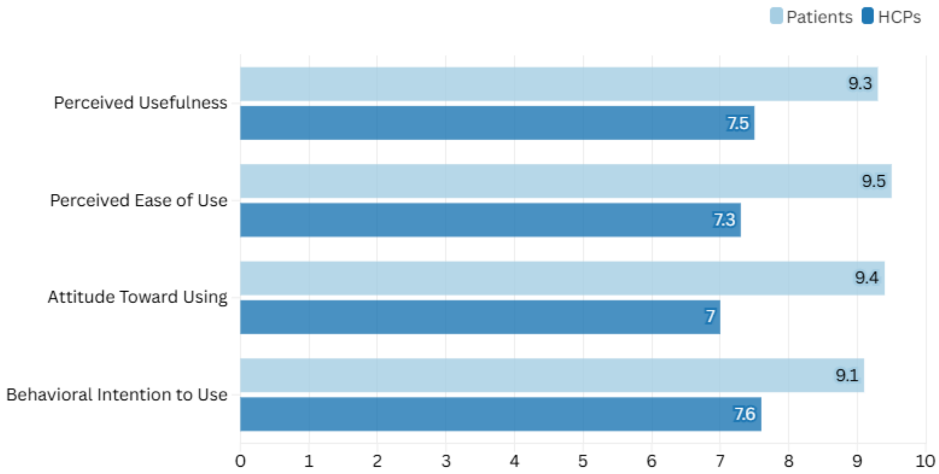


Figure 5. 4: Comparison of patients and HCPs feedback on infographic interface.

Comparative Analysis: Mann-Whitney U tests revealed significant differences between patients and HCPs across all four TAM dimensions (see Table 5.4): PU, PEOU, and ATU showed highly significant differences ($p = 0.000 < 0.01$), indicating divergent perceptions regarding the interface's utility and ease of use. BI also demonstrated a significant difference ($p = 0.001 < 0.01$), reflecting variations in willingness to integrate the interface into daily or clinical practice. These findings suggest that while patients appreciated the intuitive and visually engaging design, HCPs found it insufficient for detailed medical evaluation. However, they acknowledged its potential as a motivational tool for patient use.

Table 5. 4: Comparative analysis of Mann-Whitney U test results for patients and HCPs across four dimensions (infographic).

Dimension	**Group Median (P_{25}, P_{75})**		**U**	**z**	**p**
	HCP (n=10)	**Patient (n=10)**			
Perceived Usefulness	8.00(7.0,8.0)	9.00(9.0,10.0)	0.00	-3.93	0.000
Perceived Ease of Use	7.50(6.8,8.0)	10.00(9.0,10.0)	2.50	-3.70	0.000
Attitude Toward Using	7.00(6.8,7.3)	9.50(9.0,10.0)	1.00	-3.81	0.000
Behavioral Intention to Use	8.00(7.0,8.0)	9.00(8.0,10.0)	9.00	-3.28	0.001

Prototype 2: Data Visualization Interface

Patients found the line graph interface to be less intuitive and engaging compared to the infographic representation. The average scores were 6.3 for PU (SD = 0.48), 7.0 for PEOU (SD = 0.47), 6.4 for ATU (SD = 0.52), and 6.6 for BI (SD = 0.52). Many patients mentioned that the interface appeared too abstract and demanded more cognitive effort to interpret. Some expressed willingness to adopt the interface if additional guidance or simplified explanations were provided, indicating a need for better onboarding or tutorial support.

HCP Feedback: HCPs rated the line graph interface more favorably, with an average score of 8.4 for PU (SD = 0.70), 8.7 for PEOU (SD = 0.82), 8.5 for ATU (SD = 0.85), and 9.2 for BI (SD = 0.79). They appreciated the detailed data trends, which enabled accurate and comprehensive monitoring of patient adherence. HCPs expressed confidence in the interface's clinical utility, emphasizing its capacity to support data-driven decision-making due to its clear and structured representation of patient information.

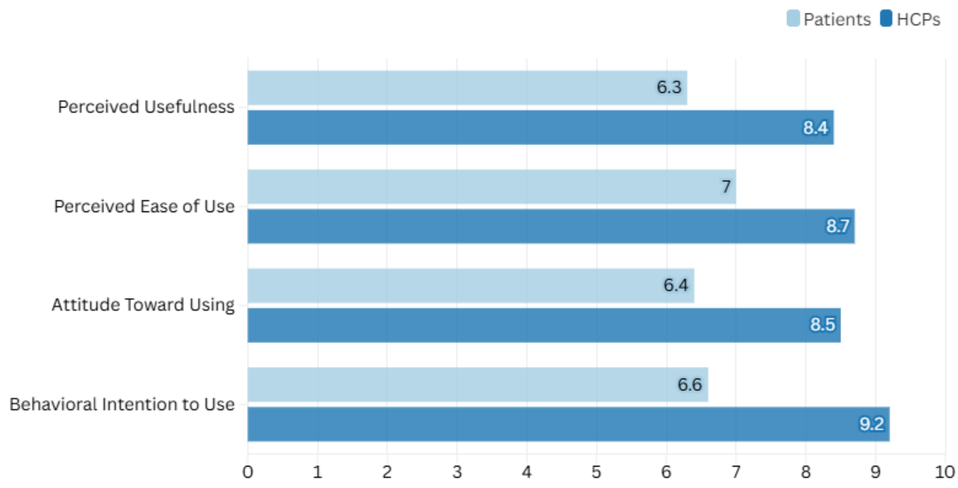


Figure 5. 5: Comparison of patients and HCPs feedback on data visualization interface.

Comparative Analysis: Mann-Whitney U tests identified significant differences between patients and HCPs across all four TAM dimensions ($p = 0.000 < 0.01$ for each; see Table 5.5), highlighting a clear divergence in perceptions. Patients generally found the interface less intuitive and more cognitively demanding, which potentially hinders regular use and reduces overall engagement. In contrast, HCPs favored the interface for its precision and clinical applicability, appreciating its capacity to display trends and adherence patterns effectively. This disparity suggests that while the line graph interface is well-suited for clinical settings where detailed monitoring and analysis are essential, its design may require simplification or enhanced user guidance to improve accessibility and usability for patients.

Table 5. 5: Comparative analysis of Mann-Whitney U test results for patients and HCPs across four dimensions (data visualization).

Dimension	**Group Median (P_{25}, P_{75})**		***U***	***z***	***p***
	HCP (*n*=10)	**Patient (*n*=10)**			
Perceived Usefulness	8.50(8.0,9.0)	6.00(6.0,7.0)	1.50	-3.81	0.000
Perceived Ease of Use	8.50(8.0,9.3)	7.00(7.0,7.0)	2.50	-3.77	0.000
Attitude Toward Using	8.50(8.0,9.0)	6.00(6.0,7.0)	2.00	-3.74	0.000
Behavioral Intention to Use	9.00(8.8,10.0)	7.00(6.0,7.0)	0.00	-3.88	0.000

Overall Comparative Analysis of Interfaces: Wilcoxon signed-rank tests conducted separately for HCPs and patients revealed distinct user experiences between the two interface designs. For patients, significant differences were observed across all four TAM dimensions, including PU ($p = 0.024 < 0.05$), PEOU ($p = 0.010 < 0.05$), ATU ($p = 0.007 < 0.01$), and BI ($p = 0.004 < 0.01$). These findings indicate a strong patient preference for the infographic interface, which was perceived as more intuitive and engaging, making it easier to understand adherence information. Conversely, for HCPs, significant differences were also found across all dimensions, with PU ($p = 0.003 < 0.01$), PEOU ($p = 0.005 < 0.01$), ATU ($p = 0.005 < 0.01$), and BI ($p = 0.005 < 0.01$). These results underscore HCPs' preference for the data visualization interface, valuing its precision and ability to present detailed insights essential for effective patient management and clinical evaluation.

Additional Suggestions:

Adaptive Interface Options: Participants emphasized the need for adaptive interface designs that could flexibly cater to different types of feedback. For daily usage, patients found the tree metaphor highly effective due to its intuitive and engaging nature. However, for longer-term feedback, such as weekly or monthly reports, they expressed a preference for simpler, more straightforward visuals that clearly indicate daily adherence outcomes—highlighting "good" or "bad" days without intricate metaphors. Conversely, HCPs prioritized accuracy and objectivity in data presentation, favoring professional visualizations that offered clear, trend-focused representations. They suggested integrating different types of data visualizations depending on the complexity and purpose of the data. For instance, line graphs for trend analysis, bar charts for adherence summaries, and scatter plots for exploring correlations. This adaptive approach would enable both patients and HCPs to access relevant information efficiently, optimizing both user experience and clinical decision-making.

Enhanced Information Display: Participants proposed enriching the tree metaphor interface by incorporating visual enhancements to improve clarity and engagement. For instance, icons or color-coded indicators could be used to represent varying adherence levels, making it easier for users to interpret their progress at a glance. Additionally, patients suggested adding background elements—like a sun or clouds—to reflect daily adherence status dynamically, offering a more immersive and personalized experience. These subtle yet meaningful enhancements were seen as a way to increase emotional connection to the interface, transforming it from a purely clinical tool into an engaging part of their daily routine. Participants believed that this would not only improve usability but also foster a stronger habit of daily engagement, ultimately supporting better adherence outcomes.

5.6 Discussion

This study focused on determining the architecture and component design of the XIAOXI intervention system through participatory design workshops. Leveraging the HFE theoretical framework established in prior research, we engaged with 10 patients and 10 HCPs, capturing their perspectives and experiences with inhalation therapy. These workshops were instrumental in ensuring that the system design aligned with user needs and behaviors, facilitating patient adherence through a user-centered approach.

The sensor deployment strategy for the XIAOXI system is grounded in the Person-Task-Physical Environment framework, as described in Chapter 2. This multi-dimensional deployment allows for real-time monitoring of patient health status (Person), inhaler usage patterns (Task), and environmental conditions (Physical Environment). This holistic monitoring strategy enables a comprehensive understanding of adherence behaviors by capturing data across these three critical dimensions(M. A. Barrett et al., 2017; D'Arcy et al., 2014; Quinde, 2020). In contrast, existing studies largely focus on single-dimensional data collection, limiting the scope of analysis to isolated aspects of adherence. Only a limited body of research acknowledges the multidimensional nature of non-adherence, with some employing IoT systems to collect diverse sensor data across different dimensions(Chakraborty et al., 2023; Hui et al., 2022; Pradeesh et al., 2022). By adopting a comprehensive framework, the XIAOXI system captures a richer, more integrated view of patient adherence, providing a robust platform for intervention

In designing the XIAOXI system, we explored interface preferences among patients and HCPs, specifically comparing metaphorical visualizations (e.g., tree metaphors) with data visualizations (e.g., line charts). The results indicated a distinct divergence in preferences: patients found metaphorical visualizations more engaging and relatable, while HCPs favored line charts for their clarity and precise representation of data trends. Additionally, we observed that user preferences were not static—they shifted depending on the timeframes of the data presented. Patients appreciated metaphorical visualizations for daily adherence feedback due to their intuitive representation but leaned towards simpler, clearer visualizations for weekly or monthly summaries. This variation in preference suggests that the design of adherence-support systems should consider not only the user type (patient vs. HCP) but also the temporal context of the data being displayed(Damman et al., 2012; Gong & Chandra, 2016). Furthermore, it underscores the importance of adaptable visualization strategies that can meet the evolving needs of different users over varying timeframes(Meyer et al., 2016).

These findings highlight the necessity for deeper exploration into visualization techniques that effectively convey multi-sensor data while catering to user-specific requirements. The integration of multi-dimensional data in a user-friendly manner is crucial for revealing nuanced patterns and relationships that inform patient adherence behaviors(Browne et al., 2015; De Folter et al., 2014). Despite advances in multi-sensor data visualization, a standardized evaluation framework remains absent, hindering consistent assessment of usability and effectiveness(S.-H. Kim, 2022; Wanderer et al., 2016; West et al., 2015). Future research should prioritize the development of robust evaluation methodologies specifically tailored for multi-sensor visualizations, ensuring these systems not only provide actionable insights but also support patient engagement and adherence more effectively.

5.7 Conclusion

This study focused on the development of a sensor-based intervention system aimed at enhancing patient adherence to inhalation therapy. The design process was rooted in participatory design workshops involving both patients and HCPs, ensuring that the system's core functionalities, components, and user interfaces were tailored to real-world user needs. By integrating sensor technologies with a user-centered interface, the XIAOXI system bridges the gap between technical innovation and practical usability. This approach not only enhances real-time monitoring and personalized feedback but also aligns with patient preferences and clinical requirements, supporting a more effective and sustainable adherence to inhalation therapy.

Chapter 6 Implementation of a Sensor-Based System for Inhalation Therapy Adherence

6.1 Introduction and Aims

Building on the user-centered design principles discussed in previous chapters, this chapter focuses on the technical development and implementation of the XIAOXI sensor-based intervention system. Designed to support patient adherence, XIAOXI integrates real-time tracking, data processing, and personalized feedback mechanisms through a network of sensors that monitor inhaler usage, physiological indicators, and environmental conditions.

The primary aim of this chapter is to document the technical development of the XIAOXI intervention system, emphasizing the integration of sensor technologies and the real-time processing capabilities that enhance adherence support.

The specific objectives of this chapter are:

1. To describe the technical development process, including the integration of sensors to monitor inhaler usage, physiological conditions, and environmental factors.

2. To detail the system architecture and how it enables real-time data processing and feedback for patient adherence.
3. To explain the implementation of user feedback mechanisms within the system, ensuring that the functionality meets patient requirements.

6.2 Research-Driven Design Foundation

The development of the XIAOXI sensor-based intervention system was directly informed by empirical outcomes from Study 1 and Study 2, ensuring that its architecture, functionalities, and interaction mechanisms were grounded in both theoretical insights and user-centered design principles.

In Study 1, the Patient Adherence to Inhalation Therapy Work System Model was established, identifying five core dimensions—Person, Task, Tool, Physical Environment, and Culture & Social—and nine key factors influencing adherence. These findings provided a comprehensive theoretical foundation for addressing adherence challenges in inhalation therapy.

Building upon this theoretical groundwork, Study 2 translated these conceptual factors into actionable design requirements through participatory design workshops involving both patients and HCPs. This collaborative process defined the necessary system functions, determined which aspects required sensor integration, and identified user preferences for data presentation and feedback mechanisms. These research-driven insights shaped the structuring of XIAOXI's architecture, guiding decisions related to sensor deployment, data processing workflows, and interactive features.

Table 6.1 summarizes the integration of findings from Studies 1 and 2 into the system's design and technical implementation. This research-driven approach ensured that XIAOXI was developed not merely as a technological solution, but as a practical embodiment of validated theoretical constructs, tailored to the needs of both patients and clinicians. The system's design reflects the principles of HFE, bridging the gap between conceptual frameworks and practical application.

Table 6. 1: Integration of study findings into XIAOXI system design.

Research Phase	Key Contributions	Impact on System Design
Study 1 (Chapter 4) Investigating Factors Affecting Patient Adherence to Inhalation Therapy	• Identified 5 themes & 9 adherence factors • Developed Patient Adherence to Inhalation Therapy Work System Model	• Provided foundation for system architecture and functional scope
Study 2 (Chapter 5) Participatory Design of a Sensor-Based Intervention System	• Specified design requirements • Identified sensor integration needs and feedback preferences	• Defined core functional areas to guide technical implementation • Customized sensor deployment and feedback strategies

6.3 Overview of System Architecture

The XIAOXI sensor-based intervention system was developed to support patient adherence to inhalation therapy, with its architecture informed by insights from participatory design workshops and grounded in HFE principles. The system integrates three core components—Monitoring, Knowledge & Awareness, and Feedback—designed to deliver personalized, actionable support for patients with asthma and COPD.

Implementation within the Tencent ecosystem facilitates multi-level technological integration, encompassing data perception and collection through sensor modules, wireless transmission and processing via development boards and cloud services, and user interaction through the WeChat-based chatbot interface. This structure enables real-time monitoring, dynamic feedback, and patient engagement (see Figure 6.1)

Additionally, custom-designed sensor casings were developed to ensure seamless deployment in daily patient routines. These casings were tailored to the specific form factors of inhalers, ensuring minimal disruption while maximizing data accuracy. To validate system stability and usability, comprehensive laboratory testing was conducted, evaluating sensor accuracy, data transmission reliability, and interface responsiveness.

The following sections provide a detailed breakdown of the technical architecture and functional implementation of each system component, demonstrating how the design effectively addresses adherence challenges identified in Studies 1 and 2.

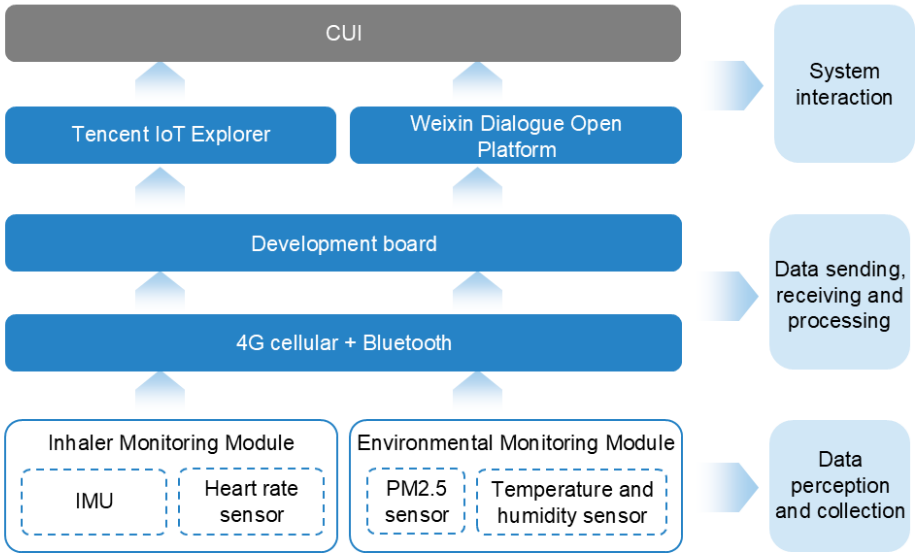


Figure 6. 1: System structure of XIAOXI.

6.4 Data Perception and Collection

6.4.1 Inhaler Monitoring Module

This module is equipped with two primary sensors that work in tandem to monitor inhaler use and patient's physical condition:

IMU (IM600 Model): The IMU sensor is mounted on the base of the inhaler to avoid interfering with the patient's use of the device, and is connected to a heart rate sensor, both powered by a shared battery (see Figure 6.2). It monitors tilt angles during inhaler use, detecting changes at 0.1-second intervals. To conserve power, the system stops data transmission if the tilt angle remains stable for 10 seconds, minimizing redundant data and conserving battery life.

When movement is detected (tilt angle exceeds 10 degrees), the IMU activates immediately, marking inhaler use precisely.

The IMU operates based on the Coriolis effect, where a vibrating element experiences a perpendicular force during rotation, known as the Coriolis force(Almabrouk et al., 2018):

$$Fc = 2m\omega v$$

- Fc: Coriolis force, representing the apparent force experienced by the vibrating element due to its motion within a rotating reference frame.
- m: Mass of the vibrating element, affecting the magnitude of the Coriolis force.
- ω: Angular velocity, indicating the rate of rotation of the system.
- v: Linear velocity of the vibrating element, representing the speed of the element along its path.

By measuring the displacement caused by the Coriolis force, the sensor outputs the angular velocity, which can then be integrated over time to obtain the angular position:

$$\theta(t) = \int_0^t \omega(t)dt$$

- $\theta(t)$: Represents the angular position (how far something has rotated) at time t.
- $\omega(t)$: Represents the angular velocity (how fast something is rotating) at time t.

The IMU uses Kalman and Complementary Filters for data accuracy(Gui et al., 2015; F. Liu et al., 2019). The Kalman Filter optimally estimates the system's state by combining predictions and measurements, reducing noise and improving accuracy:

Prediction Step:

$$\hat{x}_{k|k-1} = F\, \hat{x}_{k-1|k-1} + B\, u_k$$

Where：

- $\hat{x}_{k|k-1}$: Predicted state estimate for the current step.
- F: State transition matrix describing how the system evolves.
- B: Control input matrix.
- u_k: Control input applied at the current step.

Update Step:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k\, (z_k - H\, \hat{x}_{k|k-1})$$

Where：

- K_k: Kalman gain, determining how much the measurement influences the state update.
- z_k: Measurement at the current step.
- H: Measurement matrix linking the predicted state to the measurement.

The Prediction Step forecasts the next state, while the Update Step adjusts the estimate based on sensor measurements, reducing uncertainty.

The Complementary Filter is used to balance short-term stability from the gyroscope with long-term accuracy from the accelerometer:

$$\theta = \alpha(\theta_9 y_{\mathrm{ro}}) + (1 - \alpha)(\theta_{\mathrm{a}} cc)$$

- θ: Estimated angle.
- α: Filter coefficient (0 to 1), representing the weight of each sensor.
- $\theta_9 y_{\mathrm{ro}}$: Angle measured by the gyroscope, offering quick response.
- $\theta_{\mathrm{a}} cc$: Angle measured by the accelerometer, offering stability over time.

The filter effectively merges the rapid responsiveness of gyroscopic data with the long-term reliability of accelerometer data, ensuring smooth and accurate measurements.

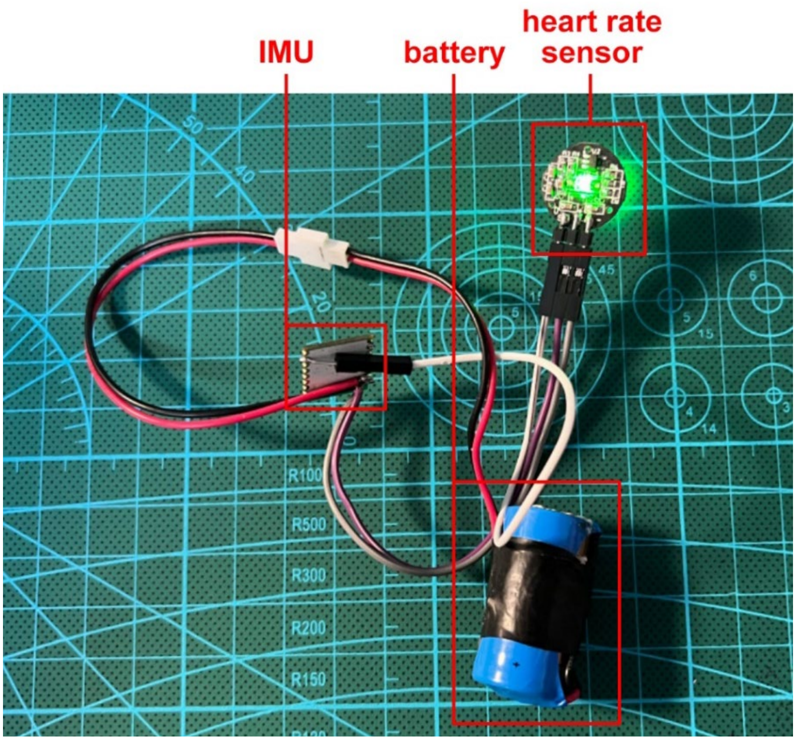


Figure 6. 2: The inhaler monitoring module.

Heart Rate Sensor (PulseSensor): The PulseSensor is an optical heart rate sensor that detects heart rate by measuring blood flow during each heartbeat(Kemis et al., 2012). It consists of two main components:

- LED (Light Emitting Diode): Emits light through the skin into the blood vessels.
- Light-sensitive Element (Photodetector): Detects the amount of light reflected back.

When the heart pumps blood, the volume of blood in the vessels changes, affecting the amount of light reflected back. These variations are converted into electrical signals, which are processed to represent heart rate. This sensor operates at 0.1-second intervals, capturing real-time physiological data during inhaler use—crucial for assessing the patient's physiological status.

The Inter Beat Interval (IBI) is measured when the signal crosses 50% of the wave amplitude during the rapid upward rise of each pulse (see Figure 6.3).

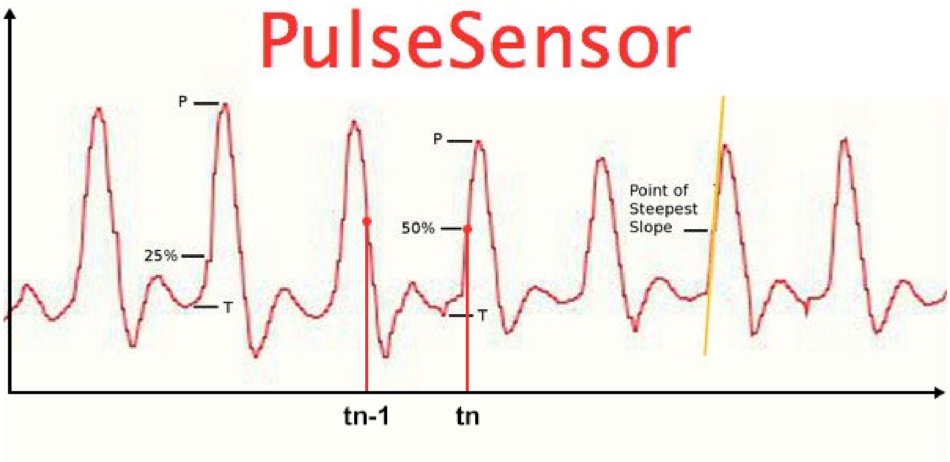


Figure 6. 3: IBI calculation.

The IBI is calculated as follows:

$$IBI = t_n - t_{n-1}$$

- t_n: Time of the current peak.
- t_{n-1}: Time of the previous peak.

The Beats Per Minute (BPM) is computed using the formula:

$$BPM = 60 / IBI$$

To ensure accuracy and reduce noise, the system averages the last 10 IBI values. This filtering stabilizes the readings, providing more reliable heart rate monitoring. If the BPM exceeds 100, it is marked in red in the XIAOXI daily adherence report to alert users to potential physiological issues(Siddiqui & Morshed, 2018).

6.4.2 Environmental Monitoring Module

This module integrates multiple sensors to monitor key environmental factors, ensuring that patients are aware of external conditions that may impact their respiratory health (see Figure 6.4).

PM2.5 Sensor (A4-CG Model): The sensor operates on the principle of light scattering, where the intensity of scattered light is used to determine particle concentrations. According to Mie scattering theory(Wriedt, 2012), the Particle Number Concentration (PNC) is calculated using the formula:

$$N = 8\pi^2 r^2 \,(I / I_0)\,(\lambda^2 / V) \sum [i_1(\theta) + i_2(\theta)] \cdot n_r(D_i) \cdot \Delta D_i$$

- N: Particle number concentration
- I: Scattered light intensity
- I_0: Incident light intensity

- λ: Wavelength of the light
- V: Air volume being analyzed
- r: Distance from particle to observation point
- $i_1(\theta)$ and $i_2(\theta)$: Scattering intensity functions at angle θ
- $n_r(D_i)$: Normalized frequency distribution function of particle diameters
- ΔD_i: Width of the particle diameter interval

The conversion between Particle Number Concentration (PNC) and Particle Mass Concentration (PMC) is derived from the volume and density of the particles:

$$N = (6M) / (\pi \rho D^3)$$

- N: Particle number concentration
- M: Particle mass concentration
- D: Average particle diameter
- ρ: Particle density

To derive the Particle Mass Concentration (PMC), the following formula is applied:

$$M = (4\pi^3 r^2 \rho / 3\lambda^2 V)\ (I / I_0) \sum [i_1(\theta) + i_2(\theta)] \cdot n_r(D_i) \cdot {D_i}^3 \cdot \Delta D_i$$

- M: Particle mass concentration
- ρ: Particle density
- D_i: Particle diameter in each size category
- ΔD_i: Width of the particle diameter interval

This formula allows the sensor to convert detected scattered light into mass concentration, which is displayed in μg/m³. PMC quantifies the total mass of fine particulate matter (PM2.5) per unit volume of air, providing a direct measure of air quality, crucial for assessing its impact on human health and environmental conditions(Azarmi et al., 2016).

According to China's Ambient Air Quality Standard(W. Chen et al., 2015), PM2.5 concentrations exceeding 75 μg/m³ are classified as "polluted." If the XIAOXI system detects pollution levels above this threshold, it will be marked in red on the daily adherence report, alerting users to potential environmental risks.

Temperature and Humidity Sensor (integrated in development board): The temperature and humidity sensor operates by converting environmental conditions into electrical signals, leveraging capacitive elements for humidity measurement and resistive or thermistor-based elements for temperature detection(Kaewwongsri & Silanon, 2020; Sasono et al., 2019). The sensor outputs 16-bit raw data values (S_{rh} for humidity and S_{t} for temperature), which are processed using conversion formulas:

Humidity Measurement: The raw humidity data (S_{rh}) is converted to relative humidity (RH) using the formula:

$$RH = 100 \times (S_{\mathrm{rh}} / (2^{16} - 1))$$

Temperature Measurement: The raw temperature data (S_{t}) is converted into Celsius ($°C$) using:

$$T[°C] = -45 + 175 \times (S_{\mathrm{t}} / (2^{16} - 1))$$

When the recorded temperature exceeds 40°C or the relative humidity surpasses 75% (Borgström et al., 2005), these conditions are marked in red in the XIAOXI daily adherence report to alert users about potentially unsuitable environmental conditions.

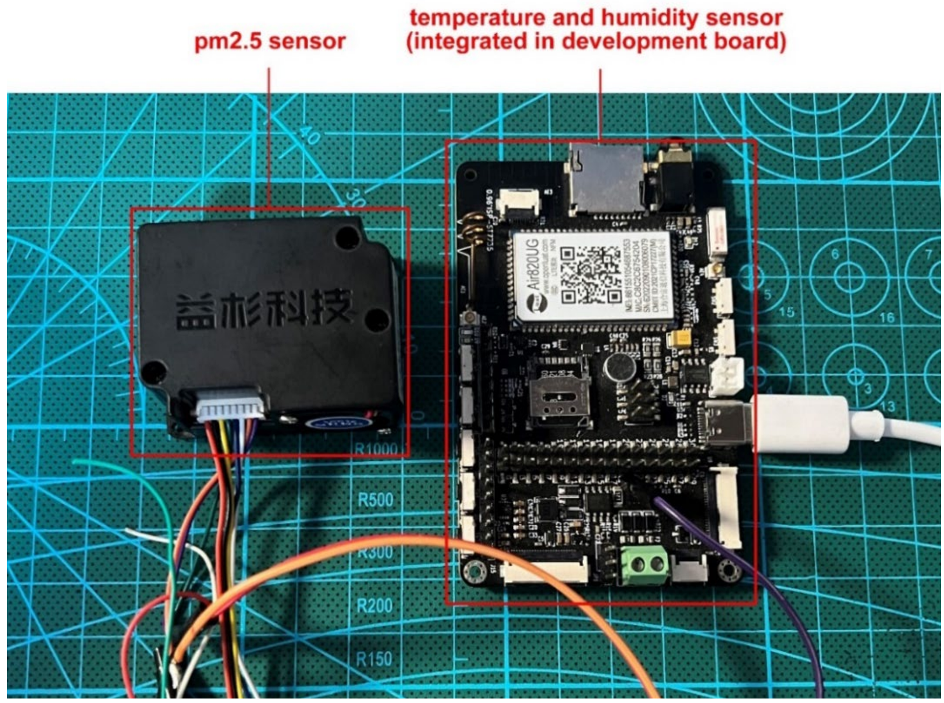


Figure 6. 4: The environmental monitoring module.

6.5 Data Sending, Receiving and Processing

The gyroscope and heart rate sensor transmit their data via Bluetooth to the Air820UG development board. In contrast, the PM2.5 sensor is directly connected to the board, while temperature and humidity are measured by onboard sensors, eliminating the need for external transmission. Once the development board captures sensor data, a remote data viewing system was developed to allow users to retrieve sensor information on their mobile devices through the WeChat platform (XIAOXI).

The system leverages Tencent IoT Explorer, an IoT PaaS platform introduced by Tencent Cloud for smart living and industrial applications. This platform supports multiple communication protocols, including WiFi, cellular, and Bluetooth, ensuring seamless cloud connectivity for various devices(Cui et al., 2022). Tencent IoT Explorer facilitates the efficient upload of sensor data to the cloud, enabling real-time processing and access.

The remote sensor data viewing solution is structured around two key components:

1. Communication Protocol: This protocol enables bi-directional interaction between the WeChat platform, the development board, and the cloud platform via the MQTT (Message Queuing Telemetry Transport) protocol. This lightweight protocol is ideal for real-time communication in IoT applications.

2. Real-time Data Updates and Display: The Air820UG development board collects sensor data, which is then transmitted to Tencent IoT Explorer using a 4G cellular module. Users can query sensor data by sending specific keywords through XIAOXI, which retrieves real-time updates from the cloud and presents the data directly in the WeChat interface.

Detailed code for the XIAOXI system deployment is provided in Appendix 6A.

6.6 System Interaction and Interface Design

6.6.1 Weixin Dialogue Open Platform

The Weixin Dialogue Open Platform was chosen for the implementation of the chatbot because it runs directly within WeChat, China's leading social media application with over 1.3 billion active users as of 2023(X. Liang et al., 2023). Leveraging this widely familiar interface enhances user engagement, as it allows seamless integration into users' daily communication routines. As a product of Tencent, the Weixin Dialogue Open Platform provides a comprehensive suite of APIs and SDKs, enabling developers to design and integrate chatbots directly within the WeChat ecosystem. This integration supports natural text interactions, facilitating smooth and intuitive conversational experiences.

The platform's robust API support allows the chatbot to access user data and preferences, enabling personalized interactions based on individual health records. This customization enhances the relevance and effectiveness of the chatbot's responses. Additionally, the system is designed to handle high volumes of user queries efficiently, making it well-suited for real-time health management applications.

The chatbot operates on keyword-based triggers, allowing users to input specific terms and receive tailored responses. These interactions are further enhanced by the platform's Natural Language Processing (NLP) capabilities, which improve the accuracy and contextual understanding of user queries. Since the chatbot is embedded within the user's existing WeChat account, there is no need for additional registration or separate application downloads, significantly reducing barriers to adoption.

Furthermore, the chatbot leverages Tencent's secure cloud infrastructure, ensuring stable, low-latency data transmission. This robust backend guarantees a reliable and secure user experience, critical for managing health-related data in real-time.

6.6.2 Knowledge Base Design

Through participatory design workshops, key knowledge areas were identified, including disease management protocols, correct inhaler techniques, proper storage of inhaled medications, and pulmonary rehabilitation guidelines. These insights informed the development of XIAOXI's knowledge base, which has been integrated into the Weixin Dialogue Open Platform.

To ensure reliability and clinical accuracy, the content in the knowledge base is curated from established sources such as the Global Initiative for Asthma (GINA)(Bateman et al., 2008; Levy et al., 2023; Masoli et al., 2004), the Global Initiative for Chronic Obstructive Lung Disease (GOLD)(The Asia Pacific COPD Roundtable Group, 2005), the Guidelines for the Diagnosis and Management of Chronic Obstructive Pulmonary Disease in China(Kurmi et al., 2018; J.-S. Li, 2020), and the Inhalation Medication Instruction Manual(García-Cárdenas et al., 2012; Giner et al., 2020). Users can easily access this information by sending specific keywords to the chatbot interface within the Weixin Dialogue Open Platform. This structure guarantees that patients receive up-to-date and clinically validated guidance tailored to their condition.

6.6.3 Enhanced User Interaction and Self-Assessment Features Design

Based on the Weixin Dialogue Open Platform and Tencent IoT Explorer, XIAOXI integrates advanced chatbot functionalities, allowing users to seamlessly query both knowledge and real-time sensor data. This integration extends XIAOXI's deployment on the WeChat platform, providing users with multiple interaction channels to access health-related information. The design includes a comprehensive “Knowledge” menu within the WeChat interface, offering visually rich and engaging content that combines text and images to effectively explain topics such as pulmonary rehabilitation, disease knowledge, and medication management for chronic respiratory conditions. This multimedia approach enhances user engagement by presenting complex medical information in a digestible and user-friendly format. Further details regarding the interface design of the 'Knowledge' menu are provided in Appendix 6B.

Additionally, an “Awareness” menu was developed to support self-assessment, addressing key needs identified during participatory design workshops. This menu includes embedded questionnaires that enable users to regularly evaluate critical health areas, including self-efficacy, disease control, emotional experience, medication beliefs, device preferences, and adherence to inhalation therapy. These self-assessment tools empower users to actively monitor their health status, offering valuable feedback that can inform adjustments to their treatment plans. By facilitating continuous self-monitoring, the system not only enhances patient engagement but also provides essential insights for HCPs to track patient progress effectively. All questionnaires used within the “Awareness” menu are available in Appendix 6C.

6.6.4 XIAOXI Structure Implementation and Interface Design

XIAOXI is designed as a user-friendly adherence intervention system with five core functionalities: Onboarding and Guidance, Real-Time Sensor Data Queries, Knowledge Delivery, User Self-Assessments, and Feedback Provision. Each function is tailored to address specific challenges in maintaining treatment adherence, empowering users to engage actively with their care plans while receiving personalized, ongoing support. XIAOXI integrates seamlessly into users' daily routines, providing a consistent, informative, and intuitive experience to enhance adherence and overall health management.

6.6.4.1 Onboarding and Guidance

XIAOXI's initial interaction with users is an intuitive and welcoming introduction that guides them through its capabilities, ensuring a smooth start (see Figure 6.5). Key elements of the onboarding process include:

- Feature Overview: XIAOXI introduces itself as a virtual inhalation assistant, listing key features such as information on asthma and COPD, pulmonary exercises, and medication instructions.

- Interactive Suggestions: Users are prompted to try specific keywords like "asthma symptoms" to explore the XIAOXI's responses and learn about available information. This helps familiarize users with the types of queries they can make.

- Data Queries: The introduction shows how users can request real-time data on temperature, humidity, air quality, and heart rate.

- Menu Navigation: A guided menu encourages users to explore further features, such as "Knowledge" for educational resources and "Awareness" for completing assessments and surveys (see Figure 6.6).

This structured introduction ensures that users, whether experienced with technology or new to using chatbots, can easily understand and interact with XIAOXI from the very first session.

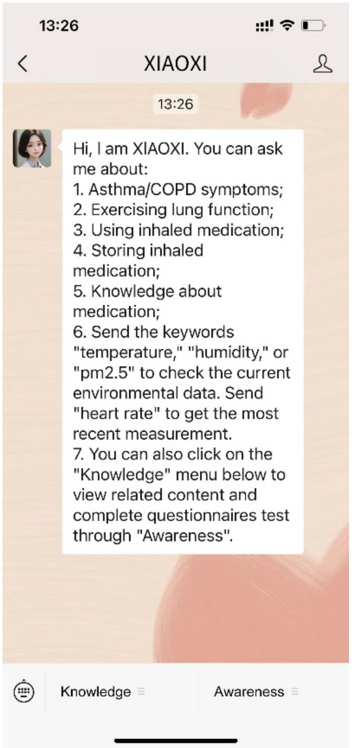


Figure 6. 5: Welcoming introduction.

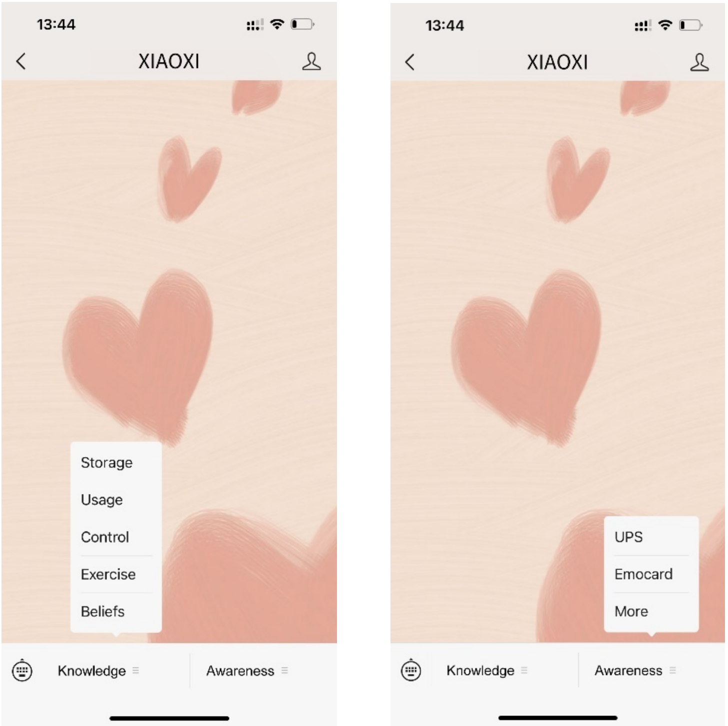


Figure 6. 6: Menu navigation ("More" contains more tests)

6.6.4.2 Real-Time Sensor Data Queries

XIAOXI enables users to retrieve real-time data from integrated sensors by simply sending specific text commands (see Figure 6.7). This feature provides immediate insights into key health and environmental metrics that are crucial for managing respiratory conditions:

- Heart Rate Monitoring: Users can send the keyword “heart rate” to receive the latest recorded value. This feature is particularly valuable for assessing physiological responses during inhalation sessions.

- Environmental Conditions: Commands like “temperature,” “humidity,” or “PM2.5” enable users to check current environmental data.

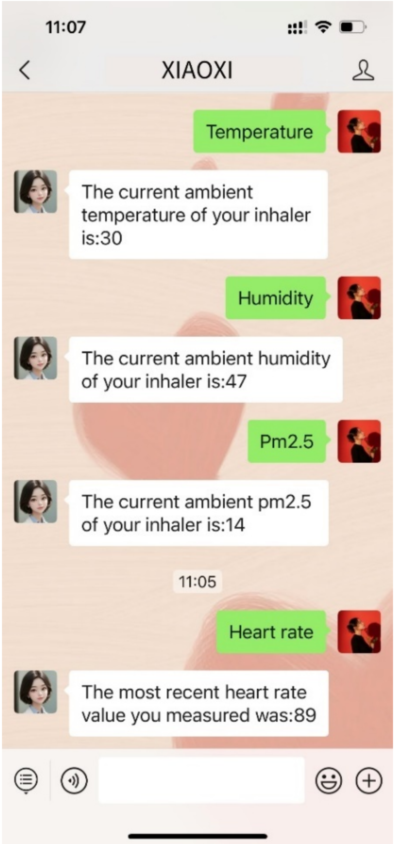


Figure 6. 7: Querying data.

6.6.4.3 Knowledge Delivery

The XIAOXI chatbot provides users with a comprehensive range of educational resources and self-management strategies tailored specifically to their needs and conditions (see Figure 6.8). The knowledge base covers critical areas of asthma and COPD management, ensuring users have access to reliable and actionable information at all times. Key categories include:

- Inhalation Techniques: By sending the keyword “inhalation techniques,” users receive step-by-step guides and instructional content that teach the correct methods for using inhalers.

- Inhaler Storage: Users can access information on optimal storage conditions by sending the keyword “inhaler storage.” This feature ensures that medications remain effective by educating users on proper storage practices.

- Disease Management: Users can send keywords like "asthma /COPD control" to receive advice on managing their condition. XIAOXI provides guidance on recognizing signs of deterioration, daily management strategies, and when to consult their HCP.

- Pulmonary Rehabilitation: The users can get information about the breathing exercises and techniques by typing the keyword “pulmonary rehabilitation.”

- Medication Awareness: To learn more about proper medication use, users can send the keyword “medication side effects.” XIAOXI addresses common misconceptions and promotes accurate beliefs regarding long-term inhaler use.

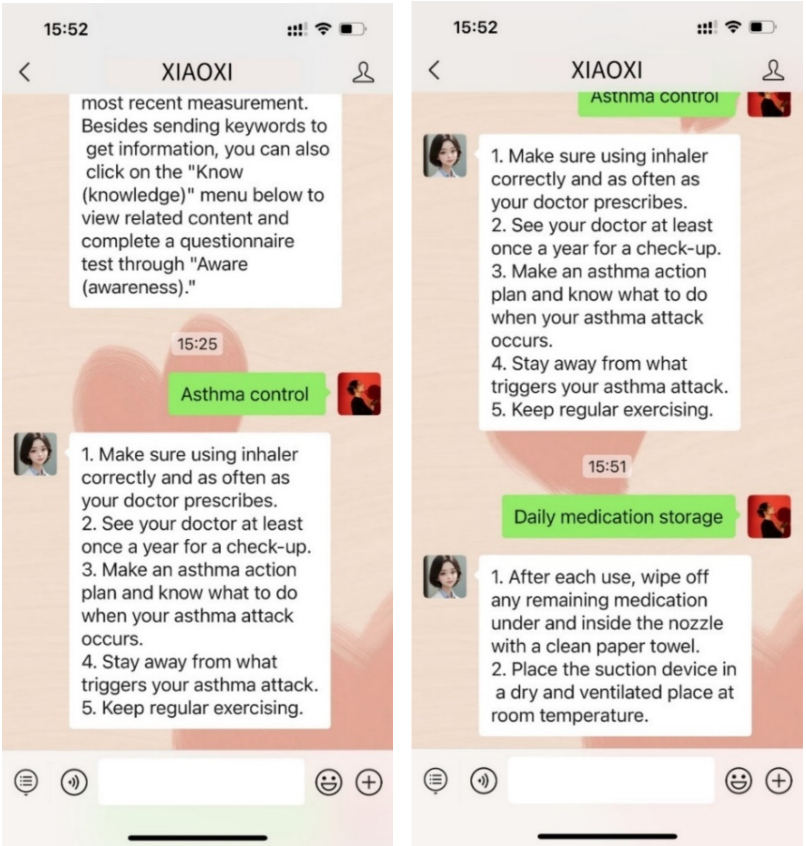


Figure 6. 8: Providing educational resources.

In addition to sending specific keywords, users can directly access related information through the “Knowledge” menu option, where relevant text and visual content are readily available for easy reference.

6.6.4.4 User Self-assessment

The XIAOXI chatbot features a comprehensive suite of assessments designed to evaluate users’ knowledge, disease control, beliefs, adherence, and emotional experience.

- Disease Knowledge Test: XIAOXI offers disease knowledge assessments, such as the Consumer Asthma Knowledge Questionnaire (CQ) and the Chronic Obstructive Pulmonary

Disease Knowledge Questionnaire (COPD-Q).

- Disease Control Evaluation: To assess how well users are managing their condition, XIAOXI utilizes tools like the COPD Assessment Test (CAT) and Asthma Control Test (ACT).
- Health Beliefs and Self-Efficacy: XIAOXI assesses users' attitudes toward their treatment and their confidence in managing their health using tools like the Beliefs about Medicines Questionnaire (BMQ) and the General Self-Efficacy Scale (GSE).
- Adherence Assessment: The Test of Adherence to Inhalers (TAI) helps XIAOXI evaluate how well users follow their prescribed inhaler schedule.
- Usability, Preference and Satisfaction Questionnaire (UPSQ): XIAOXI gathers data on the usability, preference and satisfaction of the inhaler to ensure that the devices are effective to the users as they should be.
- Emotional Experience Testing: The Emocard tool within XIAOXI assesses users' daily emotional responses to inhaler use. Users are prompted to select an image that best represents their feelings about using their inhaler, capturing emotional barriers to proper use.

6.6.4.5 Feedback Provisions

Daily Adherence Report: The Daily Adherence Report was designed based on insights gathered from participatory workshops described in Study 2. Participants expressed a strong preference for visual elements that are both informative and symbolically meaningful. Among the concepts explored, the image of a tree emerged as the central visual metaphor, symbolizing growth, vitality, and clarity—qualities that resonate with the objectives of a health adherence system.

Tree Structure as a Central Visual Metaphor:

- Natural Symbolism: The brown tree trunk and green leaves symbolize life and growth, reflecting foundational elements of health. This natural imagery is enhanced with visual elements like white clouds and a shining sun, adding warmth and accessibility to the design, supporting a holistic health approach.
- Intuitive Organization: Each branch represents one of the five adherence dimensions—Person, Task, Tool, Physical Environment, and Culture & Society. Green leaves indicate normal adherence, reflecting consistent and proper inhaler usage, while red leaves highlight areas requiring attention, signaling missed doses or improper technique (see Figure 6.9). This intuitive color scheme allows users to quickly interpret their adherence status at a glance.
- Metaphorical Depth: The leaves not only symbolize daily adherence outcomes but also represent the user's overall health journey. This metaphor reinforces the concept that sustained health management is a continuous and nurturing process, much like the growth of a tree.

To maintain routine monitoring and encourage consistent use, the Daily Adherence Report is automatically sent to users at around 10 PM each evening. This report provides a summary of the day's adherence performance, with visual cues that highlight both achievements and areas needing improvement. This metaphorical and engaging approach transforms routine feedback into a meaningful experience, promoting regular interaction and heightened awareness of therapy adherence.

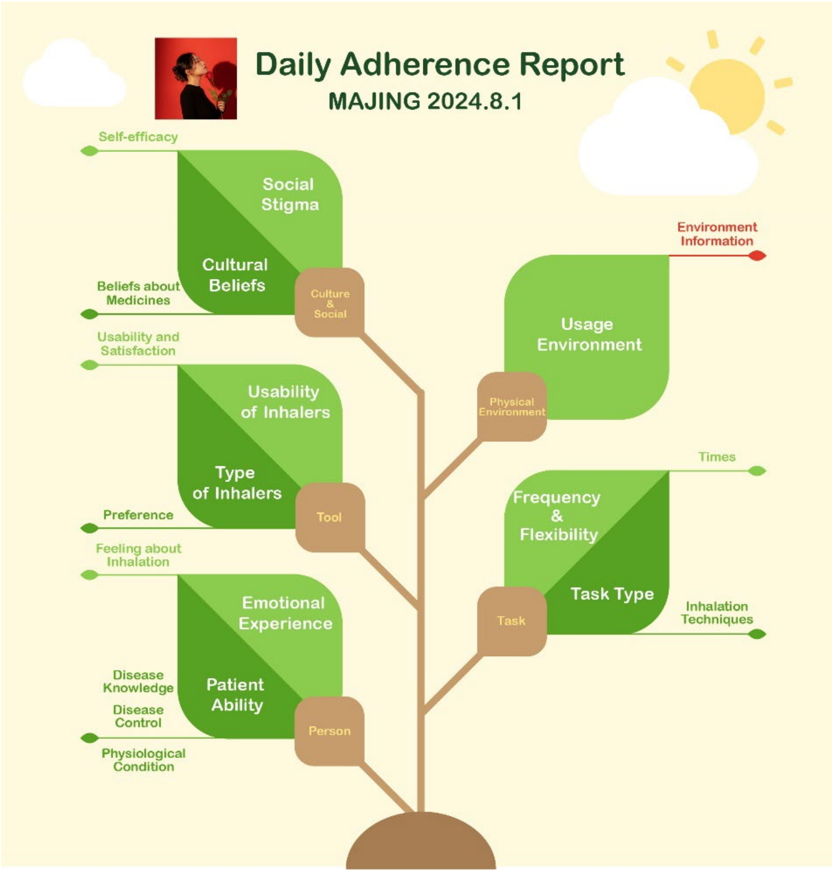


Figure 6. 9: Daily report interface.

Weekly Adherence Report: The weekly report offers a comprehensive overview by compiling data from the entire week (see Figure 6.10). It highlights key trends and areas for improvement, automatically pushed to users via WeChat at 10 PM every Sunday. The report displays adherence trends over the week in a grid format, marking each day as either normal (green) or needing attention (red). This visual format helps users quickly identify patterns in their adherence behavior. The weekly report uses simple dot plots and colours to present complex data, making it easy for users to understand without needing to read detailed text explanations.

Figure 6. 10: Weekly report interface.

Dynamic Messaging Based on Reports: In addition to the adherence reports, XIAOXI leverages the insights gained to send personalized messages that keep users engaged and informed:

- Encouragement and Motivation: Based on adherence patterns, XIAOXI sends personalized and peer-competitive messages to keep users motivated (see Figure 6.11). For instance, when a user consistently meets their goals, the chatbot provides encouragement combined with peer comparison, such as, "You've beaten 95% of your peers— that's amazing! Let's continue striving for the perfect record tomorrow!" For users falling behind, XIAOXI offers supportive and motivating prompts like, "You've made great progress—let's aim to improve even more tomorrow and catch up with the leaders!"

- Reminders and Alerts: When XIAOXI detects poor adherence or abnormal sensor data, it sends personalized reminders or alerts. For example, if a user misses a dose, XIAOXI prompts with, "It looks like you missed a dose today—don’t forget to use your inhaler tonight!" If air quality is poor, XIAOXI sends an alert like, "The air quality doesn't seem to be good—remember to open the windows for ventilation or use an air purifier."

- Educational Content Push: If the user's self-assessment results from the questionnaires indicate poor outcomes, XIAOXI proactively provides targeted educational resources to address specific areas of concern (see Figure 6.12).

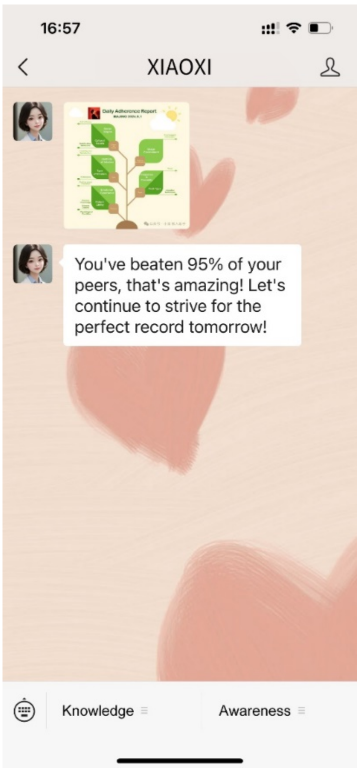


Figure 6. 11: Motivational prompts.

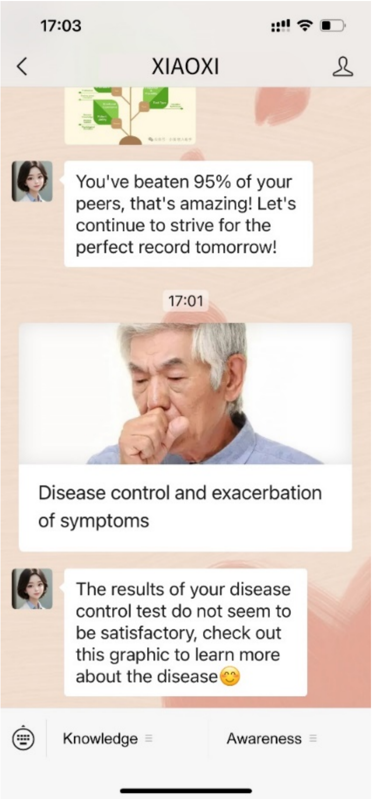


Figure 6. 12: Educational content and health reminder.

6.7 Physical Design of Sensor Casings

6.7.1 Design Inspiration and Visual Coherence

The visual design of the sensor casings is inspired by the color scheme and iconography featured in the digital interface. Green and brown tones are utilized to reflect natural elements, creating a consistent visual identity across both digital and physical components. A small sapling icon is incorporated into the sensor casing design, symbolizing growth and health. This design choice further connects the physical devices to the tree imagery used in the adherence reports (see Figure 6.13).

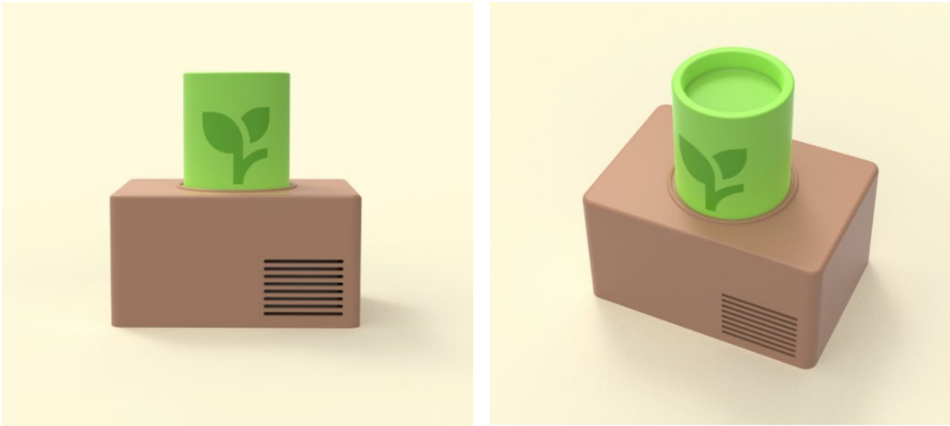


Figure 6. 13: Sensor casing design.

6.7.2 Prototyping, Materials, and User-Centered Design

The green monitoring unit houses the IMU and heart rate sensor, which are responsible for monitoring inhaler usage and physiological responses. The brown monitoring unit contains the mainboard and air quality sensors, which measure environmental factors such as temperature, humidity, and PM2.5 levels. Several iterations of 3D models were produced using ABS (Acrylonitrile Butadiene Styrene) polymers due to its rigidity, durability, and printability (see Figure 6.14).

User comfort and intuitive use were prioritized throughout the design process. The green monitoring unit features a rounded, smooth body with a groove on its upper part, facilitating secure attachment to the inhaler. This design ensures that the unit fits tightly and does not shift during use. Its ergonomic structure enhances grip, provides a comfortable form factor for users of all ages, and allows for easy attachment and detachment. The brown environmental monitoring unit is designed with strategically placed vents to ensure optimal airflow, enabling the air sensors to accurately capture environmental conditions.

Figure 6. 14: 3D printed prototypes.

6.8 Laboratory Testing

Extensive laboratory testing was conducted prior to the deployment of the XIAOXI system to assess and fine-tune both hardware and software components. The testing phase aimed to confirm the system's stability, effectiveness, and efficiency under different conditions (see Figure 6.15).

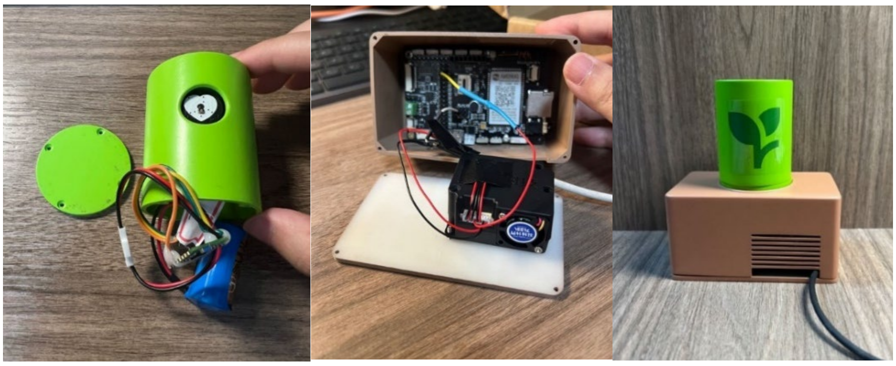


Figure 6. 15: Laboratory testing.

6.8.1 Hardware Testing

To ensure the sensors and monitoring devices functioned accurately and consistently, the following tests were performed:

- Accuracy Tests: The heart rate sensor, gyroscope, temperature, humidity, and PM2.5 sensors were evaluated under controlled environmental conditions that simulated real-world scenarios. These tests verified the precision of data capture across varying ranges. For example, the gyroscope was tested with inhalers tilted at different angles, while environmental sensors were exposed to diverse humidity, temperature, and particulate matter levels to assess their responsiveness.

- Stress and Durability Tests: Prolonged operational tests were conducted to evaluate battery life and sensor performance over extended periods. Devices were subjected to continuous operation to identify any degradation in accuracy or functionality. Stress tests also simulated rough handling and repeated attachment/detachment cycles to ensure the physical durability of the devices.

6.8.2 Software Testing

The software components underwent rigorous testing to ensure accurate data presentation and system performance:

- Data Synchronization and Integrity: Tests were performed to evaluate the system's ability to maintain continuous data synchronization among the sensors, Weixin Dialogue Open Platform, Tencent IoT Explorer, and XIAOXI. The primary focus was to ensure smooth, real-time updates with consistent and accurate data, preventing any delays or data loss during operation.

- Chatbot Response Accuracy: The XIAOXI chatbot was tested to confirm its ability to correctly interpret user inputs, access relevant data from the knowledge base, and provide accurate responses promptly.

- User Interface Testing: The user interface was thoroughly evaluated to ensure a seamless user experience. Tests focused on verifying that real-time data and adherence reports were displayed without delays, allowing users to access up-to-date information instantly. Additionally, the clarity and accuracy of the adherence reports were assessed to guarantee that the presented information was easy to understand and actionable.

6.9 Discussion

Building on insights from Study 2 (Chapter 5), the XIAOXI system was successfully implemented on the WeChat platform, integrating a suite of sensors for real-time monitoring. Through the deployment of sensors that track physiological conditions, inhaler usage, and environmental factors, the system provides users with timely feedback, encouraging healthier behaviors and improved adherence.

A key advantage of the XIAOXI system is its integration into the WeChat platform via a chatbot interface, offering significant benefits over traditional app-based solutions, particularly regarding accessibility, user engagement, and seamless integration into daily routines(Valtolina et al., 2020). During participatory design workshops, both patients and HCPs acknowledged the value of deploying a chatbot within a familiar platform like WeChat, as opposed to standalone applications that often require additional downloads, updates, and complex navigation. This strategy reduces the learning curve, enabling users to interact with the system within an environment they already trust and frequently use, effectively lowering the barrier to entry and promoting adoption. This design choice parallels other successful health chatbots deployed on widely used messaging platforms. For example, Ramjee et al. introduced CataractBot on WhatsApp to deliver expert-verified medical information to cataract patients(Ramjee et al., 2024). Both CataractBot and XIAOXI leverage well-established platforms to minimize learning costs and improve accessibility for diverse populations, including older adults and individuals with limited digital literacy(Miura et al., 2022; Ryu et al., 2020).

Unlike static interfaces typical of traditional applications, XIAOXI's chatbot facilitates real-time, contextually relevant responses, enhancing user engagement across multiple dimensions. Emotional and social engagement is fostered as users experience personalized, timely feedback that simulates supportive interactions, reducing feelings of isolation and promoting consistent self-management(De Gennaro et al., 2020; Shum et al., 2018). This interactive experience parallels the design of XiaoIce, a social chatbot developed by Zhou et al., which fosters long-term emotional connections with users through natural, empathetic conversations(Zhou et al., 2020). XiaoIce's success demonstrates that integrating emotional and social engagement within a chatbot interface can help users feel understood and supported, ultimately encouraging better health outcomes. Moreover, XIAOXI's proactive interaction model promotes behavioral engagement by prompting regular inhaler use, encouraging self-monitoring, and supporting habit formation. This aligns with findings by Hauser-Ulrich et al. (2020) and Huang et al. (2018), who observed that chatbot-based reminders effectively integrate healthy behaviors into daily routines, reinforcing adherence and enhancing long-term management of chronic conditions.

XIAOXI employs a multi-sensor approach to monitor various aspects of patient health and adherence. The IMU sensor tracks inhaler usage and technique, ensuring proper operation during each use. The heart rate sensor monitors physiological conditions, providing real-time insights into the patient's health status. Additionally, environmental sensors, including temperature, humidity, and PM2.5 sensors, track air quality—an essential factor in managing chronic respiratory conditions. This comprehensive sensor deployment enables XIAOXI to capture multi-dimensional data, offering a well-rounded perspective on adherence influences. Although this multi-sensor strategy provides extensive monitoring capabilities, each individual sensor has specific limitations. For example, while IMU sensors are effective in detecting inhaler technique, they cannot fully capture the complete inhalation process(Jourdan et al., 2021). Similarly, heart rate sensors indicate physiological changes but do not measure lung function, which is critical for assessing respiratory health(Chuang et al., 2005). Addressing these limitations calls for future research into data fusion techniques that integrate multiple sensor inputs to improve the accuracy and reliability of collected data(Gravina et al., 2017).

A relevant example is the system developed by Kalantarian et al. (2016), which combined smart bottle technology with a piezoelectric-based smart necklace to verify pill ingestion through neck movements during swallowing. This innovative fusion of sensor data ensured both bottle access and actual medication intake were accurately monitored. Drawing from this approach, future iterations of XIAOXI could benefit from sensor fusion strategies that integrate complementary measurements for more robust evaluation. For example, combining IMU data with airflow sensors could enhance the accuracy of inhaler technique assessment, while integrating heart rate monitoring with respiratory flow sensors might provide deeper insights into physiological responses during inhalation. This focused application of sensor fusion would ensure a more complete and validated view of patient adherence(Akhoundi & Valavi, 2010).

While the XIAOXI system has demonstrated successful deployment, further evaluation is required to thoroughly assess its feasibility, focusing on usability, acceptability, and user experience(Evans et al., 2024; Isaac et al., 2024; R. Steele et al., 2009). Measuring user acceptability and satisfaction is crucial for understanding the system's immediate impact on adherence and determining whether it effectively addresses user needs and expectations. These preliminary evaluations will serve as indicators of the system's potential for broader clinical application and scalability(M. O'Connor et al., 2018; Peterson et al., 2003). The next chapter will provide a comprehensive evaluation of XIAOXI's effectiveness, assessing its impact on adherence and clinical outcomes. This assessment will form the foundation for understanding how sensor-based intervention systems can transform inhalation therapy adherence in real-world settings, paving the way for future research and potential clinical adoption.

6.10 Conclusion

In this study, we developed XIAOXI, a sensor-based intervention system designed to improve patient adherence to inhalation therapy. Leveraging advanced sensor technologies, the system continuously monitors inhaler usage, physiological indicators, and environmental conditions, providing real-time insights that support timely feedback and adherence. Integrated into the WeChat platform with a user-friendly chatbot, XIAOXI seamlessly embeds into users' daily routines, enhancing accessibility and ease of use. Through real-time feedback, educational resources, and self-assessment tools, XIAOXI empowers users to interact naturally, access sensor data, and receive personalized adherence guidance in an intuitive and engaging way.

Chapter 7 Evaluation and Classification Analysis of the Sensor-based Intervention System

7.1 Introduction and Aims

In the previous chapter, we completed the development of XIAOXI. In this chapter, we evaluate the usability, effectiveness, and the capability of the system to accurately classify patient adherence behaviors based on retrospective data analysis. First, we assess whether the XIAOXI system is user-friendly and supports consistent patient adherence by utilizing both quantitative assessments and qualitative feedback from interviews with HCPs and patients. Second, we evaluate the effectiveness of XIAOXI in improving inhaler adherence through a 28-day controlled experiment, comparing outcomes between patients using XIAOXI and those following standard management practices, using both self-reported measures (e.g., TAI questionnaire) and objective sensor data. Third, we apply machine learning methods to classify daily inhaler adherence behaviors, focusing on identifying key factors influencing adherence and evaluating the performance and accuracy of various classification models.

As discussed in Section 2.2.6, this thesis conceptualizes effectiveness, safety, and usability as interrelated dimensions of inhalation therapy efficacy, synthesized from the literature. However, this conceptual framework serves to contextualize the research rather than to define the empirical evaluation scope. The evaluation conducted in this chapter focuses specifically on the behavioral effectiveness of the XIAOXI system in supporting patient adherence to inhalation therapy. This focus on adherence-related outcomes is distinct from clinical interpretations of effectiveness, safety, and usability in terms of pharmacological efficacy or device performance. This clarification is intended to prevent confusion between the broader conceptual framework and the specific evaluation objectives addressed in this chapter.

The objectives of this chapter are:

1. To evaluate the usability of the XIAOXI system from patient and HCP perspectives, focusing on system quality, acceptance, and usability.

2. To assess the effectiveness of XIAOXI in improving adherence using self-reported and sensor-based data.

3. To apply machine learning methods to classify daily inhaler adherence behaviors, identify key factors influencing adherence, and evaluate model performance.

7.2 Usability Evaluation of XIAOXI

The evaluation of XIAOXI focused on three primary areas: chatbot quality, technology acceptance, and system usability. These metrics were chosen based on Kadariya's article to provide a comprehensive understanding of both the system's effectiveness and the user experience(Kadariya et al., 2019).

7.2.1 Evaluation Metrics

The evaluation of XIAOXI focused on chatbot quality and technology acceptance, both assessed using an 11-point Likert scale (0-10). The chatbot quality assessment included three dimensions: naturalness, information delivery, and interpretability.

Naturalness: Evaluated the fluency and clarity of XIAOXI's dialogues, focusing on the chatbot's ability to use simple, understandable language and provide natural, unambiguous conversations.

Information Delivery: Assessed the accuracy and timeliness of the information provided, ensuring support for patient management of inhalation therapy.

Interpretability: Measured the chatbot's ability to understand user inputs and convey relevant health data, capturing the effectiveness of responses based on patient-reported information.

The adapted TAM measured the perceived usefulness, ease of use, and overall satisfaction with XIAOXI, with questions adapted for specific functionalities(Kadariya et al., 2019). System usability was evaluated using the SUS, a widely validated tool for measuring overall satisfaction(Lewis, 2018; Peres et al., 2013). The SUS consists of 10 items scored on a 5-point Likert scale (1 to 5), which were later normalized to a scale of 0 to 100, where scores above 68 indicate above-average usability. All questionnaires are presented in Appendix 7A and 7B.

7.2.2 Methods

This usability evaluation involved 10 patients and 5 HCPs to assess the XIAOXI system's performance, usability, and clinical applicability. The detailed recruitment criteria and procedures are described in Chapter 3, Section 3.5.5.1. The demographic characteristics of participants are summarized in Tables 7.1 and 7.2.

Table 7. 1: Participant demographics (HCPs).

Demographic	Count (n=5)	Percentage
Gender		
Male	2	40.0%
Female	3	60.0%
Age Range		
18-35	3	60.0%
36-50	1	20.0%
51-65	1	20.0%
Work Experience		
3-6	2	40.0%
7-10	3	60.0%
>10	0	0.0%

Table 7. 2: Participant demographics (patients).

Demographic	Count (n=10)	Percentage
Gender		
Male	5	50.00%
Female	5	50.00%
Age Range		
20-30	2	20.00%
30-40	5	50.00%
40-50	3	30.00%
Educational Level		
Primary	0	0.00%
Secondary	1	10.00%
Tertiary	9	90.00%
Disease Severity		
Mild	8	80.00%
Moderate	2	20.00%
Severe	0	0.00%
Number of Comorbidities		
0	7	70.00%
1	2	20.00%
2 or more	1	10.00%
Experience with Inhaler Device (Years)		
<1	3	30.00%
1-3	6	60.00%
>3	1	10.00%

The evaluation process included simulated usage scenarios based on the personas and scenarios developed in Study 2, where HCPs assessed the usability and clinical applicability of the XIAOXI system from a patient-centered perspective. Additionally, patients integrated the XIAOXI system into their daily inhalation therapy routines over a 28-day period, followed by structured usability assessments.

Quantitative data were collected using the SUS and a System Quality Questionnaire. Descriptive statistical analyses were performed using SPSS v25 to summarize responses and compare perceptions between patients and HCPs. Following the quantitative assessment, semi-structured interviews were conducted to gather qualitative insights into user experience and system interaction. The interview protocol is given in Appendix 7C. All interviews were audio-recorded, transcribed verbatim, and analyzed using thematic analysis(Charmaz, 2006; Strauss, 1987), supported by NVivo 14. This mixed-methods approach provided a comprehensive understanding of both the functional usability and user perceptions of the XIAOXI system.

7.2.3 Results

7.2.3.1 Quantitative Findings

Chatbot Quality and Technology Acceptance: The average scores for HCPs and patients across four key dimensions—Naturalness, Information Delivery, Interpretability, and Technology Acceptance—are as follows (Figure 7.1):

Naturalness: HCPs scored an average of 9.00 (SD = 0.33), while patients scored 8.83 (SD = 0.39).

Information Delivery: HCPs had an average score of 9.40 (SD = 0.55), and patients scored 9.05 (SD = 0.80).

Interpretability: HCPs scored 8.7 (SD = 0.45), while patients scored 8.35 (SD = 0.47).

Technology Acceptance: HCPs scored an average of 9.07 (SD = 0.55), and patients scored 8.80 (SD = 0.57).

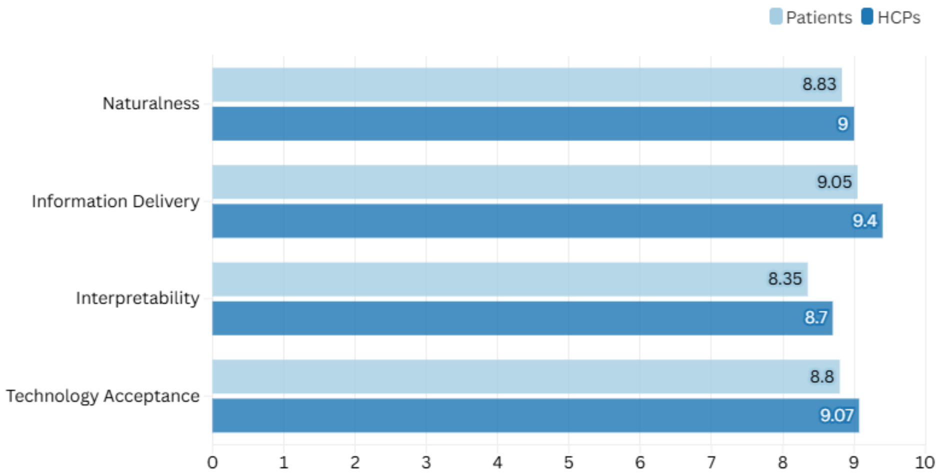


Figure 7. 1: Comparison of chatbot quality and technology acceptance between patients and HCPs.

A Mann-Whitney U test was conducted to compare the two groups across these dimensions. The results revealed no statistically significant differences between HCPs and patients in any of the dimensions (all $p > 0.05$). This suggests that both groups had comparable perceptions and experiences regarding the interface's naturalness, information delivery, interpretability, and technology acceptance. This suggests both groups had similarly positive perceptions of the system's quality.

System Usability Scale (SUS): The SUS scores were calculated based on the standard SUS methodology. Each participant answered 10 questions on a 5-point Likert scale, with some questions being positively worded and others negatively worded. For positively worded questions (Q1, Q3, Q5, Q7, Q9), the score was calculated as (score - 1). For negatively worded questions (Q2, Q4, Q6, Q8, Q10), the score was calculated as (5 - score). The total score for each participant was then multiplied by 2.5 to convert the score into a range of 0 to 100, where 0 represents the lowest possible usability and 100 represents the highest.

Both HCPs and patients scored well above the industry-standard benchmark of 68 for usability. The HCP group had a mean score of 88.00 (SD = 2.09), while the Patient group had a mean score of 83.25 (SD = 5.41). These scores indicate a high level of satisfaction with the system's design and functionality, with both groups finding the system highly usable. The results of the Mann-Whitney U test showed no statistically significant difference between HCPs and patients ($p = 0.072$).

7.2.3.2 Qualitative Feedback

User Experience and Interface: Participants highlighted XIAOXI's intuitive and user-friendly interface. Both HCPs and patients appreciated its smooth navigation and visually engaging design. One participant noted, "*The interface is simple and engaging; I believe it will be easy for patients to use and they should enjoy it.*" Patients found the tree metaphor for daily adherence reports and the dot plots for weekly reports visually appealing, easy to understand, and effective in indicating their performance. The natural imagery not only provided comfort but also enhanced privacy. As one patient mentioned, "*The design is discreet. Even if someone glimpses my screen, they wouldn't immediately know it's related to my health, which I really appreciate.*"

Chatbot Communication and User Engagement: The chatbot's communication style received widespread praise, particularly for its natural and engaging dialogue. Participants described the interactions as warm and supportive. *"It felt like I was having a real conversation, not just following a script,"* remarked one patient. Both patients and HCPs appreciated the clarity and simplicity of the chatbot prompts. Additionally, the chatbot's empathetic tone resonated with users, especially patients who valued its non-judgmental and encouraging language.

Health Support and Educational Content: Both patients and HCPs found the health support and educational content provided by XIAOXI to be highly meaningful. HCPs acknowledged that the system effectively enhanced patient education and promoted better health awareness. Patients appreciated XIAOXI as a reliable source of accurate information on inhalation therapy. One patient shared, "*Whether I wanted to learn about daily disease management or the correct steps for using my inhaler, XIAOXI was able to help me.*"

Sensor Technology and Data Utilization: HCPs expressed strong interest in the sensor technology integrated within XIAOXI, highlighting its potential for providing deeper insights into patient conditions. One HCP noted, "*If we as doctors could access this data, it would provide a more comprehensive understanding of patients' conditions, allowing us to make more informed decisions that benefit them.*" Patients also appreciated the convenience of accessing sensor data directly within XIAOXI, enabling them to easily monitor their physiological status and environmental conditions. This access contributed to a greater sense of security and control. As one patient commented, "*I feel like I have a better understanding of my own condition*."

7.3 Evaluating the Effectiveness of XIAOXI

This section evaluates the effectiveness of the XIAOXI system in supporting patient adherence to inhalation therapy. The study compared patients using XIAOXI with a control group following standard inhaler management practices. Questionnaires and sensor data were used to measure changes in patient adherence, providing insights into the accuracy and reliability of these methods.

7.3.1 Methods

A controlled experimental design was employed to evaluate the effectiveness of the XIAOXI system in enhancing patient adherence to inhalation therapy. Detailed descriptions of participant recruitment, group allocation, study procedures, and data collection instruments are provided in Chapter 3, Section 3.5.5.2. In summary, 20 patients diagnosed with asthma or COPD were assigned to either an experimental group (n = 10), utilizing the XIAOXI system alongside the Symbicort Turbuhaler, or a control group (n = 10), following standard inhalation therapy practices. Demographic characteristics of both groups are presented in Tables 7.3 and 7.4.

Table 7. 3: Participant demographics (experimental group).

Demographic	**Count (n=10)**	**Percentage**
Gender		
Male	5	50.00%
Female	5	50.00%
Age Range		
20-30	2	20.00%
30-40	5	50.00%
40-50	3	30.00%
Educational Level		
Primary	0	0.00%
Secondary	1	10.00%
Tertiary	9	90.00%
Type of Disease		

Asthma	10	100.00%
COPD	0	0.00%
Disease Severity		
Mild	8	80.00%
Moderate	2	20.00%
Severe	0	0.00%
Number of Comorbidities		
0	7	70.00%
1	2	20.00%
2 or more	1	10.00%
Experience with Inhaler Device (Years)		
<1	3	30.00%
1-3	6	60.00%
>3	1	10.00%

Table 7. 4: Participant demographics (control group).

Demographic	**Count (n=10)**	**Percentage**
Gender		
Male	6	60.00%
Female	4	40.00%
Age Range		
20-30	1	10.00%
30-40	5	50.00%
40-50	4	40.00%
Educational Level		
Primary	1	10.00%
Secondary	3	30.00%
Tertiary	6	60.00%
Type of Disease		
Asthma	7	70.00%
COPD	3	30.00%
Disease Severity		
Mild	8	80.00%
Moderate	2	20.00%
Severe	0	0.00%
Number of Comorbidities		
0	6	60.00%
1	2	20.00%
2 or more	2	20.00%
Experience with Inhaler Device (Years)		
<1	4	40.00%
1-3	4	40.00%
>3	2	20.00%

Adherence outcomes were assessed using the TAI, administered to both the experimental and control groups before and after the 28-day intervention period. For the experimental group, objective adherence data were additionally collected through XIAOXI's inhaler usage monitoring, enabling precise tracking of daily inhaler usage. Following the intervention, semi-structured interviews were conducted with participants from both groups to explore their experiences, perceived adherence barriers, and attitudes towards inhalation therapy. The interview protocol is provided in Appendix 7D.

Quantitative data were analyzed using SPSS v25 to compare adherence changes between the two groups. Qualitative data were examined through thematic analysis(Charmaz, 2006; Strauss, 1987) , facilitated by NVivo 14, to identify key themes related to adherence behaviors and patient perceptions. This mixed-methods approach allowed for a comprehensive evaluation of both objective adherence improvements and subjective patient experiences associated with the XIAOXI intervention.

7.3.2 Results

7.3.2.1 TAI Scores Comparison

At the beginning of the study, adherence levels were categorized as: high adherence (50-54), moderate adherence (46-49), and low adherence (45 or below)(Muneswarao et al., 2021; Plaza et al., 2016).

Experimental Group:

- Baseline (TAI-0): The experimental group had an average TAI score of 48.8 (SD = 5.22). Five patients demonstrated high adherence, two showed moderate adherence, and three were categorized as having low adherence.

- Post-intervention (TAI-28): After the 28-day intervention, the average TAI score increased significantly to 51.7 (SD = 2.31). Eight patients achieved high adherence, two maintained moderate adherence, and none remained in the low adherence category.

Control Group:

- Baseline (TAI-0): The control group began with an average TAI score of 48.7 (SD = 3.56), consisting of five high adherence patients, four with moderate adherence, and one with low adherence.
- Post-intervention (TAI-28): By the study's end, the average TAI score slightly declined to 47.9 (SD = 4.46). The number of high adherence patients decreased to four, while the moderate and low adherence categories adjusted to two and four, respectively, indicating a decline in adherence without the intervention.

Statistical Analysis:

- Within-Group Comparison: The Wilcoxon Signed-Rank Test revealed a significant improvement in TAI scores for the experimental group post-intervention ($p = 0.018$), highlighting the effectiveness of the intervention. In contrast, the control group did not exhibit a statistically significant change ($p = 0.168$).
- Between-Group Comparison: Mann-Whitney U tests showed no statistically significant differences at baseline ($U = 46.5$, $p = 0.790$), confirming initial comparability between the two groups. However, by the end of the 28-day period, a statistically significant difference emerged ($U = 24.0$, $p = 0.045$), indicating superior adherence in the experimental group.

These results affirm that the intervention significantly improved adherence among participants in the experimental group compared to those in the control group, underscoring the effectiveness of the XIAOXI system.

7.3.2.2 Detailed Adherence Data from XIAOXI

The XIAOXI system provides comprehensive insights into patient adherence by leveraging sensor data to track both inhaler usage frequency and the accuracy of inhalation techniques. The system's gyroscope allows for real-time monitoring, focusing on three critical aspects: correct rotation for medication loading, maintaining the proper position during inhalation, and ensuring adequate inhalation and holding duration (Figure 7.2).

(a) (b)

Figure 7. 2: Posture of device at each motion. (a) posture at rotating the grip (b) posture at inhale motion.

Evaluating Inhalation Activation and Technique via IMU: The XIAOXI system's IMU tracks angle variations to evaluate inhalation activation and technique during the use of the Symbicort Turbuhaler, the medication used in this study. Figure 7.3 illustrates the gyrometer's axial directions within the IMU, highlighting how angle variations are monitored throughout inhaler usage.

- Correct Rotation for Medication Loading: Proper inhaler usage requires the user to rotate the grip counterclockwise and then back until a click is heard, signaling that the correct dose has been loaded(Basheti et al., 2005). This action generates a significant change in the z-axis angle, shifting from a neutral position to a negative value and returning to neutral upon completion. The IMU detects these movements to confirm successful dose loading.

- Maintaining the Proper Position During Inhalation: To ensure optimal medication delivery, the device should be held horizontally during inhalation(Cain et al., 2001; Chopra et al., 2002). The x-axis angle is monitored by the IMU, and a consistent reading around 90° indicates the device is being correctly positioned, maximizing lung deposition.

- Ensuring Adequate Inhalation Duration: Effective inhalation requires both forceful breathing (typically lasting 1–2 seconds) and breath-holding for approximately 6 seconds, as recommended by the Symbicort Turbuhaler guidelines(Azouz et al., 2015; Basheti et al., 2014). The IMU verifies this by tracking the x-axis angle for stability over the required time. If the total inhalation time is less than 7 seconds, it is flagged as potentially inadequate.

- Recording a Full Inhalation: When all three criteria—correct rotation, horizontal positioning, and sufficient inhalation duration—are detected, the event is recorded as a complete inhaler use. This automated detection ensures accurate tracking of adherence. Figure 7.4 presents a schematic representation of how angle values change throughout the inhalation process.

Figure 7. 3: Axial directions of gyrometer.

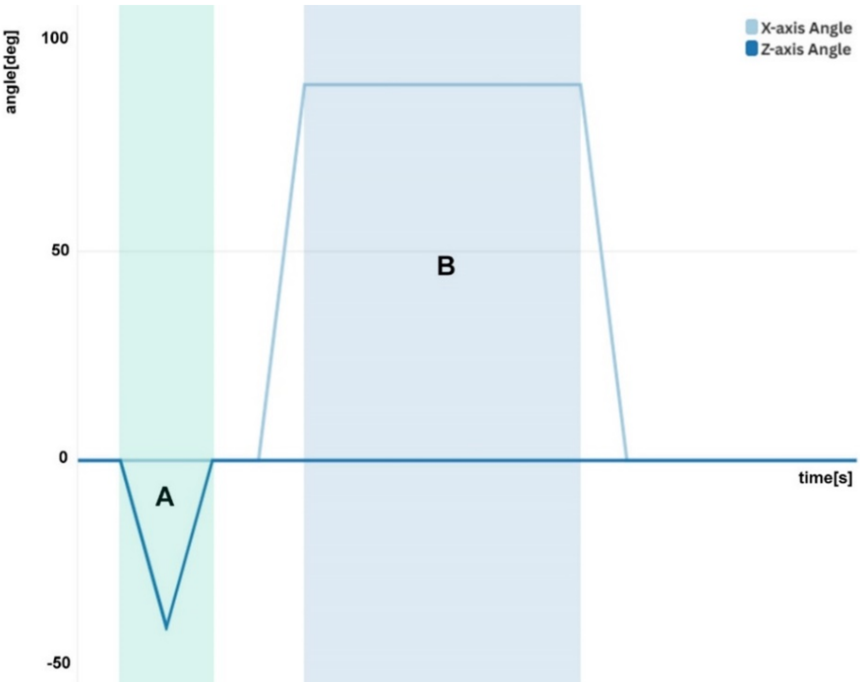


Figure 7. 4: Schematic graph of proposed device (A - representing the medication loading process; B - representing the inhalation process).

Calculating Adherence Metrics: The XIAOXI system quantifies adherence data through two primary metrics:

- Prescription Adherence: Prescription adherence is calculated as the ratio of the actual number of inhaler uses detected by the system to the total expected uses over the 28-day intervention period. Given the prescribed frequency of twice daily usage, the total expected uses amount to 56 inhalations.

- Technique Adherence: Technique adherence is evaluated by assessing the number of times the participant correctly followed all three inhalation criteria (correct rotation, maintaining the proper position, and sufficient duration). This value is computed by dividing the number of times the participant successfully performed all three steps by the total number of inhaler uses detected.

For the 10 participants in the experimental group, XIAOXI's sensor data was used to compute these metrics across the 28-day intervention period (see Table 7.5). Adherence is categorized into three levels: good adherence (≥75%), partial adherence (50%–75%), and low adherence (<50%). This structured and consistent classification enabled clear assessment of adherence performance across all participants.

Table 7. 5: The adherence data from XIAOXI.

No	**Actual number of inhaler uses**	**Prescription adherence**	**Prescription adherence level**	**Correctly technique times**	**Technique adherence**	**Technique adherence level**
1	52	92.86%	good	51	98.08%	good
2	51	91.07%	good	48	94.12%	good
3	43	76.79%	good	40	93.02%	good
4	51	91.07%	good	45	88.24%	good
5	45	80.36%	good	44	97.78%	good
6	36	64.29%	partial	33	91.67%	good
7	50	89.29%	good	47	94.00%	good
8	49	87.50%	good	49	100.00%	good
9	51	91.07%	good	49	96.08%	good
10	37	66.07%	partial	35	94.59%	good

7.3.2.3 Qualitative Insights into Patient Adherence and Experiences

Challenges and Difficulties in Inhaler Usage: Participants in the control group encountered significant challenges with proper inhaler techniques, largely due to the lack of external guidance or feedback. Many expressed uncertainty about whether they were using the inhaler correctly, and they had no means to confirm proper inhalation. As one participant noted: *"I don't know if I'm using the inhaler correctly. My condition has been under control recently. I guess it's because of the inhaled medicine."* Additionally, forgetfulness was a common issue, particularly during busy periods such as working overtime or when dealing with family commitments. The lack of reminders or feedback mechanisms contributed to missed doses and inconsistent usage.

In contrast, the experimental group, supported by the XIAOXI system, benefited from real-time feedback on their inhaler usage. XIAOXI not only provided confidence in ensuring proper technique but also allowed users to query the system when uncertain or consult instructions for clarification. Furthermore, reminders for missed doses were automatically sent, promoting consistent adherence to their medication regimen. Participants appreciated the adherence reports, which allowed them to track their progress clearly, enhancing their sense of control over their inhaler usage. *"By checking the report every day, I can see if I'm doing things right. XIAOXI tells me if the air quality is good, whether I've taken both doses of my medication, and if everything's on track."* This combination of real-time feedback, adherence tracking, and reminders simplified the inhaler usage process, significantly reducing the uncertainties and forgetfulness experienced by the control group.

Impact of Environment and Emotions on Adherent Behavior: Control group participants reported that environmental factors, such as air quality and weather conditions, had a noticeable impact on their physical well-being. Patients with asthma and COPD were particularly sensitive to changes in these conditions, often triggering discomfort and increasing their perceived need for inhaler usage: *"My airways are very sensitive, and when the seasons change or the air quality is not good, I immediately want to cough."* Issues related to temperature and humidity also emerged, especially for patients using DPIs, where improper storage could affect medication efficacy: *"I found that when the rainy season arrives, the medicine at the mouthpiece of the inhaler clumps together."*

In contrast, participants in the experimental group benefited from XIAOXI's monitoring of physiological and environmental data. The system enabled patients to track air quality, temperature, and humidity levels, allowing them to anticipate discomfort and manage inhaler storage conditions more effectively: *"I found that XIAOXI always reminded me that the air quality at home was not good around 7 pm, and I realized that it was caused by cooking fumes at home, so I will increase the suction power of the range hood and open the window when I cook now."* This proactive monitoring gave patients greater insight into their environment, empowering them to make informed adjustments to minimize risks and improve their health outcomes.

Regarding emotional experiences, control group participants often expressed "*feelings of frustration and boredom*" associated with the repetitive nature of inhaler use. Many described the daily routine of using the inhaler as monotonous and tiresome, which sometimes led to reduced motivation to adhere to their treatment. Conversely, the experimental group reported a more positive emotional experience with the support of XIAOXI. The system not only provided reminders and feedback but also helped break the monotony by offering motivational messages and tracking progress. *"Honestly, I actually look forward to XIAOXI's daily report. I don't really know why, but it makes my daily inhaler routine more interesting—kind of like having a companion along the way."* This enhanced engagement reduced the frustration and boredom commonly experienced in the control group, making the daily inhaler routine feel more purposeful and manageable.

Perception of Drug Side Effects and Disease Management: Concerns about drug side effects and limited knowledge about disease management were prevalent among control group participants. Many expressed uncertainty about their ability to effectively manage their condition due to a lack of reliable, authoritative information. Much of the information they accessed online was inconsistent, inaccurate, or not applicable to their specific circumstances. This lack of guidance left them feeling unsure about how best to manage their asthma or COPD. Traditional cultural beliefs, such as the notion that “All medicine has toxicity to some degree,” further fueled distrust in long-term inhaler use, prompting some to reduce their usage: *"This inhaler has hormones in it, and I've always thought it could be bad for the body, so I've been using it on and off."*

In contrast, participants in the experimental group who used the XIAOXI system demonstrated a better understanding of medication safety and disease management. The system provided educational content that alleviated concerns about drug side effects and empowered them to use their inhalers more confidently. While the 28-day intervention did not completely change participants' deep-seated cultural beliefs about drug toxicity, it did have a noticeable impact on their behavior. Many participants reported becoming less likely to reduce or skip medication without HCP approval, recognizing that the benefits of inhaler use outweighed perceived risks: *"Now I get that asthma needs long-term control, so even if I'm not having symptoms, I'll keep using it regularly to avoid flare-ups."* This shift in behavior, although not fully overcoming cultural beliefs, reflected a growing trust in the treatment and a stronger sense of responsibility in managing their condition with the help of the system.

7.4 Machine Learning-Based Classification of Daily Inhaler Usage as an Adherence Behavior Using XIAOXI Data

7.4.1 Materials and Methods

This study aimed to develop and validate machine learning models to classify daily patient adherence behavior based on multi-dimensional data collected by the XIAOXI system during a 28-day intervention. The classification task was defined as a binary problem, distinguishing between days of completed prescribed inhaler usage (adherent behavior) and days of incomplete or missed usage (non-adherent behavior).

Input features included physiological parameters (e.g., heart rate), environmental conditions (e.g., temperature, humidity, PM2.5), and emotional states, derived from sensor readings and daily self-reports via the Emocard questionnaire. A structured three-stage process was employed to ensure data integrity and optimize feature representation for machine learning classification (Figure 7.5):

1. Data Cleaning: Removal of outliers and noise from raw sensor and self-reported data.

2. Data Aggregation: Transformation of cleaned data into daily feature sets suitable for classification.

3. Data Classification: Implementation and evaluation of multiple machine learning algorithms to classify adherence behavior and assess model performance.

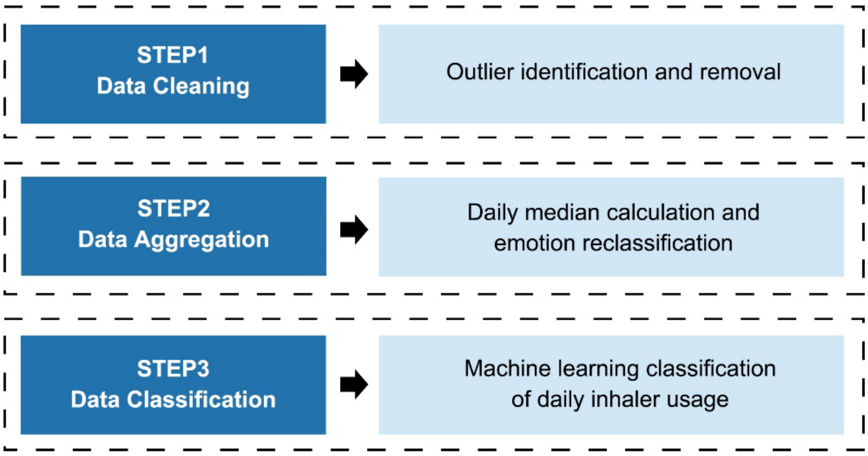


Figure 7. 5: Flowchart for the classification of daily inhaler usage.

7.4.1.1 Dataset

The dataset used in this study was collected from the XIAOXI system. The system's sensors recorded daily data on heart rate, temperature, humidity, air quality, and inhaler usage frequency. Additionally, patients were required to report their emotional experiences during inhaler use each day. In total, the dataset comprises 10 patients, each contributing 28 days of data across 6 features, resulting in a total of 1,680 data points for the machine learning analysis. This dataset serves as the basis for classifying daily inhaler adherence behaviors using machine learning methods.

7.4.1.2 Data Cleaning

Sensor data often contains outliers or erroneous readings that can negatively impact analysis. In this stage, heart rate, temperature, humidity, and PM2.5 data were cleaned by removing extreme outliers that deviated from expected ranges for patient environments. This study employed an Interquartile Range IQR-based statistical technique for anomaly detection, a common and effective approach in statistical analysis(Vinutha et al., 2018). First, the first quartile (Q1) and third quartile (Q3) of the data were calculated to determine the interquartile range ($\mathrm{IQR} = \mathrm{Q3} - \mathrm{Q1}$). Following standard practice, data points below $Q1 - 1.5 * IQR$ or above $\mathrm{Q3} + 1.5 * \mathrm{IQR}$ were identified as anomalies and subsequently removed to maintain data integrity and ensure analytical accuracy(Barbato et al., 2011). The IQR-based method effectively captures data distribution and variability, making it well-suited for detecting anomalies across diverse environments(Cho et al., 2024). The cleaned dataset was then prepared for further aggregation.

7.4.1.3 Data Aggregation

Sensor data aggregation: In this stage, the daily sensor data was aggregated to generate representative features for each day. Specifically, the median values of heart rate, temperature, humidity, and PM2.5 were calculated to capture the central tendency of each day's data while minimizing the influence of temporary fluctuations(Weisberg, 1992). For each variable X, the median was calculated as:

$$\text{Median(X)} = \begin{cases} x_{(n+1)/2} & if\ n\ is\ odd \\ \dfrac{x_{n/2} + x_{(n/2+1)}}{2} & if\ n\ is\ even \end{cases}$$

where n represents the number of data points collected throughout the day for that specific variable (e.g., heart rate, temperature, humidity, or PM2.5).

Additionally, the number of times the patient used the inhaler each day was recorded as U, representing the total daily usage, with a maximum of two uses per day. For classification purposes, adherence was defined as meeting the prescribed usage of exactly two times per day(Abdelrahim, 2010). If the patient met this criterion (U=2), it was labeled as 1 (adherent). If the patient used the inhaler fewer than twice per day (U <2), it was labeled as 0 (non-adherent), as shown in the formula below:

$$\text{Adherence Label} = \begin{cases} 1, & \text{if U} = 2 \\ 0, & \text{if U} < 2 \end{cases}$$

Emotional data aggregation: In addition to the sensor data, patient-reported emotional experiences were collected using the Emocard, which offers eight different emotional categories. To simplify the analysis and prepare the data for machine learning, these eight categories were grouped into four quadrants based on valence (pleasantness) and arousal levels (Desmet et al., 2016). Figure 7.6 provides a visual representation of these quadrants, illustrating how each emotional category is mapped. Each quadrant represents a combination of these dimensions and includes the following:

- **Quadrant 1:** High Arousal, Positive Emotion

Includes categories: *Excited Neutral, Excited Pleasant*

Encoded as: 1

- **Quadrant 2:** High Arousal, Negative Emotion

Includes category: *Excited Unpleasant*

Encoded as: 2

- **Quadrant 3:** Low Arousal, Negative Emotion

Includes categories: *Calm Unpleasant, Average Unpleasant*

Encoded as: 3

- **Quadrant 4:** Low Arousal, Positive Emotion

Includes categories: *Calm Pleasant, Average Pleasant, Calm Neutral*

Encoded as: 4

This encoding method consolidates the emotional data into broader categories, making it more manageable and suitable for machine learning analysis.

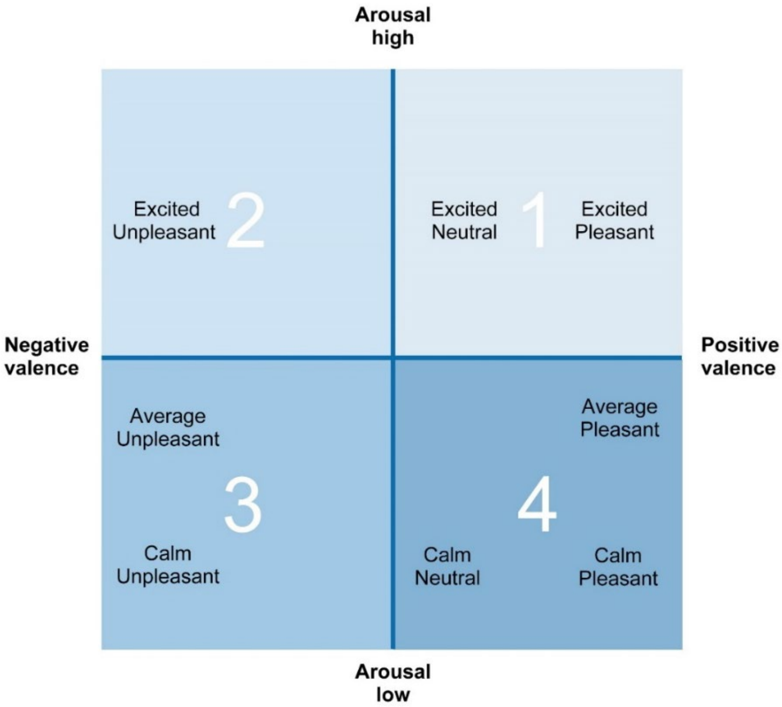


Figure 7. 6: Emotional data aggregation.

7.4.1.4 Data Classification

The classification problem in this study focuses on classifying daily inhaler adherence behaviors based on aggregated sensor and emotional data. Various machine learning algorithms were employed, including: (i) Logistic Regression, (ii) Support Vector Machine (SVM), (iii) Random Forest, (iv) Random Tree, (v) Naive Bayes, (vi) Decision Tree (J48), and (vii) Multiple Layer Perceptron (MLP).

Logistic Regression: A linear model used for binary and multi-class classification. It estimates probabilities using a logistic function and is effective for problems where the relationship between input features and the target is approximately linear. The formula for logistic regression is:

$$P(y = 1|x) = 1 / 1 + exp(-(\beta_0 + \beta_1 x_1 + ... + \beta_n x_n))$$

Where $P(y = 1|x)$ represents the probability that the outcome y is 1 given the input features x, β_0 is the intercept, and $\beta_1,\ldots, \beta_n$ are the coefficients associated with each input feature.

Support Vector Machine (SVM): A supervised learning model that seeks to find the optimal hyperplane that maximizes the margin between different classes. The SVM can handle non-linear boundaries by using kernel functions, such as the radial basis function (RBF). The decision function for SVM is:

$$f(x) \ = \ sign(w\hat{}T \ x \ + \ b)$$

Where w is the weight vector, x is the input feature vector, and b is the bias term. The sign function determines the class label.

Random Forest: An ensemble learning method composed of multiple decision trees. Each tree is trained on a bootstrapped subset of the dataset, and the final prediction is made by majority voting across all trees. The formula for a Random Forest classifier is:

$$f(x) \ = \ (1/T) \ \Sigma \ h_t(x)$$

Where T is the number of trees, and $h_t(x)$ represents the prediction made by the t-th tree.

Random Tree: The formula for a Random Tree is used to predict the output by summing the indicator functions of the regions R_i where the input x belongs:

$$y \ = \ \sum I(x \ \in \ R_i) \ y_i$$

Where $I(x \ \in \ R_i)$ is an indicator function that checks whether the input x falls into the region R_i, and y_i is the predicted class label for that region.

Naive Bayes: A probabilistic classifier based on Bayes' theorem with the assumption that features are conditionally independent given the class label. It is known for its simplicity and effectiveness in high-dimensional data, especially in cases like text classification.

$$P(y|x_1, \ldots, x_n) \propto P(y)\, \Pi\, P(x_i|y)$$

Where $P(y|x_1, \ldots, x_n)$ is the posterior probability of class y given the features $x_1, \ldots, x_n$, $P(y)$ is the prior probability of the class, and $P(x_i|y)$ is the likelihood of each feature given the class.

Decision Tree (J48): The decision tree algorithm builds a tree structure where each node represents a feature and each branch represents a decision rule. J48, an implementation of the C4.5 algorithm, splits nodes based on normalized information gain and handles both continuous and categorical data. The information gain in J48 is calculated using the entropy of the dataset before and after the split. Entropy is a measure of the randomness or impurity in the dataset, and it is represented as follows:

$$I(D) = -\sum p_i\, log_2(p_i)$$

Where p_i is the proportion of instances in class i.

Information gain is then calculated by comparing the entropy of the dataset before the split and the weighted entropy of the branches after the split. The attribute that maximizes the information gain is selected for splitting at each node. This recursive process continues until all instances are classified or a stopping criterion is met.

Multiple Layer Perceptron (MLP): A type of feedforward artificial neural network consisting of input, hidden, and output layers. MLP uses backpropagation for learning and can model complex non-linear relationships in the data.

$$f(x) = \sigma(W_2 * \sigma(W_1 x + b_1) + b_2)$$

Where W_1 and W_2 are the weight matrices, b_1 and b_2 are the bias terms, and σ is the activation function (e.g., sigmoid or ReLU).

The classifiers were implemented using the Weka software (version 3.9.6) provided by the University of Waikato.

7.4.2 Results

To evaluate the classifiers, a ten-fold stratified cross-validation procedure was employed. Given the imbalance in the dataset, with 187 instances of completed inhaler usage and 93 instances of incomplete usage, an imbalanced class handling approach was necessary. Imbalanced classes, which are common in real-world applications, can negatively impact classifier performance due to a tendency to favor the majority class.

In this study, the Synthetic Minority Over-sampling Technique (SMOTE) was applied to address this imbalance. SMOTE is an over-sampling method that generates synthetic samples for the minority class by interpolating between existing instances. It was chosen over an under-sampling approach to avoid losing potentially useful data from the majority class. For SMOTE implementation, the parameter specifying the percentage of synthetic instances created was set to 100%, effectively doubling the number of minority class samples. The number of nearest neighbors used for generating synthetic samples was set to 5, which is the default parameter of the SMOTE algorithm and was not optimized in this study.

The classification results demonstrated that applying SMOTE effectively balanced the class distribution, resulting in improved performance for most classifiers. Ten classifiers were evaluated using the selected feature set, and the confusion matrix generated from the ten-fold cross-validation is presented in Table 7.6.

Table 7. 6: Confusion matrix of different classifiers.

Classifier	Classified as	a	b	Kappa
LR	a	178	8	0.8928
	b	12	175	
SVM	a	176	10	0.8392
	b	20	167	
RF	a	174	12	0.8713
	b	12	175	
RT	a	167	19	0.8284
	b	13	174	
NB	a	178	8	0.8713
	b	16	171	
J48	a	172	14	0.8606
	b	12	175	
MLP	a	178	8	0.8820
	b	14	173	

Additionally, the classifiers were compared based on several metrics, including accuracy (Accu), true positive (TP) rate, false positive (FP) rate, precision (PPV), F1-score (F), and the area under the receiver operating characteristic (ROC) curve (AUC), as summarized in Table 7.7.

Table 7. 7: Evaluation of the classifiers in terms of different metrics.

Classifier	Evaluation metrics, %					
	Accu	TP	FP	PPV	F	AUC
LR	94.6	94.6	5.4	94.7	94.6	98.7
SVM	92.0	92.0	8.0	92.1	92.0	92.0
RF	93.6	93.6	6.4	93.6	93.6	98.4
RT	91.4	91.4	8.6	91.5	91.4	91.7
NB	93.6	93.6	6.4	93.6	93.6	97.6
J48	93.0	93.0	7.0	93.0	93.0	96.2
MLP	94.1	94.1	5.9	94.1	94.1	98.1

Based on the evaluation metrics summarized in Figure 7.7, Logistic Regression achieved the best overall performance for this dataset. Logistic Regression obtained the highest accuracy (94.6%), TP rate (94.6%), precision/PPV (94.7%), F-measure (94.6%), and the highest

AUC value (98.7%), indicating excellent classification ability. These results suggest that Logistic Regression is the most suitable classifier for predicting daily inhaler adherence in this study.

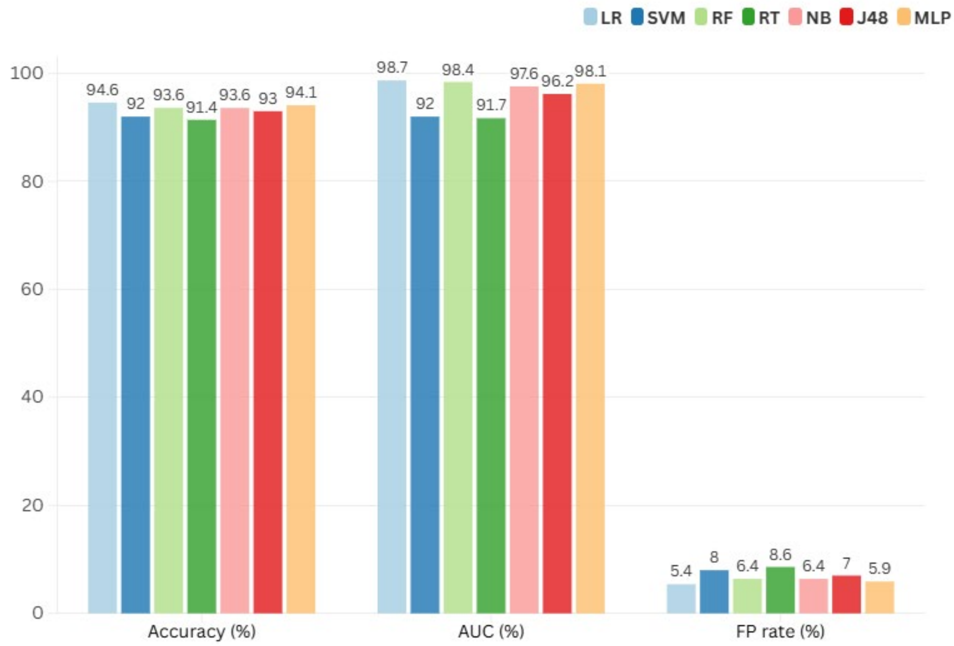


Figure 7. 7: Bar diagram showing accuracy (%), AUC (%), and FP rate (%) of different classifiers.

The feature selection process was conducted using Weka, with InfoGainAttributeEval as the attribute evaluator and Ranker as the search method to rank attributes by importance (see Figure 7.8). The evaluation was performed using the full training set, which allows for a comprehensive assessment of attribute importance across the entire dataset. This approach was chosen to capture the complete distribution of data, reflecting the key influencing factors in the observed environment.

Results indicate that emotional experience and air quality (PM2.5) are the two most significant attributes influencing patients' daily inhaler adherence. Emotional data, encoded by grouping based on valence (pleasantness) and arousal levels, revealed distinct patterns in adherence behavior. Analyzing the distribution of inhaler usage across different emotional states reveals that high-arousal positive emotions are associated with a high proportion of inhaler usage cases, while low-arousal negative emotions predominantly consist of non-usage cases. For low-arousal positive emotions, there is a balanced distribution with a slightly higher proportion of non-usage cases. Furthermore, Spearman correlation analysis identified a statistically significant positive correlation between PM2.5 levels and inhaler usage (Spearman's $\rho = 0.515$, $p < 0.001$), suggesting that higher PM2.5 levels are moderately associated with increased adherence. The consistency between the InfoGain ranking and the Spearman correlation results supports the robustness of PM2.5 as a key environmental factor in influencing adherence.

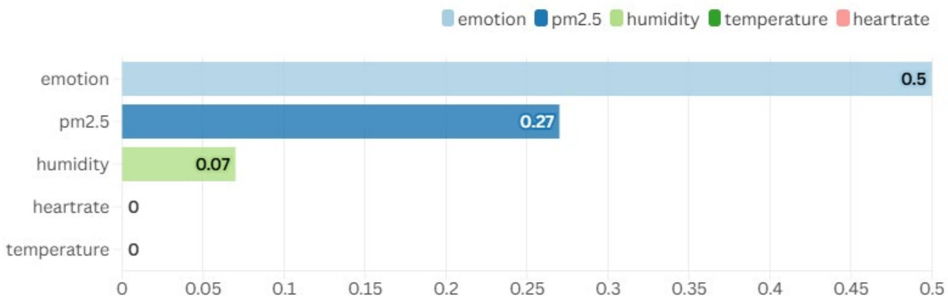


Figure 7. 8: Feature importance.

7.5 Discussion

7.5.1 Usability Evaluation of XIAOXI

The current XIAOXI system demonstrates strong usability and acceptance among both patients and HCPs. The Chatbot Quality and Technology Acceptance evaluation showed high scores across key dimensions such as naturalness, information delivery, interpretability, and technology acceptance, with no significant differences between HCPs and patients. Additionally, the SUS scores averaged 83.25 for patients and 88 for HCPs, both well above the industry standard benchmark(Kadariya et al., 2019) , indicating positive perceptions of the system's usability and experience. Users appreciated the intuitive design, clear feedback mechanisms, and personalized interactions. The chatbot's natural and empathetic communication style received particular praise, aligning with previous research emphasizing the importance of conversational agents in enhancing patient engagement(Aggarwal et al., 2023; Z. Chen et al., 2020; Chowdhury & Haque, 2023).

XIAOXI's empathetic, personalized feedback effectively engages patients and enhances their comprehension of health data. The metaphorical interfaces are not only engaging and visually appealing but also protect user privacy through abstract imagery, disguising sensitive health information and addressing psychological needs. In our study, patients appreciated that even if someone glimpsed their screen, the nature of the information was not immediately apparent, thus preserving their privacy. This observation aligns with research suggesting that privacy management should be systematically integrated into intervention system designs, considering cognitive aspects (e.g., aesthetics and comprehensibility) as well as psychological aspects (e.g., privacy and comfort)(Ackerman & Mainwaring, 2005; Al Ameen et al., 2012).

For example, Wu et al. (2021) emphasized the importance of privacy in telepresence interface design for older adults by incorporating specific features into the 'InTouch' UI. These privacy-enhancing elements included controls to restrict certain rooms from the telepresence robot, such as blocking access to private areas like bedrooms. Inspired by this, future iterations of XIAOXI could incorporate features like data anonymization, role-based access control, and user-adjustable privacy settings to provide users with more control over their information and enhance their overall sense of security(Ataei et al., 2018; Cavoukian, 2012). These features would not only safeguard user data but also align with individual privacy preferences, fostering greater user trust and adoption.

Despite the high usability ratings from HCPs, it is important to note that these evaluations were based on their perception of the system as used by patients, not necessarily as a tool for their own clinical practice. Balancing the needs of both HCPs and patients is critical for ensuring the system's effectiveness and widespread adoption(Morgan et al., 2015; Pakianathan et al., 2024). HCPs acknowledged that XIAOXI has the potential to be integrated into clinical healthcare systems, allowing them to access patient data more effectively. However, a crucial consideration is whether XIAOXI can be seamlessly incorporated into existing healthcare infrastructures without increasing the workload of HCPs(Ye, 2021).

Potential barriers include compatibility with current health information systems, data security concerns, and the risk of information overload, which could disrupt HCPs' decision-making processes(Pakianathan et al., 2024). Applying progressive disclosure—a design principle where only essential information is shown initially, with additional details available upon request—could help minimize cognitive load for HCPs(Springer & Whittaker, 2018). The primary goal should be to integrate XIAOXI's features into Electronic Health Record (EHR) systems in a manner that supports clinical workflows while reducing cognitive strain(Windle et al., 2021). Such design improvements would enable HCPs to access actionable insights without additional data entry burdens, aligning with effective clinical decision support principles (Hoffmann et al., 2020; Horsky et al., 2012).

7.5.2 Effectiveness of the XIAOXI in Enhancing Adherence

The 28-day controlled experiment involving 20 participants—10 in the experimental group using XIAOXI and 10 in the control group—demonstrated that the XIAOXI system significantly improved adherence among asthma patients. This improvement was particularly evident in the increase in TAI scores within the experimental group.

A key strength of the XIAOXI system lies in its ability to integrate real-time feedback with traditional adherence tracking methods such as the TAI questionnaire. The TAI provides a valuable snapshot of overall patient behavior over a set period(Muneswarao et al., 2021; Plaza et al., 2016), but it may overlook daily variations in adherence(Schoenwald & Garland, 2013; Shi et al., 2010). In contrast, XIAOXI enables day-to-day tracking, offering users immediate feedback and progress reports through its chatbot interface. This enhances the precision of adherence monitoring and provides timely interventions through reminders, effectively preventing lapses in medication usage.

The combination of subjective patient-reported adherence (via TAI) and objective sensor-based data from XIAOXI—such as inhaler usage frequency and technique—creates a more comprehensive view of patient behavior(Linn et al., 2011; Shi et al., 2010). Notably, XIAOXI's ability to continuously monitor inhaler technique, including medication loading, inhalation angle and duration, represents a significant advancement over traditional clinical assessments, which are typically limited to specific time points during clinical visits. Continuous monitoring allows for the detection of real-world behaviors and habitual errors that may be missed in controlled clinical settings(Normansell et al., 2017).

Qualitative feedback from post-experiment interviews further supports the effectiveness of XIAOXI. Participants reported that real-time feedback and environmental monitoring not only enhanced their confidence in using the inhaler but also helped them maintain a sense of control over their treatment. The system's motivational support, combined with daily adherence reports, reduced uncertainty and added structure to their medication routines. Although cultural beliefs about drug toxicity were not entirely altered during the intervention, XIAOXI helped patients better understand the benefits of consistent inhaler use, thereby reducing the likelihood of missed doses.

These findings suggest that while short-term interventions can positively influence adherence behaviors, addressing deeply ingrained cultural beliefs may require longer-term efforts(Shahin et al., 2019). Incorporating belief-related theories, such as the HBM or SCT, could be effective in designing future interventions that target these beliefs. These models emphasize modifying health-related behaviors by reshaping perceptions of risks, benefits, and self-efficacy(Simon, 2013; Y. Zhang & Zhao, 2021; Y. C. Zhao et al., 2022), offering a theoretical basis for sustained improvements in adherence. Future iterations of XIAOXI could leverage these theoretical frameworks to drive more sustainable behavioral changes and deeper cultural shifts in adherence.

7.5.3 Performance of Machine Learning Models in Classifying Daily Inhaler Usage as an Adherence Behavior

The machine learning-based classification of daily inhaler usage—specifically identifying whether patients fully completed their inhaler usage or partially/completely missed it—using retrospective data collected by the XIAOXI system, provided valuable insights into patient adherence behaviors. In this study, daily inhaler usage completion was treated as a primary behavioral indicator of adherence, making this classification task directly relevant to understanding patient adherence patterns.

Among the classifiers evaluated, Logistic Regression (LR) demonstrated the highest overall performance, achieving superior results in accuracy, true positive rate, precision, F-measure, and the area under the ROC curve (AUC). These findings align with previous studies that highlight LR's effectiveness in datasets characterized by relatively clear linear relationships and moderate dimensionality(Bae et al., 2022; Tsang et al., 2022; Xiong et al., 2023). The robust performance of LR in this study likely stems from its capability to effectively model linear relationships between predictor variables and binary outcomes, making it particularly effective for well-defined binary adherence classification tasks(Bae et al., 2022; Eguchi et al., 2022; Kumamaru et al., 2018).

A key innovation in this study was the inclusion of emotional data, which was processed using quadrant encoding. This method categorized emotional experiences based on their valence (pleasantness) and arousal levels(Gerdes et al., 2010). Compared to previous adherence studies that primarily focused on demographic and clinical data, integrating emotional data provided novel insights into patient behavior, emphasizing emotional states as critical but previously underexplored predictors of adherence. The results revealed that low-arousal negative emotions (e.g., calm unpleasantness) were strongly correlated with incomplete or missed inhaler usage, suggesting that patients experiencing low levels of arousal may lack the motivation to maintain daily adherence routines. These findings are consistent with psychological theories linking low-arousal negative emotions to reduced action or urgency, potentially leading to neglect in following prescribed routines(Bodenhausen, 1993; Boekaerts, 2010).

In contrast, environmental factors, particularly PM2.5 levels, exhibited a positive correlation with adherence. Patients were more likely to follow inhaler usage guidelines when pollution levels were elevated, likely due to increased symptom awareness or heightened concern about environmental triggers. This behavior is supported by previous research indicating that poor air quality exacerbates asthma symptoms, prompting patients to use their inhalers more consistently as either a preventive or reactive measure(Delfino et al., 2002; Tiotiu et al., 2020).

These findings underscore the importance of adopting a multi-dimensional approach to understanding daily inhaler usage as a specific, measurable adherence behavior. Future iterations of the classification model could integrate additional adherence-related factors identified from the theoretical framework in Study 1, such as patient ability, device usability, and cultural beliefs, to develop more holistic models that fully capture the complexities of inhalation adherence behaviors. For instance, patient ability could be evaluated through functional assessments, such as lung function tests or inhaler knowledge evaluations, to capture physical and cognitive capabilities relevant to proper inhaler usage(J. R. Lee et al., 2021; Usmani, 2019). Furthermore, device usability could be assessed using patient-reported outcomes regarding ease of use, handling, and maintenance of inhaler devices(Dal Negro et al., 2019). Cultural beliefs could be quantified through surveys evaluating attitudes toward medication(Shahin et al., 2019). Expanding the dataset to include these dimensions would enable the development of more comprehensive and holistic classification models that better capture the full range of factors influencing inhaler usage completion.

Although this analysis was retrospective, classifying daily inhaler usage based on previously collected data, the high accuracy achieved underscores the potential of sensor-based monitoring combined with emotional data to effectively identify adherence risks and understand patient behavior patterns in asthma and COPD populations. This retrospective classification validates the effectiveness of machine learning algorithms, particularly Logistic Regression, in distinguishing between adherent and non-adherent behaviors. This not only provides critical insights into patient adherence patterns but also informs future real-time adherence monitoring and proactive intervention strategies.

However, the retrospective design implies that predictive performance in prospective, real-world settings may differ. Future research should thus focus on the prospective application of these validated models, transitioning from retrospective analysis to real-time detection and timely support for incomplete or missed inhaler usage. This transition would mark a significant step toward proactive health management, enabling early intervention and potentially reducing the risk of exacerbations and hospitalizations in asthma and COPD patients.

7.6 Conclusion

This chapter presented the key findings on the usability of the XIAOXI system, its effectiveness in supporting patient inhalation adherence, and the application of machine learning models for classifying daily inhaler usage based on retrospective data. The usability evaluation demonstrated high acceptance among both patients and HCPs, particularly emphasizing the system's engaging interface design, intuitive user experience, and real-time feedback capabilities. These features contributed to a positive user experience, fostering confidence and promoting consistent adherence to inhalation therapy.

The integration of sensor-based monitoring with traditional adherence questionnaires enabled a comprehensive evaluation of daily inhaler usage, providing precise identification of completed versus incomplete inhaler usage events. This multi-dimensional monitoring approach allowed for real-time assessments, empowering users to understand their own adherence behaviors and make timely adjustments.

Among the classifiers evaluated, LR achieved the highest overall performance, demonstrating strong accuracy, true positive rate, precision, F-measure, and AUC. These results validate the potential of machine learning methods, particularly LR, to effectively distinguish between days with completed inhaler usage and days with incomplete or missed usage. The high classification accuracy highlights the feasibility of using relatively simple, interpretable models for adherence monitoring, aligning with the need for practical and understandable solutions in clinical settings.

Future research should incorporate additional influencing factors identified in earlier studies—such as patient ability, device usability, and cultural beliefs—to enhance model comprehensiveness. Moreover, expanding sample sizes and conducting prospective validations will be crucial for transitioning from retrospective classification to real-time adherence monitoring, ultimately improving the effectiveness and scalability of intervention systems like XIAOXI.

Chapter 8 Discussion

8.1 Introduction and Aims

The overall aim of this thesis was to investigate how sensor-based interventions, guided by HFE principles, can enhance patient adherence to inhalation therapy for chronic respiratory conditions such as asthma and COPD. This study primarily focuses on three key areas: 1) understanding the HFE factors influencing patient adherence to inhalation therapy, 2) designing and developing a sensor-based intervention system, and 3) assessing the effectiveness of the system in supporting patient adherence, and classifying adherence behaviors through data-driven approaches. These themes are explored in turn within this discussion:

1. Application and evaluation of the Patient Adherence to Inhalation Therapy Work System Model,

2. The role of HFE in enhancing adherence to inhalation therapy, and

3. The strengths and challenges of data-driven approaches to supporting adherence.

8.2 Application and Evaluation of the Patient Adherence to Inhalation Therapy Work System Model

8.2.1 Framework and Application of the Patient Adherence to Inhalation Therapy Work System Model

The SEIPS 2.0 model provides a comprehensive HFE framework for systematically understanding and optimizing patient safety and adherence behaviors within healthcare systems(Martinez et al., 2017; Werner et al., 2020). Building upon this foundation, the Patient Adherence to Inhalation Therapy Work System Model was developed to specifically address the challenges associated with adherence to inhalation therapy, particularly for patients with asthma and COPD(Aldan et al., 2022; Ayele & Tegegn, 2017; Gutiérrez et al., 2017; Khdour et al., 2012; Monteiro et al., 2021). While this model is informed by the SEIPS 2.0 framework(Holden et al., 2013), it incorporates adapted dimensions—Person, Task, Tool, Physical Environment, and Culture & Social—designed to capture the complex interactions influencing patient adherence behaviors in the context of inhalation therapy.

The model identifies nine key factors influencing adherence, including patient ability, emotional experience, task type, frequency and flexibility of use, inhaler type and usability, daily environment, cultural beliefs, and social stigma. These factors interact to shape patients' adherence behaviors and outcomes. Notably, this model highlights specific adherence barriers, such as emotional experiences(A. Agarwal & Meyer, 2009; Bonito et al., 2013; De Angeli et al., 2020), environmental influences(Bamashmoos et al., 2018; Dong et al., 2019; Fong & Fong, 2011), and cultural beliefs(Andrews & Jones, 2009; Emilsson et al., 2011; Fischer et al., 2018; Md Hatah et al., 2015), which emerged as particularly significant in this study. Addressing these barriers requires targeted interventions aimed at improving adherence by directly confronting emotional challenges, adapting to environmental factors, and countering cultural misconceptions related to inhaler use.

The Person-Task-Physical Environment structure used in deploying the XIAOXI system was derived from an extensive synthesis of literature on sensor-based interventions for chronic respiratory diseases (e.g., Bowler et al., 2019; Chakraborty et al., 2023; Hasegawa et al., 2023; Pradeesh et al., 2022). This synthesis revealed that sensor data could be effectively categorized into these three dimensions: Person (patient behavior and physiological data), Task (inhaler usage and adherence patterns), and Physical Environment (external conditions like air quality and temperature).

Interestingly, this structure aligns with the theoretical framework developed through semi-structured interviews, which similarly identified Person, Task, and Physical Environment as critical dimensions in patient adherence to inhalation therapy(Ma et al., 2023). This alignment further underscores the model's practical relevance. Organizing sensor data within these dimensions allows for a comprehensive approach to identifying adherence challenges and designing tailored interventions.

Furthermore, the model's alignment with the "Person-Task-Physical Environment" structure enhances its capacity not only to support real-time monitoring and deliver personalized interventions but also to evaluate their effectiveness in addressing patient-specific needs and improving inhalation therapy outcomes(M. A. Barrett et al., 2017; A. H. Y. Chan, Stewart, et al., 2015; Hesso et al., 2020). The model facilitates thorough evaluation by examining whether the interventions lead to improvements across the core dimensions of the work system. By systematically assessing these dimensions pre- and post-intervention, the model provides a comprehensive view of whether the interventions have successfully mitigated identified barriers and enhanced overall adherence behaviors.

8.2.2 Evaluation and Validation of the Patient Adherence to Inhalation Therapy Work System Model

The Patient Adherence to Inhalation Therapy Work System Model was developed to address specific adherence challenges in the context of inhalation therapy for asthma and COPD patients. This model draws from the SEIPS 2.0 framework but extends it by focusing on factors that uniquely influence patient adherence. The implementation of the XIAOXI system provided an opportunity to evaluate how the model's core dimensions—Person, Task, Tool, Physical Environment, and Culture & Social—were applied in practice and whether they effectively addressed adherence barriers.

Person Dimension: The Person dimension in the Patient Adherence to Inhalation Therapy Work System Model integrates patient ability and emotional experience, both of which played a crucial role in supporting patient self-management during inhalation therapy. In this study, heart rate sensors were deployed to monitor patients' physiological conditions, providing real-time insights into their physical state during inhaler use. Additionally, patients conducted self-assessments of their disease control via questionnaires, enabling them to better understand and track their health status. The XIAOXI system also provided disease-related knowledge, which patients reported as valuable for improving their understanding of their condition.

Notably, patients indicated that the combination of physiological monitoring, self-assessment tools, and educational content gave them a clearer sense of control over their condition, which they perceived as beneficial for adherence. These findings highlight that tools designed to support physical and cognitive abilities are valuable for empowering patients in managing their disease(R. M. Anderson & Funnell, 2010; Bravo et al., 2015). Furthermore, the scope of the Person dimension could be expanded by incorporating additional physiological indicators, such as blood oxygen levels (SpO_2) and lung function metrics, which are particularly relevant for asthma and COPD management(Dierick et al., 2022; Hale et al., 2023; Pradeesh et al., 2022; Raji et al., 2016). Integrating these measures would offer patients a more comprehensive understanding of their physiological state, potentially enhancing self-management practices and improving adherence to inhalation therapy.

This study highlighted the significant impact of emotional experience on patient adherence to inhalation therapy. A key contribution was the inclusion of emotional data, collected using the Emocard questionnaire and categorized through quadrant encoding based on valence (pleasantness) and arousal levels(Gerdes et al., 2010). The findings showed that low-arousal negative emotions were strongly linked to non-adherence, suggesting that such emotional states may reduce motivation for regular inhaler use. Additionally, the XIAOXI system provided encouraging feedback during inhaler use, which helped reduce the boredom often associated with the repetitive inhalation process, making patients feel more engaged. This emphasizes the need to integrate emotional considerations into intervention designs to improve adherence(Bukstein, 2016; Norman, 2007; Rekaya et al., 2020).

Although the Emocard provided useful insights, future research could enhance emotional monitoring by incorporating more advanced multimodal techniques, such as facial expression recognition, voice tone analysis, or physiological electrical signals (M. G. Calvo & Nummenmaa, 2016; Moridis & Economides, 2012; Stikic et al., 2014). For example, one study by Daly et al. (2015) demonstrated that galvanic skin response (GSR) can effectively measure users' emotional states, as it was used to verify the intended affective responses induced by an affectively driven music generation system. These techniques could enable real-time emotional assessments and dynamic adjustments to feedback, potentially improving engagement and adherence.

Task Dimension: The Task Dimension encompasses two key components: Task Type and Frequency and Flexibility. Task Type focuses on inhaler technique guidance, inhaler usage monitoring, and reminders provided by the system to ensure proper use of the device. In this study, the XIAOXI system played a central role by delivering feedback and reminders based on monitored usage data. Specifically, the system captured critical steps of the inhalation process, such as inhaler orientation and duration of use, helping patients adjust their technique according to these key factors.

The Frequency and Flexibility component is reflected in the system’s provision of daily and weekly adherence reports, offering patients a comprehensive overview of their adherence to inhalation therapy across all dimensions of the Patient Adherence to Inhalation Therapy Work System Model. These reports covered not only inhaler usage but also included feedback on critical factors such as patient ability, emotional experience, and environmental influences. The daily reports allowed patients to track their progress in real-time, identifying missed doses or deviations from their prescribed routine. Additionally, the system provided a weekly summary of adherence patterns, allowing patients to reflect on longer-term trends and performance. Patients responded positively to these reports, noting that they helped integrate inhalation therapy more smoothly into their daily lives. This flexible, comprehensive feedback system empowered patients to proactively adjust their routines, addressing any barriers to adherence and reinforcing their self-management efforts(R. M. Anderson & Funnell, 2010; M. A. Barrett et al., 2017; Bravo et al., 2015; Cadel et al., 2021).

However, while the system effectively monitored key aspects of inhaler use, the current IMU sensors did not capture the entire inhalation process, focusing mainly on steps such as inhaler orientation(Hasegawa et al., 2023). Future developments could enhance the Task Dimension by integrating additional sensors, such as flow sensors and sound sensors, to monitor the full inhalation process and provide more detailed feedback on technique(Dierick et al., 2022; O'Dwyer et al., 2016). For example, Taylor et al. (2018) developed an audio-based method to estimate inhalation flow profiles, using sensors to remotely monitor patient inhaler technique. This approach demonstrated high accuracy and potential clinical benefits for assessing inhalation parameters such as peak inspiratory flow and inspiratory capacity, contributing to improved monitoring of patient adherence to inhalation therapy. This would allow patients to receive more comprehensive guidance on their inhalation performance, potentially further improving adherence.

Moreover, the feedback on inhaler technique provided by the system is not real-time. Future iterations could explore the use of real-time feedback mechanisms, such as audio-visual feedback, to guide patients during inhaler use(A. H. Y. Chan, Stewart, et al., 2015; O'Dwyer et al., 2016). Real-time feedback could offer immediate corrections, reinforcing proper inhaler usage and ensuring a more engaging and responsive user experience(Chakraborty et al., 2023; C.-

Y. Huang et al., 2018; Kamei et al., 2022). Additionally, while the current adherence reports are patient-focused, future iterations could develop a customized panel for HCPs. This HCP panel could present adherence-related data tailored to the specific needs of HCPs, allowing them to monitor patient adherence more closely and intervene when necessary(Hill et al., 2020; Phillips et al., 2011). By integrating key adherence metrics and patient progress visualizations, this dashboard could help identify areas requiring additional guidance or intervention, further strengthening the support provided by the system(Valero-Ramon et al., 2023; J. C. Wong et al., 2018).

Tool Dimension: The Tool Dimension encompasses two key aspects: Type of Inhalers and Usability of Inhalers. The Type of Inhalers refers to patient preferences for different inhaler designs, while Usability of Inhalers involves patients' assessments of the device's ease of use and their overall satisfaction with the therapy. In this study, patients were given questionnaires to self-evaluate their experiences with both aspects of the inhaler. While no single inhaler design can fully meet all patients' needs, the XIAOXI system provided valuable support in bridging the usability gaps inherent in inhalers.

One key outcome from the effectiveness evaluation was the role that XIAOXI played in making the inhalation process more engaging and less monotonous for patients. By offering personalized feedback, encouraging messages, and interactive features, XIAOXI improved patients' perceptions of their inhaler experience. Patients felt more supported and connected to their treatment, which mitigated some of the frustrations associated with the repetitive nature of inhalation therapy. This suggests that the usability of the intervention system—in this case, XIAOXI—can enhance the overall experience of inhalation therapy, even when the physical design of the inhaler itself remains unchanged(Hentati et al., 2021; Nesvåg & McKay, 2018). XIAOXI's interactive and responsive features helped to address some of the emotional and cognitive barriers that patients face, making the treatment more tolerable and even enjoyable. By creating a positive feedback loop that tackled both emotional and cognitive barriers, XIAOXI increased patients' engagement with their therapy, ultimately leading to higher satisfaction with the treatment process(Morrison, 2015; Patrick et al., 2016).

The enhanced usability of the system translated into better adherence, as patients were more likely to stick to their prescribed regimens due to the consistent support provided by XIAOXI. While these findings were observed within the 28-day intervention period, the long-term effects of XIAOXI's usability on patient adherence remain an open question(Ngwatu et al., 2018; Velardo et al., 2017; Woods et al., 2023). It is unclear whether the system's ability to enhance the inhalation experience can be sustained over extended periods. Further research is needed to determine whether these positive effects continue over time, and whether prolonged use of the system could lead to consistent improvements in adherence and patient satisfaction(Vrijens et al., 2008; Zwikker et al., 2014).

Conducting longitudinal studies would be essential to understanding whether XIAOXI's usability continues to offer similar benefits or whether the novelty of the system wears off, potentially requiring new strategies to maintain patient engagement and adherence. Future developments could also explore additional features that enhance usability, such as adaptive interfaces or interactive tutorials that guide patients through the inhalation process step by step(Fedele et al., 2018; C.-Y. Huang et al., 2018; N. Li et al., 2018). These enhancements could further solidify the system's role in supporting long-term adherence by continuously engaging patients in their therapy routine.

Physical Environment Dimension: The Physical Environment Dimension in the Patient Adherence to Inhalation Therapy Work System Model centers on daily living conditions, particularly the impact of temperature, humidity, and air quality on patient adherence. In this study, the XIAOXI system monitored these environmental factors in real-time, providing patients with critical insights into how their surroundings might influence their need for inhalation therapy. Machine learning analysis of the sensor data revealed that air quality, specifically PM2.5 levels, had a significant impact on adherence. Patients were more likely to use their inhalers when air quality worsened, demonstrating the direct connection between environmental conditions and symptom management in asthma and COPD patients(Delfino et al., 2002; Tiotiu et al., 2020).

While temperature and humidity did not show a strong correlation with adherence in this analysis, these factors may still play an indirect role by affecting comfort and convenience during inhaler use. For instance, extreme temperatures or high humidity levels may reduce patients' comfort during physical activity or limit their willingness to go outdoors, indirectly impacting their routine and inhaler use(Eschenbacher et al., 1992; H. C. Lam et al., 2016). It is worth noting that the study was conducted during the spring season, which may explain the lack of significant variation in temperature and humidity. Future studies conducted during more extreme weather conditions, such as summer heat or heavy humidity, could provide deeper insights into how these factors might influence patient adherence.

Although XIAOXI currently monitors indoor environmental factors, particularly within home settings, future iterations could expand its capabilities to include other environments where patients spend significant time, such as workplaces or outdoor areas(Dales et al., 2004; Guarnieri & Balmes, 2014). Extending the system to monitor outdoor environmental factors like ozone levels, pollen counts, or other allergens, as well as improving the accuracy of indoor measurements for ventilation and air pollution, would provide a more comprehensive understanding of how different environments affect adherence(W. Anderson et al., 2001; d'Amato et al., 2020). This broader scope of monitoring could enable the system to deliver more personalized and context-specific recommendations, better addressing environmental triggers that influence respiratory conditions(Darrow et al., 2012; White et al., 1994).

Culture and Social Dimension: Under the Culture and Social Dimension, both Cultural Beliefs and Social Stigma play substantial roles in shaping patient adherence behaviors. Many patients in this study held traditional beliefs, such as "All medicine has poison to some degree," which negatively impacted their approach to inhaler use and overall adherence. To address these challenges, the XIAOXI system provided educational content aimed at helping patients better understand the necessity and benefits of consistent inhaler use. Although these deeply ingrained beliefs are not easily changed, the system supported patients in recognizing the value of regular adherence, even if complete shifts in mindset were not achieved during the intervention period. This indicates that while Cultural Beliefs remain a strong influence, educational tools and consistent feedback can still help mitigate their impact(Simon, 2013; Vaughn et al., 2009).

However, addressing such deeply rooted beliefs requires a long-term approach that extends beyond short-term interventions(Shura et al., 2011; Vaughn et al., 2009). Future research should focus on designing sustained educational programs and interventions that provide consistent, tailored guidance over extended periods(Gold &

McClung, 2006). This could include reinforcing positive medication behaviors through regular educational content, periodic check-ins with HCPs, and community-based initiatives aimed at gradually shifting traditional views(K.-J. Son et al., 2019). With ongoing dialogue and targeted interventions, future systems could help guide patients toward more health-positive beliefs, reducing the influence of cultural misconceptions on treatment adherence(Araújo-Soares et al., 2018; Brooks et al., 2019).

In terms of Social Stigma, the XIAOXI system incorporated persuasive elements such as peer comparisons, self-efficacy assessments, and achievement recognition to counteract psychological barriers associated with inhaler use in public or perceived dependence on medication. These features boosted patient confidence and reduced the negative impact of social stigma, allowing patients to focus more on their treatment without feeling judged. Patients responded positively to these elements, highlighting the value of creating a supportive and encouraging environment to alleviate stigma-related barriers(De Gennaro et al., 2020; Grossman et al., 2017; Kelders et al., 2012; Latalova et al., 2014).

Further research could explore integrating additional persuasive elements into the XIAOXI system or similar platforms to enhance patient engagement. Techniques such as gamification, reward systems, or social support networks could make the treatment process more interactive and motivating, helping to sustain patient interest over time(De Simoni et al., 2021; Miller et al., 2016; Sardi et al., 2017). In particular, social support could foster peer-based communities where patients share experiences, find encouragement, and reduce feelings of isolation(DiMatteo, 2004; Fernandes et al., 2018). Optimizing these persuasive features to resonate with diverse patient populations could enable future interventions to be more effectively tailored to individual needs, leading to improved adherence outcomes and greater patient satisfaction(Ali Alkhoshaiban et al., 2019; Alwashmi et al., 2021; L. J. Anderson et al., 2020).

8.3 The Role of HFE in Enhancing Adherence to Inhalation Therapy

8.3.1 Integrating HFE into the Design and Development of Drug-Device Combination Inhalers

HFE is essential throughout the lifecycle of DDCPs like inhalers, where precise and repeated user interactions are required to ensure proper device operation(Hegde, 2013; Leiner et al., 2015). Incorporating HFE principles into the design of inhalation devices enhances usability, reduces error, and aids patient compliance by lowering the cognitive load and frustration often associated with complex device designs(Barber et al., 2005; Holden et al., 2021). Patients using inhalers must perform specific actions, such as medication loading or inhalation, which can be particularly challenging for individuals managing long-term respiratory conditions like asthma and COPD. These patients may experience poor lung capacity, difficulty coordinating inhalation with the device, or limited hand strength or dexterity, making precise and consistent use of the inhaler problematic(García-Cárdenas et al., 2012; Giner et al., 2020; Ma et al., 2023).

By applying HFE principles in the early stages of the design process, designers and researchers can identify and address usability issues, ensuring that the resulting devices are more intuitive and meet the diverse needs of users(Leiner et al., 2015). For instance, Smyth et al. (2018) demonstrated that integrating HFE into inhaler design significantly reduces technical errors by simplifying device operation and improving overall patient adherence, which is crucial for the success of inhalation therapy. This user-centered approach not only improves safety and effectiveness but also increases the likelihood that patients use their inhalers correctly and consistently(Barber et al., 2005; Carayon & Wooldridge, 2020).

Despite these advances, certain patient populations, particularly those with severe cognitive or physical impairments, may continue to face challenges in using inhalers effectively(H. Y. Lee et al., 2021; Lexmond et al., 2014). While HFE can address many usability concerns, some complexities in device design persist. This underscores the need for future inhaler designs to adopt more personalized approaches, potentially incorporating adaptive technologies or simplified mechanisms to accommodate a broader range of patient needs(de Boer et al., 2017; Hickey, 2013). Additionally, as regulatory guidelines increasingly emphasize the integration of HFE in medical device development—particularly for DDCPs—manufacturers are required to ensure that their devices are not only compliant but also designed with the patient experience in mind(Beaman & Wallace, 2009; Medicines & Healthcare products Regulatory Agency, 2017; Singh et al., 2023). This growing recognition of HFE's role reflects its capacity to address both ergonomic and cognitive challenges, ultimately improving patient outcomes and adherence(J. Anderson et al., 2010; Carayon et al., 2006; Carayon & Wooldridge, 2020).

8.3.2 Integrating HFE into Understanding Patient

Interactions with Inhalers and Digital Adherence Systems

HFE not only informs the design of inhalers but also provides crucial insights into patient behavior, particularly how patients interact with both their devices and digital intervention systems. In this study, the application of HFE methodologies—specifically the SEIPS 2.0 model—enabled the identification of nine key factors influencing patient adherence. However, emotional factors—such as anxiety related to device noise and boredom stemming from the repetitive nature of inhalation therapy—were identified through the HFE framework as significant contributors to non-adherence, insights that might have been overlooked without this structured approach(Ma et al., 2023). These findings underscore the critical role of HFE in not only understanding physical and cognitive challenges but also recognizing the emotional dimensions that shape patient behavior(Reinares-Lara et al., 2019; J. Turner & Kelly, 2000). For example, XIAOXI's feedback mechanisms were specifically designed to mitigate boredom and alleviate anxiety, making the inhalation process more engaging and emotionally supportive for patients. This user-centered design approach, grounded in HFE principles, contributed to a more positive experience, which in turn encouraged better adherence.

Beyond patient-device interaction, HFE plays a fundamental role in understanding how patients engage with digital adherence systems, such as the XIAOXI system. During the development of XIAOXI, participatory workshops were instrumental in aligning the system's design with the real-world needs of patients and HCPs(Abdolkhani et al., 2020; Z. Chen et al., 2020; Davies et al., 2020; Davis et al., 2018; Donetto et al., 2015). End-users actively contributed to the design of key features, feedback mechanisms, and overall functionality, ensuring that the system effectively addressed patient preferences and challenges.

To facilitate this process, Personas and Scenarios were employed during the workshops to identify typical patient profiles and usage contexts, ensuring that the system was both intuitive and relevant (Lopez-Lorca et al., 2014; Massanari, 2010; Nißen et al., 2022). These insights informed the development of features that enhanced usability, making the system more user-friendly and aligned with patients' daily routines. For future research, these workshops could be expanded to include a wider variety of stakeholders, such as family members or inhaler manufacturers, whose perspectives could further enhance the system's design and usability(Lingg & Lütschg, 2020; Norris et al., 2017; Vogel et al., 2013). Including these additional stakeholders could not only optimize patient adherence but also contribute to a broader ecosystem of support, involving family care, manufacturer insights, and HCP engagement.

Evaluating these systems using structured HFE methodologies is equally critical. Tools such as the SUS and the TAM questionnaires, alongside interview guides informed by these models, provided both qualitative and quantitative insights into how patients interacted with the XIAOXI system(Borsci et al., 2022; Holden & Karsh, 2010; Holmes et al., 2019). Integrating questionnaire data with qualitative feedback allowed for a comprehensive understanding of how the system supported patient adherence and identified areas for further refinement(Bravo et al., 2015; R. A. Calvo et al., 2023). Future research could benefit from employing additional HFE evaluation methods, such as Cognitive Task Analysis (CTA) to explore how patients make decisions about their therapy, and Failure Mode and Effects Analysis (FMEA) to identify potential points of failure within the system(DeRosier et al., 2002; Holden et al., 2020). Expanding the range of HFE tools used in the evaluation process would provide a deeper, more nuanced understanding of how digital intervention systems like XIAOXI can be improved to better support adherence over time.

8.4 The Strengths and Potential Challenges of Data-Driven Approaches

8.4.1 Data Collection

The effectiveness of data-driven adherence interventions relies heavily on the collection of complete and accurate data from multiple dimensions and sources(Akhoundi & Valavi, 2010; Gravina et al., 2017; Kadariya et al., 2019). In the XIAOXI system, the "Person-Task-Physical Environment" framework is employed to collect data across different dimensions. For the Person dimension, heart rate data is collected to monitor patients' physiological states during inhalation therapy, while the Task dimension includes data on inhaler usage, capturing critical aspects of the inhalation process. The Physical Environment dimension tracks temperature, humidity, and air quality to assess how environmental conditions influence adherence. While this multi-dimensional framework has proven effective, there are opportunities to expand each dimension to enhance the comprehensiveness of data collection. For example, the Person dimension could be enriched with additional physiological indicators such as lung function and SpO2, which are essential for understanding patient health during inhalation therapy(Hale et al., 2023; Pradeesh et al., 2022; Siddiqui & Morshed, 2018). Emotional experiences could also be measured through physiological electrical signals, such as Galvanic Skin Response (GSR) or Photoplethysmography (PPG), enabling real-time monitoring of emotional states(Udovičić et al., 2017). For the Task dimension, integrating optical sensors could monitor inhaler maintenance and cleanliness by detecting residue buildup, offering a more comprehensive understanding of task performance(J. Wang & Dong, 2020). In the Physical Environment dimension, adding sensors for pollen or allergens could provide deeper insights into environmental factors affecting adherence(Hui et al., 2021).

Beyond sensor-based data, other dimensions of the Patient Adherence to Inhalation Therapy Work System Model, such as the Tool and Culture & Social dimensions, also require data collection through specific types of questionnaires. For instance, the XIAOXI system employed usability questionnaires for the Tool dimension to assess patient experiences with inhaler design and ease of use. The Culture & Social dimension included self-efficacy assessments to understand how cultural beliefs and social stigma influenced adherence. These methods provided valuable insights into patient behavior and perceptions; however, limitations in sample size underscore the need for further research to better integrate these dimensions into comprehensive, data-driven classification models that can enhance the understanding and management of adherence behaviors(Koesmahargyo et al., 2020; Y.-J. Son et al., 2010; Zakeri et al., 2022).

Furthermore, the reliability of sensor data is paramount to effective adherence monitoring. Since no single sensor is flawless, data fusion, which involves integrating data from multiple sources, is crucial for improving data validity and robustness across key indicators(Akhoundi & Valavi, 2010; Cui et al., 2022; Gui et al., 2015). For instance, while the current system uses an IMU to capture specific steps in the inhalation process, integrating advanced sensors like flow sensors or sound sensors could provide a more comprehensive understanding. These sensors could measure airflow dynamics, including the rate, consistency, peak inspiratory flow (PIF), and inhalation duration, helping to detect issues such as suboptimal speed or incomplete breaths(Dierick et al., 2022; Hale et al., 2023; O'Dwyer et al., 2016). Addressing these gaps could significantly improve the system's ability to monitor adherence accurately and provide actionable feedback.

Additionally, addressing privacy and security concerns in data collection is crucial to ensure patient trust and willingness to engage with the system(Masood et al., 2018; Yi et al., 2015). Implementing end-to-end encryption and adhering to GDPR standards can demonstrate a strong commitment to data security(Barati et al., 2019). Furthermore, transparent communication about data handling practices, encryption protocols, and compliance with privacy regulations can alleviate concerns, thereby encouraging more effective data collection and system engagement(Motti & Caine, 2015). Ensuring robust security measures not only protects patient information but also strengthens confidence in the system, supporting long-term engagement and adherence.

8.4.2 Data Processing

Data processing is a critical component of data-driven adherence interventions, transforming raw sensor data into actionable insights. In the XIAOXI system, patient behavior is analyzed to generate timely recommendations, but future capabilities could be significantly enhanced with improved data handling and advanced computational techniques(Bhat et al., 2021). A foundational step in the data processing pipeline is data preprocessing, which ensures that raw sensor data is clean, structured, and ready for analysis(Abate et al., 2014; Famili et al., 1997). In this study, data cleaning primarily focused on removing outliers to maintain data integrity. After cleaning, data aggregation was performed, where sensor data was summarized by calculating the daily median values to represent typical usage patterns(MacNeill et al., 2012). Emotional data, on the other hand, was processed separately by grouping it into four quadrants based on valence and arousal levels(Gerdes et al., 2010). This structured approach allowed for a meaningful analysis of both sensor-based and emotional data, providing deeper insights into adherence behavior.

Looking ahead, preprocessing could incorporate additional methods such as data imputation for missing values, advanced outlier detection techniques like clustering-based methods, and feature scaling to normalize sensor data, enhancing the accuracy of machine learning-based classification(Azar et al., 2022; Jiang et al., 2010). Further improvements might include time-series decomposition, which can help identify underlying trends and patterns in adherence behavior, providing a clearer picture of how patient usage evolves over time(Wiemken et al., 2019). These enhancements would not only improve data quality but also support more robust predictive modeling for adherence monitoring.

In terms of classification, advanced machine learning algorithms could further improve the predictive performance of the XIAOXI system. In this study, the Logistic Regression algorithm achieved the best results for classifying patient adherence behaviors. Its effectiveness is largely attributed to its ability to model clear linear relationships between predictor variables and binary outcomes, making it particularly well-suited for adherence classification tasks(Bae et al., 2022; Kanyongo & Ezugwu, 2023; Tsang et al., 2022). While Logistic Regression demonstrated strong performance, there remains significant potential to explore more advanced models, such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), which are particularly adept at handling time-series analysis and recognizing complex patterns across multiple sensor inputs(Gu et al., 2021; Mathivanan et al., 2024). These models could capture intricate temporal dependencies in patient behavior, potentially leading to even greater classification accuracy.

Additionally, reinforcement learning could be employed to adaptively personalize interventions in real time. Through deep reinforcement learning, the system could continuously optimize its recommendations based on real-world feedback, supporting long-term adherence and responding dynamically to changes in patient behavior(Abdellatif et al., 2021). Furthermore, integrating ensemble methods such as gradient boosting machines could enhance classification by combining the strengths of different algorithms, reducing errors, and increasing model robustness(Mateo et al., 2021; Yin et al., 2024). These collective improvements in data processing and analysis could significantly advance the XIAOXI system's ability to support patient adherence through more precise monitoring and adaptive intervention strategies.

8.4.3 Feedback Mechanisms

Feedback mechanisms are a critical element of data-driven adherence interventions, directly engaging patients by offering tailored insights. In the XIAOXI system, feedback is provided through multiple channels, including adherence reports, reminders, and chatbot interactions, all designed to encourage patients to remain engaged with their therapy. These mechanisms help patients monitor their progress and foster a sense of control over their treatment(Ivers et al., 2012; Scott et al., 2016).

Effective feedback presentation is crucial from a cognitive perspective, as patients need to comprehend and trust the data to be motivated to engage actively with their treatment(Faiola et al., 2015; Park et al., 2022). In this study, adherence data is primarily delivered through infographics. However, as the complexity of the data increases—especially with inputs from various sensor types, time scales, and user demographics—it becomes necessary to explore more refined methods of presenting this information(Cajamarca et al., 2020; Theis et al., 2017).

Different dimensions of data, such as long-term versus short-term adherence patterns or environmental versus physiological factors, may require distinct presentation strategies to optimize comprehension and usability without increasing cognitive load(E. W. Anderson et al., 2011; Faiola et al., 2015). Ensuring that feedback remains clear and intuitive is essential so that patients are not overwhelmed by excessive information. While this study primarily utilized graphic and text-based feedback, future iterations of the system could explore alternative feedback modalities. For example, multi-sensory engagement could be enhanced by using light or sound alerts to convey important information intuitively(Boll et al., 2010). Additionally, feedback mechanisms could extend beyond software interfaces, such as chatbots, to include hardware interfaces like display screens or sound alerts integrated into the sensor casing, providing direct prompts via the device itself(A. H. Y. Chan, Stewart, et al., 2015; Houghton et al., 2012; Wafaie et al., 2023).

From a psychological and emotional perspective, the study integrated persuasive elements such as achievement recognition and peer comparison to motivate adherence(Grossman et al., 2017; Kelders et al., 2012). While the current system personalizes feedback based on patient behavior, future mechanisms could further leverage personalization by incorporating patients' cultural beliefs, communication preferences, and emotional status(De la Fuente-Martos et al., 2018; Palumbo, 2016). Adapting feedback to match a patient's cultural context or emotional state could significantly enhance engagement. For instance, adjusting messages based on a patient's mood or motivational level would ensure that the content remains relevant and supportive. Drawing on behavior change models like the Fogg Behavior Model, feedback can be designed to trigger action when motivation and ability are aligned(Hamper et al., 2016; Mukhtar et al., 2012). Additionally, to maintain long-term engagement, feedback strategies should evolve with patient progress. For patients demonstrating high adherence, feedback could transition towards celebrating milestones or reducing reminders, while those struggling might benefit from more motivational nudges and personalized goal-setting(Grossman et al., 2017; Kelders et al., 2012; A. Xu et al., 2014; J. Zhang et al., 2020). Over time, the system could shift from relying on external motivators to fostering intrinsic motivation, promoting a sense of autonomy and mastery over their therapy(Klasnja et al., 2015; McCarthy et al., 2022).

Privacy and security are equally critical to patients' willingness to engage with the system(Al Ameen et al., 2012; Ataei et al., 2018). In this study, the use of metaphorical visualizations in the infographics was well received, as they protect patient privacy by making the data less immediately recognizable to others while still understandable to the user(Cox, 2006; Y.-N. Li et al., 2017). This feature reassures patients that their information remains confidential. Future developments could further enhance privacy by exploring new ways to present sensitive data in abstract or metaphorical forms, ensuring that only the intended users can easily interpret it(Abouelmehdi et al., 2018; Yang et al., 2019). Additionally, integrating privacy-enhancing features such as secure data-sharing options and anonymized reports would further reinforce patients' confidence in the system's ability to safeguard their data(Ali et al., 2023; Cripps & Standing, 2012; Holm et al., 2021). This focus on privacy, combined with intuitive and personalized feedback, has the potential to significantly enhance patient adherence by building trust and engagement with the intervention system.

8.5 Conclusion

This chapter discussed the application and evaluation of the Patient Adherence to Inhalation Therapy Work System Model through the XIAOXI system, highlighting how the dimensions of Person, Task, Tool, Physical Environment, and Culture & Social influence patient adherence. Analysis of sensor data and Emocard assessments using machine learning identified PM2.5 levels and emotional states as key predictors, underscoring the need to address environmental and emotional barriers in intervention design.

The integration of HFE principles enhanced usability and patient engagement, with participatory design ensuring alignment with patient needs. Data-driven feedback mechanisms provided personalized adherence insights, while metaphorical visualizations protected privacy without sacrificing clarity. These design choices promoted trust and engagement, reinforcing the importance of intuitive and secure data representation.

Future research should focus on expanding multimodal monitoring to capture more comprehensive physiological and environmental data, alongside longitudinal studies to understand long-term adherence patterns. Strengthening privacy measures and exploring adaptive feedback technologies could further enhance patient support. These improvements would build on the current findings to optimize adherence and therapeutic outcomes in chronic respiratory disease management.

Chapter 9 Conclusion

9.1 Introduction and Aims

Adherence to inhalation therapy is of utmost importance for the effective management of chronic respiratory disorders such as asthma and COPD, significantly impacting long-term health outcomes. Despite this, adherence rates remain suboptimal due to several challenges, including device usability, environmental factors, and emotional barriers. This research aimed to address these barriers by integrating HFE principles with sensor-based interventions to develop more effective strategies for improving adherence. By adopting a multidisciplinary approach—combining real-time sensor monitoring and HFE design principles—this study identified key factors influencing patient adherence and developed innovative, personalized interventions. The research emphasized the importance of tailoring interventions to patient-specific needs, enabling timely support and fostering a deeper understanding of patient adherence behavior. In this chapter, the research findings are synthesized, the central research questions of this thesis are addressed, and the main contributions and areas for future research are outlined.

9.2 Contribution to Knowledge

This research makes substantial contributions across four key areas: theoretical, methodological, technological, and practical. At the core of these contributions is the advancement of theoretical understanding through the adaptation and extension of the SEIPS 2.0 framework. By developing the Patient Adherence to Inhalation Therapy Work System Model, this study provides a context-specific theoretical foundation that systematically captures the multifactorial factors influencing patient adherence in inhalation therapy, with a particular focus on asthma and COPD management.

The following sections demonstrate how each research question contributed to these four areas, emphasizing how theoretical insights were not only developed but also operationalized and validated through iterative design, system implementation, and real-world evaluation. This integrated approach underscores the dynamic interplay between theory and practice, ensuring that the proposed framework contributes both to academic knowledge and to practical solutions in digital health interventions.

9.2.1 HFE Factors Influencing Patient Adherence to Inhalation Therapy

RQ1. What are the key factors influencing patient adherence to inhalation therapy?

Study 1 (Chapter 4) explored the HFE dimensions impacting patient adherence to inhalation therapy. Through semi-structured interviews with asthma and COPD patients, as well as HCPs, this study identified specific factors shaping adherence behaviors, providing critical insights to inform the design of effective, patient-centered interventions. The analysis revealed nine key factors, categorized within five core domains adapted from the SEIPS 2.0 model: Person, Task, Tool, Physical Environment, and Culture & Social. These domains comprehensively capture the multifaceted influences on patient adherence, including patient abilities, emotional experiences, task type, frequency and flexibility of use, inhaler type and usability, daily environment, cultural beliefs, and social stigma.

By applying a systems-based perspective through SEIPS 2.0, this study advanced theoretical understanding of adherence behaviors within the context of inhalation therapy. Notably, the research extended the original framework by explicitly integrating emotional, environmental, and cultural factors—dimensions often underrepresented in existing adherence models(Ma et al., 2023). This led to the development of the Patient Adherence to Inhalation Therapy Work System Model, a context-specific theoretical framework that offers a holistic lens for analyzing adherence challenges in chronic respiratory care. This adapted model contributes to theory by demonstrating how HFE principles can be tailored to address the complexities of DDCPs, providing a replicable structure for future research across similar healthcare contexts. It emphasizes that effective adherence interventions must move beyond technical considerations to encompass behavioral, environmental, and socio-cultural dimensions.

Building on this theoretical foundation, the study also offers practical guidance for designing personalized interventions. By addressing emotional experiences, environmental constraints, and culture-based beliefs, these interventions can deliver comprehensive, patient-centered support to enhance adherence in real-world settings. This approach underscores the necessity of considering HFE-driven design principles to reduce barriers and improve patient engagement in inhalation therapy.

Detailed results from this study have been published in:

Ma, J., Sun, X., Wang, X., Liu, B., & Shi, K. (2023). Factors Affecting Patient Adherence to Inhalation Therapy: An Application of SEIPS Model 2.0. *Patient preference and adherence*, 17, 531–545.

9.2.2 Design of Sensor-Based Interventions to Support Patient Adherence to Inhalation Therapy

RQ2: How can sensor-based interventions be designed to support patient adherence to inhalation therapy?

Studies 2 (Chapter 5) and 3 (Chapter 6) presented a systematic, theory-driven process for designing and developing a sensor-based intervention system aimed at improving patient adherence to inhalation therapy. Guided by the Patient Adherence to Inhalation Therapy Work System Model, derived from SEIPS 2.0, this process translated conceptual insights into practical system functionalities through participatory workshops and iterative development.

The core system functions: The first phase of the participatory workshop process was crucial in conceptualizing the core functions of the sensor-based intervention system. Using Personas and Scenarios, key user archetypes and typical use cases were identified. This phase was grounded in the Patient Adherence to Inhalation Therapy Work System Model, developed in Study 1, which provided a structured framework for addressing adherence across five dimensions: Person, Task, Tool, Physical Environment, and Culture & Social. By considering the nine identified factors influencing adherence, this phase ensured that the system's design would directly meet the real-world needs and preferences of patients and HCPs. It also laid the foundation for subsequent development stages, resulting in a user-centered system that can be easily integrated into patients' daily routines to enhance adherence to therapy.

System Components and Sensor Deployment: The second step built upon these initial insights, emphasizing the development of a robust system architecture specifically designed for sensor-based data capture. Using the Person-Task-Physical Environment framework detailed in Chapter 2, sensor deployment strategically targeted three critical dimensions: physiological states (Person), inhaler usage patterns (Task), and environmental factors (Physical Environment). This structured deployment ensured comprehensive monitoring of adherence-related metrics. The architecture was systematically organized into three primary components—Monitoring, Knowledge & Awareness, and Feedback—collectively embodying a holistic approach informed by theoretical principles. Monitoring facilitated real-time tracking across different dimensions, Knowledge & Awareness provided personalized educational content and self-assessment tools, and Feedback delivered timely, personalized reminders, adherence reports, and motivational messaging. This comprehensive design ensured that the final intervention addressed diverse patient needs, promoting effective and sustained inhalation therapy adherence.

Interface Design Preferences: The final phase of the participatory workshops focused on refining the system's interface based on direct feedback from patients and HCPs. Patients expressed a strong preference for intuitive visual metaphors, such as the tree infographic, which facilitated daily feedback and enhanced engagement. Meanwhile, HCPs valued detailed yet clear data presentations, recognizing the importance of simplicity and usability in encouraging patient adherence. Based on these insights, minor modifications were implemented to enhance visual clarity and simplify long-term feedback reports. These adjustments underscored the importance of theory-informed, patient-centered design principles, minimizing cognitive load and maximizing usability.

Architecture and Solution Design: Following the participatory workshops, the XIAOXI sensor-based intervention system was fully developed, integrating advanced sensor technologies with user-centered design principles. The finalized system featured heart rate sensors, IMUs, temperature, humidity, and PM2.5 sensors, providing real-time monitoring of physiological and environmental conditions. Additionally, rigorous laboratory testing and practical sensor casing designs ensured durability and seamless integration into daily routines. Deployed via the WeChat platform with an intuitive chatbot interface, XIAOXI provided real-time feedback, educational resources, and self-assessment tools, significantly enhancing patient interaction and user experience.

Theoretical and Practical Significance of XIAOXI System: In addition to its practical functionality, the XIAOXI system embodies core academic contributions by operationalizing the Patient Adherence to Inhalation Therapy Work System Model and applying HFE principles. It serves as both a tangible validation of the theoretical and methodological frameworks developed in this study and as a transferable prototype for future sensor-based interventions. XIAOXI exemplifies how structured adherence factors and user-centered design principles can be effectively translated into a practical, functional intervention model, suitable for broader applications within inhalation therapy and other DDCP contexts.

Detailed results from the system design process have been published in:

Ma, J., Sun, X. (2024) Designing an IoT-based intervention system for supporting patient adherence to inhalation therapy. *IET Conference Proceedings*, 2024(18), 8–14.

Additionally, the “Person-Task-Physical Environment” framework, detailed in Chapter 2 and developed through a comprehensive literature review on sensor-based interventions for patient adherence to inhalation therapy, has been published in:

Ma, J., Sun, X., & Liu, B. (2024). A Review of Sensor-Based Interventions for Supporting Patient Adherence to Inhalation Therapy. *Patient Preference and Adherence*, 18, 2397–2413.

9.2.3 The Impact of Sensor-Based Interventions on Patient Adherence to Inhalation Therapy

RQ3: How can sensor-based interventions impact patient adherence to inhalation therapy?

Study 4 (Chapter 7) provided a comprehensive evaluation of how the XIAOXI system impacted patient adherence to inhalation therapy, focusing on both usability and effectiveness from a user-centered perspective, while also applying advanced analytical methods to deepen understanding of adherence behaviors.

System Usability and Effectiveness: The XIAOXI system, grounded in HFE principles and the Patient Adherence to Inhalation Therapy Work System Model, was designed to deliver real-time monitoring and personalized support for patients with asthma and COPD. Usability evaluations demonstrated high satisfaction among both patients and HCPs, reflecting the success of the system's user-centered design. Patients reported that the intuitive interface and personalized feedback enhanced their confidence and understanding of inhaler usage, while HCPs highlighted its practicality in supporting consistent adherence. The system's effectiveness was further validated through improvements in adherence metrics, particularly TAI scores, where patients using XIAOXI outperformed those following conventional care. This phase contributes methodologically by demonstrating how an integrated, multi-perspective evaluation—combining usability, acceptance, and effectiveness—can be applied to assess digital health interventions in real-world settings. It also reinforces the practical contribution by providing evidence that a theory-informed, sensor-based system can meaningfully enhance adherence outcomes in chronic respiratory care.

Machine Learning and Adherence Classification: A key methodological innovation of this research was the application of machine learning algorithms to retrospectively analyze sensor-generated environmental data and patient-reported emotional states. Using models such as Logistic Regression, the study successfully classified daily inhaler adherence behaviors and identified key factors associated with non-adherence, particularly PM2.5 levels and emotional states. While this classification capability has not yet been embedded into the live system, the findings highlight the potential for integrating adaptive analytics into future iterations of XIAOXI, enabling more proactive and personalized interventions. This aspect of the study advances both methodological and technological contributions by illustrating how data-driven techniques can complement HFE-based system design, offering scalable solutions for dynamic adherence monitoring and behavior classification.

By combining a theory-informed design, rigorous evaluation methods, and advanced data analytics, this research demonstrates how sensor-based interventions can positively impact patient adherence to inhalation therapy. The findings not only validate the practical effectiveness of the XIAOXI system but also contribute to a broader theoretical understanding of how multifactorial influences—captured through the Patient Adherence to Inhalation Therapy Work System Model—can be systematically operationalized and evaluated in real-world healthcare contexts. Furthermore, the application of machine learning illustrates how data-driven classification techniques can enhance HFE-based intervention design. These contributions position XIAOXI as both a functional intervention and a scalable reference model for future digital health solutions targeting adherence in chronic disease management, effectively bridging theory, methodology, technology, and clinical practice.

9.3 Limitations of the Research Undertaken

This study provides important insights into how sensor-based interventions can support patient adherence to inhalation therapy. However, several limitations should be acknowledged.

First, while the study incorporated physiological data (heart rate), environmental data (PM2.5 levels, temperature, and humidity), inhaler usage data (angle variations), and daily patient-reported emotional experiences, these measures do not capture all potential influences on adherence. Critical factors such as self-efficacy and health beliefs—though recognized as important—were not collected on a daily basis, nor were they integrated into the classification models. This limits the comprehensiveness of the analysis in understanding the full spectrum of factors affecting adherence behavior, potentially overlooking dimensions that influence patient engagement and consistency.

Second, all participants were recruited from a single hospital in Ningbo, Zhejiang Province, China. This concentrated geographic focus may limit the generalizability of the findings, particularly for broader populations, including those from different cultural backgrounds or healthcare settings. Cultural differences, healthcare accessibility, and socioeconomic factors are known to impact adherence behaviors, and these contextual elements were not fully accounted for in this study(Eh et al., 2016; Vaughn et al., 2009). Consequently, the results should be interpreted with caution when considering more diverse patient populations or international healthcare contexts.

Third, the evaluation of the XIAOXI system's effectiveness was conducted over a 28-day period with a relatively small sample size. Although the findings indicated positive impacts on adherence, the short duration restricts the ability to assess long-term adherence behaviors and the sustainability of intervention effects. Adherence is inherently dynamic and evolves over time, suggesting that longer-term studies are necessary to validate the findings and evaluate the system's long-term efficacy(Gold & McClung, 2006; Sabaté, 2003). Moreover, the small sample size may have impacted the statistical power of the results, potentially limiting the robustness of the conclusions, particularly in the context of machine learning analysis(Tsang et al., 2022; X.-W. Wu et al., 2020).

Addressing these limitations in future research could enhance the understanding of adherence behaviors and strengthen the evidence supporting sensor-based interventions for chronic respiratory diseases.

9.4 Reliability and Validity

This research addressed issues of reliability and validity through several key strategies. To ensure the reliability of the findings, triangulation was employed(Thurmond, 2001). By utilizing both qualitative and quantitative methods—such as combining interview data with questionnaire responses—the study validated its results through multiple data sources(Zohrabi, 2013). For instance, patient-reported adherence levels from questionnaires were cross-verified with data collected from sensor-based monitoring systems, enhancing the overall credibility of the findings and ensuring they reflect real-world patient behaviors.

In addition to triangulation, standardized data collection methods were consistently applied across all phases of the research. This study utilized a variety of well-established tools, including structured interviews and validated questionnaires such as the SUS, the TAM, the Emocard, and the TAI measures(Lewis, 2018; Muneswarao et al., 2021; Van De Hei et al., 2022; Zenk et al., 2008). These methods are widely recognized in HFE and healthcare research, ensuring a rigorous approach to data collection. Where necessary, slight adjustments were made to align the tools with the cultural context of participants, enhancing both the accuracy and relevance of the collected data(King et al., 2004; Md Hatah et al., 2015).

The research also referenced existing literature to substantiate its findings. For example, the challenges identified in patient adherence to inhalation therapy were consistent with findings from previous studies(Aldan et al., 2022; Bhattacharyya & S Sogali, 2018). This alignment between the study's findings and the established body of literature further supports the robustness of the conclusions drawn.

To enhance the validity of the findings, user validation was incorporated throughout the research process. Participants were not only involved as subjects but also contributed as informants and co-designers during the participatory workshops(Abdolkhani et al., 2020; Donetto et al., 2015). Their feedback was sought regularly, allowing them to verify the accuracy of the system's design and implementation. This iterative communication with end-users ensured that the interpretations made by researchers accurately reflected the experiences and needs of the participants(Baxter et al., 2015; Slattery et al., 2020).

Additionally, pilot testing of the XIAOXI system was conducted in a laboratory setting prior to the full-scale experiment(Borsci et al., 2022; Pronovost et al., 2003). Both the software and hardware components of the system were tested to confirm that all functionalities—such as data collection, real-time monitoring, and feedback mechanisms—worked as intended. This step ensured the reliability of the tools used during the full experiment and minimized the likelihood of technical issues affecting data integrity(Soori, 2024).

9.5 Future Research

9.5.1 Expanding Sample Diversity and Study Duration

Future research should aim to broaden participant diversity and extend study duration to better capture the long-term impact of sensor-based interventions on adherence to inhalation therapy.

Although this study employed a robust mixed-methods approach, further methodological innovation is needed to systematically understand adherence behavior across a wider range of populations, timeframes, and medication types.

One of the primary limitations of this study is its relatively small sample size, which may affect the robustness and generalizability of the findings. This research focused on participants from southeastern China, where cultural beliefs—such as the traditional perspective that "all medicines have toxicity to some degree"—notably influenced adherence behavior. Expanding the sample size and incorporating participants from diverse regions and cultural contexts, including Western countries and varying socio-economic backgrounds, would provide a more comprehensive understanding of adherence behaviors across populations. Such diversity would enable researchers to assess the impact of cultural and regional factors on adherence, offering valuable insights for designing interventions that are effective across different settings.

Additionally, the current study exclusively targeted patients using the Symbicort Turbuhaler for inhalation therapy. While this focused approach allowed for in-depth analysis of adherence to a specific medication, future research should consider broadening the scope to include other inhaler types and medications. Adapting the XIAOXI intervention system for different inhaler devices would allow researchers to evaluate whether the system's benefits extend to other forms of inhalation therapy. This expansion would provide important insights into the system's scalability and versatility, enhancing its utility as a comprehensive tool for supporting adherence across various inhalation medications.

Furthermore, although this study focused on patients with asthma and COPD—the most common indications for inhalation therapy—

inhaled medications are also widely used for managing other respiratory diseases such as cystic fibrosis and pulmonary infections(Hoo et al., 2016; Maselli et al., 2017). Future research should include patients receiving inhalation therapy for a broader range of conditions to better assess the generalizability and adaptability of sensor-based adherence interventions. Expanding the disease scope would provide a deeper understanding of the challenges and needs associated with inhalation therapy across diverse clinical contexts.

Finally, adherence to inhalation therapy, particularly for chronic conditions like asthma and COPD, involves long-term behavior change(Cambach et al., 1999; De Geest & Sabaté, 2003; Van De Hei et al., 2023; Velardo et al., 2017). The 28-day study period in this research may not have fully captured the dynamics of patient adherence. Longer-term studies spanning several months or even years are needed to observe how the sustained use of sensor-based interventions affects long-term adherence. This would enable researchers to assess whether the initial improvements observed with the XIAOXI system are maintained over time and to identify emerging factors that influence adherence in the long run.

9.5.2 Expanding Data Dimensions and Machine Learning for Adherence Classification and Future Prediction

The integration of sensor-based technologies in this research demonstrated significant potential for enhancing patient adherence to inhalation therapy. While this study focused primarily on classifying adherence behaviors using retrospective data, future research could extend these foundations to develop predictive models capable of forecasting patient adherence in real-time scenarios. Achieving this requires expanding the dimensions of sensor data collection and employing more advanced data analysis techniques to improve the precision and efficacy of intervention strategies.

This study leveraged the Person-Task-Physical Environment framework, focusing on specific metrics such as physiological monitoring (heart rate), environmental conditions (temperature, humidity, and PM2.5), and patient interactions with inhalation devices (angle variations during usage). However, the full potential of this framework can be further realized by expanding data collection across all five dimensions of the proposed Patient Adherence to Inhalation Therapy Work System Model(Ma et al., 2023). A broader range of dimensions and metrics would not only enhance the comprehensiveness of adherence analysis but also support the transition from classification to predictive capabilities, enabling proactive and personalized interventions in real-world settings.

Furthermore, data collected from a single type of sensor may be inherently limited, as each sensor has its unique strengths and weaknesses(Akhoundi & Valavi, 2010; Cui et al., 2022; Gui et al., 2015). To address these limitations, employing data fusion—integrating data from multiple sensors to cross-reference and validate inputs—could significantly improve the reliability of adherence monitoring. This fusion approach would enhance the robustness of the collected data, setting a strong foundation for developing predictive models capable of identifying adherence risks before they result in missed treatments.

In addition to sensor data, the XIAOXI chatbot serves as a valuable channel for collecting adherence-related information(Brandtzaeg & Følstad, 2017; Zumstein & Hundertmark, 2017). The built-in questionnaires and patient interactions provide a rich source of behavioral data, which, when combined with sensor inputs, could further enhance the accuracy of adherence classification. As larger datasets become available, these interactions could be leveraged to develop predictive models capable of anticipating non-adherent behaviors, allowing for timely interventions.

While this study utilized machine learning algorithms via Weka to classify adherence-related data, future research should explore more advanced algorithms, such as deep learning and reinforcement learning, which are well-suited for handling large-scale, complex datasets(Abdellatif et al., 2021; Gu et al., 2021). These techniques can capture intricate patterns within multi-dimensional data, facilitating not only more precise classification but also real-time prediction of adherence risks. Moreover, adaptive learning systems that continuously improve as more data is accumulated could significantly enhance the long-term effectiveness of adherence monitoring and intervention strategies(Finkelstein & Jeong, 2017; Gilbert et al., 2021). These advancements could enable the XIAOXI system to move beyond retrospective analysis, evolving into a dynamic, predictive intervention platform that proactively supports patients in maintaining adherence to inhalation therapy.

9.5.3 Enhancing the User Experience of Digital Health Interventions

Future research should focus on optimizing feedback mechanisms and enhancing patient engagement, particularly within sensor-based intervention systems for inhalation therapy. Although the current study successfully integrated personalized feedback through visual and text-based methods, there remains considerable potential to further refine these mechanisms to accommodate a broader range of user needs, contexts, and emotional experiences.

Effective feedback is highly dependent on how data is presented to patients. Future research should investigate optimal methods for delivering information across different data types (e.g., real-time vs. longitudinal trends), various time frames (e.g., daily, weekly, monthly), and diverse user groups (e.g., patients vs. HCPs, elderly vs. younger users)(De Folter et al., 2014; Faiola et al., 2015; N. Li et al., 2018; Pandey et al., 2014). Achieving a balance between providing comprehensive insights and avoiding cognitive overload is crucial. Information must remain engaging and accessible while still delivering meaningful insights. Beyond cognitive needs, future studies should also explore emotional aspects of feedback, such as addressing privacy concerns through metaphorical representations that make data less immediately interpretable to others while remaining actionable to the user(Abouelmehdi et al., 2018; Ackerman & Mainwaring, 2005; Alkhariji et al., 2022). Visual designs that reduce patients' anxiety about public data exposure, especially in shared family environments or social settings, should also be examined.

While this study incorporated some persuasive elements like motivational messages and peer competition, there is substantial room for expanding these strategies to improve long-term engagement. Techniques such as gamification, loss aversion, and social support have proven effective in other chronic disease management contexts (e.g., diabetes, heart disease) but remain underexplored in inhalation therapy adherence(A. K. Agarwal et al., 2021; Fortunato et al., 2019; L. Xu et al., 2022). Future research should focus on developing standardized methodologies to evaluate how such elements impact adherence, specifically within the context of inhalation therapy. Additionally, incorporating feedback loops where patients can track their adherence against personalized goals or benchmarks could further boost engagement. Empirical testing is needed to confirm the efficacy of these enhanced strategies.

Currently, feedback in the XIAOXI system relies primarily on text and visual representations delivered through a chatbot interface. While this approach has proven effective for personalized support, future iterations could further enhance user engagement by integrating multisensory feedback, such as audio prompts, vibrations, or light indicators, to make the system more accessible and reduce cognitive load for specific user groups(Devaram, 2020; Riener et al., 2017; S. Xu et al., 2020). For example, voice-based interactions may be particularly beneficial for patients with reading difficulties or visual impairments(Pradhan et al., 2018). These natural communication methods could minimize user friction and create a more seamless, intuitive experience. Furthermore, auditory or tactile feedback could provide real-time notifications for inhaler usage, reinforcing adherence without overwhelming users with excessive visual data(Sigrist et al., 2013).

9.6 Conclusion

The primary conclusion of this thesis is that sensor-based interventions, when guided by HFE principles, can significantly enhance patient adherence to inhalation therapy, particularly among individuals with asthma and COPD. Through real-time monitoring, tailored interventions, and chatbot-based interactions, the XIAOXI system effectively supported patient engagement and improved adherence behaviors.

The integration of a chatbot interface proved particularly impactful, providing timely, personalized feedback that enhanced the accessibility and usability of the intervention. Meanwhile, sensor-based technologies offered a holistic view of adherence behaviors, capturing inhaler usage patterns, environmental influences, and physiological data. The application of machine learning techniques enabled effective classification of adherence behaviors, illustrating the potential of data-driven methods to monitor and distinguish between different adherence patterns.

Despite these advances, challenges remain. Enhancing data visualization, further personalizing intervention strategies, and ensuring long-term reliability and scalability are critical areas for future development. Addressing these aspects will be crucial to promote broader clinical adoption, particularly in chronic respiratory disease management.

As digital health technologies become increasingly integrated into healthcare, designing systems that support long-term monitoring, ensure secure data management, and foster sustained patient engagement will be essential. Future improvements should prioritize adaptive feedback mechanisms that dynamically adjust to individual patient needs. Sensor-based interventions hold substantial potential to transform chronic disease management and improve patient outcomes through continuous innovation and refinement.

Bibliography

Aardoom, J. J., Loheide-Niesmann, L., Ossebaard, H. C., & Riper, H. (2020). Effectiveness of Electronic Health Interventions in Improving Treatment Adherence for Adults With Obstructive Sleep Apnea: Meta-Analytic Review. *Journal of Medical Internet Research*, *22*(2), e16972. https://doi.org/10.2196/16972

Abate, F., Huang, V. K., Monte, G., Paciello, V., & Pietrosanto, A. (2014). A comparison between sensor signal preprocessing techniques. *IEEE Sensors Journal*, *15*(5), 2479–2487.

Abdellatif, A. A., Mhaisen, N., Chkirbene, Z., Mohamed, A., Erbad, A., & Guizani, M. (2021). Reinforcement learning for intelligent healthcare systems: A comprehensive survey. *arXiv Preprint arXiv:2108.04087*.

Abdelrahim, M. E. (2010). Emitted dose and lung deposition of inhaled terbutaline from turbuhaler at different conditions. *Respiratory Medicine*, *104*(5), 682–689.

Abdolkhani, R., Gray, K., Borda, A., & DeSouza, R. (2020). Quality assurance of health wearables data: Participatory workshop on barriers, solutions, and expectations. *JMIR mHealth and uHealth*, *8*(1), e15329. https://doi.org/10.2196/15329

Abdulmalek, S., Nasir, A., Jabbar, W. A., Almuhaya, M. A. M., Bairagi, A. K., Khan, Md. A.-M., & Kee, S.-H. (2022). IoT-Based Healthcare-Monitoring System towards Improving Quality of Life: A Review. *Healthcare*, *10*(10), 1993. https://doi.org/10.3390/healthcare10101993

Abouelmehdi, K., Beni-Hessane, A., & Khaloufi, H. (2018). Big healthcare data: Preserving security and privacy. *Journal of Big Data*, *5*(1), 1–18.

Ackerman, M. S., & Mainwaring, S. D. (2005). Privacy issues and human-computer interaction. *Computer*, *27*(5), 19–26.

Adams, E. (2010). The joys and challenges of semi-structured interviewing. *Community Practitioner*, *83*(7), 18–22.

Adams, S. A., Leach, M. C., Feudtner, C., Miller, V. A., & Kenyon, C. C. (2017). Automated Adherence Reminders for High Risk Children With Asthma: A Research Protocol. *JMIR Research Protocols*, *6*(3), e48. https://doi.org/10.2196/resprot.6674

Adejumo, I., Patel, M., McKeever, T. M., Shaw, D. E., & Bains, M. (2022). Qualitative study of user perspectives and experiences of digital inhaler technology. *Npj Primary Care Respiratory Medicine*, *32*(1), 57. https://doi.org/10.1038/s41533-022-00320-9

Agarwal, A. K., Waddell, K. J., Small, D. S., Evans, C., Harrington, T. O., Djaraher, R., Oon, A. L., & Patel, M. S. (2021). Effect of gamification with and without financial incentives to increase physical activity among veterans classified as having obesity or overweight: A randomized clinical trial. *JAMA Network Open*, *4*(7), e2116256–e2116256.

Agarwal, A., & Meyer, A. (2009). Beyond usability: Evaluating emotional response as an integral part of the user experience. *CHI '09 Extended Abstracts on Human Factors in Computing Systems*, 2919–2930. https://doi.org/10.1145/1520340.1520420

Agarwal, P., Mukerji, G., Desveaux, L., Ivers, N. M., Bhattacharyya, O., Hensel, J. M., Shaw, J., Bouck, Z., Jamieson, T., Onabajo, N., Cooper, M., Marani, H., Jeffs, L., & Bhatia, R. S. (2019). Mobile app for improved self-management of type 2 diabetes: Multicenter pragmatic randomized controlled trial. *JMIR mHealth and uHealth*, *7*(1), e10321. https://doi.org/10.2196/10321

Aggarwal, A., Tam, C. C., Wu, D., Li, X., & Qiao, S. (2023). Artificial Intelligence–Based Chatbots for Promoting Health Behavioral Changes: Systematic Review. *Journal of Medical Internet Research*, *25*, e40789. https://doi.org/10.2196/40789

Ait-Khaled, N., Enarson, D., & Bousquet, J. (2001). Chronic respiratory diseases in developing countries: The burden and strategies for prevention and management. *Bulletin of the World Health*

Organization, *79*, 971–979.

Akhoundi, M. A. A., & Valavi, E. (2010). *Multi-sensor fuzzy data fusion using sensors with different characteristics*. https://doi.org/10.48550/ARXIV.1010.6096

Al Ameen, M., Liu, J., & Kwak, K. (2012). Security and privacy issues in wireless sensor networks for healthcare applications. *Journal of Medical Systems*, *36*(1), 93–101. https://doi.org/10.1007/s10916-010-9449-4

Alazzam, M. B., Alassery, F., & Almulihi, A. (2021). A Novel Smart Healthcare Monitoring System Using Machine Learning and the Internet of Things. *Wireless Communications and Mobile Computing*, *2021*, 1–7. https://doi.org/10.1155/2021/5078799

Albahri, O. S., Albahri, A. S., Mohammed, K. I., Zaidan, A. A., Zaidan, B. B., Hashim, M., & Salman, O. H. (2018). Systematic review of real-time remote health monitoring system in triage and priority-based sensor technology: Taxonomy, open challenges, motivation and recommendations. *Journal of Medical Systems*, *42*(5), 80. https://doi.org/10.1007/s10916-018-0943-4

Aldan, G., Helvaci, A., Ozdemir, L., Satar, S., & Ergun, P. (2022). Multidimensional factors affecting medication adherence among patients with chronic obstructive pulmonary disease. *Journal of Clinical Nursing*, *31*(9–10), 1202–1215. https://doi.org/10.1111/jocn.15976

Aldeer, M., Javanmard, M., & Martin, R. (2018). A review of medication adherence monitoring technologies. *Applied System Innovation*, *1*(2), 14. https://doi.org/10.3390/asi1020014

Al-Durra, M., Torio, M.-B., & Cafazzo, J. A. (2015). The use of behavior change theory in internet-based asthma self-management interventions: A systematic review. *Journal of Medical Internet Research*, *17*(4), e89. https://doi.org/10.2196/jmir.4110

Alexander, I. F., & Maiden, N. (2005). *Scenarios, stories, use cases: Through the systems development life-cycle*. John Wiley & Sons.

Ali Alkhoshaiban, Yahaya Hassan, Mathumalar Loganathan, Mohammad Alomary, Donald E. Morisky, & Bader Alawwad. (2019). Type II diabetic patients’ satisfaction, medication adherence, and glycemic control after application of pharmacist counselling program. *Archives of Pharmacy Practice*, *10*(4), 127–136.

Ali, S., Abdullah, Armand, T. P. T., Athar, A., Hussain, A., Ali, M., Yaseen, M., Joo, M.-I., & Kim, H.-C. (2023). Metaverse in healthcare integrated with explainable AI and blockchain: Enabling immersiveness, ensuring trust, and providing patient data security. *Sensors*, *23*(2), 565.

Al-kahtani, M. S., Khan, F., & Taekeun, W. (2022). Application of internet of things and sensors in healthcare. *Sensors*, *22*(15), 5738. https://doi.org/10.3390/s22155738

Alkhariji, L., De, S., Rana, O., & Perera, C. (2022). Poster: Ontology enabled chatbot for applying privacy by design in IoT systems. *Proceedings of the 2022 ACM SIGSAC Conference on Computer and Communications Security*, 3323–3325. https://doi.org/10.1145/3548606.3563504

Almabrouk, H., Kaziz, S., Mezghani, B., Tounsi, F., & Bernard, Y. (2018). Performance enhancement of an improved design of 6-axis single-mass piezoelectric IMU. *2018 30th International Conference on Microelectronics (ICM)*, 140–143. https://doi.org/10.1109/ICM.2018.8703996

Alshammari, T. M. (2016). Drug safety: The concept, inception and its importance in patients’ health. *Saudi Pharmaceutical Journal*, *24*(4), 405–412. https://doi.org/10.1016/j.jsps.2014.04.008

Alshenqeeti, H. (2014). Interviewing as a data collection method: A critical review. *English Linguistics Research*, *3*(1), 39–45.

Altman, P., Wehbe, L., Dederichs, J., Guerin, T., Ament, B., Moronta, M. C., Pino, A. V., & Goyal, P. (2018). Comparison of peak inspiratory flow rate via the breezhaler®, ellipta® and HandiHaler® dry powder inhalers in patients with moderate to very severe COPD: A randomized cross-over trial. *BMC Pulmonary Medicine*, *18*(1), 100. https://doi.org/10.1186/s12890-018-0662-0

Alwashmi, M. F., Mugford, G., Vokey, B., Abu-Ashour, W., & Hawboldt, J. (2021). Effectiveness of the BreatheSuite Device in Assessing the Technique of Metered-Dose Inhalers: Validation Study. *JMIR Biomedical Engineering*, *6*(4), e26556. https://doi.org/10.2196/26556

Ammari, W. G., Mohammad, M. K., & Tayyem, R. F. (2019). The impact of patients' real-life environmental temperature and humidity use conditions of tiotropium dry powder inhaler on its aerosol emission characteristics. *European Journal of Pharmaceutical Sciences*, *133*, 137–144. https://doi.org/10.1016/j.ejps.2019.04.002

Anderson, E. W., Potter, K. C., Matzen, L. E., Shepherd, J. F., Preston, G. A., & Silva, C. T. (2011). *A user study of visualization effectiveness using EEG and cognitive load*. *30*(3), 791–800.

Anderson, J., Gosbee, L. L., Bessesen, M., & Williams, L. (2010). Using human factors engineering to improve the effectiveness of infection prevention and control: *Critical Care Medicine*, *38*, S269–S281. https://doi.org/10.1097/CCM.0b013e3181e6a058

Anderson, L. J., Nuckols, T. K., Coles, C., Le, M. M., Schnipper, J. L., Shane, R., Jackevicius, C., Lee, J., Pevnick, J. M., Members of the PHARM-DC Group, Choudhry, N. K., O'Mahony, D., & Sarkisian, C. (2020). A systematic overview of systematic reviews evaluating medication adherence interventions. *American Journal of Health-System Pharmacy*, *77*(2), 138–147. https://doi.org/10.1093/ajhp/zxz284

Anderson, P. (2005). Patient preference for and satisfaction with inhaler devices. *European Respiratory Review*, *14*(96), 109–116. https://doi.org/10.1183/09059180.05.00009606

Anderson, R. M., & Funnell, M. M. (2010). Patient empowerment: Myths and misconceptions. *Patient Education and Counseling*, *79*(3), 277–282. https://doi.org/10.1016/j.pec.2009.07.025

Anderson, S., Atkins, P., Bäckman, P., Cipolla, D., Clark, A., Daviskas, E., Disse, B., Entcheva-Dimitrov, P., Fuller, R., Gonda, I., Lundbäck, H., Olsson, B., & Weers, J. (2022). Inhaled medicines: Past, present, and future. *Pharmacological Reviews*, *74*(1), 48–118. https://doi.org/10.1124/pharmrev.120.000108

Anderson, W., Prescott, G. J., Packham, S., Mullins, J., Brookes, M., & Seaton, A. (2001). Asthma admissions and thunderstorms: A study of pollen, fungal spores, rainfall, and ozone. *Qjm*, *94*(8), 429–433.

Andrews, K. L., & Jones, S. C. (2009). We would have got it by now if we were going to get it…' an analysis of asthma awareness and beliefs in older adults. *Health Promotion Journal of Australia*, *20*(2), 146–150. https://doi.org/10.1071/HE09146

Anghel, L. A., Farcas, A. M., & Oprean, R. N. (2019). An overview of the common methods used to measure treatment adherence. *Medicine and Pharmacy Reports*, *92*(2), 117.

Araújo-Soares, V., Hankonen, N., Presseau, J., Rodrigues, A., & Sniehotta, F. F. (2018). Developing behavior change interventions for self-management in chronic illness. *European Psychologist*.

Asamoah-Boaheng, M., Osei Bonsu, K., Farrell, J., Oyet, A., & Midodzi, W. K. (2021). Measuring Medication Adherence in a Population-Based Asthma Administrative Pharmacy Database: A Systematic Review and Meta-Analysis. *Clinical Epidemiology*, *Volume 13*, 981–1010. https://doi.org/10.2147/CLEP.S333534

Association for the Advancement of Medical Instrumentation (with American National Standards Institute). (2018). *Human factors engineering—Design of medical devices*. Association for the Advancement of Medical Instrumentation.

Ataei, M., Degbelo, A., & Kray, C. (2018). Privacy theory in practice: Designing a user interface for managing location privacy on mobile devices. *Journal of Location Based Services*, *12*(3–4), 141–178.

Awad, A., Trenfield, S. J., Pollard, T. D., Ong, J. J., Elbadawi, M., McCoubrey, L. E., Goyanes, A., Gaisford, S., & Basit, A. W. (2021). Connected healthcare: Improving patient care using digital health technologies. *Advanced Drug Delivery Reviews*, *178*, 113958. https://doi.org/10.1016/j.addr.2021.113958

Axelsson, A., Buschmeier, H., & Skantze, G. (2022). Modeling feedback in interaction with conversational agents—A review. *Frontiers in Computer Science*, *4*, 744574. https://doi.org/10.3389/fcomp.2022.744574

Ayaz, M., Ammad-Uddin, M., & Baig, I. (2017). Wireless sensor's civil applications, prototypes, and future integration possibilities: A review. *IEEE Sensors Journal*, *18*(1), 4–30.

Ayele, A. A., & Tegegn, H. G. (2017). Non adherence to inhalational medications and associated factors among patients with asthma in a referral hospital in ethiopia, using validated tool TAI. *Asthma Research and Practice*, *3*(1), 7. https://doi.org/10.1186/s40733-017-0035-0

Azar, K., Hajiakhondi-Meybodi, Z., & Naderkhani, F. (2022). Semi-supervised clustering-based method for fault diagnosis and prognosis: A case study. *Reliability Engineering & System Safety*, *222*, 108405.

Azarmi, F., Kumar, P., Marsh, D., & Fuller, G. (2016). Assessment of the long-term impacts of PM 10 and PM 2.5 particles from construction works on surrounding areas. *Environmental Science: Processes & Impacts*, *18*(2), 208–221.

Azouz, W., Chetcuti, P., Hosker, H. S. R., Saralaya, D., Stephenson, J., & Chrystyn, H. (2015). The inhalation characteristics of patients when they use different dry powder inhalers. *Journal of Aerosol Medicine and Pulmonary Drug Delivery*, *28*(1), 35–42. https://doi.org/10.1089/jamp.2013.1119

Bae, W. D., Alkobaisi, S., Horak, M., Park, C.-S., Kim, S., & Davidson, J. (2022). Predicting Health Risks of Adult Asthmatics Susceptible to Indoor Air Quality Using Improved Logistic and Quantile Regression Models. *Life*, *12*(10), 1631. https://doi.org/10.3390/life12101631

Bae, W. D., Kim, S., Park, C.-S., Alkobaisi, S., Lee, J., Seo, W., Park, J. S., Park, S., Lee, S., & Lee, J. W. (2021). Performance improvement of machine learning techniques predicting the association of exacerbation of peak expiratory flow ratio with short term exposure level to indoor air quality using adult asthmatics clustered data. *PLOS ONE*, *16*(1), e0244233. https://doi.org/10.1371/journal.pone.0244233

Balkrishnan, R. (2005). The importance of medication adherence in improving chronic-disease related outcomes: What we know and what we need to further know. *Medical Care*, *43*(6), 517–520. https://doi.org/10.1097/01.mlr.0000166617.68751.5f

Bamashmoos, F., Woznowski, P., & Tryfonas, T. (2018). A review of air quality sensing technologies and their potential interfaces with IoT for asthma management. *Proceedings of the 11th PErvasive Technologies Related to Assistive Environments Conference*, 470–475. https://doi.org/10.1145/3197768.3201559

Barati, M., Petri, I., & Rana, O. F. (2019). *Developing GDPR compliant user data policies for internet of things*. 133–141.

Barbato, G., Barini, E., Genta, G., & Levi, R. (2011). Features and performance of some outlier detection methods. *Journal of Applied Statistics*, *38*(10), 2133–2149.

Barber, N., Safdar, A., & Franklin, B. D. (2005). Can human error theory explain non-adherence? *Pharmacy World & Science*, *27*(4), 300–304. https://doi.org/10.1007/s11096-005-0355-7

Barjaktarevic, I. Z., & Milstone, A. P. (2020). Nebulized therapies in COPD: Past, present, and the future. *International Journal of Chronic Obstructive Pulmonary Disease*, *Volume 15*, 1665–1677. https://doi.org/10.2147/COPD.S252435

Barrett, M. A., Humblet, O., Marcus, J. E., Henderson, K., Smith, T., Eid, N., Sublett, J. W., Renda, A., Nesbitt, L., Van Sickle, D., Stempel, D., & Sublett, J. L. (2017). Effect of a mobile health, sensor-driven asthma management platform on asthma control. *Annals of Allergy, Asthma & Immunology*, *119*(5), 415-421.e1. https://doi.org/10.1016/j.anai.2017.08.002

Basheti, I. A., Armour, C. L., Bosnic-Anticevich, S. Z., & Reddel, H. K. (2008). Evaluation of a novel educational strategy, including inhaler-based reminder labels, to improve asthma inhaler technique. *Patient Education and Counseling*, *72*(1), 26–33. https://doi.org/10.1016/j.pec.2008.01.014

Basheti, I. A., Bosnic-Anticevich, S. Z., Armour, C. L., & Reddel, H. K. (2014). Checklists for powder inhaler technique: A review and recommendations. *Respiratory Care*, *59*(7), 1140–1154.

Basheti, I. A., Reddel, H. K., Armour, C. L., & Bosnic-Anticevich, S. Z. (2005). Counseling about turbuhaler technique: Needs assessment and effective strategies for community pharmacists. *Respiratory Care*, *50*(5), 617–623.

Bateman, E. D., Hurd, S. S., Barnes, P. J., Bousquet, J., Drazen, J. M., FitzGerald, M., Gibson, P., Ohta, K., O'Byrne, P., Pedersen, S. E., Pizzichini, E., Sullivan, S. D., Wenzel, S. E., & Zar, H. J. (2008). Global strategy for asthma management and prevention: GINA executive summary. *European Respiratory Journal*, *31*(1), 143–178. https://doi.org/10.1183/09031936.00138707

Baumgartner, P. C., Haynes, R. B., Hersberger, K. E., & Arnet, I. (2018). A systematic review of medication adherence thresholds dependent of clinical outcomes. *Frontiers in Pharmacology*, *9*, 1290. https://doi.org/10.3389/fphar.2018.01290

Baxter, K., Courage, C., & Caine, K. (2015). *Understanding your users: A practical guide to user research methods*. Morgan Kaufmann.

Beaman, J. V., & Wallace, R. (2009). Combination Products/Drugs in Devices. In K. Huynh-Ba (Ed.), *Handbook of Stability Testing in Pharmaceutical Development* (pp. 323–351). Springer New York. https://doi.org/10.1007/978-0-387-85627-8_16

Beck, S., Frank, S., Hakamian, A., Merino, L., & Hoorn, A. V. (2021). TransVis: Using Visualizations and Chatbots for Supporting Transient Behavior in Microservice Systems. *2021 Working Conference on Software Visualization (VISSOFT)*, 65–75.

https://doi.org/10.1109/VISSOFT52517.2021.00016

Belfin, R. V., Shobana, A. J., Manilal, M., Mathew, A. A., & Babu, B. (2019). A Graph Based Chatbot for Cancer Patients. *2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS)*, 717–721. https://doi.org/10.1109/ICACCS.2019.8728499

Bender, B., Wamboldt, F., O'Connor, S. L., Rand, C., Szefler, S., Milgrom, H., & Wamboldt, M. Z. (2000). Measurement of children's asthma medication adherence by self report, mother report, canister weight, and doser CT. *Annals of Allergy, Asthma & Immunology*, *85*(5), 416–421. https://doi.org/10.1016/S1081-1206(10)62557-4

Benke, I., Knierim, M. T., & Maedche, A. (2020). Chatbot-based emotion management for distributed teams: A participatory design study. *Proceedings of the ACM on Human-Computer Interaction*, *4*(CSCW2), 1–30. https://doi.org/10.1145/3415189

Bennett, B., Sharma, M., Bennett, R., Mawson, A. R., Buxbaum, S. G., & Sung, J. H. (2018). Using social cognitive theory to predict medication compliance behavior in patients with depression in southern united states in 2016 in a cross-sectional study. *Journal of Caring Sciences*, *7*(1), 1–8. https://doi.org/10.15171/jcs.2018.001

Beran, D., Zar, H. J., Perrin, C., Menezes, A. M., & Burney, P. (2015). Burden of asthma and chronic obstructive pulmonary disease and access to essential medicines in low-income and middle-income countries. *The Lancet Respiratory Medicine*, *3*(2), 159–170. https://doi.org/10.1016/S2213-2600(15)00004-1

Berman, L., Kavalier, M., Gelana, B., Tesfaw, G., Siraj, D., Shirley, D., & Yilma, D. (2021). Utilizing the SEIPS model to guide hand hygiene interventions at a tertiary hospital in ethiopia. *PLOS ONE*, *16*(10), e0258662. https://doi.org/10.1371/journal.pone.0258662

Bertella, G., Lupini, S., Romanelli, C. R., & Font, X. (2021). Workshop methodology design: Innovation-oriented participatory processes for sustainability. *Annals of Tourism Research*, *89*, 103251.

Bharti, U., Bajaj, D., Batra, H., Lalit, S., Lalit, S., & Gangwani, A. (2020). Medbot: Conversational Artificial Intelligence Powered Chatbot for Delivering Tele-Health after COVID-19. *2020 5th International Conference on Communication and Electronics Systems (ICCES)*, 870–875. https://doi.org/10.1109/ICCES48766.2020.9137944

Bhat, G. S., Shankar, N., Song, D. J., Seo, S., Panahi, I. M. S., & Tamil, L. (2021). *Machine Learning-Based Asthma Risk Prediction Using IoT and Smartphone Applications*. *9*.

Bhatia, H., Panda, S. N., & Nagpal, D. (2020). Internet of things and its applications in healthcare-a survey. *2020 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)*, 305–310. https://doi.org/10.1109/ICRITO48877.2020.9197816

Bhattacharyya, S., & S Sogali, B. (2018). Inhalation therapy—Approaches and challenges. *Asian Journal of Pharmaceutical and Clinical Research*, *11*(4), 9. https://doi.org/10.22159/ajpcr.2018.v11i4.24117

Bird, J., Marshall, P., & Rogers, Y. (2009). *Low-fi skin vision: A case study in rapid prototyping a sensory substitution system*.

Bischofberger, W. R., & Pomberger, G. (2012). *Prototyping-oriented software development: Concepts and tools*. Springer Science & Business Media.

Biswas, R., Patel, G., Mohsin, A., Hanania, N., & Sabharwal, A. (2016). Measuring Competence in Metered Dose Inhaler Use Using Capmedic Electronic Inhaler Monitoring Tool. *Chest*, *150*(4), 14A. https://doi.org/10.1016/j.chest.2016.08.017

Bitkina, O. Vl., Kim, H. K., & Park, J. (2020). Usability and user experience of medical devices: An overview of the current state, analysis methodologies, and future challenges. *International Journal of Industrial Ergonomics*, *76*, 102932. https://doi.org/10.1016/j.ergon.2020.102932

Blakey, J. D., Bender, B. G., Dima, A. L., Weinman, J., Safioti, G., & Costello, R. W. (2018). Digital technologies and adherence in respiratory diseases: The road ahead. *European Respiratory Journal*, *52*(5), 1801147. https://doi.org/10.1183/13993003.01147-2018

Blumenschein, K., Johannesson, M., Yokoyama, K., & Freeman, P. (2001). Hypothetical versus real willingness to pay in the health care sector: Results from a field experiment. *Value in Health*, *4*(2), 79–79.

Boddy, C. E., Naveed, S., Craner, M., Murphy, A. C., Siddiqui, S., & Bradding, P. (2021). Clinical outcomes in people with difficult-to-control asthma using electronic monitoring to support medication adherence. *The Journal of Allergy and Clinical Immunology: In Practice*, *9*(4), 1529-1538.e2. https://doi.org/10.1016/j.jaip.2020.10.059

Bodenhausen, G. V. (1993). Emotions, arousal, and stereotypic judgments: A heuristic model of affect and stereotyping. In *Affect, cognition and stereotyping* (pp. 13–37). Elsevier.

Boekaerts, M. (2010). The crucial role of motivation and emotion in classroom learning. *The Nature of Learning: Using Research to Inspire Practice*, 91–111.

Bohnsack, R. (2004). Group discussion and focus groups. *A Companion to Qualitative Research*, 214–221.

Boll, S., Heuten, W., Meyer, E. M., & Meis, M. (2010). Development of a multimodal reminder system for older persons in their residential home. *Informatics for Health and Social Care*, *35*(3–4), 104–124.

Bonito, A., Horowitz, N., McCorkle, R., & Chagpar, A. B. (2013). Do healthcare professionals discuss the emotional impact of cancer with patients? *Psycho-Oncology*, *22*(9), 2046–2050. https://doi.org/10.1002/pon.3258

Bordier, M., Goutard, F. L., Antoine-Moussiaux, N., Pham-Duc, P., Lailler, R., & Binot, A. (2021). Engaging stakeholders in the design of one health surveillance systems: A participatory approach. *Frontiers in Veterinary Science*, *8*, 646458. https://doi.org/10.3389/fvets.2021.646458

Borghardt, J. M., Kloft, C., & Sharma, A. (2018). Inhaled Therapy in

Respiratory Disease: The Complex Interplay of Pulmonary Kinetic Processes. *Canadian Respiratory Journal*, *2018*, 1–11. https://doi.org/10.1155/2018/2732017

Borgström, L., Asking, L., & Lipniunas, P. (2005). An *in vivo* and *in vitro* comparison of two powder inhalers following storage at hot/humid conditions. *Journal of Aerosol Medicine*, *18*(3), 304–310. https://doi.org/10.1089/jam.2005.18.304

Borsci, S., Malizia, A., Schmettow, M., Van Der Velde, F., Tariverdiyeva, G., Balaji, D., & Chamberlain, A. (2022). The chatbot usability scale: The design and pilot of a usability scale for interaction with AI-based conversational agents. *Personal and Ubiquitous Computing*, *26*(1), 95–119. https://doi.org/10.1007/s00779-021-01582-9

Bosnic-Anticevich, S., Bakerly, N. D., Chrystyn, H., Hew, M., & van der Palen, J. (2023). Advancing digital solutions to overcome longstanding barriers in asthma and COPD management. *Patient Preference and Adherence*, 259–272.

Bosnic-Anticevich, S., Callan, C., Chrystyn, H., Lavorini, F., Nikolaou, V., Kritikos, V., Dekhuijzen, P. N. R., Roche, N., Bjermer, L., Rand, C., Zwar, N., & Price, D. B. (2018). Inhaler technique mastery and maintenance in healthcare professionals trained on different devices. *Journal of Asthma*, *55*(1), 79–88. https://doi.org/10.1080/02770903.2017.1310227

Bourbeau, J., & Bartlett, S. J. (2008). Patient adherence in COPD. *Thorax*, *63*(9), 831–838. https://doi.org/10.1136/thx.2007.086041

Bousquet, J., & Weltgesundheitsorganisation (Eds.). (2007). *Global surveillance, prevention and control of chronic respiratory diseases: A comprehensive approach*. World Health Organization.

Bowler, R., Allinder, M., Jacobson, S., Miller, A., Miller, B., Tal-Singer, R., & Locantore, N. (2019). Real-world use of rescue inhaler sensors, electronic symptom questionnaires and physical activity monitors in COPD. *BMJ Open Respiratory Research*, *6*(1), e000350. https://doi.org/10.1136/bmjresp-2018-000350

Brandstetter, S., Finger, T., Fischer, W., Brandl, M., Böhmer, M., Pfeifer, M., & Apfelbacher, C. (2017). Differences in medication adherence are associated with beliefs about medicines in asthma and COPD. *Clinical and Translational Allergy*, *7*(1), 39. https://doi.org/10.1186/s13601-017-0175-6

Brandtzaeg, P. B., & Følstad, A. (2017). *Why people use chatbots*. 377–392.

Brauer, P. M., Hanning, R. M., Arocha, J. F., Royall, D., Goy, R., Grant, A., Dietrich, L., Martino, R., & Horrocks, J. (2009). Creating case scenarios or vignettes using factorial study design methods. *Journal of Advanced Nursing*, *65*(9), 1937–1945. https://doi.org/10.1111/j.1365-2648.2009.05055.x

Bravo, P., Edwards, A., Barr, P. J., Scholl, I., Elwyn, G., McAllister, M., & the Cochrane Healthcare Quality Research Group, Cardiff University. (2015). Conceptualising patient empowerment: A mixed methods study. *BMC Health Services Research*, *15*(1), 252. https://doi.org/10.1186/s12913-015-0907-z

Brick, R., Hekman, D. J., Werner, N. E., Rodakowski, J., Cadmus-Bertram, L., & Fields, B. (2023). Health system and patient-level factors associated with multidisciplinary care and patient education among hospitalized, older cancer survivors. *PEC Innovation*, *3*, 100192. https://doi.org/10.1016/j.pecinn.2023.100192

Bridle, C., Riemsma, R. P., Pattenden, J., Sowden, A. J., Mather, L., Watt, I. S., & Walker, A. (2005). Systematic review of the effectiveness of health behavior interventions based on the transtheoretical model. *Psychology & Health*, *20*(3), 283–301. https://doi.org/10.1080/08870440512331333997

Brocklebank, D., Ram, F., Wright, J., Barry, P., Cates, C., Davies, L., Douglas, G., Muers, M., Smith, D., & White, J. (2001). Comparison of the effectiveness of inhaler devices in asthma and chronic obstructive airways disease: A systematic review of the literature. *Health Technology Assessment*, *5*(26).

https://doi.org/10.3310/hta5260

Brooks, H., Irmansyah, I., Lovell, K., Savitri, I., Utomo, B., Prawira, B., Iskandar, L., Renwick, L., Pedley, R., Kusumayati, A., & Bee, P. (2019). Improving mental health literacy among young people aged 11–15 years in java, indonesia: Co-development and feasibility testing of a culturally-appropriate, user-centred resource (IMPeTUs) – a study protocol. *BMC Health Services Research*, *19*(1), 484. https://doi.org/10.1186/s12913-019-4328-2

Browne, S. H., Behzadi, Y., & Littlewort, G. (2015). Let Visuals Tell the Story: Medication Adherence in Patients with Type II Diabetes Captured by a Novel Ingestion Sensor Platform. *JMIR mHealth and uHealth*, *3*(4), e108. https://doi.org/10.2196/mhealth.4292

Bryant, J., McDonald, V. M., Boyes, A., Sanson-Fisher, R., Paul, C., & Melville, J. (2013). Improving medication adherence in chronic obstructive pulmonary disease: A systematic review. *Respiratory Research*, *14*(1), 109. https://doi.org/10.1186/1465-9921-14-109

Bukstein, D. A. (2016). Patient adherence and effective communication. *Annals of Allergy, Asthma & Immunology*, *117*(6), 613–619.

Butt, M., Mhd Ali, A., Bakry, M. M., & Mustafa, N. (2016). Impact of a pharmacist led diabetes mellitus intervention on HbA1c, medication adherence and quality of life: A randomised controlled study. *Saudi Pharmaceutical Journal*, *24*(1), 40–48. https://doi.org/10.1016/j.jsps.2015.02.023

Cadel, L., Cimino, S. R., Rolf Von Den Baumen, T., James, K. A., McCarthy, L., & Guilcher, S. J. (2021). Medication Management Frameworks in the Context of Self-Management: A Scoping Review. *Patient Preference and Adherence*, *Volume 15*, 1311–1329. https://doi.org/10.2147/PPA.S308223

Cain, W. T., Cable, G., & Oppenheimer, J. J. (2001). The ability of the community pharmacist to learn the proper actuation techniques of inhaler devices. *Journal of Allergy and Clinical Immunology*, *108*(6), 918–920.

Cajamarca, G., Herskovic, V., & Rossel, P. O. (2020). Enabling older adults' health self-management through self-report and visualization—A systematic literature review. *Sensors*, *20*(15), 4348.

Calvillo-Arbizu, J., Naranjo-Hernández, D., Barbarov-Rostán, G., Talaminos-Barroso, A., Roa-Romero, L. M., & Reina-Tosina, J. (2021). A sensor-based mHealth platform for remote monitoring and intervention of frailty patients at home. *International Journal of Environmental Research and Public Health*, *18*(21), 11730. https://doi.org/10.3390/ijerph182111730

Calvo, M. G., & Nummenmaa, L. (2016). Perceptual and affective mechanisms in facial expression recognition: An integrative review. *Cognition and Emotion*, *30*(6), 1081–1106.

Calvo, R. A., Peters, D., Moradbakhti, L., Cook, D., Rizos, G., Schuller, B., Kallis, C., Wong, E., & Quint, J. (2023). Assessing the Feasibility of a Text-Based Conversational Agent for Asthma Support: Protocol for a Mixed Methods Observational Study. *JMIR Research Protocols*, *12*, e42965. https://doi.org/10.2196/42965

Cambach, W., Wagenaar, R. C., Koelman, T. W., van Keimpema, T., & Kemper, H. C. (1999). The long-term effects of pulmonary rehabilitation in patients with asthma and chronic obstructive pulmonary disease: A research synthesis. *Archives of Physical Medicine and Rehabilitation*, *80*(1), 103–111.

Camburn, B., Viswanathan, V., Linsey, J., Anderson, D., Jensen, D., Crawford, R., Otto, K., & Wood, K. (2017). Design prototyping methods: State of the art in strategies, techniques, and guidelines. *Design Science*, *3*, e13.

Carayon, P., Schoofs Hundt, A., Karsh, B.-T., Gurses, A. P., Alvarado, C. J., Smith, M., & Flatley Brennan, P. (2006). Work system design for patient safety: The SEIPS model. *Quality in Health Care*, *15*(suppl 1), i50–i58. https://doi.org/10.1136/qshc.2005.015842

Carayon, P., & Wooldridge, A. R. (2020). Improving patient safety in the patient journey: Contributions from human factors engineering. In A.

E. Smith (Ed.), *Women in Industrial and Systems Engineering* (pp. 275–299). Springer International Publishing. https://doi.org/10.1007/978-3-030-11866-2_12

Card, D., DellaVigna, S., & Malmendier, U. (2011). The role of theory in field experiments. *Journal of Economic Perspectives*, *25*(3), 39–62.

Cassidy, C. A. (1999). Using the transtheoretical model to facilitate behavior change in patients with chronic illness. *Journal of the American Academy of Nurse Practitioners*, *11*(7), 281–287. https://doi.org/10.1111/j.1745-7599.1999.tb00578.x

Cavoukian, A. (2012). Privacy by design and user interfaces. *Emerging Design Criteria–Keep It User-Centric*.

Chakraborty, A., Gupta, R. D., Kabir, Md. Z., & Dhar, S. (2023). Development of an IoT-enabled cost-effective asthma patient monitoring system: Integrating health and indoor environment data with statistical analysis and data visualization. *Internet of Things*, *24*, 100942. https://doi.org/10.1016/j.iot.2023.100942

Chan, A., De Simoni, A., Wileman, V., Holliday, L., Newby, C. J., Chisari, C., Ali, S., Zhu, N., Padakanti, P., Pinprachanan, V., Ting, V., & Griffiths, C. J. (2022). Digital interventions to improve adherence to maintenance medication in asthma. *Cochrane Database of Systematic Reviews*, *2022*(6). https://doi.org/10.1002/14651858.CD013030.pub2

Chan, A. H. Y., Harrison, J., Black, P. N., Mitchell, E. A., & Foster, J. M. (2015). *Using electronic monitoring devices to measure inhaler adherence: A practical guide for clinicians*.

Chan, A. H. Y., Pleasants, R. A., Dhand, R., Tilley, S. L., Schworer, S. A., Costello, R. W., & Merchant, R. (2021). Digital Inhalers for Asthma or Chronic Obstructive Pulmonary Disease: A Scientific Perspective. *Pulmonary Therapy*, *7*(2), 345–376. https://doi.org/10.1007/s41030-021-00167-4

Chan, A. H. Y., Stewart, A. W., Harrison, J., Camargo, C. A., Black, P. N., & Mitchell, E. A. (2015). The effect of an electronic monitoring device with audiovisual reminder function on adherence to inhaled corticosteroids and school attendance in children with asthma: A randomised controlled trial. *The Lancet Respiratory Medicine*, *3*(3), 210–219. https://doi.org/10.1016/S2213-2600(15)00008-9

Chan, H., & Perrig, A. (2003). Security and privacy in sensor networks. *Computer*, *36*(10), 103–105.

Chang, Y., Lim, Y., & Stolterman, E. (2008). Personas: From theory to practices. *Proceedings of the 5th Nordic Conference on Human-Computer Interaction: Building Bridges*, 439–442. https://doi.org/10.1145/1463160.1463214

Charmaz, K. (2006). *Constructing grounded theory: A practical guide through qualitative analysis*. sage.

Chen, J., Xu, J., Zhao, L., Zhang, J., Yin, Y., & Zhang, F. (2020). The effect of electronic monitoring combined with weekly feedback and reminders on adherence to inhaled corticosteroids in infants and younger children with asthma: A randomized controlled trial. *Allergy, Asthma & Clinical Immunology*, *16*(1), 68. https://doi.org/10.1186/s13223-020-00466-6

Chen, W., Wang, F., Xiao, G., Wu, K., & Zhang, S. (2015). Air quality of beijing and impacts of the new ambient air quality standard. *Atmosphere*, *6*(8), 1243–1258.

Chen, Z., Lu, Y., Nieminen, M. P., & Lucero, A. (2020). Creating a Chatbot for and with Migrants: Chatbot Personality Drives Co-Design Activities. *Proceedings of the 2020 ACM Designing Interactive Systems Conference*, 219–230. https://doi.org/10.1145/3357236.3395495

Chmelik, F., & Kao, N. (1996). Compliance with asthma therapy: Measurement and implications. *Clinical Immunotherapeutics*, *5*(3), 193–204. https://doi.org/10.1007/BF03259082

Cho, J., Lim, K., Kim, J., Shin, Y., Park, Y., & Yeon, J. (2024). RETRACTED: Enhancing data quality management in structural health monitoring through irregular time-series data anomaly detection using IoT sensors. *Buildings*, *14*(7), 2223. https://doi.org/10.3390/buildings14072223

Choi, H., Hamanaka, T., & Matsui, K. (2017). Design and implementation of interactive product manual system using chatbot and sensed data. *2017 IEEE 6th Global Conference on Consumer Electronics (GCCE)*, 1–5. https://doi.org/10.1109/GCCE.2017.8229223

Chopra, N., Oprescu, N., Fask, A., & Oppenheimer, J. (2002). Does introduction of new “easy to use” inhalational devices improve medical personnel’s knowledge of their proper use? *Annals of Allergy, Asthma & Immunology*, *88*(4), 395–400.

Chorão, P., Pereira, A. M., & Fonseca, J. A. (2014). Inhaler devices in asthma and COPD – an assessment of inhaler technique and patient preferences. *Respiratory Medicine*, *108*(7), 968–975. https://doi.org/10.1016/j.rmed.2014.04.019

Chowdhury, M. N.-U.-R., & Haque, A. (2023). *Chatbots: A game changer in mHealth* [Preprint]. https://doi.org/10.36227/techrxiv.22548532.v1

Chrystyn, H., Audibert, R., Keller, M., Quaglia, B., Vecellio, L., & Roche, N. (2019). Real-life inhaler adherence and technique: Time to get smarter! *Respiratory Medicine*, *158*, 24–32. https://doi.org/10.1016/j.rmed.2019.09.008

Chuang, K.-J., Chan, C.-C., Shiao, G.-M., & Su, T.-C. (2005). Associations between submicrometer particles exposures and blood pressure and heart rate in patients with lung function impairments. *Journal of Occupational and Environmental Medicine*, *47*(11), 1093–1098.

Clark, A. R., Weers, J. G., & Dhand, R. (2020). The confusing world of dry powder inhalers: It is all about inspiratory pressures, not inspiratory flow rates. *Journal of Aerosol Medicine and Pulmonary Drug Delivery*, *33*(1), 1–11. https://doi.org/10.1089/jamp.2019.1556

Cochrane, M. G., Bala, M. V., Downs, K. E., Mauskopf, J., & Ben-Joseph, R. H. (2000). Inhaled Corticosteroids for Asthma Therapy. *Chest*, *117*(2), 542–550. https://doi.org/10.1378/chest.117.2.542

Cohen, J. L., Mann, D. M., Wisnivesky, J. P., Horne, R., Leventhal, H., Musumeci-Szabó, T. J., & Halm, E. A. (2009). Assessing the validity of self-reported medication adherence among inner-city asthmatic adults: The Medication Adherence Report Scale for Asthma. *Annals of Allergy, Asthma & Immunology*, *103*(4), 325–331. https://doi.org/10.1016/S1081-1206(10)60532-7

Cohen, L., Manion, L., & Morrison, K. (2017). Validity and reliability. In *Research methods in education* (pp. 245–284). Routledge.

Conner, M., & Norman, P. (Eds.). (2015). *Predicting and changing health behaviour: Research and practice with social cognition models* (Third edition). Open University Press.

Conway, C. M., & Kelechi, T. J. (2017). Digital health for medication adherence in adult diabetes or hypertension: An integrative review. *JMIR Diabetes*, *2*(2), e20. https://doi.org/10.2196/diabetes.8030

Cowen, M. K., Wakefield, D. B., & Cloutier, M. M. (2007). Classifying asthma severity: Objective versus subjective measures. *Journal of Asthma*, *44*(9), 711–715. https://doi.org/10.1080/02770900701595576

Cox, D. (2006). *Metaphoric mappings: The art of visualization*.

Cripps, H., & Standing, C. (2012). *Building patient trust in electronic health records*.

Cui, J., Cui, L., Huang, Z., Li, X., & Han, F. (2022). IoT wheelchair control system based on multi-mode sensing and human-machine interaction. *Micromachines*, *13*(7), 1108. https://doi.org/10.3390/mi13071108

Cvengros, J. A., Christensen, A. J., Hillis, S. L., & Rosenthal, G. E. (2007). Patient and physician attitudes in the health care context: Attitudinal symmetry predicts patient satisfaction and adherence. *Annals of Behavioral Medicine*, *33*(3), 262–268. https://doi.org/10.1007/BF02879908

d’Amato, G., Chong-Neto, H. J., Monge Ortega, O. P., Vitale, C., Ansotegui, I., Rosario, N., Haahtela, T., Galan, C., Pawankar, R., & Murrieta-Aguttes, M. (2020). The effects of climate change on respiratory allergy and asthma induced by pollen and mold allergens. *Allergy*, *75*(9), 2219–2228.

Dabrowska, M., Luczak-Wozniak, K., Miszczuk, M., Domagala, I., Lubanski, W., Leszczynski, A., Maskey-Warzechowska, M., Rubinsztajn, R., Hermanowicz-Salamon, J., & Krenke, R. (2019). Impact of a single session of inhalation technique training on inhalation skills and the course of asthma and COPD. *Respiratory Care*, *64*(10), 1250–1260. https://doi.org/10.4187/respcare.06740

Dahlberg, K., Stenberg, E., Liang, Y., Nilsson, U., & Jaensson, M. (2022). The General Self-Efficacy Scale in a population planned for bariatric surgery in Sweden: A psychometric evaluation study. *BMJ Open*, *12*(11), e061509. https://doi.org/10.1136/bmjopen-2022-061509

Dal Negro, R. W., Turco, P., & Povero, M. (2019). Patients' usability of seven most used dry-powder inhalers in COPD. *Multidisciplinary Respiratory Medicine*, *14*(1), 30. https://doi.org/10.1186/s40248-019-0192-5

Dalby, R., Spallek, M., & Voshaar, T. (2004). A review of the development of Respimat® Soft Mist™ Inhaler. *International Journal of Pharmaceutics*, *283*(1–2), 1–9. https://doi.org/10.1016/j.ijpharm.2004.06.018

Dalby, R., & Suman, J. (2003). Inhalation therapy: Technological milestones in asthma treatment. *Advanced Drug Delivery Reviews*, *55*(7), 779–791. https://doi.org/10.1016/S0169-409X(03)00077-2

Dales, R. E., Cakmak, S., Judek, S., Dann, T., Coates, F., Brook, J. R., & Burnett, R. T. (2004). Influence of outdoor aeroallergens on hospitalization for asthma in canada. *Journal of Allergy and Clinical Immunology*, *113*(2), 303–306.

Daly, I., Malik, A., Weaver, J., Hwang, F., Nasuto, S. J., Williams, D., Kirke, A., & Miranda, E. (2015). Towards human-computer music interaction: Evaluation of an affectively-driven music generator via galvanic skin response measures. *2015 7th Computer Science and Electronic Engineering Conference (CEEC)*, 87–92. https://doi.org/10.1109/CEEC.2015.7332705

Damman, O. C., Hendriks, M., Rademakers, J., Spreeuwenberg, P., Delnoij, D. M., & Groenewegen, P. P. (2012). Consumers' interpretation and use of comparative information on the quality of health care: The effect of presentation approaches. *Health Expectations*, *15*(2), 197–211.

Danielsson, K., Naghsh, A. M., Gumm, D., & Warr, A. (2008). Distributed participatory design. In *CHI'08 extended abstracts on Human factors in computing systems* (pp. 3953–3956).

D'Arcy, S., MacHale, E., Seheult, J., Holmes, M. S., Hughes, C., Sulaiman, I., Hyland, D., O'Reilly, C., Glynn, S., Al-Zaabi, T., McCourt, J., Taylor, T., Keane, F., Killane, I., Reilly, R. B., & Costello, R. W. (2014). A method to assess adherence in inhaler use through analysis of acoustic recordings of inhaler events. *PLoS ONE*, *9*(6), e98701. https://doi.org/10.1371/journal.pone.0098701

Darrow, L. A., Hess, J., Rogers, C. A., Tolbert, P. E., Klein, M., & Sarnat, S. E. (2012). Ambient pollen concentrations and emergency department visits for asthma and wheeze. *Journal of Allergy and Clinical Immunology*, *130*(3), 630–638.

Davies, A., Mueller, J., Hennings, J., Caress, A.-L., & Jay, C. (2020). Recommendations for developing support tools with people suffering from chronic obstructive pulmonary disease: Co-design and pilot testing of a mobile health prototype. *JMIR Human Factors*, *7*(2), e16289. https://doi.org/10.2196/16289

Davis, S., Peters, D., Calvo, R., Sawyer, S., Foster, J., & Smith, L. (2018). "Kiss myAsthma": Using a participatory design approach to develop a self-management app with young people with asthma. *Journal of Asthma*, *55*(9), 1018–1027. https://doi.org/10.1080/02770903.2017.1388391

De Angeli, D., Kelly, R. M., & O'Neill, E. (2020). Beyond Happy-or-Not:

Using Emoji to Capture Visitors' Emotional Experience. *Curator: The Museum Journal*, *63*(2), 167–191. https://doi.org/10.1111/cura.12352

de Boer, A. H., Hagedoorn, P., Hoppentocht, M., Buttini, F., Grasmeijer, F., & Frijlink, H. W. (2017). Dry powder inhalation: Past, present and future. *Expert Opinion on Drug Delivery*, *14*(4), 499–512.

De Folter, J., Gokalp, H., Fursse, J., Sharma, U., & Clarke, M. (2014). Designing effective visualizations of habits data to aid clinical decision making. *BMC Medical Informatics and Decision Making*, *14*(1), 102. https://doi.org/10.1186/s12911-014-0102-x

De Geest, S., & Sabaté, E. (2003). Adherence to long-term therapies: Evidence for action. *European Journal of Cardiovascular Nursing*, *2*(4), 323–323. https://doi.org/10.1016/S1474-5151(03)00091-4

De Gennaro, M., Krumhuber, E. G., & Lucas, G. (2020). Effectiveness of an empathic chatbot in combating adverse effects of social exclusion on mood. *Frontiers in Psychology*, *10*, 3061.

De la Fuente-Martos, C., Rojas-Amezcua, M., Gómez-Espejo, M., Lara-Aguayo, P., Morán-Fernandez, E., & Aguilar-Alonso, E. (2018). Humanization in healthcare arises from the need for a holistic approach to illness. *Medicina Intensiva (English Edition)*, *42*(2), 99–109.

De Simoni, A., Fleming, L., Holliday, L., Horne, R., Priebe, S., Bush, A., Sheikh, A., & Griffiths, C. (2021). Electronic reminders and rewards to improve adherence to inhaled asthma treatment in adolescents: A non-randomised feasibility study in tertiary care. *BMJ Open*, *11*(10), e053268. https://doi.org/10.1136/bmjopen-2021-053268

Delfino, R. J., Zeiger, R. S., Seltzer, J. M., Street, D. H., & McLaren, C. E. (2002). Association of asthma symptoms with peak particulate air pollution and effect modification by anti-inflammatory medication use. *Environmental Health Perspectives*, *110*(10), A607–A617.

DeRosier, J., Stalhandske, E., Bagian, J. P., & Nudell, T. (2002). Using health care failure mode and effect analysis™: The VA national center for patient safety's prospective risk analysis system. *The Joint Commission Journal on Quality Improvement*, *28*(5), 248–267.

Desmet, P. M., Vastenburg, M. H., & Romero, N. (2016). Mood measurement with pick-a-mood: Review of current methods and design of a pictorial self-report scale. *Journal of Design Research*, *14*(3), 241–279.

Devaram, S. (2020). Empathic chatbot: Emotional intelligence for empathic chatbot: Emotional intelligence for mental health well-being. *arXiv Preprint arXiv:2012.09130*.

Dhand, R., Cavanaugh, T., & Skolnik, N. (2018). Considerations for optimal inhaler device selection in chronic obstructive pulmonary disease. *Cleveland Clinic Journal of Medicine*, *85*(2 suppl 1), S19–S27. https://doi.org/10.3949/ccjm.85.s1.04

Dhunnoo, P., Kemp, B., McGuigan, K., Meskó, B., O'Rourke, V., & McCann, M. (2024). Evaluation of telemedicine consultations using health outcomes and user attitudes and experiences: Scoping review. *Journal of Medical Internet Research*, *26*, e53266. https://doi.org/10.2196/53266

Diamond, J. (1986). Laboratory experiments, field experiments, and natural experiments. *Community Ecology*, 3–22.

Dierick, B. H. J., Achterbosch, M., Been-Buck, S., Klemmeier, T., Van De Hei, S. J., Hagedoorn, P., Kerstjens, H. A. M., Kocks, J. W. H., & Van Boven, J. F. M. (2022). Can electronic monitoring with a digital smart spacer support personalised medication adherence and inhaler technique education in patients with asthma?: Protocol of the randomised controlled OUTERSPACE trial. *BMJ Open*, *12*(6), e059929. https://doi.org/10.1136/bmjopen-2021-059929

Dima, A. L., Hernandez, G., Cunillera, O., Ferrer, M., De Bruin, M., & the ASTRO-LAB group. (2015). Asthma inhaler adherence determinants in adults: Systematic review of observational data. *European Respiratory Journal*, *45*(4), 994–1018. https://doi.org/10.1183/09031936.00172114

DiMatteo, M. R. (2004). Variations in patients' adherence to medical recommendations: A quantitative review of 50 years of research. *Medical Care*, *42*(3), 200–209. https://doi.org/10.1097/01.mlr.0000114908.90348.f9

Donaldson, L. J., Kelley, E. T., Dhingra-Kumar, N., Kieny, M.-P., & Sheikh, A. (2017). Medication without harm: WHO's third global patient safety challenge. *The Lancet*, *389*(10080), 1680–1681. https://doi.org/10.1016/S0140-6736(17)31047-4

Donetto, S., Pierri, P., Tsianakas, V., & Robert, G. (2015). Experience-based Co-design and Healthcare Improvement: Realizing Participatory Design in the Public Sector. *The Design Journal*, *18*(2), 227–248. https://doi.org/10.2752/175630615X14212498964312

Dong, Q., Li, B., Downen, R. S., Tran, N., Chorvinsky, E., Pillai, D., Zaghloul, M., & Li, Z. (2019). Wearable and Stationary Point-of-Care IoT Air Pollution Sensors for Pediatric Asthma Research and Management. *2019 IEEE Healthcare Innovations and Point of Care Technologies, (HI-POCT)*, 123–126. https://doi.org/10.1109/HI-POCT45284.2019.8962865

Drotar, D., & Bonner, M. S. (2009). Influences on adherence to pediatric asthma treatment: A review of correlates and predictors. *Journal of Developmental & Behavioral Pediatrics*, *30*(6), 574–582. https://doi.org/10.1097/DBP.0b013e3181c3c3bb

Du Toit, M., Malau-Aduli, B., Vangaveti, V., Sabesan, S., & Ray, R. A. (2019). Use of telehealth in the management of non-critical emergencies in rural or remote emergency departments: A systematic review. *Journal of Telemedicine and Telecare*, *25*(1), 3–16. https://doi.org/10.1177/1357633X17734239

Dutta, A., Ma, O., Toledo, M., Pregonero, A. F., Ainsworth, B. E., Buman, M. P., & Bliss, D. W. (2018). Identifying free-living physical activities using lab-based models with wearable accelerometers. *Sensors*, *18*(11), 3893.

Eguchi, K., Yabuuchi, T., Nambu, M., Takeyama, H., Azuma, S., Chin, K.,

& Kuroda, T. (2022). Investigation on factors related to poor CPAP adherence using machine learning: A pilot study. *Scientific Reports*, *12*(1), 19563. https://doi.org/10.1038/s41598-022-21932-8

Eh, K., McGill, M., Wong, J., & Krass, I. (2016). Cultural issues and other factors that affect self-management of type 2 diabetes mellitus (T2D) by Chinese immigrants in australia. *Diabetes Research and Clinical Practice*, *119*, 97–105. https://doi.org/10.1016/j.diabres.2016.07.006

Eikholt, A. A., Wiertz, M. B. R., Hew, M., Chan, A. H. Y., & Van Boven, J. F. M. (2023). Electronic Monitoring Devices to Support Inhalation Technique in Patients with Asthma: A Narrative Review. *Current Treatment Options in Allergy*, *10*(1), 28–52. https://doi.org/10.1007/s40521-023-00328-7

Emilsson, M., Berndtsson, I., Lötvall, J., Millqvist, E., Lundgren, J., Johansson, Å., & Brink, E. (2011). The influence of personality traits and beliefs about medicines on adherence to asthma treatment. *Primary Care Respiratory Journal*, *20*(2), 141–147. https://doi.org/10.4104/pcrj.2011.00005

Eschenbacher, W. L., Moore, T. B., Lorenzen, T. J., Weg, J. G., & Gross, K. B. (1992). Pulmonary responses of asthmatic and normal subjects to different temperature and humidity conditions in an environmental chamber. *Lung*, *170*, 51–62.

Evans, R. P., Bryant, L. D., Russell, G., & Absolom, K. (2024). Trust and acceptability of data-driven clinical recommendations in everyday practice: A scoping review. *International Journal of Medical Informatics*, 105342.

Faiola, A., Srinivas, P., & Hillier, S. (2015). *Improving patient safety: Integrating data visualization and communication into ICU workflow to reduce cognitive load*. *4*(1), 55–61.

Faisal, S., Samoth, D., Aslam, Y., Patel, H., Park, S., Baby, B., & Patel, T. (2023). Key Features of Smart Medication Adherence Products: Updated Scoping Review. *JMIR Aging*, *6*, e50990.

https://doi.org/10.2196/50990

Famili, A., Shen, W.-M., Weber, R., & Simoudis, E. (1997). Data preprocessing and intelligent data analysis. *Intelligent Data Analysis*, *1*(1), 3–23.

Farzandipour, M., Nabovati, E., Sharif, R., Arani, M., & Anvari, S. (2017). Patient self-management of asthma using mobile health applications: A systematic review of the functionalities and effects. *Applied Clinical Informatics*, *08*(04), 1068–1081. https://doi.org/10.4338/ACI-2017-07-R-0116

Fay, D., Hurwitz, J., & Teare, S. (1990). *The use of low-fidelity prototypes in user interface design*. 23–31.

Fedele, D. A., McConville, A., Graham Thomas, J., McQuaid, E. L., Janicke, D. M., Turner, E. M., Moon, J., & Abu-Hasan, M. (2018). Applying Interactive Mobile health to Asthma Care in Teens (AIM2ACT): Development and design of a randomized controlled trial. *Contemporary Clinical Trials*, *64*, 230–237. https://doi.org/10.1016/j.cct.2017.09.007

Fernandes, L. de S., Calado, C., & Araujo, C. A. S. (2018). Social networks and health practices: Influence of a diabetes online community on adherence to treatment. *Ciência & Saúde Coletiva*, *23*, 3357–3368.

Ficke, D. L., & Farris, K. B. (2005). Use of the transtheoretical model in the medication use process. *Annals of Pharmacotherapy*, *39*(7–8), 1325–1330. https://doi.org/10.1345/aph.1G122

Fink, J. B., & Rubin, B. K. (2005). Problems with inhaler use: A call for improved clinician and patient education. *Respiratory Care*, *50*(10), 1360–1375.

Finkelstein, J., & Jeong, I. C. (2017). Machine learning approaches to personalize early prediction of asthma exacerbations. *Annals of the New York Academy of Sciences*, *1387*(1), 153–165. https://doi.org/10.1111/nyas.13218

Fischer, W., Brandstetter, S., Brandl, M., Finger, T., Böhmer, M. M., Pfeifer, M., & Apfelbacher, C. (2018). Specific, but not general beliefs about medicines are associated with medication adherence in patients with COPD, but not asthma: Cohort study in a population of people with chronic pulmonary disease. *Journal of Psychosomatic Research*, *107*, 46–52. https://doi.org/10.1016/j.jpsychores.2018.02.004

Fong, A. C. M., & Fong, B. (2011). Indoor air quality control for asthma patients using smart home technology. *2011 IEEE 15th International Symposium on Consumer Electronics (ISCE)*, 18–19. https://doi.org/10.1109/ISCE.2011.5973774

Fortuna, K. L., Brooks, J. M., Umucu, E., Walker, R., & Chow, P. I. (2019). Peer support: A human factor to enhance engagement in digital health behavior change interventions. *Journal of Technology in Behavioral Science*, *4*(2), 152–161. https://doi.org/10.1007/s41347-019-00105-x

Fortunato, M., Harrison, J., Oon, A. L., Small, D., Hilbert, V., Rareshide, C., & Patel, M. (2019). Remotely monitored gamification and social incentives to improve glycemic control among adults with uncontrolled type 2 diabetes (iDiabetes): Protocol for a randomized controlled trial. *JMIR Research Protocols*, *8*(11), e14180.

Foster, J. M., Smith, L., Bosnic-Anticevich, S. Z., Usherwood, T., Sawyer, S. M., Rand, C. S., & Reddel, H. K. (2012). Identifying patient-specific beliefs and behaviours for conversations about adherence in asthma. *Internal Medicine Journal*, *42*(6). https://doi.org/10.1111/j.1445-5994.2011.02541.x

Foster, J. M., Smith, L., Usherwood, T., Sawyer, S. M., Rand, C. S., & Reddel, H. K. (2012). The reliability and patient acceptability of the SmartTrack device: A new electronic monitor and reminder device for metered dose inhalers. *Journal of Asthma*, *49*(6), 657–662. https://doi.org/10.3109/02770903.2012.684253

Foster, J. M., Usherwood, T., Smith, L., Sawyer, S. M., Xuan, W., Rand, C. S., & Reddel, H. K. (2014). Inhaler reminders improve adherence with controller treatment in primary care patients with asthma. *Journal of Allergy and Clinical Immunology*, *134*(6), 1260-1268.e3. https://doi.org/10.1016/j.jaci.2014.05.041

Franklin, C., & Ballan, M. (2001). Reliability and validity in qualitative research. *The Handbook of Social Work Research Methods*, *4*(273–292).

Frith, K. H. (2013). Medication errors in the intensive care unit. *AACN Advanced Critical Care*, *24*(4), 389–404. https://doi.org/10.4037/NCI.0b013e3182a8b516

Garber, M. C., Nau, D. P., Erickson, S. R., Aikens, J. E., & Lawrence, J. B. (2004). The concordance of self-report with other measures of medication adherence: A summary of the literature. *Medical Care*, *42*(7), 649–652. https://doi.org/10.1097/01.mlr.0000129496.05898.02

García-Cárdenas, V., Sabater-Hernández, D., García-Corpas, J. P., Faus, M. J., Martínez-Martínez, F., & Benrimoj, S. I. (2012). Errors in turbuhaler technique in a spanish population of asthmatic patients. *Respiratory Care*, *57*(5), 817–818.

Garcia-Contreras, L., Ibrahim, M., & Verma, R. (2015). Inhalation drug delivery devices: Technology update. *Medical Devices: Evidence and Research*, 131. https://doi.org/10.2147/MDER.S48888

Garin, N., Zarate-Tamames, B., Gras-Martin, L., Milà, R., Crespo-Lessmann, A., Curto, E., Hernandez, M., Mestres, C., & Plaza, V. (2023). Clinical Impact of Electronic Monitoring Devices of Inhalers in Adults with Asthma or COPD: A Systematic Review and Meta-Analysis. *Pharmaceuticals*, *16*(3), 414. https://doi.org/10.3390/ph16030414

George, M. (2018). Adherence in Asthma and COPD: New Strategies for an Old Problem. *Respiratory Care*, *63*(6), 818–831. https://doi.org/10.4187/respcare.05905

George, M., & Bender, B. (2019). New insights to improve treatment adherence in asthma and COPD. *Patient Preference and Adherence*, *Volume 13*, 1325–1334. https://doi.org/10.2147/PPA.S209532

Gerdes, A. B., Wieser, M. J., Mühlberger, A., Weyers, P., Alpers, G. W., Plichta, M. M., Breuer, F., & Pauli, P. (2010). Brain activations to emotional pictures are differentially associated with valence and arousal ratings. *Frontiers in Human Neuroscience*, *4*, 175.

Ghose, A., Guo, X., Li, B., & Dang, Y. (2021). Empowering patients using smart mobile health platforms: Evidence from a randomized field experiment. *arXiv Preprint arXiv:2102.05506*.

Ghozali, M. T. (2023). Implementation of the IoT-Based Technology on Patient Medication Adherence: A Comprehensive Bibliometric and Systematic Review. *Journal of Information and Communication Technology*, *22*. https://doi.org/10.32890/jict2023.22.4.1

Gilbert, S., Fenech, M., Hirsch, M., Upadhyay, S., Biasiucci, A., & Starlinger, J. (2021). Algorithm Change Protocols in the Regulation of Adaptive Machine Learning–Based Medical Devices. *Journal of Medical Internet Research*, *23*(10), e30545. https://doi.org/10.2196/30545

Giner, J., Villarnovo Cerrillo, M., Aboín Sierra, J., Casas Herrero, L., Patino, O., & Plaza, V. (2020). Assessment of inhalation errors, training time and patient preference for DuoResp® spiromax® and symbicort® turbuhaler® in patients with asthma and COPD. *European Clinical Respiratory Journal*, *7*(1), 1833411.

Godin, G., & Kok, G. (1996). The theory of planned behavior: A review of its applications to health-related behaviors. *American Journal of Health Promotion*, *11*(2), 87–98. https://doi.org/10.4278/0890-1171-11.2.87

Gold, D. T., & McClung, B. (2006). Approaches to patient education: Emphasizing the long-term value of compliance and persistence. *The American Journal of Medicine*, *119*(4), S32–S37.

Gong, Y., & Chandra, A. (2016). Developing an integrated display of health data for aging in place. *Human Factors and Ergonomics in Manufacturing & Service Industries*, *26*(4), 473–482.

Grant, A. C., Walker, R., Hamilton, M., & Garrill, K. (2015). The ELLIPTA® dry powder inhaler: Design, functionality, in vitro dosing performance and critical task compliance by patients and caregivers. *Journal of Aerosol Medicine and Pulmonary Drug Delivery*, *28*(6), 474–485.

Gravina, R., Alinia, P., Ghasemzadeh, H., & Fortino, G. (2017). Multi-sensor fusion in body sensor networks: State-of-the-art and research challenges. *Information Fusion*, *35*, 68–80. https://doi.org/10.1016/j.inffus.2016.09.005

Gray, W. N., Netz, M., McConville, A., Fedele, D., Wagoner, S. T., & Schaefer, M. R. (2018). Medication adherence in pediatric asthma: A systematic review of the literature. *Pediatric Pulmonology*, *53*(5), 668–684. https://doi.org/10.1002/ppul.23966

Greene, G., & Costello, R. W. (2019). Personalizing medicine—Could the smart inhaler revolutionize treatment for COPD and asthma patients? *Expert Opinion on Drug Delivery*, *16*(7), 675–677. https://doi.org/10.1080/17425247.2019.1628017

Gregoriano, C., Dieterle, T., Breitenstein, A.-L., Dürr, S., Baum, A., Maier, S., Arnet, I., Hersberger, K. E., & Leuppi, J. D. (2018). Use and inhalation technique of inhaled medication in patients with asthma and COPD: Data from a randomized controlled trial. *RESPIRATORY RESEARCH*, *19*(1), 237. https://doi.org/10.1186/s12931-018-0936-3

Gregoriano, C., Dieterle, T., Dürr, S., Arnet, I., Hersberger, K. E., & Leuppi, J. D. (2017). Impact of an electronic monitoring intervention to improve adherence to inhaled medication in patients with asthma and chronic obstructive pulmonary disease: Study protocol for a randomized controlled trial. *JMIR Research Protocols*, *6*(10), e204. https://doi.org/10.2196/resprot.7522

Grossman, B., Conner, S., Mosnaim, G., Albers, J., Leigh, J., Jones, S., & Kenyon, R. (2017). Application of Human Augmentics: A Persuasive Asthma Inhaler. *Journal of Biomedical Informatics*, *67*, 51–58.

https://doi.org/10.1016/j.jbi.2017.02.003

Gu, Y., Zalkikar, A., Liu, M., Kelly, L., Hall, A., Daly, K., & Ward, T. (2021). Predicting medication adherence using ensemble learning and deep learning models with large scale healthcare data. *Scientific Reports*, *11*(1), 18961. https://doi.org/10.1038/s41598-021-98387-w

Guarnieri, M., & Balmes, J. R. (2014). Outdoor air pollution and asthma. *The Lancet*, *383*(9928), 1581–1592.

Gudjonsdottir, R., & Lindquist, S. (2008). *Personas and scenarios: Design tool or a communication device?*

Gui, P., Tang, L., & Mukhopadhyay, S. (2015). MEMS based IMU for tilting measurement: Comparison of complementary and kalman filter based data fusion. *2015 IEEE 10th Conference on Industrial Electronics and Applications (ICIEA)*, 2004–2009. https://doi.org/10.1109/ICIEA.2015.7334442

Gupta, R. S., Fierstein, J. L., Boon, K. L., Kanaley, M. K., Bozen, A., Kan, K., Vojta, D., & Warren, C. M. (2021). Sensor-Based Electronic Monitoring for Asthma: A Randomized Controlled Trial. *Pediatrics*, *147*(1), e20201330. https://doi.org/10.1542/peds.2020-1330

Gutiérrez, F. J. Á., Galván, M. F., Gallardo, J. F. M., Mancera, M. B., Romero, B. R., & Falcón, A. R. (2017). Predictive factors for moderate or severe exacerbations in asthma patients receiving outpatient care. *BMC Pulmonary Medicine*, *17*(1), 77. https://doi.org/10.1186/s12890-017-0422-6

Haddad, T. C., Maita, K. C., Inselman, J. W., Avila, F. R., Torres-Guzman, R. A., Coffey, J. D., Christopherson, L. A., Leuenberger, A. M., Bell, S. J., Pahl, D. F., Garcia, J. P., Manka, L., Forte, A. J., & Maniaci, M. J. (2023). Patient satisfaction with a multisite, multiregional remote patient monitoring program for acute and chronic condition management: Survey-based analysis. *Journal of Medical Internet Research*, *25*, e44528. https://doi.org/10.2196/44528

Hale, E. M., Greene, G., Mulvey, C., Mokoka, M. C., Van Boven, J. F. M., Cushen, B., Sulaiman, I., Brennan, V., Lombard, L., Walsh, J., Plunkett, S., McCartan, T. A., Kerr, P. J., Reilly, R. B., Hughes, C., Kent, B. D., Jackson, D. J., Butler, M., Counihan, I., … McCartan, T. A. (2023). Use of digital measurement of medication adherence and lung function to guide the management of uncontrolled asthma (INCA sun): A multicentre, single-blinded, randomised clinical trial. *The Lancet Respiratory Medicine*, *11*(7), 591–601. https://doi.org/10.1016/S2213-2600(22)00534-3

Hamine, S., Gerth-Guyette, E., Faulx, D., Green, B. B., & Ginsburg, A. S. (2015). Impact of mHealth Chronic Disease Management on Treatment Adherence and Patient Outcomes: A Systematic Review. *Journal of Medical Internet Research*, *17*(2), e52. https://doi.org/10.2196/jmir.3951

Hamper, A., Wendt, J., Zagel, C., & Bodendorf, F. (2016). *Behavior change support for physical activity promotion: A theoretical view on mobile health and fitness applications*. 3349–3358.

Hasegawa, A., Shimono, T., Takano, S., Masaki, K., Nakada, H., Nishie, M., & Hakamata, J. (2023). Inhaler motion evaluation via weighted DP matching. *IEEJ Journal of Industry Applications*, *12*(5), 885–893. https://doi.org/10.1541/ieejjia.22004514

Hashemzadeh, M., Rahimi, A., Zare-Farashbandi, F., Alavi-Naeini, A., & Daei, A. (2019). Transtheoretical model of health behavioral change: A systematic review. *Iranian Journal of Nursing and Midwifery Research*, *24*(2), 83. https://doi.org/10.4103/ijnmr.IJNMR_94_17

Hauser-Ulrich, S., Künzli, H., Meier-Peterhans, D., & Kowatsch, T. (2020). A Smartphone-Based Health Care Chatbot to Promote Self-Management of Chronic Pain (SELMA): Pilot Randomized Controlled Trial. *JMIR mHealth and uHealth*, *8*(4), e15806. https://doi.org/10.2196/15806

Hegde, V. (2013). Role of human factors / usability engineering in medical device design. *2013 Proceedings Annual Reliability and Maintainability Symposium (RAMS)*, 1–5. https://doi.org/10.1109/RAMS.2013.6517650

Heidari-Soureshjani, S., Yarmohammadi, P., Torabi-Farsani, Z., Solati, K., & Ahmadi, A. (2018). Relationship between adherence to health behaviors and several social cognitive theory structures in diabetic women. *Zbmu-Jdn*, *6*(3), 517–529.

Heijsters, F., Santema, J., Mullender, M., Bouman, M.-B., Bruijne, M. D., & Van Nassau, F. (2022). Stakeholders barriers and facilitators for the implementation of a personalised digital care pathway: A qualitative study. *BMJ Open*, *12*(11), e065778. https://doi.org/10.1136/bmjopen-2022-065778

Hennink, M., Hutter, I., & Bailey, A. (2020). *Qualitative research methods*. Sage.

Hentati, A., Forsell, E., Ljótsson, B., Kaldo, V., Lindefors, N., & Kraepelien, M. (2021). The effect of user interface on treatment engagement in a self-guided digital problem-solving intervention: A randomized controlled trial. *Internet Interventions*, *26*, 100448.

Hesso, I., Nabhani Gebara, S., Greene, G., Co Stello, R. W., & Kayyali, R. (2020). A quantitative evaluation of adherence and inhalation technique among respiratory patients: An observational study using an electronic inhaler assessment device. *International Journal of Clinical Practice*, *74*(2). https://doi.org/10.1111/ijcp.13437

Hesso, I., Nabhani-Gebara, S., & Kayyali, R. (2023). Objective assessment of adherence and inhaler technique among asthma and COPD patients in london: A study in community pharmacies using an electronic monitoring device. *Pharmacy*, *11*(3), 94. https://doi.org/10.3390/pharmacy11030094

Hickey, A. J. (2013). Back to the future: Inhaled drug products. *Journal of Pharmaceutical Sciences*, *102*(4), 1165–1172.

Hignett, S., Carayon, P., Buckle, P., & Catchpole, K. (2013). State of science: Human factors and ergonomics in healthcare. *Ergonomics*, *56*(10), 1491–1503. https://doi.org/10.1080/00140139.2013.822932

Hill, L. M., Golin, C. E., Pack, A., Carda-Auten, J., Wallace, D. D., Cherkur, S., Farel, C. E., Rosen, E. P., Gandhi, M., & Prince, H. M.

A. (2020). Using real-time adherence feedback to enhance communication about adherence to antiretroviral therapy: Patient and clinician perspectives. *Journal of the Association of Nurses in AIDS Care*, *31*(1), 25–34.

Hillyer, Price, D., Haughney, Sims, Ali, Von Ziegenweidt, Lee, A., Chisholm, & Barnes. (2011). Effectiveness of inhaler types for real-world asthma management: Retrospective observational study using the GPRD. *Journal of Asthma and Allergy*, 37. https://doi.org/10.2147/JAA.S17709

Himes, B. E., Leszinsky, L., Walsh, R., Hepner, H., & Wu, A. C. (2019). Mobile health and inhaler-based monitoring devices for asthma management. *The Journal of Allergy and Clinical Immunology: In Practice*, *7*(8), 2535–2543. https://doi.org/10.1016/j.jaip.2019.08.034

Hirsch, J. D., Kong, N., Nguyen, K. T., Cadiz, C. L., Zhou, C., Bajorek, S. A., Bounthavong, M., & Morello, C. M. (2021). Improved patient-reported medication adherence, patient satisfaction, and glycemic control in a collaborative care pharmacist-led diabetes "tune-up" clinic. *International Journal of Environmental Research and Public Health*, *18*(17), 9242. https://doi.org/10.3390/ijerph18179242

Ho, C. P., & Lee, T. J. F. (2014). An evaluation of medication adherence in hypertensive patients using the theory of planned behavior. *Value in Health*, *17*(7), A763. https://doi.org/10.1016/j.jval.2014.08.270

Hoffmann, M., Vander Stichele, R., Bates, D. W., Björklund, J., Alexander, S., Andersson, M. L., Auraaen, A., Bennie, M., Dahl, M.-L., & Eiermann, B. (2020). Guiding principles for the use of knowledge bases and real-world data in clinical decision support systems: Report by an international expert workshop at karolinska institutet. *Expert Review of Clinical Pharmacology*, *13*(9), 925–934.

Holden, R. J., & Abebe, E. (2021). Medication transitions: Vulnerable periods of change in need of human factors and ergonomics. *Applied Ergonomics*, *90*, 103279. https://doi.org/10.1016/j.apergo.2020.103279

Holden, R. J., Abebe, E., Russ-Jara, A. L., & Chui, M. A. (2021). Human factors and ergonomics methods for pharmacy research and clinical practice. *Research in Social and Administrative Pharmacy*, *17*(12), 2019–2027.

Holden, R. J., Carayon, P., Gurses, A. P., Hoonakker, P., Hundt, A. S., Ozok, A. A., & Rivera-Rodriguez, A. J. (2013). SEIPS 2.0: A human factors framework for studying and improving the work of healthcare professionals and patients. *Ergonomics*, *56*(11), 1669–1686. https://doi.org/10.1080/00140139.2013.838643

Holden, R. J., Daley, C. N., Mickelson, R. S., Bolchini, D., Toscos, T., Cornet, V. P., Miller, A., & Mirro, M. J. (2020). Patient decision-making personas: An application of a patient-centered cognitive task analysis (P-CTA). *Applied Ergonomics*, *87*, 103107.

Holden, R. J., & Karsh, B.-T. (2010). The technology acceptance model: Its past and its future in health care. *Journal of Biomedical Informatics*, *43*(1), 159–172.

Hollenbach, J. P., Simoneau, T., Sun, Y., Becene, I., Almeida, S., Langton, C., & Flores, G. (2021). Design, methods, and baseline characteristics of a pilot, randomized, controlled trial of the effects of an electronic monitoring device on medication adherence in children with asthma. *Contemporary Clinical Trials Communications*, *21*, 100706. https://doi.org/10.1016/j.conctc.2021.100706

Holm, S., Kristiansen, T. B., & Ploug, T. (2021). Control, trust and the sharing of health information: The limits of trust. *Journal of Medical Ethics*, *47*(12), e35–e35.

Holmes, S., Moorhead, A., Bond, R., Zheng, H., Coates, V., & Mctear, M. (2019). Usability testing of a healthcare chatbot: Can we use conventional methods to assess conversational user interfaces? *Proceedings of the 31st European Conference on Cognitive Ergonomics*, 207–214. https://doi.org/10.1145/3335082.3335094

Hoo, Z. H., Curley, R., Campbell, M. J., Walters, S. J., Hind, D., & Wildman, M. J. (2016). Accurate reporting of adherence to inhaled therapies in adults with cystic fibrosis: Methods to calculate normative adherence. *Patient Preference and Adherence*, 887. https://doi.org/10.2147/PPA.S105530

Horne, R., & Weinman, J. (2020). Predicting treatment adherence: An overview of theoretical models. *Adherance to Treatment in Medical Conditions*, 25–50.

Horsky, J., Schiff, G. D., Johnston, D., Mercincavage, L., Bell, D., & Middleton, B. (2012). Interface design principles for usable decision support: A targeted review of best practices for clinical prescribing interventions. *Journal of Biomedical Informatics*, *45*(6), 1202–1216.

Houben, M., Van As, N., Sawhney, N., Unbehaun, D., & Lee, M. (2023). Participatory design for whom? Designing conversational user interfaces for sensitive settings and vulnerable populations. *Proceedings of the 5th International Conference on Conversational User Interfaces*, 1–4. https://doi.org/10.1145/3571884.3597439

Houghton, C. E., Casey, D., Shaw, D., & Murphy, K. (2012). Staff and students' perceptions and experiences of teaching and assessment in Clinical Skills Laboratories: Interview findings from a multiple case study. *Nurse Education Today*, *32*(6), e29–e34. https://doi.org/10.1016/j.nedt.2011.10.005

Huang, C., Wang, X., Liu, W., Cai, J., Shen, L., Zou, Z., Lu, R., Chang, J., Wei, X., Sun, C., Zhao, Z., Sun, Y., & Sundell, J. (2016). Household indoor air quality and its associations with childhood asthma in Shanghai, China: On-site inspected methods and preliminary results. *Environmental Research*, *151*, 154–167. https://doi.org/10.1016/j.envres.2016.07.036

Huang, C.-Y., Yang, M.-C., Huang, C.-Y., Chen, Y.-J., Wu, M.-L., & Chen, K.-W. (2018). A Chatbot-supported Smart Wireless Interactive Healthcare System for Weight Control and Health Promotion. *2018 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, 1791–1795. https://doi.org/10.1109/IEEM.2018.8607399

Hui, C. Y., McKinstry, B., Fulton, O., Buchner, M., & Pinnock, H. (2021). Patients' and clinicians' visions of a future internet-of-things system to support asthma self-management: Mixed methods study. *Journal of Medical Internet Research*, *23*(4), e22432. https://doi.org/10.2196/22432

Hui, C. Y., McKinstry, B., Mclean, S., Buchner, M., & Pinnock, H. (2022). Assessing the technical feasibility of a flexible, integrated internet-of-things connected for asthma (C4A) system to support self-management: A mixed method study exploring patients and healthcare professionals perspectives. *JAMIA Open*, *5*(4), ooac110. https://doi.org/10.1093/jamiaopen/ooac110

Huurne, K. K., Movig, K., Van Der Valk, P., Van Der Palen, J., & Brusse-Keizer, M. (2015). Differences in adherence to common inhaled medications in COPD. *COPD: Journal of Chronic Obstructive Pulmonary Disease*, *12*(6), 643–648. https://doi.org/10.3109/15412555.2014.995292

Isaac, S., Phillips, M. R., Chen, K. A., Carlson, R., Greenberg, C. C., & Khairat, S. (2024). Usability, acceptability, and implementation of artificial intelligence (AI) and machine learning (ML) techniques in surgical coaching and training: A scoping review. *Journal of Surgical Education*, S193172042400165X. https://doi.org/10.1016/j.jsurg.2024.03.018

Islam, N., & Gladki, E. (2008). Dry powder inhalers (DPIs)—A review of device reliability and innovation. *International Journal of Pharmaceutics*, *360*(1–2), 1–11. https://doi.org/10.1016/j.ijpharm.2008.04.044

Ivers, N., Jamtvedt, G., Flottorp, S., Young, J. M., Odgaard-Jensen, J., French, S. D., O'Brien, M. A., Johansen, M., Grimshaw, J., & Oxman, A. D. (2012). Audit and feedback: Effects on professional practice and healthcare outcomes. *Cochrane Database of Systematic Reviews*, *6*.

Jácome, C., Almeida, R., Pereira, A. M., Amaral, R., Mendes, S., Alves-

Correia, M., Vidal, C., López Freire, S., Méndez Brea, P., Araújo, L., Couto, M., Antolín-Amérigo, D., De La Hoz Caballer, B., Barra Castro, A., Gonzalez-De-Olano, D., Todo Bom, A., Azevedo, J., Leiria Pinto, P., Pinto, N., … Almeida Fonseca, J. (2021). Feasibility and acceptability of an asthma app to monitor medication adherence: Mixed methods study. *JMIR mHealth and uHealth*, *9*(5), e26442. https://doi.org/10.2196/26442

Janjua, S., Carter, D., Threapleton, C. J., Prigmore, S., & Disler, R. T. (2021). Telehealth interventions: Remote monitoring and consultations for people with chronic obstructive pulmonary disease (COPD). *Cochrane Database of Systematic Reviews*, *2021*(7). https://doi.org/10.1002/14651858.CD013196.pub2

Jansen, E. M., Van De Hei, S. J., Dierick, B. J. H., Kerstjens, H. A. M., Kocks, J. W. H., & Van Boven, J. F. M. (2021). Global burden of medication non-adherence in chronic obstructive pulmonary disease (COPD) and asthma: A narrative review of the clinical and economic case for smart inhalers. *Journal of Thoracic Disease*, *13*(6), 3846–3864. https://doi.org/10.21037/jtd-20-2360

Janssoone, T., Bic, C., Kanoun, D., Hornus, P., & Rinder, P. (2018). *Machine Learning on Electronic Health Records: Models and Features Usages to predict Medication Non-Adherence* (No. arXiv:1811.12234). arXiv. http://arxiv.org/abs/1811.12234

Janz, N. K., & Becker, M. H. (1984). The health belief model: A decade later. *Health Education Quarterly*, *11*(1), 1–47. https://doi.org/10.1177/109019818401100101

Jayaratne, M., Nallaperuma, D., De Silva, D., Alahakoon, D., Devitt, B., Webster, K. E., & Chilamkurti, N. (2019). A data integration platform for patient-centered e-healthcare and clinical decision support. *Future Generation Computer Systems*, *92*, 996–1008. https://doi.org/10.1016/j.future.2018.07.061

Jeminiwa, R., Hohmann, L., Qian, J., Garza, K., Hansen, R., & Fox, B. I. (2019). Impact of eHealth on medication adherence among patients with asthma: A systematic review and meta-analysis. *Respiratory Medicine*, *149*, 59–68. https://doi.org/10.1016/j.rmed.2019.02.011

Jensen, F. F., Håkansson, K. E. J., Overgaard Nielsen, B., Weinreich, U. M., & Ulrik, C. S. (2021). Self-reported vs. Objectively assessed adherence to inhaled corticosteroids in asthma. *Asthma Research and Practice*, *7*(1), 7. https://doi.org/10.1186/s40733-021-00072-2

Jiang, H., Han, J., Zhu, Z., Xu, W., Zheng, J., & Zhu, Y. (2009). Patient compliance with assessing and monitoring of asthma. *Journal of Asthma*, *46*(10), 1027–1031. https://doi.org/10.3109/02770900903229685

Jiang, H., Jin, S., & Wang, C. (2010). Prediction or not? An energy-efficient framework for clustering-based data collection in wireless sensor networks. *IEEE Transactions on Parallel and Distributed Systems*, *22*(6), 1064–1071.

Jochmann, A., Artusio, L., Jamalzadeh, A., Nagakumar, P., Delgado-Eckert, E., Saglani, S., Bush, A., Frey, U., & Fleming, L. J. (2017). Electronic monitoring of adherence to inhaled corticosteroids: An essential tool in identifying severe asthma in children. *European Respiratory Journal*, *50*(6), 1700910. https://doi.org/10.1183/13993003.00910-2017

Johnson, S. S., Driskell, M.-M., Johnson, J. L., Prochaska, J. M., Zwick, W., & Prochaska, J. O. (2006). Efficacy of a transtheoretical model-based expert system for antihypertensive adherence. *Disease Management*, *9*(5), 291–301. https://doi.org/10.1089/dis.2006.9.291

Jones, C. J., Smith, H., & Llewellyn, C. (2014). Evaluating the effectiveness of health belief model interventions in improving adherence: A systematic review. *Health Psychology Review*, *8*(3), 253–269. https://doi.org/10.1080/17437199.2013.802623

Jones, C., Santanello, N. C., Boccuzzi, S. J., Wogen, J., Strub, P., & Nelsen, L. M. (2003). Adherence to prescribed treatment for asthma: Evidence from pharmacy benefits data. *Journal of Asthma*, *40*(1), 93–101. https://doi.org/10.1081/JAS-120017212

Jourdan, T., Debs, N., & Frindel, C. (2021). The Contribution of Machine Learning in the Validation of Commercial Wearable Sensors for Gait Monitoring in Patients: A Systematic Review. *Sensors*, *21*(14), 4808. https://doi.org/10.3390/s21144808

Juliá Nehme, B., Torres Irribarra, D., Cumsille, P., & Yoon, S. (2021). Waiting room physical environment and outpatient experience: The spatial user experience model as analytical tool. *Journal of Interior Design*, *46*(4), 27–48. https://doi.org/10.1111/joid.12205

Kadariya, D., Venkataramanan, R., Yip, H. Y., Kalra, M., Thirunarayanan, K., & Sheth, A. (2019). kBot: Knowledge-Enabled Personalized Chatbot for Asthma Self-Management. *2019 IEEE International Conference on Smart Computing (SMARTCOMP)*, 138–143. https://doi.org/10.1109/SMARTCOMP.2019.00043

Kaewwongsri, K., & Silanon, K. (2020). *Design and implement of a weather monitoring station using CoAP on NB-IoT network*. 230–233.

Kalantarian, H., Motamed, B., Alshurafa, N., & Sarrafzadeh, M. (2016). A wearable sensor system for medication adherence prediction. *Artificial Intelligence in Medicine*, *69*, 43–52. https://doi.org/10.1016/j.artmed.2016.03.004

Kamei, T., Kanamori, T., Yamamoto, Y., & Edirippulige, S. (2022). The use of wearable devices in chronic disease management to enhance adherence and improve telehealth outcomes: A systematic review and meta-analysis. *Journal of Telemedicine and Telecare*, *28*(5), 342–359. https://doi.org/10.1177/1357633X20937573

Kanyongo, W., & Ezugwu, A. E. (2023). Machine learning approaches to medication adherence amongst NCD patients: A systematic literature review. *Informatics in Medicine Unlocked*, *38*, 101210. https://doi.org/10.1016/j.imu.2023.101210

Kaplan, A., Boivin, M., Bouchard, J., Kim, J., Hayes, S., & Licskai, C. (2023). The emerging role of digital health in the management of asthma. *Therapeutic Advances in Chronic Disease*, *14*, 20406223231209329. https://doi.org/10.1177/20406223231209329

Kaplan, A., & Price, D. (2018). Matching inhaler devices with patients: The role of the primary care physician. *Canadian Respiratory Journal*, *2018*(1), 9473051.

Kelders, S. M., Kok, R. N., Ossebaard, H. C., & Van Gemert-Pijnen, J. E. (2012). Persuasive system design does matter: A systematic review of adherence to web-based interventions. *Journal of Medical Internet Research*, *14*(6), e152. https://doi.org/10.2196/jmir.2104

Keller, S. C., Gurses, A. P., Werner, N., Hohl, D., Hughes, A., Leff, B., & Arbaje, A. I. (2017). Older adults and management of medical devices in the home: Five requirements for appropriate use. *Population Health Management*, *20*(4), 278–286. https://doi.org/10.1089/pop.2016.0070

Kemis, H., Bruce, N., Ping, W., Antonio, T., Gook, L. B., & Lee, H. J. (2012). *Healthcare monitoring application in ubiquitous sensor network: Design and implementation based on pulse sensor with arduino*. 34–38.

Kenyon, C. C., Chang, J., Wynter, S.-A., Fowler, J. C., Long, J., & Bryant-Stephens, T. C. (2016). Electronic adherence monitoring in a high-utilizing pediatric asthma cohort: A feasibility study. *JMIR Research Protocols*, *5*(2), e132. https://doi.org/10.2196/resprot.5362

Khdour, M. R., Hawwa, A. F., Kidney, J. C., Smyth, B. M., & McElnay, J. C. (2012). Potential risk factors for medication non-adherence in patients with chronic obstructive pulmonary disease (COPD). *European Journal of Clinical Pharmacology*, *68*(10), 1365–1373. https://doi.org/10.1007/s00228-012-1279-5

Kikidis, D., Konstantinos, V., Tzovaras, D., & Usmani, O. S. (2016). The Digital Asthma Patient: The History and Future of Inhaler Based Health Monitoring Devices. *Journal of Aerosol Medicine and Pulmonary Drug Delivery*, *29*(3), 219–232. https://doi.org/10.1089/jamp.2015.1267

Killane, I., Sulaiman, I., MacHale, E., Breathnach, A., Taylor, T. E., Holmes, M. S., Reilly, R. B., & Costello, R. W. (2016). Predicting asthma exacerbations employing remotely monitored adherence. *Healthcare Technology Letters*, *3*(1), 51–55. https://doi.org/10.1049/htl.2015.0058

Kim, S., Park, Y., & Ackerman, M. K. (2021). Designing an Indoor Air Quality Monitoring App for Asthma Management in Children: User-Centered Design Approach. *JMIR Formative Research*, *5*(9), e27447. https://doi.org/10.2196/27447

Kim, S.-H. (2022). A systematic review on visualizations for self-generated health data for daily activities. *International Journal of Environmental Research and Public Health*, *19*(18), 11166. https://doi.org/10.3390/ijerph191811166

King, G., Murray, C. J., Salomon, J. A., & Tandon, A. (2004). Enhancing the validity and cross-cultural comparability of measurement in survey research. *American Political Science Review*, *98*(1), 191–207.

Klasnja, P., Kendall, L., Pratt, W., & Blondon, K. (2015). *Long-term engagement with health-management technology: A dynamic process in diabetes*. *2015*, 756.

Koesmahargyo, V., Abbas, A., Zhang, L., Guan, L., Feng, S., Yadav, V., & Galatzer-Levy, I. R. (2020). Accuracy of machine learning-based prediction of medication adherence in clinical research. *Psychiatry Research*, *294*, 113558. https://doi.org/10.1016/j.psychres.2020.113558

Komalla, V., Wong, C. Y. J., Sibum, I., Muellinger, B., Nijdam, W., Chaugule, V., Soria, J., Ong, H. X., Buchmann, N. A., & Traini, D. (2023). Advances in soft mist inhalers. *Expert Opinion on Drug Delivery*, *20*(8), 1055–1070. https://doi.org/10.1080/17425247.2023.2231850

Kosse, R. C., Bouvy, M. L., Belitser, S. V., De Vries, T. W., Van Der Wal, P. S., & Koster, E. S. (2019). Effective engagement of adolescent asthma patients with mobile health–supporting medication adherence. *JMIR mHealth and uHealth*, *7*(3), e12411.

https://doi.org/10.2196/12411

Kritikos, V., Krass, I., Chan, H. S., & Bosnic-Anticevich, S. Z. (2005). The Validity and Reliability of Two Asthma Knowledge Questionnaires. *Journal of Asthma*, *42*(9), 795–801. https://doi.org/10.1080/02770900500308627

Kuipers, E., Poot, C. C., Wensing, M., Chavannes, N. H., De Smet, P. A., & Teichert, M. (2019). Self-management maintenance inhalation therapy with eHealth (SELFIE): Observational study on the use of an electronic monitoring device in respiratory patient care and research. *Journal of Medical Internet Research*, *21*(5), e13551. https://doi.org/10.2196/13551

Kumamaru, H., Lee, M. P., Choudhry, N. K., Dong, Y.-H., Krumme, A. A., Khan, N., Brill, G., Kohsaka, S., Miyata, H., Schneeweiss, S., & Gagne, J. J. (2018). Using Previous Medication Adherence to Predict Future Adherence. *Journal of Managed Care & Specialty Pharmacy*, *24*(11), 1146–1155. https://doi.org/10.18553/jmcp.2018.24.11.1146

Kurmi, O. P., Davis, K. J., Hubert Lam, K. B., Guo, Y., Vaucher, J., Bennett, D., Wang, J., Bian, Z., Du, H., Li, L., Clarke, R., & Chen, Z. (2018). Patterns and management of chronic obstructive pulmonary disease in urban and rural China: A community-based survey of 25 000 adults across 10 regions. *BMJ Open Respiratory Research*, *5*(1), e000267. https://doi.org/10.1136/bmjresp-2017-000267

Kwan, Y. H., Weng, S. D., Loh, D. H. F., Phang, J. K., Oo, L. J. Y., Blalock, D. V., Chew, E. H., Yap, K. Z., Tan, C. Y. K., Yoon, S., Fong, W., Østbye, T., Low, L. L., Bosworth, H. B., & Thumboo, J. (2020). Measurement properties of existing patient-reported outcome measures on medication adherence: Systematic review. *Journal of Medical Internet Research*, *22*(10), e19179. https://doi.org/10.2196/19179

Lam, H. C., Li, A. M., Chan, E. Y., & Goggins, W. B. (2016). The short-term association between asthma hospitalisations, ambient temperature, other meteorological factors and air pollutants in hong kong: A time-series study. *Thorax*, *71*(12), 1097–1109.

Lam, W. Y., & Fresco, P. (2015). Medication adherence measures: An overview. *BioMed Research International*, *2015*, 1–12. https://doi.org/10.1155/2015/217047

Lamont, M., & Swidler, A. (2014). Methodological pluralism and the possibilities and limits of interviewing. *Qualitative Sociology*, *37*, 153–171.

LaNoue, M., Gentsch, A., Cunningham, A., Mills, G., Doty, A. M., Hollander, J. E., Carr, B. G., Loebell, L., Weingarten, G., & Rising, K. L. (2019). Eliciting patient-important outcomes through group brainstorming: When is saturation reached? *Journal of Patient-Reported Outcomes*, *3*, 1–5.

Laranjo, L., Dunn, A. G., Tong, H. L., Kocaballi, A. B., Chen, J., Bashir, R., Surian, D., Gallego, B., Magrabi, F., Lau, A. Y. S., & Coiera, E. (2018). Conversational agents in healthcare: A systematic review. *Journal of the American Medical Informatics Association*, *25*(9), 1248–1258. https://doi.org/10.1093/jamia/ocy072

Latalova, K., Kamaradova, D., & Prasko, J. (2014). Perspectives on perceived stigma and self-stigma in adult male patients with depression. *Neuropsychiatric Disease and Treatment*, 1399. https://doi.org/10.2147/NDT.S54081

Lauritsen, K., & Nguyen, T. (2009). Combination products regulation at the FDA. *Clinical Pharmacology & Therapeutics*, *85*(5), 468–470. https://doi.org/10.1038/clpt.2009.28

Lavorini, F., Buttini, F., & Usmani, O. S. (2019). 100 years of drug delivery to the lungs. In J. E. Barrett, C. P. Page, & M. C. Michel (Eds.), *Concepts and Principles of Pharmacology* (Vol. 260, pp. 143–159). Springer International Publishing. https://doi.org/10.1007/164_2019_335

Lavorini, F., Janson, C., Braido, F., Stratelis, G., & Løkke, A. (2019). What to consider before prescribing inhaled medications: A pragmatic approach for evaluating the current inhaler landscape.

Therapeutic Advances in Respiratory Disease, *13*, 1753466619884532. https://doi.org/10.1177/1753466619884532

Leader, A., Benyamini, N., Gafter-Gvili, A., Dreyer, J., Calvarysky, B., Amitai, A., Yarchovsky-Dolberg, O., Sharf, G., Tousset, E., Caspi, O., Ellis, M., Levi, I., De Geest, S., & Raanani, P. (2018). Effect of adherence-enhancing interventions on adherence to tyrosine kinase inhibitor treatment in chronic myeloid leukemia (TAKE-IT): A quasi-experimental pre–post intervention multicenter pilot study. *Clinical Lymphoma Myeloma and Leukemia*, *18*(11), e449–e461. https://doi.org/10.1016/j.clml.2018.06.026

Lee, H. Y., Song, J. H., Won, H.-K., Park, Y., Chung, K. B., Lim, H.-J., Ahn, Y. M., & Lee, B. J. (2021). Comparing Inhaler Use Technique Based on Inhaler Type in Elderly Patients with Respiratory Disease. *Tuberculosis and Respiratory Diseases*, *84*(1), 46–54. https://doi.org/10.4046/trd.2020.0021

Lee, J. R., Leo, S., Liao, S., Ng, W. R., Tay, T. Y. N., Wang, Y., Ang, W. H. D., & Lau, Y. (2021). Electronic adherence monitoring devices for children with asthma: A systematic review and meta-analysis of randomised controlled trials. *International Journal of Nursing Studies*, *122*, 104037. https://doi.org/10.1016/j.ijnurstu.2021.104037

Lee, J., Tay, T. R., Radhakrishna, N., Hore-Lacy, F., Mackay, A., Hoy, R., Dabscheck, E., O'Hehir, R., & Hew, M. (2018). Nonadherence in the era of severe asthma biologics and thermoplasty. *European Respiratory Journal*, *51*(4), 1701836. https://doi.org/10.1183/13993003.01836-2017

Leiner, S., Parkins, D., & Lastow, O. (2015). Inhalation devices and patient interface: Human factors. *The AAPS Journal*, *17*(2), 457–461. https://doi.org/10.1208/s12248-015-9717-9

Leventhal, H., Diefenbach, M., & Leventhal, E. A. (1992). Illness cognition: Using common sense to understand treatment adherence and affect cognition interactions. *Cognitive Therapy and Research*, *16*(2), 143–163. https://doi.org/10.1007/BF01173486

Levy, M. L., Bacharier, L. B., Bateman, E., Boulet, L.-P., Brightling, C., Buhl, R., Brusselle, G., Cruz, A. A., Drazen, J. M., Duijts, L., Fleming, L., Inoue, H., Ko, F. W. S., Krishnan, J. A., Mortimer, K., Pitrez, P. M., Sheikh, A., Yorgancıoğlu, A., & Reddel, H. K. (2023). Key recommendations for primary care from the 2022 global initiative for asthma (GINA) update. *Npj Primary Care Respiratory Medicine*, *33*(1), 7. https://doi.org/10.1038/s41533-023-00330-1

Lewis, J. R. (2018). The system usability scale: Past, present, and future. *International Journal of Human–Computer Interaction*, *34*(7), 577–590. https://doi.org/10.1080/10447318.2018.1455307

Lexmond, A. J., Kruizinga, T. J., Hagedoorn, P., Rottier, B. L., Frijlink, H. W., & de Boer, A. H. (2014). Effect of inhaler design variables on paediatric use of dry powder inhalers. *PLoS One*, *9*(6), e99304.

Li, H., Zhang, R., Lee, Y.-C., Kraut, R. E., & Mohr, D. C. (2023). Systematic review and meta-analysis of AI-based conversational agents for promoting mental health and well-being. *Npj Digital Medicine*, *6*(1), 236. https://doi.org/10.1038/s41746-023-00979-5

Li, J.-S. (2020). International clinical practice guideline of Chinese medicine: Chronic obstructive pulmonary disease. *World Journal of Traditional Chinese Medicine*, *6*(1), 39. https://doi.org/10.4103/wjtcm.wjtcm_9_20

Li, N., Brossard, D., Scheufele, D. A., Wilson, P. H., & Rose, K. M. (2018). Communicating data: Interactive infographics, scientific data and credibility. *Journal of Science Communication*, *17*(02), A06. https://doi.org/10.22323/2.17020206

Li, Y.-N., Li, D.-J., & Zhang, K. (2017). The impact of metaphors on information visualization. *Journal of Visualization*, *20*, 487–504.

Liang, X., Yan, M., Li, H., Deng, Z., Lu, Y., Lu, P., Cai, S., Li, W., Fang, L., & Xu, Z. (2023). WeChat official accounts' posts on medication use of 251 community healthcare centers in shanghai, China: Content analysis and quality assessment. *Frontiers in Medicine*, *10*, 1155428.

Liang, Y., & Mak, J. C. W. (2021). Inhaled therapies for asthma and chronic obstructive pulmonary disease. *Current Pharmaceutical Design*, *27*(12), 1469–1481. https://doi.org/10.2174/1389201021666201126144057

Lin, C.-C., Huang, A. Y. Q., & Yang, S. J. H. (2023). A review of AI-driven conversational chatbots implementation methodologies and challenges (1999–2022). *Sustainability*, *15*(5), 4012. https://doi.org/10.3390/su15054012

Lin, C.-Y., Updegraff, J. A., & Pakpour, A. H. (2016). The relationship between the theory of planned behavior and medication adherence in patients with epilepsy. *Epilepsy & Behavior*, *61*, 231–236. https://doi.org/10.1016/j.yebeh.2016.05.030

Lingg, M., & Lütschg, V. (2020). Health system stakeholders' perspective on the role of mobile health and its adoption in the swiss health system: Qualitative study. *JMIR mHealth and uHealth*, *8*(5), e17315.

Linn, A. J., Vervloet, M., Van Dijk, L., Smit, E. G., & Van Weert, J. C. (2011). Effects of eHealth Interventions on Medication Adherence: A Systematic Review of the Literature. *Journal of Medical Internet Research*, *13*(4), e103. https://doi.org/10.2196/jmir.1738

Liu, F., Li, X., Wang, J., & Zhang, J. (2019). An adaptive UWB/MEMS-IMU complementary kalman filter for indoor location in NLOS environment. *Remote Sensing*, *11*(22), 2628. https://doi.org/10.3390/rs11222628

Liu, K., Xie, Z., & Or, C. K. (2020). Effectiveness of mobile app-assisted self-care interventions for improving patient outcomes in type 2 diabetes and/or hypertension: Systematic review and meta-analysis of randomized controlled trials. *JMIR mHealth and uHealth*, *8*(8), e15779. https://doi.org/10.2196/15779

Liu, Y. (2021). *Healing with poisons: Potent medicines in medieval China*. University of Washington Press.

López-Campos, J. L., Quintana Gallego, E., & Carrasco Hernández, L. (2019). Status of and strategies for improving adherence to COPD treatment. *International Journal of Chronic Obstructive Pulmonary*

Disease, *Volume 14*, 1503–1515. https://doi.org/10.2147/COPD.S170848

Lopez-Lorca, A. A., Miller, T., Pedell, S., Mendoza, A., Keirnan, A., & Sterling, L. (2014). *One size doesn't fit all: Diversifying" the user" using personas and emotional scenarios*. 25–32.

Low, J. (2019). Unstructured and semi–structured interviews in health research. *Researching Health: Qualitative, Quantitative and Mixed Methods. London: Sage Publications*, 123–141.

Luszczynska, A., Scholz, U., & Schwarzer, R. (2005). The general self-efficacy scale: Multicultural validation studies. *The Journal of Psychology*, *139*(5), 439–457.

Lycett, H. J., Raebel, E. M., Wildman, E. K., Guitart, J., Kenny, T., Sherlock, J.-P., & Cooper, V. (2018). Theory-based digital interventions to improve asthma self-management outcomes: Systematic review. *Journal of Medical Internet Research*, *20*(12), e293. https://doi.org/10.2196/jmir.9666

Ma, J., Sun, X., Wang, X., Liu, B., & Shi, K. (2023). Factors affecting patient adherence to inhalation therapy: An application of SEIPS model 2.0. *Patient Preference and Adherence*, *Volume 17*, 531–545. https://doi.org/10.2147/PPA.S395327

Mack, N. (2005). *Qualitative research methods: A data collector's field guide*.

MacNeill, M., Wallace, L., Kearney, J., Allen, R., Van Ryswyk, K., Judek, S., Xu, X., & Wheeler, A. (2012). Factors influencing variability in the infiltration of PM2. 5 mass and its components. *Atmospheric Environment*, *61*, 518–532.

Mäkelä, M. J., Backer, V., Hedegaard, M., & Larsson, K. (2013). Adherence to inhaled therapies, health outcomes and costs in patients with asthma and COPD. *Respiratory Medicine*, *107*(10), 1481–1490. https://doi.org/10.1016/j.rmed.2013.04.005

Makhecha, S., Chan, A., Pearce, C., Jamalzadeh, A., & Fleming, L. (2020). Novel electronic adherence monitoring devices in children with asthma: A mixed-methods study. *BMJ Open Respiratory Research*, *7*(1), e000589. https://doi.org/10.1136/bmjresp-2020-000589

Mancuso, C. A., & Rincon, M. (2006). Asthma patients' assessments of health care and medical decision making: The role of health literacy. *Journal of Asthma*, *43*(1), 41–44. https://doi.org/10.1080/02770900500447052

Maples, P., Franks, A., Ray, S., Stevens, A. B., & Wallace, L. S. (2010). Development and validation of a low-literacy Chronic Obstructive Pulmonary Disease knowledge Questionnaire (COPD-Q). *Patient Education and Counseling*, *81*(1), 19–22. https://doi.org/10.1016/j.pec.2009.11.020

Margolis, R., Bellin, M. H., Sacco, P., Harrington, D., & Butz, A. (2019). Evaluation of MOS social support in low-income caregivers of African American children with poorly controlled asthma. *Journal of Asthma*, *56*(9), 951–958. https://doi.org/10.1080/02770903.2018.1510504

Marshall, R., Cook, S., Mitchell, V., Summerskill, S., Haines, V., Maguire, M., Sims, R., Gyi, D., & Case, K. (2015). Design and evaluation: End users, user datasets and personas. *Applied Ergonomics*, *46*, 311–317. https://doi.org/10.1016/j.apergo.2013.03.008

Martinez, V. I., Marquard, J. L., Saver, B., Garber, L., & Preusse, P. (2017). Consumer health informatics interventions must support user workflows, be easy-to-use, and improve cognition: Applying the SEIPS 2.0 model to evaluate patients' and clinicians' experiences with the CONDUIT-HID intervention. *International Journal of Human–Computer Interaction*, *33*(4), 333–343. https://doi.org/10.1080/10447318.2016.1278340

Maselli, D., Keyt, H., & Restrepo, M. (2017). Inhaled Antibiotic Therapy in Chronic Respiratory Diseases. *International Journal of Molecular Sciences*, *18*(5), 1062. https://doi.org/10.3390/ijms18051062

Masoli, M., Fabian, D., Holt, S., Beasley, R., & Global Initiative for

Asthma (GINA) Program. (2004). The global burden of asthma: Executive summary of the GINA Dissemination Committee Report. *Allergy*, *59*(5), 469–478. https://doi.org/10.1111/j.1398-9995.2004.00526.x

Masood, I., Wang, Y., Daud, A., Aljohani, N. R., & Dawood, H. (2018). Towards smart healthcare: Patient data privacy and security in sensor-cloud infrastructure. *Wireless Communications and Mobile Computing*, *2018*(1), 2143897.

Massanari, A. L. (2010). Designing for imaginary friends: Information architecture, personas and the politics of user-centered design. *New Media & Society*, *12*(3), 401–416. https://doi.org/10.1177/1461444809346722

Mateo, J., Rius-Peris, J., Maraña-Pérez, A., Valiente-Armero, A., & Torres, A. (2021). Extreme gradient boosting machine learning method for predicting medical treatment in patients with acute bronchiolitis. *Biocybernetics and Biomedical Engineering*, *41*(2), 792–801.

Mathers, C. D., & Loncar, D. (2006). Projections of global mortality and burden of disease from 2002 to 2030. *PLoS Medicine*, *3*(11), e442. https://doi.org/10.1371/journal.pmed.0030442

Mathivanan, S. K., Shivahare, B. D., Chandan, R. R., & Shah, M. A. (2024). A comprehensive health assessment approach using ensemble deep learning model for remote patient monitoring with IoT. *Scientific Reports*, *14*(1), 15661.

McCarthy, L. M., Farrell, B., Howell, P., & Quast, T. (2022). Supporting deprescribing in long-term care: An approach using stakeholder engagement, behavioural science and implementation planning. *Exploratory Research in Clinical and Social Pharmacy*, *7*, 100168.

McGillicuddy, J. W., Taber, D. J., Mueller, M., Patel, S., Baliga, P. K., Chavin, K. D., Sox, L., Favela, A. P., Brunner-Jackson, B. M., & Treiber, F. A. (2015). Sustainability of improvements in medication adherence through a mobile health intervention. *Progress in*

Transplantation, *25*(3), 217–223. https://doi.org/10.7182/pit2015975

Md Hatah, E., Lim, K. P., Mohd Ali, A., Mohamed Shah, N., & Islahudin, F. (2015). The influence of cultural and religious orientations on social support and its potential impact on medication adherence. *Patient Preference and Adherence*, 589. https://doi.org/10.2147/PPA.S79477

Medicines & Healthcare products Regulatory Agency. (2017, September). *Human factors and usability engineerin—Guidance for medical devices including drug-device combination products*.

Meister, D. (2018). *The history of human factors and ergonomics* (1st ed.). CRC Press. https://doi.org/10.1201/9781315276069

Melani, A. S. (2021). Inhaler technique in asthma and COPD: Challenges and unmet knowledge that can contribute to suboptimal use in real life. *Expert Review of Clinical Pharmacology*, *14*(8), 991–1003. https://doi.org/10.1080/17512433.2021.1929922

Melvin, E., Cushing, A., Tam, A., Kitada, R., & Manice, M. (2017). Assessing the use of BreatheSmart® mobile technology in adult patients with asthma: A remote observational study. *BMJ Open Respiratory Research*, *4*(1), e000204. https://doi.org/10.1136/bmjresp-2017-000204

Merchant, R., Inamdar, R., Henderson, K., Barrett, M., Su, J. G., Riley, J., Van Sickle, D., & Stempel, D. (2018). Digital health intervention for asthma: Patient-reported value and usability. *JMIR mHealth and uHealth*, *6*(6), e133. https://doi.org/10.2196/mhealth.7362

Meyer, J., Kazakova, A., Büsing, M., & Boll, S. (2016). Visualization of complex health data on mobile devices. *Proceedings of the 2016 ACM Workshop on Multimedia for Personal Health and Health Care*, 31–34. https://doi.org/10.1145/2985766.2985774

Miller, A. S., Cafazzo, J. A., & Seto, E. (2016). A game plan: Gamification design principles in mHealth applications for chronic disease management. *Health Informatics Journal*, *22*(2), 184–193. https://doi.org/10.1177/1460458214537511

Milne-Ives, M., De Cock, C., Lim, E., Shehadeh, M. H., De Pennington, N., Mole, G., Normando, E., & Meinert, E. (2020). The effectiveness of artificial intelligence conversational agents in health care: Systematic review. *Journal of Medical Internet Research*, *22*(10), e20346. https://doi.org/10.2196/20346

Minian, N., Mehra, K., Rose, J., Veldhuizen, S., Zawertailo, L., Ratto, M., Lecce, J., & Selby, P. (2023). Cocreation of a conversational agent to help patients adhere to their varenicline treatment: A study protocol. *DIGITAL HEALTH*, *9*, 20552076231182807. https://doi.org/10.1177/20552076231182807

Miravitlles, M., Montero-Caballero, J., Richard, F., Santos, S., García-Rivero, J. L., Ortega, F., & Ribera, X. (2016). A cross-sectional study to assess inhalation device handling and patient satisfaction in COPD. *International Journal of Chronic Obstructive Pulmonary Disease*, 407. https://doi.org/10.2147/COPD.S91118

Miura, C., Chen, S., Saiki, S., Nakamura, M., & Yasuda, K. (2022). Assisting personalized healthcare of elderly people: Developing a rule-based virtual caregiver system using mobile chatbot. *Sensors*, *22*(10), 3829.

Mokoka, M. C., Lombard, L., MacHale, E. M., Walsh, J., Cushen, B., Sulaiman, I., Carthy, D. M., Boland, F., Doyle, F., Hunt, E., Murphy, D. M., Faul, J., Butler, M., Hetherington, K., Mark FitzGerald, J., Boven, J. F. V., Heaney, L. G., Reilly, R. B., & Costello, R. W. (2017). In patients with severe uncontrolled asthma, does knowledge of adherence and inhaler technique using electronic monitoring improve clinical decision making? A protocol for a randomised controlled trial. *BMJ Open*, *7*(6), e015367. https://doi.org/10.1136/bmjopen-2016-015367

Monteiro, C., Maricoto, T., Prazeres, F., Augusto Simões, P., & Augusto Simões, J. (2021). Determining factors associated with inhaled therapy adherence on asthma and COPD treatment: A systematic review and meta-analysis of the global literature. *SSRN Electronic*

Journal. https://doi.org/10.2139/ssrn.3823219

Moore, A., Preece, A., Sharma, R., Heaney, L. G., Costello, R. W., Wise, R. A., Ludwig-Sengpiel, A., Mosnaim, G., Rees, J., Tomlinson, R., Tal-Singer, R., Stempel, D. A., & Barnes, N. (2021). A randomised controlled trial of the effect of a connected inhaler system on medication adherence in uncontrolled asthmatic patients. *European Respiratory Journal*, *57*(6), 2003103. https://doi.org/10.1183/13993003.03103-2020

Morgan, J. L., Burton, M., Collins, K., Lifford, K. J., Robinson, T. G., Cheung, K., Audisio, R., Reed, M. W., Wyld, L., & Bridging the Age Gap Trial Management Team. (2015). The balance of clinician and patient input into treatment decision-making in older women with operable breast cancer. *Psycho-Oncology*, *24*(12), 1761–1766.

Moridis, C. N., & Economides, A. A. (2012). Affective learning: Empathetic agents with emotional facial and tone of voice expressions. *IEEE Transactions on Affective Computing*, *3*(3), 260–272.

Morrison, L. G. (2015). Theory-based strategies for enhancing the impact and usage of digital health behaviour change interventions: A review. *Digital Health*, *1*, 2055207615595335.

Mortimer, K., Reddel, H. K., Pitrez, P. M., & Bateman, E. D. (2022). Asthma management in low and middle income countries: Case for change. *European Respiratory Journal*, *60*(3), 2103179. https://doi.org/10.1183/13993003.03179-2021

Mosnaim, G. S., Greiwe, J., Jariwala, S. P., Pleasants, R., & Merchant, R. (2022). Digital Inhalers and Remote Patient Monitoring for Asthma. *The Journal of Allergy and Clinical Immunology: In Practice*, *10*(10), 2525–2533. https://doi.org/10.1016/j.jaip.2022.06.026

Mosnaim, G., Safioti, G., Brown, R., DePietro, M., Szefler, S. J., Lang, D. M., Portnoy, J. M., Bukstein, D. A., Bacharier, L. B., & Merchant, R. K. (2021). Digital health technology in asthma: A comprehensive scoping review. *The Journal of Allergy and Clinical Immunology: In*

Practice, *9*(6), 2377–2398. https://doi.org/10.1016/j.jaip.2021.02.028

Motti, V. G., & Caine, K. (2015). *Users' privacy concerns about wearables: Impact of form factor, sensors and type of data collected*. 231–244.

Mukhtar, H., Ali, A., Lee, S., & Belaïd, D. (2012). *Personalized healthcare self-management using social persuasion*. 66–73.

Muneswarao, J., Hassali, M. A., Ibrahim, B., Saini, B., Naqvi, A. A., Hyder Ali, I. A., Rao, J. M., Ur Rehman, A., & Verma, A. K. (2021). Translation and validation of the test of adherence to inhalers (TAI) questionnaire among adult patients with asthma in malaysia. *Journal of Asthma*, *58*(9), 1229–1236. https://doi.org/10.1080/02770903.2020.1776728

Murphy, A. C., Proeschal, A., Brightling, C. E., Wardlaw, A. J., Pavord, I., Bradding, P., & Green, R. H. (2012). The relationship between clinical outcomes and medication adherence in difficult-to-control asthma: Table 1. *Thorax*, *67*(8), 751–753. https://doi.org/10.1136/thoraxjnl-2011-201096

Nagamachi, M. (1995). Kansei engineering: A new ergonomic consumer-oriented technology for product development. *International Journal of Industrial Ergonomics*, *15*(1), 3–11. https://doi.org/10.1016/0169-8141(94)00052-5

Nagamachi, M. (2002). Kansei engineering as a powerful consumer-oriented technology for product development. *Applied Ergonomics*, *33*(3), 289–294.

Najafabadi, M. M., Villanustre, F., Khoshgoftaar, T. M., Seliya, N., Wald, R., & Muharemagic, E. (2015). Deep learning applications and challenges in big data analytics. *Journal of Big Data*, *2*(1), 1. https://doi.org/10.1186/s40537-014-0007-7

National Research Council, Division of Behavioral, Social Sciences, Board on Human-Systems Integration, & Committee on the Role of Human Factors in Home Health Care. (2011). *Health care comes home: The human factors*. National Academies Press.

Negoescu, E., Marcilly, R., Cromie, S., Koay, A., & Grimes, T. (2023). The medication self-management work system of patients and informal carers from a human factors & ergonomics perspective: A scoping review protocol. *HRB Open Research*, *6*, 4. https://doi.org/10.12688/hrbopenres.13674.1

Nelson, H. S. (2016). Inhalation devices, delivery systems, and patient technique. *Annals of Allergy, Asthma & Immunology*, *117*(6), 606–612. https://doi.org/10.1016/j.anai.2016.05.006

Nesvåg, S., & McKay, J. R. (2018). Feasibility and effects of digital interventions to support people in recovery from substance use disorders: Systematic review. *Journal of Medical Internet Research*, *20*(8), e255.

Newman, S. (2014). Improving inhaler technique, adherence to therapy and the precision of dosing: Major challenges for pulmonary drug delivery. *Expert Opinion on Drug Delivery*, *11*(3), 365–378. https://doi.org/10.1517/17425247.2014.873402

Newman-Casey, P. A., Niziol, L. M., Mackenzie, C. K., Resnicow, K., Lee, P. P., Musch, D. C., & Heisler, M. (2018). Personalized behavior change program for glaucoma patients with poor adherence: A pilot interventional cohort study with a pre-post design. *Pilot and Feasibility Studies*, *4*(1), 128. https://doi.org/10.1186/s40814-018-0320-6

Ngwatu, B. K., Nsengiyumva, N. P., Oxlade, O., Mappin-Kasirer, B., Nguyen, N. L., Jaramillo, E., Falzon, D., & Schwartzman, K. (2018). The impact of digital health technologies on tuberculosis treatment: A systematic review. *European Respiratory Journal*, *51*(1).

Nie, B., Chapman, S. C., Chen, Z., Wang, X., & Wei, L. (2019). Utilization of the beliefs about medicine questionnaire and prediction of medication adherence in China: A systematic review and meta-analysis. *Journal of Psychosomatic Research*, *122*, 54–68.

Nikander, K., Nicholls, C., Denyer, J., & Pritchard, J. (2014). The evolution of spacers and valved holding chambers. *Journal of*

Aerosol Medicine and Pulmonary Drug Delivery, *27*(S1), S-4-S-23. https://doi.org/10.1089/jamp.2013.1076

Nikander, K., Turpeinen, M., Pelkonen, A. S., Bengtsson, T., Selroos, O., & Haahtela, T. (2011). True adherence with the turbuhaler in young children with asthma. *Archives of Disease in Childhood*, *96*(2), 168–173. https://doi.org/10.1136/adc.2010.187724

Nißen, M., Rüegger, D., Stieger, M., Flückiger, C., Allemand, M., V Wangenheim, F., & Kowatsch, T. (2022). The Effects of Health Care Chatbot Personas With Different Social Roles on the Client-Chatbot Bond and Usage Intentions: Development of a Design Codebook and Web-Based Study. *Journal of Medical Internet Research*, *24*(4), e32630. https://doi.org/10.2196/32630

Norman, D. (2007). *Emotional design: Why we love (or hate) everyday things*. Basic books.

Normansell, R., Kew, K. M., & Mathioudakis, A. G. (2017). Interventions to improve inhaler technique for people with asthma. *Cochrane Database Syst Rev*, *3*, CD012286.

Norris, J. M., White, D. E., Nowell, L., Mrklas, K., & Stelfox, H. T. (2017). How do stakeholders from multiple hierarchical levels of a large provincial health system define engagement? A qualitative study. *Implementation Science*, *12*, 1–13.

Nousias, S., Lalos, A. S., Arvanitis, G., Moustakas, K., Tsirelis, T., Kikidis, D., Votis, K., & Tzovaras, D. (2018). An mHealth System for Monitoring Medication Adherence in Obstructive Respiratory Diseases Using Content Based Audio Classification. *IEEE Access*, *6*, 11871–11882. https://doi.org/10.1109/ACCESS.2018.2809611

Nurmagambetov, T., Kuwahara, R., & Garbe, P. (2018). The economic burden of asthma in the united states, 2008–2013. *Annals of the American Thoracic Society*, *15*(3), 348–356. https://doi.org/10.1513/AnnalsATS.201703-259OC

O'Connor, M., Munnelly, A., Whelan, R., & McHugh, L. (2018). The efficacy and acceptability of third-wave behavioral and cognitive eHealth treatments: A systematic review and meta-analysis of randomized controlled trials. *Behavior Therapy*, *49*(3), 459–475.

O'Connor, S., Hanlon, P., O'Donnell, C. A., Garcia, S., Glanville, J., & Mair, F. S. (2016). Understanding factors affecting patient and public engagement and recruitment to digital health interventions: A systematic review of qualitative studies. *BMC Medical Informatics and Decision Making*, *16*(1), 120. https://doi.org/10.1186/s12911-016-0359-3

O'Connor, S. L., Bender, B. G., Gavin-Devitt, L. A., Wamboldt, M. Z., Milgrom, H., Szefler, S., Rand, C., & Wamboldt, F. S. (2004). Measuring adherence with the doser CT in children with asthma. *Journal of Asthma*, *41*(6), 663–670. https://doi.org/10.1081/JAS-200026434

O'Dwyer, S. M., MacHale, E., Sulaiman, I., Holmes, M., Hughes, C., D'Arcy, S., Rapcan, V., Taylor, T., Boland, F., Bosnic-Anticevich, S., Reilly, R. B., Ryder, S. A., & Costello, R. W. (2016). The effect of providing feedback on inhaler technique and adherence from an electronic audio recording device, INCA®, in a community pharmacy setting: Study protocol for a randomised controlled trial. *Trials*, *17*(1), 226. https://doi.org/10.1186/s13063-016-1362-9

Osterberg, L., & Blaschke, T. (2005). Adherence to medication. *New England Journal of Medicine*, *353*(5), 487–497. https://doi.org/10.1056/NEJMra050100

Ozkaynak, M., Sircar, C. M., Frye, O., & Valdez, R. S. (2021). *A Systematic Review of Design Workshops for Health Information Technologies*.

Pai, F.-Y., & Huang, K.-I. (2011). Applying the technology acceptance model to the introduction of healthcare information systems. *Technological Forecasting and Social Change*, *78*(4), 650–660.

Pakianathan, P. V., Kumar, D., Jayatissa, P., Rada, H., Niebauer, J., Schmidt, A., & Smeddinck, J. (2024). *Barriers and enablers in integrating patient-generated health data for shared decision-making* *between healthcare professionals and patients: A scoping review*.

Palumbo, R. (2016). Contextualizing co-production of health care: A systematic literature review. *International Journal of Public Sector Management*, *29*(1), 72–90.

Pandey, A. V., Manivannan, A., Nov, O., Satterthwaite, M., & Bertini, E. (2014). The Persuasive Power of Data Visualization. *IEEE Transactions on Visualization and Computer Graphics*, *20*(12), 2211–2220. https://doi.org/10.1109/TVCG.2014.2346419

Pansiot, J., Stoyanov, D., McIlwraith, D., Lo, B. P., & Yang, G.-Z. (2007). *Ambient and wearable sensor fusion for activity recognition in healthcare monitoring systems*. 208–212.

Papautsky, E. L. (2019). Adjusting for patient context in inpatient breastfeeding education: A human factors perspective. *Journal of Midwifery & Women's Health*, *64*(6), 695–698. https://doi.org/10.1111/jmwh.13041

Park, S., Bekemeier, B., Flaxman, A., & Schultz, M. (2022). Impact of data visualization on decision-making and its implications for public health practice: A systematic literature review. *Informatics for Health and Social Care*, *47*(2), 175–193.

Patel, M., Pilcher, J., Travers, J., Perrin, K., Shaw, D., Black, P., Weatherall, M., & Beasley, R. (2013). Use of metered-dose inhaler electronic monitoring in a real-world asthma randomized controlled trial. *The Journal of Allergy and Clinical Immunology: In Practice*, *1*(1), 83–91. https://doi.org/10.1016/j.jaip.2012.08.004

Patel, R., Mehta, M., Dahiya, M., & Jose, V. (2021). A review of use errors reported in human factor validation studies of biological combination products. *Journal of Medical Engineering & Technology*, *45*(7), 582–592. https://doi.org/10.1080/03091902.2021.1936239

Patel, R., Mehta, M., Pipalava, P., Dahiya, M., Singh, I., & Jose, V. (2019). Insights into human factor studies conducted for US FDA-approved biological combination products. *Expert Opinion on Drug*

Delivery, *16*(12), 1333–1353. https://doi.org/10.1080/17425247.2019.1682995

Patrick, K., Hekler, E. B., Estrin, D., Mohr, D. C., Riper, H., Crane, D., Godino, J., & Riley, W. T. (2016). The pace of technologic change: Implications for digital health behavior intervention research. *American Journal of Preventive Medicine*, *51*(5), 816–824.

Patton, J. S., & Byron, P. R. (2007). Inhaling medicines: Delivering drugs to the body through the lungs. *Nature Reviews Drug Discovery*, *6*(1), 67–74. https://doi.org/10.1038/nrd2153

Pereira, J., & Díaz, Ó. (2019). Using Health Chatbots for Behavior Change: A Mapping Study. *Journal of Medical Systems*, *43*(5), 135. https://doi.org/10.1007/s10916-019-1237-1

Peres, S. C., Pham, T., & Phillips, R. (2013). Validation of the system usability scale (SUS): SUS in the wild. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *57*(1), 192–196. https://doi.org/10.1177/1541931213571043

Peterson, A. M., Takiya, L., & Finley, R. (2003). Meta-analysis of trials of interventions to improve medication adherence. *American Journal of Health-System Pharmacy*, *60*(7), 657–665.

Phillips, L. A., Leventhal, E. A., & Leventhal, H. (2011). Factors associated with the accuracy of physicians' predictions of patient adherence. *Patient Education and Counseling*, *85*(3), 461–467. https://doi.org/10.1016/j.pec.2011.03.012

Pincus, T., & Sokka, T. (2009). Laboratory tests to assess patients with rheumatoid arthritis: Advantages and limitations. *Rheumatic Disease Clinics*, *35*(4), 731–734.

Pirozynski, M., & Sosnowski, T. R. (2016). Inhalation devices: From basic science to practical use, innovative vs generic products. *Expert Opinion on Drug Delivery*, *13*(11), 1559–1571. https://doi.org/10.1080/17425247.2016.1198774

Plaza, V., Fernández-Rodríguez, C., Melero, C., Cosío, B. G., Entrenas, L. M., De Llano, L. P., Gutiérrez-Pereyra, F., Tarragona, E., Palomino, R., López-Viña, A., & on behalf of the TAI Study Group. (2016). Validation of the 'test of the adherence to inhalers' (TAI) for asthma and COPD patients. *Journal of Aerosol Medicine and Pulmonary Drug Delivery*, *29*(2), 142–152. https://doi.org/10.1089/jamp.2015.1212

Pleasants, R. A., Chan, A. Hy., Mosnaim, G., Costello, R. W., Dhand, R., Schworer, S. A., Merchant, R., & Tilley, S. L. (2022). Integrating digital inhalers into clinical care of patients with asthma and chronic obstructive pulmonary disease. *Respiratory Medicine*, *205*, 107038. https://doi.org/10.1016/j.rmed.2022.107038

Pollard, S., Bansback, N., FitzGerld, J. M., & Bryan, S. (2017). The burden of nonadherence among adults with asthma: A role for shared decision-making. *Allergy*, *72*(5), 705–712. https://doi.org/10.1111/all.13090

Powell-Cope, G., Nelson, A. L., & Patterson, E. S. (2008). Patient care technology and safety. In R. G. Hughes (Ed.), *Patient Safety and Quality: An Evidence-Based Handbook for Nurses*. Agency for Healthcare Research and Quality (US). http://www.ncbi.nlm.nih.gov/books/NBK2686/

Pradeesh, E. L., Vivek, V. V., Bhuvaneshwari, M., Thilakavarshini, T., Guruprasad, V., & Vaishnavi, A. S. (2022). Investigation on IoT based smart E-inhaler integrated with mobile application. *Materials Today: Proceedings*, *66*, 1082–1087. https://doi.org/10.1016/j.matpr.2022.04.889

Pradhan, A., Mehta, K., & Findlater, L. (2018). *' Accessibility came by accident' use of voice-controlled intelligent personal assistants by people with disabilities*. 1–13.

Price, D., Bosnic-Anticevich, S., Briggs, A., Chrystyn, H., Rand, C., Scheuch, G., & Bousquet, J. (2013). Inhaler competence in asthma: Common errors, barriers to use and recommended solutions. *Respiratory Medicine*, *107*(1), 37–46. https://doi.org/10.1016/j.rmed.2012.09.017

Price, D., Harrow, B., Small, M., Pike, J., & Higgins, V. (2015). Establishing the relationship of inhaler satisfaction, treatment adherence, and patient outcomes: A prospective, real-world, cross-sectional survey of US adult asthma patients and physicians. *World Allergy Organization Journal*, *8*, 26. https://doi.org/10.1186/s40413-015-0075-y

Pritchard, J. N., & Nicholls, C. (2015). Emerging Technologies for Electronic Monitoring of Adherence, Inhaler Competence, and True Adherence. *Journal of Aerosol Medicine and Pulmonary Drug Delivery*, *28*(2), 69–81. https://doi.org/10.1089/jamp.2014.1163

Privitera, M. B., Evans, M., & Southee, D. (2017). Human factors in the design of medical devices – approaches to meeting international standards in the european union and USA. *Applied Ergonomics*, *59*, 251–263. https://doi.org/10.1016/j.apergo.2016.08.034

Prochaska, J. O., Wright, J. A., & Velicer, W. F. (2008). Evaluating theories of health behavior change: A hierarchy of criteria applied to the transtheoretical model. *Applied Psychology*, *57*(4), 561–588. https://doi.org/10.1111/j.1464-0597.2008.00345.x

Pronovost, P. J., Berenholtz, S. M., Ngo, K., McDowell, M., Holzmueller, C., Haraden, C., Resar, R., Rainey, T., Nolan, T., & Dorman, T. (2003). Developing and pilot testing quality indicators in the intensive care unit. *Journal of Critical Care*, *18*(3), 145–155.

Pruitt, J., & Adlin, T. (2010). *The persona lifecycle: Keeping people in mind throughout product design*. Elsevier.

Pruitt, J., & Grudin, J. (2003). Personas: Practice and theory. *Proceedings of the 2003 Conference on Designing for User Experiences*, 1–15. https://doi.org/10.1145/997078.997089

Quaderi, S. A., & Hurst, J. R. (2018). The unmet global burden of COPD. *Global Health, Epidemiology and Genomics*, *3*, e4. https://doi.org/10.1017/gheg.2018.1

Quinde, M. (2020). ADAPT: Approach to develop context-aware solutions for personalised asthma managemenT. *Journal of*

Biomedical Informatics.

Quirke-McFarlane, S., Weinman, J., & d'Ancona, G. (2023). A systematic review of patient-reported adherence measures in asthma: Which questionnaire is most useful in clinical practice? *The Journal of Allergy and Clinical Immunology: In Practice*, *11*(8), 2493–2503. https://doi.org/10.1016/j.jaip.2023.03.034

Rajan, S., & Gogtay, J. (2014). Ease-of-use, preference, confidence, and satisfaction with Revolizer ® , a novel dry powder inhaler, in an Indian population. *Lung India*, *31*(4), 366. https://doi.org/10.4103/0970-2113.142122

Raji, A., Kanchana Devi, P., Golda Jeyaseeli, P., & Balaganesh, N. (2016). Respiratory monitoring system for asthma patients based on IoT. *2016 Online International Conference on Green Engineering and Technologies (IC-GET)*, 1–6. https://doi.org/10.1109/GET.2016.7916737

Ramjee, P., Sachdeva, B., Golechha, S., Kulkarni, S., Fulari, G., Murali, K., & Jain, M. (2024). *CataractBot: An LLM-powered expert-in-the-loop chatbot for cataract patients* (Version 2). arXiv. https://doi.org/10.48550/ARXIV.2402.04620

Rand, C. S., & Wise, R. A. (1994). Measuring adherence to asthma medication regimens. *American Journal of Respiratory and Critical Care Medicine*, *149*(2_pt_2), S69–S76. https://doi.org/10.1164/ajrccm/149.2_Pt_2.S69

Rau, J. L. (2005). Determinants of patient adherence to an aerosol regimen. *Respiratory Care*, *50*(10), 1346–1356; discussion 1357-1359.

Reijneveld, K., De Looze, M., Krause, F., & Desmet, P. (2003). *Measuring the emotions elicited by office chairs*. 6–10.

Reinares-Lara, P., Rodríguez-Fuertes, A., & Garcia-Henche, B. (2019). The cognitive dimension and the affective dimension in the patient's experience. *Frontiers in Psychology*, *10*, 2177.

Rekaya, N., Vicik, S. M., Hulesch, B. T., & McDonald, L. L. (2020).

Enhancement of an Auto-Injector Device for Self-Administration of Etanercept in Patients With Rheumatoid Arthritis Confers Emotional and Functional Benefits. *Rheumatology and Therapy*, *7*(3), 537–552. https://doi.org/10.1007/s40744-020-00216-5

Restrepo, R. (2008). Medication adherence issues in patients treated for COPD. *International Journal of Chronic Obstructive Pulmonary Disease*, *Volume 3*, 371–384. https://doi.org/10.2147/COPD.S3036

Riener, A., Jeon, M., Alvarez, I., & Frison, A. K. (2017). Driver in the loop: Best practices in automotive sensing and feedback mechanisms. *Automotive User Interfaces: Creating Interactive Experiences in the Car*, 295–323.

Rodriguez, C. C. G., & Déry-Pinna, A.-M. (2012). Visualizing sensor data: Towards an experiment and validation platform. In M. Winckler, P. Forbrig, & R. Bernhaupt (Eds.), *Human-Centered Software Engineering* (Vol. 7623, pp. 352–359). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-34347-6_27

Rogliani, P., Calzetta, L., Coppola, A., Cavalli, F., Ora, J., Puxeddu, E., Matera, M. G., & Cazzola, M. (2017). Optimizing drug delivery in COPD: The role of inhaler devices. *Respiratory Medicine*, *124*, 6–14. https://doi.org/10.1016/j.rmed.2017.01.006

Rogliani, P., Ora, J., Puxeddu, E., Matera, M. G., & Cazzola, M. (2017). Adherence to COPD treatment: Myth and reality. *Respiratory Medicine*, *129*, 117–123. https://doi.org/10.1016/j.rmed.2017.06.007

Rousek, J. B., & Hallbeck, M. S. (2011). Improving medication management through the redesign of the hospital code cart medication drawer. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *53*(6), 626–636. https://doi.org/10.1177/0018720811426427

Rumi, G., Canonica, G. W., Foster, J. M., Chavannes, N. H., Valenti, G., Contiguglia, R., Rapsomaniki, E., Kocks, J. W. H., De Brasi, D., & Braido, F. (2022). Digital coaching using smart inhaler technology to improve asthma management in patients with asthma in italy:

Community-based study. *JMIR mHealth and uHealth*, *10*(11), e25879. https://doi.org/10.2196/25879

Ryu, H., Kim, S., Kim, D., Han, S., Lee, K., & Kang, Y. (2020). Simple and Steady Interactions Win the Healthy Mentality: Designing a Chatbot Service for the Elderly. *Proceedings of the ACM on Human-Computer Interaction*, *4*(CSCW2), 1–25. https://doi.org/10.1145/3415223

Sabaté, E. (2003). *Adherence to long-term therapies: Evidence for action*. World health organization.

Saidi, T., Mutswangwa, C. T., & Douglas, T. S. (2019). Design thinking as a complement to human factors engineering for enhancing medical device usability. *Engineering Studies*, *11*(1), 34–50. https://doi.org/10.1080/19378629.2019.1567521

Salminen, J., Guan, K., Jung, S., Chowdhury, S. A., & Jansen, B. J. (2020). *A literature review of quantitative persona creation*. 1–14.

Salwei, M. E., Carayon, P., Hoonakker, P. L. T., Hundt, A. S., Wiegmann, D., Pulia, M., & Patterson, B. W. (2021). Workflow integration analysis of a human factors-based clinical decision support in the emergency department. *Applied Ergonomics*, *97*, 103498. https://doi.org/10.1016/j.apergo.2021.103498

Sanchis, J., Gich, I., & Pedersen, S. (2016). Systematic review of errors in inhaler use. *CHEST*, *150*(2), 394–406. https://doi.org/10.1016/j.chest.2016.03.041

Sanduzzi, A., Balbo, P., Candoli, P., Catapano, G. A., Contini, P., Mattei, A., Puglisi, G., Santoiemma, L., & Stanziola, A. A. (2014). COPD: Adherence to therapy. *Multidisciplinary Respiratory Medicine*, *9*. https://doi.org/10.4081/mrm.2014.395

Sansoni, S., Speer, L., Wodehouse, A., & Buis, A. (2016). Aesthetic of prosthetic devices: From medical equipment to a work of design. In S. Fukuda (Ed.), *Emotional Engineering Volume 4* (pp. 73–92). Springer International Publishing. https://doi.org/10.1007/978-3-319-29433-9_5

Santos, A. L. R., Wauben, L. S. G. L., Dewo, P., Goossens, R., & Brezet, H. (2013). Medical emergency dynamics in disaster-prone countries—Implications for medical device design. *International Journal of Human Factors and Ergonomics*, *2*(2/3), 87. https://doi.org/10.1504/IJHFE.2013.057609

Sardi, L., Idri, A., & Fernández-Alemán, J. L. (2017). A systematic review of gamification in e-Health. *Journal of Biomedical Informatics*, *71*, 31–48. https://doi.org/10.1016/j.jbi.2017.05.011

Sasono, S., Kusumastuti, S., Supriyanto, E., & Putri, I. D. (2019). Sensor data analysis on monitoring and control system of temperature and humidity based on android in soybean seed storage room using nodemcu. *Jaict*, *3*(1), 8.

Schaffer, S. D., & Tian, L. (2004). Promoting adherence: Effects of theory-based asthma education. *Clinical Nursing Research*, *13*(1), 69–89. https://doi.org/10.1177/1054773803259300

Schmitt, Z., & Yarosh, S. (2018). Participatory Design of Technologies to Support Recovery from Substance Use Disorders. *Proceedings of the ACM on Human-Computer Interaction*, *2*(CSCW), 1–27. https://doi.org/10.1145/3274425

Schoenwald, S. K., & Garland, A. F. (2013). A review of treatment adherence measurement methods. *Psychological Assessment*, *25*(1), 146–156. https://doi.org/10.1037/a0029715

Scott, J., Heavey, E., Waring, J., Jones, D., & Dawson, P. (2016). Healthcare professional and patient codesign and validation of a mechanism for service users to feedback patient safety experiences following a care transfer: A qualitative study. *BMJ Open*, *6*(7), e011222.

Selzler, A.-M., Habash, R., Robson, L., Lenton, E., Goldstein, R., & Brooks, D. (2020). Self-efficacy and health-related quality of life in chronic obstructive pulmonary disease: A meta-analysis. *Patient Education and Counseling*, *103*(4), 682–692. https://doi.org/10.1016/j.pec.2019.12.003

Serdaroglu, K., Uslu, G., & Baydere, S. (2015). Medication intake adherence with real time activity recognition on IoT. *2015 IEEE 11th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*, 230–237. https://doi.org/10.1109/WiMOB.2015.7347966

Shahin, W., Kennedy, G. A., & Stupans, I. (2019). The impact of personal and cultural beliefs on medication adherence of patients with chronic illnesses: A systematic review. *Patient Preference and Adherence*, *Volume 13*, 1019–1035. https://doi.org/10.2147/PPA.S212046

Sheehan, P., Joy, A., Fleming, A., Vosper, H., & McCarthy, S. (2022). Human factors and patient safety in undergraduate healthcare education: A systematic review. *Human Factors in Healthcare*, *2*, 100019. https://doi.org/10.1016/j.hfh.2022.100019

Sherman, J., Hutson, A., Baumstein, S., & Hendeles, L. (2000). Telephoning the patient's pharmacy to assess adherence with asthma medications by measuring refill rate for prescriptions. *The Journal of Pediatrics*, *136*(4), 532–536. https://doi.org/10.1016/S0022-3476(00)90019-2

Shi, L., Liu, J., Koleva, Y., Fonseca, V., Kalsekar, A., & Pawaskar, M. (2010). Concordance of adherence measurement using self-reported adherence questionnaires and medication monitoring devices. *Pharmacoeconomics*, *28*, 1097–1107.

Shum, H.-Y., He, X., & Li, D. (2018). From eliza to XiaoIce: Challenges and opportunities with social chatbots. *Frontiers of Information Technology & Electronic Engineering*, *19*, 10–26.

Shura, R., Siders, R. A., & Dannefer, D. (2011). Culture change in long-term care: Participatory action research and the role of the resident. *The Gerontologist*, *51*(2), 212–225.

Siddiqui, T., & Morshed, B. I. (2018). Severity Classification of Chronic Obstructive Pulmonary Disease and Asthma with Heart Rate and SpO2 Sensors. *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2929–

2932. https://doi.org/10.1109/EMBC.2018.8512927

Sigrist, R., Rauter, G., Riener, R., & Wolf, P. (2013). Augmented visual, auditory, haptic, and multimodal feedback in motor learning: A review. *Psychonomic Bulletin & Review*, *20*, 21–53.

Silva, G. R. S., & Canedo, E. D. (2024). Towards user-centric guidelines for chatbot conversational design. *International Journal of Human–Computer Interaction*, *40*(2), 98–120. https://doi.org/10.1080/10447318.2022.2118244

Simon, J. (2013). Attitudes of hungarian asthmatic and COPD patients affecting disease control: Empirical research based on health belief model. *Frontiers in Pharmacology*, *4*. https://doi.org/10.3389/fphar.2013.00135

Singh, S., Malik, A., Prakash Rawat, A., Tevetia, N., Aggarwal, R., Goswami, S., Sharma, K., Raghavendra Rao, N. G., & Pathak, A. (2023). Regulatory considerations of material used for medical devices and combination products in different countries: A review. *Materials Today: Proceedings*, S2214785323049520. https://doi.org/10.1016/j.matpr.2023.10.045

Skoner, D. P. (2002). Balancing safety and efficacy in pediatric asthma management. *Pediatrics*, *109*(Supplement_E1), 381–392. https://doi.org/10.1542/peds.109.SE1.381

Skrabal Ross, X., Gunn, K. M., Suppiah, V., Patterson, P., & Olver, I. (2020). A review of factors influencing non-adherence to oral antineoplastic drugs. *Supportive Care in Cancer*, *28*(9), 4043–4050. https://doi.org/10.1007/s00520-020-05469-y

Slattery, P., Saeri, A. K., & Bragge, P. (2020). Research co-design in health: A rapid overview of reviews. *Health Research Policy and Systems*, *18*, 1–13.

Smyth, H. D., Colthorpe, P., George, M., Jansen, P., Fuglsang, A., Armstrong, K. E., & Lyapustina, S. (2018). Highlights from the 2017 IPAC-RS/ISAM joint workshop “new frontiers in inhalation technology”. *Journal of Aerosol Medicine and Pulmonary Drug*

Delivery, *31*(4), 199–203. https://doi.org/10.1089/jamp.2017.1425

Son, K.-J., Son, H.-R., Park, B., Kim, H.-J., & Kim, C.-B. (2019). A community-based intervention for improving medication adherence for elderly patients with hypertension in korea. *International Journal of Environmental Research and Public Health*, *16*(5), 721.

Son, Y.-J., Kim, H.-G., Kim, E.-H., Choi, S., & Lee, S.-K. (2010). Application of support vector machine for prediction of medication adherence in heart failure patients. *Healthcare Informatics Research*, *16*(4), 253. https://doi.org/10.4258/hir.2010.16.4.253

Soori, H. (2024). Study guide: Pilot, pre-test, quality assurance, quality control, and protocol modifications. In *Errors in Medical Science Investigations* (pp. 193–204). Springer.

Soriano, J. B., Abajobir, A. A., Abate, K. H., Abera, S. F., Agrawal, A., Ahmed, M. B., Aichour, A. N., Aichour, I., Aichour, M. T. E., Alam, K., Alam, N., Alkaabi, J. M., Al-Maskari, F., Alvis-Guzman, N., Amberbir, A., Amoako, Y. A., Ansha, M. G., Antó, J. M., Asayesh, H., … Vos, T. (2017). Global, regional, and national deaths, prevalence, disability-adjusted life years, and years lived with disability for chronic obstructive pulmonary disease and asthma, 1990–2015: A systematic analysis for the global burden of disease study 2015. *The Lancet Respiratory Medicine*, *5*(9), 691–706. https://doi.org/10.1016/S2213-2600(17)30293-X

Sorino, C., Negri, S., Spanevello, A., Visca, D., & Scichilone, N. (2020). Inhalation therapy devices for the treatment of obstructive lung diseases: The history of inhalers towards the ideal inhaler. *European Journal of Internal Medicine*, *75*, 15–18. https://doi.org/10.1016/j.ejim.2020.02.023

Spinuzzi, C. (2005). The methodology of participatory design. *Technical Communication*, *52*(2), 163–174.

Springer, A., & Whittaker, S. (2018). Progressive disclosure: Designing for effective transparency. *arXiv Preprint arXiv:1811.02164*.

Steele, M. L., Talley, B., & Frith, K. H. (2018). Application of the SEIPS model to analyze medication safety in a crisis residential center. *Archives of Psychiatric Nursing*, *32*(1), 7–11. https://doi.org/10.1016/j.apnu.2017.09.005

Steele, R., Lo, A., Secombe, C., & Wong, Y. K. (2009). Elderly persons' perception and acceptance of using wireless sensor networks to assist healthcare. *International Journal of Medical Informatics*, *78*(12), 788–801.

Steiropoulos, P., Bakakos, P., Hatziagorou, E., Katsaounou, P., Loukides, S., Papaioannou, A., Porpodis, K., Samaras, K., Tzouvelekis, A., Kalafatakis, K., & Kostikas, K. (2021). The present and future of inhalation therapy forthe management of obstructive airway diseases:Emphasis on pressurized metered-dose inhalers. *Pneumon*, 1–13. https://doi.org/10.18332/pne/144614

Stephenson, T. (2014). *Expert clinical advice–MHRA medical devices*.

Stepnowsky, C. J., Marler, M. R., Palau, J., & Annette Brooks, J. (2006). Social-cognitive correlates of CPAP adherence in experienced users. *Sleep Medicine*, *7*(4), 350–356. https://doi.org/10.1016/j.sleep.2005.11.004

Stikic, M., Johnson, R. R., Tan, V., & Berka, C. (2014). EEG-based classification of positive and negative affective states. *Brain-Computer Interfaces*, *1*(2), 99–112.

Strauss, A. L. (1987). *Qualitative analysis for social scientists*. Cambridge university press.

Strauven, G., Vanhaecht, K., Anrys, P., De Lepeleire, J., Spinewine, A., & Foulon, V. (2020). Development of a process-oriented quality improvement strategy for the medicines pathway in nursing homes using the SEIPS model. *Research in Social and Administrative Pharmacy*, *16*(3), 360–376. https://doi.org/10.1016/j.sapharm.2019.06.003

Su, G., & Deng, D. (2023). Evolution of China regulatory guidance on the clinical evaluation of medical devices and its implication on pre-market and post-approval clinical evaluation strategies. *Expert*

Review of Medical Devices, *20*(3), 167–178. https://doi.org/10.1080/17434440.2023.2184258

Su, J. G., Barrett, M. A., Henderson, K., Humblet, O., Smith, T., Sublett, J. W., Nesbitt, L., Hogg, C., Van Sickle, D., & Sublett, J. L. (2017). Feasibility of Deploying Inhaler Sensors to Identify the Impacts of Environmental Triggers and Built Environment Factors on Asthma Short-Acting Bronchodilator Use. *Environmental Health Perspectives*, *125*(2), 254–261. https://doi.org/10.1289/EHP266

Suehs, C. M., Vachier, I., Galeazzi, D., Vaast, F., Cardon, F., Molinari, N., & Bourdin, A. (2023). Standard patient training versus Vik-Asthme chatbot-guided training: 'AsthmaTrain' – a protocol for a randomised controlled trial for patients with asthma. *BMJ Open*, *13*(2), e067039. https://doi.org/10.1136/bmjopen-2022-067039

Sun, X., & May, A. (2013). A comparison of field-based and lab-based experiments to evaluate user experience of personalised mobile devices. *Advances in Human-Computer Interaction*, *2013*(1), 619767.

Svensson, R. J., Ribbing, J., Kotani, N., Dolton, M., Vadhavkar, S., Cheung, D., Staton, T., Choy, D. F., Putnam, W., Jin, J., Budha, N., Karlsson, M. O., Quartino, A., & Zhu, R. (2021). Population repeated time-to-event analysis of exacerbations in asthma patients: A novel approach for predicting asthma exacerbations based on biomarkers, spirometry, and diaries/questionnaires. *CPT: Pharmacometrics & Systems Pharmacology*, *10*(10), 1221–1235. https://doi.org/10.1002/psp4.12690

Tashkin, D. (2016). A review of nebulized drug delivery in COPD. *International Journal of Chronic Obstructive Pulmonary Disease*, *Volume 11*, 2585–2596. https://doi.org/10.2147/COPD.S114034

Taylor, T. E., Holmes, M. S., Sulaiman, I., Costello, R. W., & Reilly, R. B. (2016). Monitoring inhaler inhalations using an acoustic sensor proximal to inhaler devices. *Journal of Aerosol Medicine and Pulmonary Drug Delivery*, *29*(5), 439–446. https://doi.org/10.1089/jamp.2015.1276

Taylor, T. E., Lacalle Muls, H., Costello, R. W., & Reilly, R. B. (2018). Estimation of inhalation flow profile using audio-based methods to assess inhaler medication adherence. *PLOS ONE*, *13*(1), e0191330. https://doi.org/10.1371/journal.pone.0191330

Taylor, T. E., Zigel, Y., Egan, C., Hughes, F., Costello, R. W., & Reilly, R. B. (2018). Objective assessment of patient inhaler user technique using an audio-based classification approach. *Scientific Reports*, *8*(1), 2164. https://doi.org/10.1038/s41598-018-20523-w

The Asia Pacific COPD Roundtable Group. (2005). Global initiative for chronic obstructive lung disease strategy for the diagnosis, management and prevention of chronic obstructive pulmonary disease: An asia–pacific perspective. *Respirology*, *10*(1), 9–17. https://doi.org/10.1111/j.1440-1843.2005.00692.x

Theis, S., Rasche, P., Mertens, A., & Schlick, C. M. (2017). *An age-differentiated perspective on visualizations of personal health data*. 289–308.

Thurmond, V. A. (2001). The point of triangulation. *Journal of Nursing Scholarship*, *33*(3), 253–258.

Tian, J., Song, X., Wang, Y., Cheng, M., Lu, S., Xu, W., Gao, G., Sun, L., Tang, Z., Wang, M., & Zhang, X. (2022). Regulatory perspectives of combination products. *Bioactive Materials*, *10*, 492–503. https://doi.org/10.1016/j.bioactmat.2021.09.002

Tiong, E., Seow, O., Camburn, B., Teo, K., Silva, A., Wood, K. L., Jensen, D. D., & Yang, M. C. (2019). The economies and dimensionality of design prototyping: Value, time, cost, and fidelity. *Journal of Mechanical Design*, *141*(3), 031105.

Tiotiu, A. I., Novakova, P., Nedeva, D., Chong-Neto, H. J., Novakova, S., Steiropoulos, P., & Kowal, K. (2020). Impact of air pollution on asthma outcomes. *International Journal of Environmental Research and Public Health*, *17*(17), 6212.

Ţîrcă, S. M., Ciontea, M. S., Vlad, E., & Mihălţan, F. D. (2022). A clinical trial of the relationship between anxiety and lung function and respiratory symptoms in patients with asthma, copd and copd-asthma. Assessment of life quality. *Internal Medicine*, *19*(1), 19–42.

Tsang, K. C., Pinnock, H., Wilson, A. M., & Shah, S. A. (2022). Application of Machine Learning Algorithms for Asthma Management with mHealth: A Clinical Review. *Journal of Asthma and Allergy*, *Volume 15*, 855–873. https://doi.org/10.2147/JAA.S285742

Tsao, L., Li, L., & Ma, L. (2019). Human work and status evaluation based on wearable sensors in human factors and ergonomics: A review. *IEEE Transactions on Human-Machine Systems*, *49*(1), 72–84. https://doi.org/10.1109/THMS.2018.2878824

Turner, A. M., Reeder, B., & Ramey, J. (2013). Scenarios, personas and user stories: User-centered evidence-based design representations of communicable disease investigations. *Journal of Biomedical Informatics*, *46*(4), 575–584.

Turner, J., & Kelly, B. (2000). Emotional dimensions of chronic disease. *Western Journal of Medicine*, *172*(2), 124.

Udovičić, G., Đerek, J., Russo, M., & Sikora, M. (2017). Wearable Emotion Recognition System based on GSR and PPG Signals. *Proceedings of the 2nd International Workshop on Multimedia for Personal Health and Health Care*, 53–59. https://doi.org/10.1145/3132635.3132641

Usmani, O. S. (2019). Choosing the right inhaler for your asthma or COPD patient. *Therapeutics and Clinical Risk Management*, *Volume 15*, 461–472. https://doi.org/10.2147/TCRM.S160365

Usmani, O. S., Lavorini, F., Marshall, J., Dunlop, W. C. N., Heron, L., Farrington, E., & Dekhuijzen, R. (2018). Critical inhaler errors in asthma and COPD: A systematic review of impact on health outcomes. *Respiratory Research*, *19*(1), 10. https://doi.org/10.1186/s12931-017-0710-y

Valaitis, R., Longaphy, J., Ploeg, J., Agarwal, G., Oliver, D., Nair, K., Kastner, M., Avilla, E., & Dolovich, L. (2019). Health TAPESTRY:

Co-designing interprofessional primary care programs for older adults using the persona-scenario method. *BMC Family Practice*, *20*, 1–11.

Valero-Ramon, Z., Fernandez-Llatas, C., Collantes, G., Valdivieso, B., Billis, A., Bamidis, P., & Traver, V. (2023). Analytical exploratory tool for healthcare professionals to monitor cancer patients' progress. *Frontiers in Oncology*, *12*, 1043411.

Valtolina, S., Barricelli, B. R., & Di Gaetano, S. (2020). Communicability of traditional interfaces VS chatbots in healthcare and smart home domains. *Behaviour & Information Technology*, *39*(1), 108–132. https://doi.org/10.1080/0144929X.2019.1637025

Van De Hei, S. J., Kim, C. H., Honkoop, P. J., Sont, J. K., Schermer, T. R. J., MacHale, E., Costello, R. W., Kocks, J. W. H., Postma, M. J., & Van Boven, J. F. M. (2023). Long-term cost-effectiveness of digital inhaler adherence technologies in difficult-to-treat asthma. *The Journal of Allergy and Clinical Immunology: In Practice*, *11*(10), 3064-3073.e15. https://doi.org/10.1016/j.jaip.2023.06.051

Van De Hei, S. J., Poot, C. C., Van Den Berg, L. N., Meijer, E., Van Boven, J. F. M., Flokstra-de Blok, B. M. J., Postma, M. J., Chavannes, N. H., & Kocks, J. W. H. (2022). Effectiveness, usability and acceptability of a smart inhaler programme in patients with asthma: Protocol of the multicentre, pragmatic, open-label, cluster randomised controlled ACCEPTANCE trial. *BMJ Open Respiratory Research*, *9*(1), e001400. https://doi.org/10.1136/bmjresp-2022-001400

van der Bijl-Brouwer, M., & van der Voort, M. C. (2013). Exploring future use: Scenario based design. In *Advanced design methods for succesful innovation* (pp. 57–77). Design United.

Van Dulmen, S., Sluijs, E., Van Dijk, L., De Ridder, D., Heerdink, R., & Bensing, J. (2007). Patient adherence to medical treatment: A review of reviews. *BMC Health Services Research*, *7*(1), 55. https://doi.org/10.1186/1472-6963-7-55

Vaughn, L. M., Jacquez, F., & Baker, R. C. (2009). Cultural health attributions, beliefs, and practices: Effects on healthcare and medical education. *Mental*, *10*, 11.

Vaughn-Cooke, M., Nembhard, H. B., Ulbrecht, J., & Gabbay, R. (2015). Informing patient self-management technology design using a patient adherence error classification. *Engineering Management Journal*, *27*(3), 124–130.

Velardo, C., Shah, S. A., Gibson, O., Clifford, G., Heneghan, C., Rutter, H., Farmer, A., Tarassenko, L., & EDGE COPD Team Andreas Triantafyllidis Veronika Williams Maxine Hardinge Christy Toms Louise Jones Stephanie Robinson Jonathan Price Linda Heritage. (2017). Digital health system for personalised COPD long-term management. *BMC Medical Informatics and Decision Making*, *17*, 1–13.

Vinutha, H., Poornima, B., & Sagar, B. (2018). *Detection of outliers using interquartile range technique from intrusion dataset*. 511–518.

Vitolins, M. Z., Rand, C. S., Rapp, S. R., Ribisl, P. M., & Sevick, M. A. (2000). Measuring adherence to behavioral and medical interventions. *Controlled Clinical Trials*, *21*(5), S188–S194. https://doi.org/10.1016/S0197-2456(00)00077-5

Vogel, J. P., Oxman, A. D., Glenton, C., Rosenbaum, S., Lewin, S., Gülmezoglu, A. M., & Souza, J. P. (2013). Policymakers' and other stakeholders' perceptions of key considerations for health system decisions and the presentation of evidence to inform those considerations: An international survey. *Health Research Policy and Systems*, *11*, 1–9.

Vrijens, B., De Geest, S., Hughes, D. A., Przemyslaw, K., Demonceau, J., Ruppar, T., Dobbels, F., Fargher, E., Morrison, V., Lewek, P., Matyjaszczyk, M., Mshelia, C., Clyne, W., Aronson, J. K., Urquhart, J., & for the ABC Project Team. (2012). A new taxonomy for describing and defining adherence to medications. *British Journal of Clinical Pharmacology*, *73*(5), 691–705.

https://doi.org/10.1111/j.1365-2125.2012.04167.x

Vrijens, B., Vincze, G., Kristanto, P., Urquhart, J., & Burnier, M. (2008). Adherence to prescribed antihypertensive drug treatments: Longitudinal study of electronically compiled dosing histories. *Bmj*, *336*(7653), 1114–1117.

Wafaie, K., Rizk, M. Z., Basyouni, M. E., Daniel, B., & Mohammed, H. (2023). Tele-orthodontics and sensor-based technologies: A systematic review of interventions that monitor and improve compliance of orthodontic patients. *European Journal of Orthodontics*, *45*(4), 450–461. https://doi.org/10.1093/ejo/cjad004

Wagner, G. J. (2002). Predictors of antiretroviral adherence as measured by self-report, electronic monitoring, and medication diaries. *AIDS Patient Care and STDs*, *16*(12), 599–608. https://doi.org/10.1089/108729102761882134

Wahyuni, A. S., Hamid, R. Z., Bachtiar, A., & Nerdy, N. (2018). The Correlation between Adherence and Asthma Patients Quality of Life in Medan, Indonesia. *Open Access Macedonian Journal of Medical Sciences*, *6*(11), 2198–2205. https://doi.org/10.3889/oamjms.2018.362

Walker, M., Takayama, L., & Landay, J. A. (2002). *High-fidelity or low-fidelity, paper or computer? Choosing attributes when testing web prototypes*. *46*(5), 661–665.

Wanderer, J. P., Nelson, S. E., Ehrenfeld, J. M., Monahan, S., & Park, S. (2016). Clinical Data Visualization: The Current State and Future Needs. *Journal of Medical Systems*, *40*(12), 275. https://doi.org/10.1007/s10916-016-0643-x

Wang, C., Yan, J., & Ma, C. (2023). Psychological distress and its associated factors among patients with chronic obstructive pulmonary disease in Hunan, China: A cross-sectional study. *Scientific Reports*, *13*(1), 5199. https://doi.org/10.1038/s41598-023-32408-8

Wang, J., & Dong, J. (2020). Optical waveguides and integrated optical devices for medical diagnosis, health monitoring and light therapies. *Sensors*, *20*(14), 3981. https://doi.org/10.3390/s20143981

Wang, Y., & Burgess, D. J. (2010). Drug–device combination products. In *Drug-Device Combination Products* (pp. 3–28). Elsevier. https://doi.org/10.1533/9781845697488.1.3

Weisberg, H. (1992). *Central tendency and variability* (Issue 83). Sage.

Werner, N. E., Rutkowski, R., Graske, A., Finta, M. K., Sellers, C. R., Seshadri, S., & Shah, M. N. (2020). Exploring SEIPS 2.0 as a model for analyzing care transitions across work systems. *Applied Ergonomics*, *88*, 103141. https://doi.org/10.1016/j.apergo.2020.103141

West, V. L., Borland, D., & Hammond, W. E. (2015). Innovative information visualization of electronic health record data: A systematic review. *Journal of the American Medical Informatics Association*, *22*(2), 330–339. https://doi.org/10.1136/amiajnl-2014-002955

Whichello, C., Van Overbeeke, E., Janssens, R., Schölin Bywall, K., Russo, S., Veldwijk, J., Cleemput, I., Juhaeri, J., Levitan, B., & Kübler, J. (2019). Factors and situations affecting the value of patient preference studies: Semi-structured interviews in europe and the US. *Frontiers in Pharmacology*, *10*, 1009.

White, M. C., Etzel, R. A., Wilcox, W. D., & Lloyd, C. (1994). Exacerbations of childhood asthma and ozone pollution in atlanta. *Environmental Research*, *65*(1), 56–68.

Wiemken, T. L., Hainaut, L., Bodenschatz, H., & Varghese, R. (2019). Hand hygiene compliance surveillance with time series anomaly detection. *American Journal of Infection Control*, *47*(12), 1449–1452.

Wilson, S. R., Strub, P., Buist, A. S., Knowles, S. B., Lavori, P. W., Lapidus, J., & Vollmer, W. M. (2010). Shared treatment decision making improves adherence and outcomes in poorly controlled asthma. *American Journal of Respiratory and Critical Care Medicine*, *181*(6), 566–577. https://doi.org/10.1164/rccm.200906-

0907OC
Windle, J. R., Windle, T. A., Shamavu, K. Y., Nelson, Q. M., Clarke, M. A., Fruhling, A. L., & Tcheng, J. E. (2021). Roadmap to a more useful and usable electronic health record. *Cardiovascular Digital Health Journal*, *2*(6), 301–311.
Wong, J. C., Izadi, Z., Schroeder, S., Nader, M., Min, J., Neinstein, A. B., & Adi, S. (2018). A pilot study of use of a software platform for the collection, integration, and visualization of diabetes device data by health care providers in a multidisciplinary pediatric setting. *Diabetes Technology & Therapeutics*, *20*(12), 806–816.
Wong, Q. Y. A., Lim, J. J., Ng, J. Y., Malipeddi, P., Lim, Y. Y. E., Sio, Y. Y., & Chew, F. T. (2023). An updated prevalence of asthma, its phenotypes, and the identification of the potential asthma risk factors among young Chinese adults recruited in singapore. *World Allergy Organization Journal*, *16*(3), 100757. https://doi.org/10.1016/j.waojou.2023.100757
Wood-Baker, R., Walters, Robinson, A., Walters, & Wills. (2012). Clinical diaries in COPD: Compliance and utility in predicting acute exacerbations. *International Journal of Chronic Obstructive Pulmonary Disease*, 427. https://doi.org/10.2147/COPD.S32222
Woods, L., Eden, R., Canfell, O. J., Nguyen, K., Comans, T., & Sullivan, C. (2023). Show me the money: How do we justify spending health care dollars on digital health? *The Medical Journal of Australia*, *218*(2), 53.
Wooldridge, A. R., Carayon, P., Hundt, A. S., & Hoonakker, P. L. T. (2017). SEIPS-based process modeling in primary care. *Applied Ergonomics*, *60*, 240–254. https://doi.org/10.1016/j.apergo.2016.11.010
Wriedt, T. (2012). Mie theory: A review. *The Mie Theory: Basics and Applications*, 53–71.
Wu, C.-T., Li, G.-H., Huang, C.-T., Cheng, Y.-C., Chen, C.-H., Chien, J.-Y., Kuo, P.-H., Kuo, L.-C., & Lai, F. (2021). Acute exacerbation of a

chronic obstructive pulmonary disease prediction system using wearable device data, machine learning, and deep learning: Development and cohort study. *JMIR mHealth and uHealth*, *9*(5), e22591. https://doi.org/10.2196/22591

Wu, J.-R., Moser, D. K., Chung, M. L., & Lennie, T. A. (2008). Predictors of medication adherence using a multidimensional adherence model in patients with heart failure. *Journal of Cardiac Failure*, *14*(7), 603–614. https://doi.org/10.1016/j.cardfail.2008.02.011

Wu, X. (2021). The design, development, and evaluation of telepresence interfaces for aging adults: Investigating user perceptions of privacy and usability. *Computer Studies*.

Wu, X.-W., Yang, H.-B., Yuan, R., Long, E.-W., & Tong, R.-S. (2020). Predictive models of medication non-adherence risks of patients with T2D based on multiple machine learning algorithms. *BMJ Open Diabetes Research & Care*, *8*(1), e001055. https://doi.org/10.1136/bmjdrc-2019-001055

Xiong, S., Chen, W., Jia, X., Jia, Y., & Liu, C. (2023). Machine learning for prediction of asthma exacerbations among asthmatic patients: A systematic review and meta-analysis. *BMC Pulmonary Medicine*, *23*(1), 278. https://doi.org/10.1186/s12890-023-02570-w

Xiroudaki, S., Schoubben, A., Giovagnoli, S., & Rekkas, D. M. (2021). Dry Powder Inhalers in the Digitalization Era: Current Status and Future Perspectives. *Pharmaceutics*, *13*(9), 1455. https://doi.org/10.3390/pharmaceutics13091455

Xu, A., Chomutare, T., & Iyengar, S. (2014). Persuasive attributes of medication adherence interventions for older adults: A systematic review. *Technology and Health Care*, *22*(2), 189–198. https://doi.org/10.3233/THC-140812

Xu, L., Li, J., Zhang, X., Pang, Y., Yu, T., Lian, X., Yu, T., Zhu, L., Tong, Q., & Li, F. (2022). Mobile health-based gamification intervention to increase physical activity participation among patients with coronary heart disease: Study protocol of a randomised controlled trial. *BMJ*

Open, *12*(1), e054623.

Xu, S., Yang, C., Ge, W., Yu, C., & Shi, Y. (2020). Virtual paving: Rendering a smooth path for people with visual impairment through vibrotactile and audio feedback. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *4*(3), 1–25.

Yang, Y., Zheng, X., Guo, W., Liu, X., & Chang, V. (2019). Privacy-preserving smart IoT-based healthcare big data storage and self-adaptive access control system. *Information Sciences*, *479*, 567–592.

Ye, J. (2021). The impact of electronic health record–integrated patient-generated health data on clinician burnout. *Journal of the American Medical Informatics Association*, *28*(5), 1051–1056.

Yi, X., Bouguettaya, A., Georgakopoulos, D., Song, A., & Willemson, J. (2015). Privacy protection for wireless medical sensor data. *IEEE Transactions on Dependable and Secure Computing*, *13*(3), 369–380.

Yin, H., Sharma, B., Hu, H., Liu, F., Kaur, M., Cohen, G., McConnell, R., & Eckel, S. P. (2024). Predicting the climate impact of healthcare facilities using gradient boosting machines. *Cleaner Environmental Systems*, *12*, 100155.

Yu, X., Li, C., Shi, Y., & Yu, M. (2010). Pharmaceutical supply chain in China: Current issues and implications for health system reform. *Health Policy*, *97*(1), 8–15. https://doi.org/10.1016/j.healthpol.2010.02.010

Zakeri, M., Sansgiry, S. S., & Abughosh, S. M. (2022). Application of machine learning in predicting medication adherence of patients with cardiovascular diseases: A systematic review of the literature. *Journal of Medical Artificial Intelligence*, *5*, 5–5. https://doi.org/10.21037/jmai-21-26

Zeller, A., Ramseier, E., Teagtmeyer, A., & Battegay, E. (2008). Patients' self-reported adherence to cardiovascular medication using electronic monitors as comparators. *Hypertension Research*, *31*(11), 2037–2043. https://doi.org/10.1291/hypres.31.2037

Zenk, R., Franz, M., & Bubb, H. (2008). Emocard–an approach to bring more emotion in the comfort concept. *SAE International Journal of Passenger Cars-Mechanical Systems*, *1*(2008-01–0890), 775–782.

Zhang, J., Oh, Y. J., Lange, P., Yu, Z., & Fukuoka, Y. (2020). Artificial Intelligence Chatbot Behavior Change Model for Designing Artificial Intelligence Chatbots to Promote Physical Activity and a Healthy Diet: Viewpoint. *Journal of Medical Internet Research*, *22*(9), e22845. https://doi.org/10.2196/22845

Zhang, Y., & Zhao, X. (2021). Effects of the health belief model-based intervention on anxiety, depression, and quality of life in chronic obstructive pulmonary disease. *Neuroimmunomodulation*, *28*(3), 129–136. https://doi.org/10.1159/000512993

Zhao, A., O'Callaghan, C., & Liu, X. (2021). A novel adherence sensor system for valved holding chambers suitable for children and adults with asthma. *IEEE Sensors Journal*, *21*(10), 12276–12283. https://doi.org/10.1109/JSEN.2021.3064886

Zhao, Y. C., Zhao, M., & Song, S. (2022). Online health information seeking among patients with chronic conditions: Integrating the health belief model and social support theory. *Journal of Medical Internet Research*, *24*(11), e42447. https://doi.org/10.2196/42447

Zhou, L., Gao, J., Li, D., & Shum, H.-Y. (2020). The design and implementation of xiaoice, an empathetic social chatbot. *Computational Linguistics*, *46*(1), 53–93.

Zohrabi, M. (2013). Mixed method research: Instruments, validity, reliability and reporting findings. *Theory and Practice in Language Studies*, *3*(2), 254.

Zumstein, D., & Hundertmark, S. (2017). Chatbots—An interactive technology for personalized communication, transactions and services. *IADIS International Journal on WWW/Internet*, *15*(1).

Zwikker, H. E., van den Bemt, B. J., Vriezekolk, J. E., van den Ende, C. H., & van Dulmen, S. (2014). Psychosocial predictors of non-adherence to chronic medication: Systematic review of longitudinal studies. *Patient Preference and Adherence*, 519–563.

Appendices

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Appendix 4A: Interview Protocol for Identifying Factors Influencing Adherence to Inhalation Therapy

Patient Interview Protocol

A. Introductory Questions

1.Tell me about your understanding/beliefs of inhalation therapy.

2.How long have you been undergoing inhalation therapy? How do you feel about it?

B. SEIPS Elements Questions

Person(s):

1.Can you recall a time when someone (including yourself) made it easier for you to adhere to inhalation therapy?

2.Can you recall a time when someone (including yourself) made it more difficult for you to adhere to inhalation therapy?

Tasks:

1.Could you please describe your usual process for conducting inhalation therapy?

2.Is there anything in this process that makes adhering to inhalation therapy easier?

3.Is there anything in this process that makes adhering to inhalation therapy more difficult?

Tools and Technology:

1.How has the tool(device)/technology assisted you in adhering to inhalation therapy?

2.How has the tool(device)/technology hindered your ability to adhere to inhalation therapy?

Environment:

1.What factors in your surrounding environment (e g. home, work etc.) make it easier for you to adhere to inhalation therapy?

2.What factors in your surrounding environment (e g. home, work etc.) make it more difficult for you to adhere to inhalation therapy?

Organization:

1.Would you be able to describe a time in which the organization (e g. the system, the society, etc.) helped you adhere to inhalation therapy?

2.Would you be able to describe a time in which the organization (e g. the system, the society, etc.) hindered you adhere to inhalation therapy?

Do you have anything you'd like to add before we end? (Special experience? Advice for inhaler design?)

HCP Interview Protocol

A. Introductory Questions

1.Please tell me what you do in inhalation therapy.

2.What method(s) do you use to assess if patients are adhering to their inhalation therapy?

B. SEIPS Elements Questions

Person(s):

1.Who do you think can help your patient more easily adhere to inhalation therapy？

2.Who do you think will prevent your patient from adhering to inhalation therapy?

Tasks:

1.Have you ever trained/educated your patients on how to use inhalation devices?

If yes

a. Could you please describe the usual process for training/educating patient using their inhaler device?

b. Is there anything in this process that makes your patient adhering to inhalation therapy easier?

c. Is there anything in this process that makes your patient adhering to inhalation therapy more difficult?

Tools and Technology:

1.Can you describe any tools/technology that can make it easier for your patients to adhere to inhalation therapy?

2.Can you describe any tools/technology that can make it more difficult for your patients to adhere to inhalation therapy?

Environment:

1.What factors in your patient's surrounding environment do you think make it easier for them to adhere to inhalation therapy?

2.What factors in your patient's surrounding environment do you think make it more difficult for them to adhere to inhalation therapy?

Organization:

1.In your opinion, what kind of organization (e g. the system, the society, etc.) could make it easier for patients to adhere to inhalation therapy?

2.In your opinion, what kind of organization (e g. the system, the society, etc.) could make it more difficult for patients to adhere to inhalation therapy?

Do you have anything you'd like to add before we end? (Special experience? Advice for inhaler design? Adherence interventions?)

Appendix 5A: Adapted TAM Questionnaire

Please select the response that best reflects your opinion on each statement. If you have any additional thoughts or feedback regarding the question, feel free to write them in the space provided below each statement.

Perceived Usefulness (PU)	Strongly Agree					Neutral					Strongly Disagree
1. "Using this interface helps me understand patient adherence data effectively."	10	9	8	7	6	5	4	3	2	1	0
2. "This interface provides valuable insights into patient adherence."	10	9	8	7	6	5	4	3	2	1	0
3. "The data on this interface supports my decision-making about adherence."	10	9	8	7	6	5	4	3	2	1	0
Comments:											
Perceived Ease of Use (PEOU)	Strongly Agree					Neutral					Strongly Disagree
1. "The design of this interface makes it easy to interpret adherence data."	10	9	8	7	6	5	4	3	2	1	0
2. "I find this interface straightforward to navigate."	10	9	8	7	6	5	4	3	2	1	0
3. "This interface presents adherence data in a clear and accessible format."	10	9	8	7	6	5	4	3	2	1	0
Comments:											

Attitude Toward Using (ATU)	Strongly Agree					Neutral					Strongly Disagree
1. "I feel positive about using this interface to review adherence data."	10	9	8	7	6	5	4	3	2	1	0
2. "Viewing adherence data on this interface is a pleasant experience."	10	9	8	7	6	5	4	3	2	1	0
3. "I am satisfied with the way this interface displays adherence data."	10	9	8	7	6	5	4	3	2	1	0
Comments:											
Behavioral Intention to Use (BI)	Strongly Agree					Neutral					Strongly Disagree
1. "I plan to use this interface regularly to check adherence data."	10	9	8	7	6	5	4	3	2	1	0
2. "I would recommend this interface to others for monitoring adherence."	10	9	8	7	6	5	4	3	2	1	0
3. "I am likely to rely on this interface for tracking adherence."	10	9	8	7	6	5	4	3	2	1	0
Comments:											

Appendix 6A: XIAOXI System Deployment Code

```csharp
namespace Starts.Profabx.CloudTencent.Dto
{
    public class RuleFeedInput
    {
        public RuleFeedPayloadDto Payload { get; set; }
        public long Timemills { get; set; }
        public int Timestamp { get; set; }
        public long Seq { get; set; }
        public string Topic { get; set; } = string.Empty;
        public string ProductId { get; set; } = string.Empty;
        public string DeviceName { get; set; } = string.Empty;
    }

    public class RuleFeedPayloadDto
    {
        public int? Humi { get; set; }
        public int? Temp { get; set; }
        public double? PPG { get; set; }
        public int? PM25 { get; set; }
        public double? Wx { get; set; }
        public double? Wy { get; set; }
        public double? Wz { get; set; }
        public double? Anglex { get; set; }
        public double? Angley { get; set; }
        public double? Anglez { get; set; }
    }
}
```

Figure 1: Data structure definition for integration with Tencent Cloud.

```csharp
    [RemoteService(IsEnabled = false)]
    public class DeviceQueryAppService : ApplicationService, IDeviceQueryAppService
    {
        private readonly IRepository<DeviceLogEntry, Guid> _repository;
        private readonly IRepository<UserDeviceBinding> _bindings;
        public DeviceQueryAppService(
            IRepository<DeviceLogEntry, Guid> repository,
            IRepository<UserDeviceBinding> bindings)
        {
            _repository = repository;
            _bindings = bindings;
        }
        public async Task<ListResultDto<DeviceLogEntryDto>> GetListAsync(DateTime? from = null, DateTime? to = null)
        {
            if (!from.HasValue) from = DateTime.Now.Date;
            if (!to.HasValue) to = from.Value.AddDays(1).Date;

            var items = await AsyncExecuter.ToListAsync(
                (await _repository.GetQueryableAsync())
                .Where(i => i.CreationTime >= from && i.CreationTime <= to)
                .OrderBy(i => i.DeviceName)
                .ThenBy(i => i.CreationTime)
                .AsNoTracking()
            );

            return new ListResultDto<DeviceLogEntryDto>
            {
                Items = ObjectMapper.Map<List<DeviceLogEntry>, List<DeviceLogEntryDto>>(items)
            };
        }
        public async Task<ListResultDto<DeviceLogEntryDto>> QueryAsync(string user, string type)
        {
            Check.NotNullOrWhiteSpace(user, nameof(user));

            var related = await AsyncExecuter.FirstOrDefaultAsync(
                (await _bindings.GetQueryableAsync())
                .Where(b => b.FromUserName == user)
                );
            if (related == null)
            {
                throw new BusinessException("400");
            }

            var items = await AsyncExecuter.ToListAsync(
                (await _repository.GetQueryableAsync())
                .Where(i => i.DeviceName == related.DeviceName)
                .WhereIf(type == nameof(DeviceLogEntry.Temp), e => e.Temp != null)
                .WhereIf(type == nameof(DeviceLogEntry.Humi), e => e.Humi != null)
                .WhereIf(type == nameof(DeviceLogEntry.PPG), e => e.PPG != null)
                .WhereIf(type == nameof(DeviceLogEntry.PM25), e => e.PM25 != null)
                .OrderByDescending(i => i.CreationTime)
                .Take(10)
                .AsNoTracking()
            );
            return new ListResultDto<DeviceLogEntryDto>
            {
                Items = ObjectMapper.Map<List<DeviceLogEntry>, List<DeviceLogEntryDto>>(items)
            };
        }
    }
}
```

Figure 2: Database structure and service code.

Figure 3: WeChat and chatbot integration.

IWeChatAppApi.cs M ×

Starts.Profabx > WechatApp > IWeChatAppApi.cs > ...

```
using WebApiClientCore.Attributes;

namespace Starts.Profabx.WechatApp
{

    You, 1 hour ago | 1 author (You)
    [HttpHost("https://api.weixin.qq.com")]
    4 references
    public interface IWeChatAppApi : IHttpApi
    {
        /// <summary>
        /// get client_credential app level access token  (refresh)
        /// https://api.weixin.qq.com/cgi-bin/token?grant_type=client_credential&appid=APPID&secret=APPSECRET
        /// </summary>
        /// <param name="appid"></param>
        /// <param name="secret"></param>
        /// <param name="grant_type"></param>
        /// <returns></returns>
        [HttpPost("/cgi-bin/stable_token")]
        [JsonReturn]
        1 reference
        ITask<AppAccessTokenResult> GetStableAccessTokenAsync([JsonContent] object input);

        [HttpPost("/cgi-bin/menu/create")]
        [JsonReturn]
        0 references
        ITask<HttpResponseMessage> CreateMenuAsync(string access_token, [JsonContent] object menu);

        [HttpPost("/cgi-bin/menu/create")]
        [JsonReturn]
        2 references
        ITask<HttpResponseMessage> CreateMenuByRawJsonStringAsync(string access_token, [RawJsonContent] string rawMenuJson);

        [HttpGet("/cgi-bin/get_current_selfmenu_info")]
        [JsonReturn]
        2 references
        ITask<HttpResponseMessage> GetCurrentSelfMenuInfoAsync(string access_token);

        [HttpGet("/cgi-bin/menu/delete")]
        [JsonReturn]
        0 references
        ITask<HttpResponseMessage> DeleteMenuAsync(string access_token);

        [HttpPost("/cgi-bin/freepublish/batchget")]
        1 reference
        ITask<HttpResponseMessage> GetArticlesAsync(string access_token, [JsonContent] object paging);

    }
}       You, 7 months ago • debug menu
```

Figure 4: WeChat integration API.

Appendix 6B: Interface Design of the “Knowledge” Menu

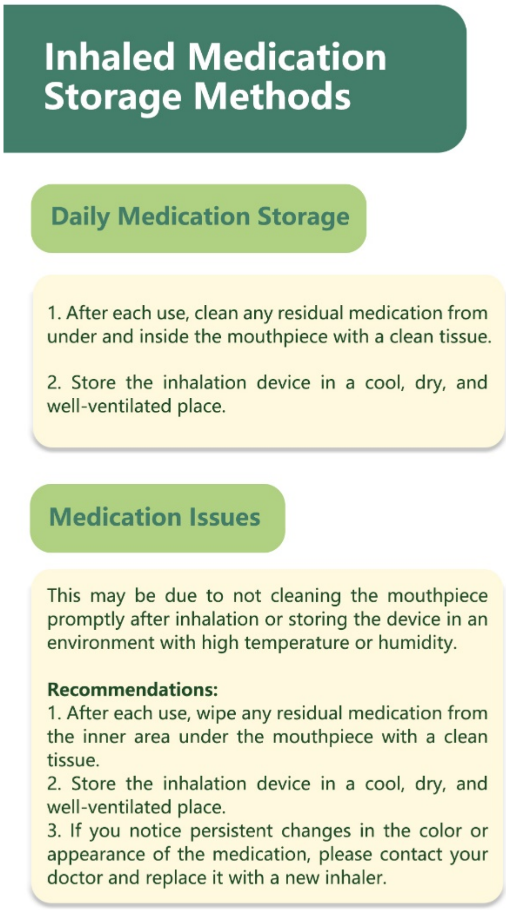
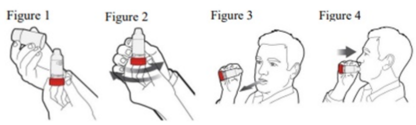


Figure 5: Inhaled medication storage methods.

The foundation for ensuring therapeutic efficacy is the patient's ability to correctly operate the inhalation device (inhalation technique) and effectively inhale the medication in the right dosage at the right time (treatment adherence), demonstrating adequate inhalation skills.

Symbicort Turbuhaler



How to prepare a NEW inhaler for use

STEP 1 Unscrew and lift off the cover(Figure 1). You will hear a rattling sound when you unscrew the cover. This is normal.

STEP 2 Hold the inhaler upright. Do not hold the inhaler by the mouthpiece.
a. Turn the **red grip** as far as it will go in one direction (clockwise or counterclockwise, it does not matter which way you turn it first).
b. Then turn the red grip as far as it will go in the opposite direction(Figure 2).
c. At some point when you are turning the grip, **you will hear a "click"**. This is part of the preparation process.

STEP 3 Repeat STEP 2 one more time. Then follow the steps under "How to take a dose", starting at STEP 2.

How to take a dose

STEP 1 Unscrew and lift off the cover(Figure 1). You will hear a rattling sound when you unscrew the cover. This is normal.

STEP 2 Hold the inhaler upright. Do not hold the inhaler by the mouthpiece.
a. Turn the **red grip** as far as it will go in one direction (clockwise or counterclockwise, it does not matter which way you turn it first).
b. Then turn the red grip as far as it will go in the opposite direction(Figure 2).
c. At some point when you are turning the grip, **you will hear a "click"**. This is part of the preparation process.

STEP 3 **Breathe out**, with your mouth away from the mouthpiece(Figure 3). Then, place the mouthpiece gently between your teeth.

STEP 4 Now close your lips over the mouthpiece. Do not bite or chew the mouthpiece.
• **Inhale as deeply and strongly** as you can(Figure 4).
• You may not feel or taste the medication when inhaling. This is common.
• Before you exhale, remember to remove the inhaler from your mouth.

Repeat STEPS 2-4 if more than one dose has been prescribed. When you have taken the prescribed amount of doses, **replace the cover of the inhaler by screwing it back on**. Rinse your mouth with water, and do not swallow.

Figure 6: How to use inhaled medication.

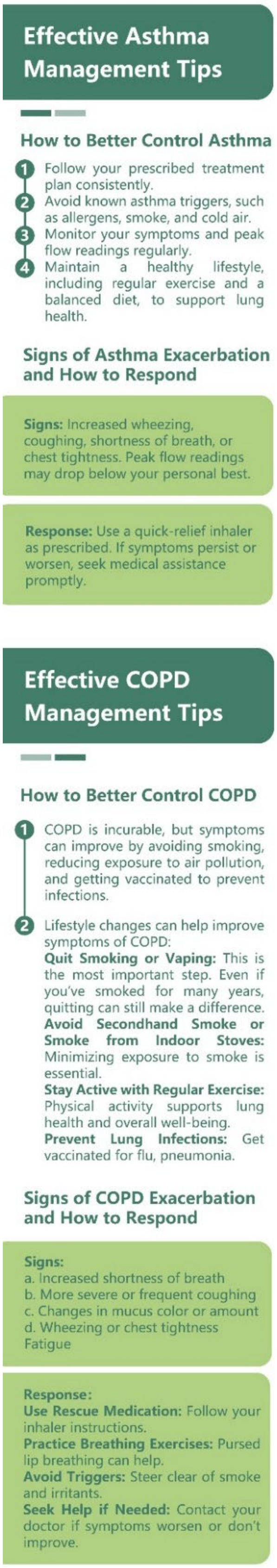


Figure 7: Disease management tips.

Figure 8: Lung function exercise methods.

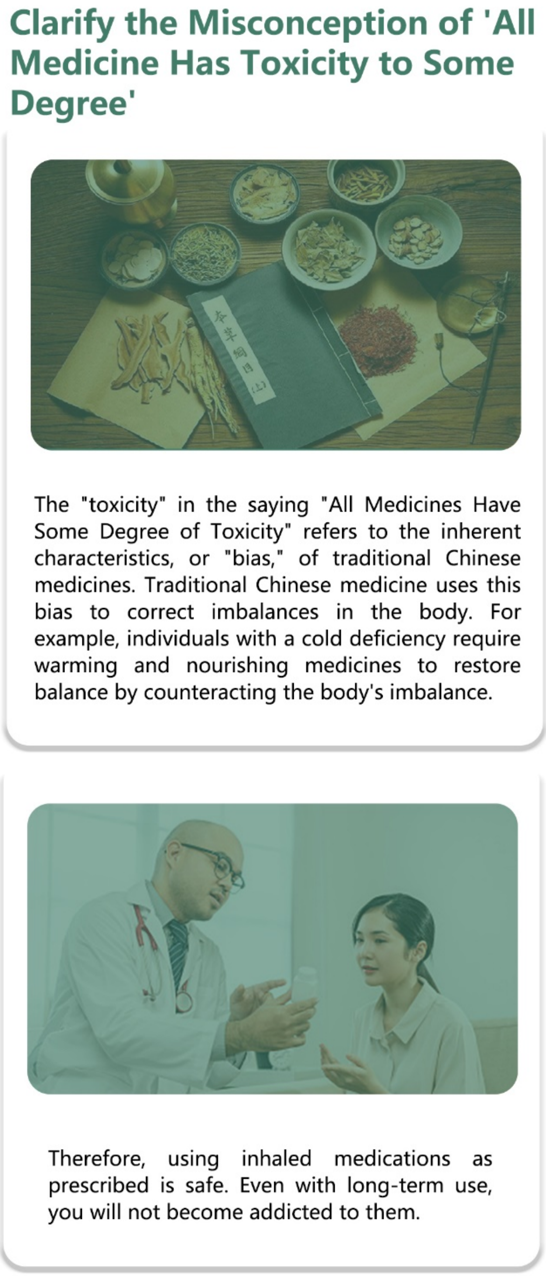


Figure 9: Clarify the misconception.

Appendix 6C: Questionnaires in the XIAOXI System

6C-1: Sample Disease Knowledge Test

Please read each statement carefully and select whether you believe it to be true or false based on your current knowledge.

12-ITEM CONSUMER ASTHMA KNOWLEDGE QUESTIONNAIRE (CQ)	**TRUE**	**FALSE**
1. You can become addicted to asthma medications if you use them all the time.		
2. An asthma action plan can prevent hospitalizations due to asthma.		
3. When you know that you are going to be exposed to something that triggers your asthma, you should take the recommended medication just before exposure.		
4. When you know that you are going to be exposed to something that triggers your asthma, you should wait until you develop symptoms before taking medication.		
5. Side effects are less likely with inhaled medications than with tablets.		
6. With preventer medications, it does not matter if some doses are missed or if you go on and off them.		
7. If you get a cold or flu, you should increase your asthma medications.		
8. Some medications can trigger asthma attacks.		
9. You should use ‘‘preventer medication’’ when you have an asthma attack.		
10. Going from a cold to hot environment can trigger asthma, but going from a hot to cold environment does not trigger asthma.		
11. Parents should give ‘‘reliever medication’’ to a child as soon as they recognize the first sign of asthma.		
12. Blue puffer (Ventolin), Brown puffer (Flixotide) and Green puffer (Serevent) are called ‘‘preventer medications,’’ so they should be used everyday although you are well.		

Chronic Obstructive Pulmonary Disease Knowledge Questionnaire (COPD-Q)	**TRUE**	**FALSE**
People with COPD should get a pneumonia shot.		
Using oxygen at home can help people with COPD live longer.		
COPD medicines keep the disease from getting worse.		
COPD can be prevented.		
People can stop taking their long-acting breathing medications (inhalers) when their COPD symptoms get better.		
People with COPD often have a cough that won't go away.		
Stopping smoking will keep COPD from getting worse.		
Cigarette smoking or secondhand smoke causes most COPD.		
People with COPD may feel short of breath.		
The medicine albuterol (inhaler) can be used anytime you are short of breath.		
People with COPD should have a flu shot every year.		
People should only use their COPD inhalers (medicines) when they can't breathe.		
COPD can be reversed.		

6C-2: Sample Disease Control Evaluation Questionnaire

The following questions are designed to assess the impact of your respiratory condition on your daily life and your level of symptom control over the past few weeks. For each statement, please select the response that best reflects your experience.

ACT Questionnaire					
Question	**Frequency**				
In the past 4 weeks, how often did your asthma prevent you from getting as much done at work, school, or home?	Always	Often	Sometimes	Rarely	Never
During the past 4 weeks, how often have you had shortness of breath?	Always	Often	Sometimes	Rarely	Never
During the past 4 weeks, how often did your asthma symptoms wake you up at night or earlier than usual in the morning?	Always	Often	Sometimes	Rarely	Never
During the past 4 weeks, how often have you used your rescue inhaler or nebulizer medication?	Always	Often	Sometimes	Rarely	Never
How would you rate your asthma control during the past 4 weeks?	Not controlled at all	Poorly controlled	Somewhat controlled	Well controlled	Completely controlled

CAT Questionnaire						
Question	**Frequency**					
Cough	Never	Rarely	Sometimes	Often	Very often	Always
Phlegm	None	Very little	Some	Moderate	Quite a bit	Full
Chest tightness	No tightness	Slight	Moderate	Tight	Very tight	Extremely tight
Breathless	Not breathless	Slightly breathless	Moderately breathless	Breathless	Very breathless	Extremely breathless
Activities	Not limited (doing any activities at home)	Slight	Moderate	Limited	Very	Extremely limited (doing any activities at home)
Confidence	Very confident (leaving my home despite my lung condition)	Fairly confident	Moderate	Slightly confident	Low confidence	Not confident (leaving my home despite my lung condition)
Sleep	Very good sleep	Good sleep	Average sleep	Fair sleep	Poor sleep	No sleep
Energy	High energy	Fair energy	Moderate energy	Low energy	Very low energy	No energy

6C-3: Sample Health Beliefs and Self-Efficacy Questionnaire

The following statements are designed to assess your beliefs about medicines. For each statement, please indicate the extent of your agreement, using a scale from 1 to 5, where 1 means 'Strongly Disagree' and 5 means 'Strongly Agree.' Your responses will help us understand your perspectives on medication.

The Beliefs about Medicines Questionnaire (BMQ)	Strongly Agree				Strongly Disagree
BMQ-Specific					
Without my medicines I would be very ill	5	4	3	2	1
My life would be impossible without my medicines	5	4	3	2	1
My health, at present, depends on my medicines	5	4	3	2	1
My health in the future will depend on my medicines	5	4	3	2	1
My medicines protect me from becoming worse	5	4	3	2	1
I sometimes worry about becoming too dependent on my medicines	5	4	3	2	1
My medicines disrupt my life	5	4	3	2	1
My medicines are a mystery to me	5	4	3	2	1
Having to take medicines worries me	5	4	3	2	1
I sometimes worry about long-term effects of my medicines	5	4	3	2	1
These medicines give me unpleasant side effects	5	4	3	2	1
BMQ-General					
Medicines do more harm than good	5	4	3	2	1
All medicines are poisons	5	4	3	2	1
Most medicines are addictive	5	4	3	2	1
People who take medicines should stop their treatment for a while every now and again	5	4	3	2	1
Natural remedies are safer than medicines	5	4	3	2	1
Doctors use too many medicines	5	4	3	2	1
If doctors had more time with patients they would prescribe fewer medicines	5	4	3	2	1
Doctors place too much trust on medicines	5	4	3	2	1

The following statements are intended to assess your beliefs in your ability to handle various situations effectively. Please select the option that best describes how true each statement is for you.

General Self-Efficacy Scale (GSE)				
1. I can always manage to solve difficult problems if I try hard enough.	Not at all true	Hardly true	Moderately true	Exactly true
2. If someone opposes me, I can find the means and ways to get what I want.	Not at all true	Hardly true	Moderately true	Exactly true
3. It is easy for me to stick to my aims and accomplish my goals.	Not at all true	Hardly true	Moderately true	Exactly true
4. I am confident that I could deal efficiently with unexpected events.	Not at all true	Hardly true	Moderately true	Exactly true
5. Thanks to my resourcefulness, I know how to handle unforeseen situations.	Not at all true	Hardly true	Moderately true	Exactly true
6. I can solve most problems if I invest the necessary effort.	Not at all true	Hardly true	Moderately true	Exactly true
7. I can remain calm when facing difficulties because I can rely on my coping abilities.	Not at all true	Hardly true	Moderately true	Exactly true
8. When I am confronted with a problem, I can usually find several solutions.	Not at all true	Hardly true	Moderately true	Exactly true
9. If I am in trouble, I can usually think of a solution.	Not at all true	Hardly true	Moderately true	Exactly true
10. I can usually handle whatever comes my way.	Not at all true	Hardly true	Moderately true	Exactly true

6C-4: Sample Adherence Assessment Questionnaire

The following questions aim to assess your adherence to inhaler use. Please select the response that best reflects your actual experience with using your inhaler.

Test of the Adherence to Inhalers (TAI) Questionnaire					
Patient domain: questions, responses					
1. During the last 7 days, how many times did you forget to take your usual inhalers?	All	More than half	Approximately a half	Less than half	None
2. Do you forget to take inhalers?	Always	Mostly	Sometimes	Rarely	Never
3. When you feel good about your illness, do you stop taking your inhalers?	Always	Mostly	Sometimes	Rarely	Never
4. When you are on vacation or weekend, do you stop taking your inhalers?	Always	Mostly	Sometimes	Rarely	Never
5. When you are nervous or sad, do you stop taking your inhalers?	Always	Mostly	Sometimes	Rarely	Never
6. Do you stop taking your inhalers because of fear of side effects?	Always	Mostly	Sometimes	Rarely	Never
7. Do you stop taking your inhalers because of considering they are useless to treat your condition?	Always	Mostly	Sometimes	Rarely	Never
8. Do you take fewer inhalations than those prescribed by your doctor?	Always	Mostly	Sometimes	Rarely	Never
9. Do you stop taking your inhalers because you believe they interfere with your everyday or working life?	Always	Mostly	Sometimes	Rarely	Never
10. Do you stop taking your inhalers because you have difficulties to pay them?	Always	Mostly	Sometimes	Rarely	Never
Health care professional domain: questions, responses					
11. Does the patient remember the prescribed regimen (dose and frequency)? (checking the medical record)	Yes	No			
12. The technique of using the evaluated inhaler device by the patient is* (checking the inhalation technique)	With critical mistakes	Without critical mistakes			

6C-5: Sample Usability, Preference, and Satisfaction Questionnaire

The following questions are designed to assess your experience with the usability, your preferences, and your satisfaction with the system. Please choose the response that best reflects your overall experience.

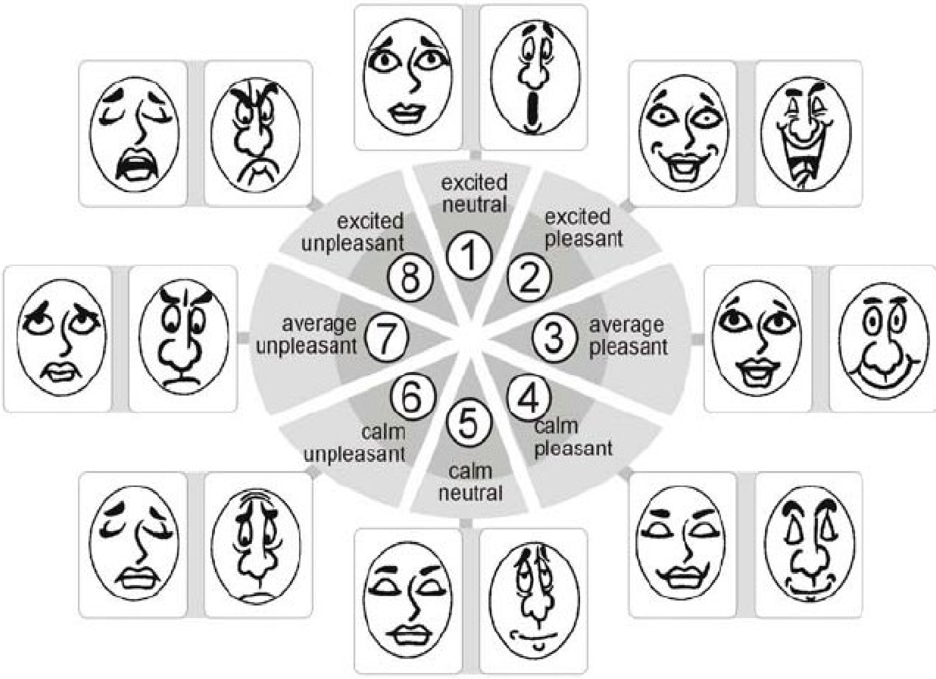
Usability, Preference, and Satisfaction Questionnaire						
Usability assessment	Strongly Agree					Strongly Disagree
1. I found it was easy to understand how to use the inhaler.	6	5	4	3	2	1
2. I found it was easy to operate the inhaler.	6	5	4	3	2	1
3. I found it was easy for me to remember how to use the inhaler	6	5	4	3	2	1
Preference assessment	Strongly Agree					Strongly Disagree
1. How do you like the device?	6	5	4	3	2	1
2. How does it feel to hold the device?	6	5	4	3	2	1
3. How do you like the shape and colour of the device?	6	5	4	3	2	1
4. How comfortable is the device to carry?	6	5	4	3	2	1
5. How easy is it to open the device and prepare it for inhalation?	6	5	4	3	2	1
6. How do you like the comfort of the mouthpiece of the device?	6	5	4	3	2	1
7. Was it easy or difficult to inhale long and deeply with the device?	6	5	4	3	2	1
8. How did you like the inhalation manoeuvre with this device?	6	5	4	3	2	1
9. I can easily see whether I inhaled correctly with this device.	6	5	4	3	2	1
10. I can easily see how much medication remains in the device.	6	5	4	3	2	1
11. The device be used quickly in cases of emergency, if necessary.	6	5	4	3	2	1
12. How did you like overall handling the device? (preparation, handling, inhalation manoeuvre, storage, cleaning)	6	5	4	3	2	1

Satisfaction assessment	Strongly Agree				Strongly Disagree
1. Was it easy to keep the inhaler clean?	5	4	3	2	1
2. After you have used the inhaler, do you have the feeling that you used it correctly?	5	4	3	2	1
3. Overall, considering your responses to the previous questions, were you satisfied with the inhaler?	5	4	3	2	1

6C-6: Sample Emotional Experience Test

The following images represent different emotional expressions. Please review each option and select the one that best matches your current emotional state.

Emocard



1	2	3	4	5	6	7	8

Appendix 7A: System Quality Questionnaire

The following questions are designed to assess the quality of the XIAOXI system. Please select the response that best reflects your experience with XIAOXI.

Metrics	Questions	Strongly Agree										Strongly Disagree
Naturalness	XIAOXI uses simple and understandable vocabulary.	10	9	8	7	6	5	4	3	2	1	0
	XIAOXI dialogues were unambiguous.	10	9	8	7	6	5	4	3	2	1	0
	XIAOXI dialogues were natural.	10	9	8	7	6	5	4	3	2	1	0
Information delivery	XIAOXI provides me/the patient with the right information at the right time.	10	9	8	7	6	5	4	3	2	1	0
	Information provided by XIAOXI helps me/the patient manage my/their disease better.	10	9	8	7	6	5	4	3	2	1	0
Interpretability	XIAOXI properly understood what I/the patient intended to say during the conversation.	10	9	8	7	6	5	4	3	2	1	0
	I/the patient will be able to express my/their current asthma/COPD condition and medication usage accurately during the conversation.	10	9	8	7	6	5	4	3	2	1	0
Technology acceptance	The information that XIAOXI aims to collect through the conversation adequately conveys my/the patient's condition.	10	9	8	7	6	5	4	3	2	1	0
	I recommend that XIAOXI monitor and manage my/the patient's daily condition.	10	9	8	7	6	5	4	3	2	1	0
	Overall, I am very satisfied with XIAOXI.	10	9	8	7	6	5	4	3	2	1	0

Appendix 7B: System Usability Scale Questionnaire

The following questions aim to evaluate the usability of the XIAOXI system. Please select the response that best reflects your level of agreement with each statement.

Questions	Strongly Agree				Strongly Disagree
I think that I would like to use XIAOXI frequently.	5	4	3	2	1
I found the system unnecessarily complex.	5	4	3	2	1
I thought XIAOXI was easy to use.	5	4	3	2	1
I think that I would need the support of a technical person to be able to use XIAOXI.	5	4	3	2	1
I found the various functions in XIAOXI were well integrated.	5	4	3	2	1
I thought there was too much inconsistency in XIAOXI.	5	4	3	2	1
I would imagine that most people would learn to use XIAOXI very quickly.	5	4	3	2	1
I found XIAOXI very cumbersome to use.	5	4	3	2	1
I felt very confident using XIAOXI.	5	4	3	2	1
I needed to learn a lot of things before I could get going with XIAOXI.	5	4	3	2	1

Appendix 7C: Interview Protocol for Qualitative Feedback on XIAOXI Usability

1. Opening Questions:

- Can you describe your overall experience using the XIAOXI system?
- What were your initial impressions when you first interacted with the system?

2. System Quality Feedback:

- How would you describe the system's reliability and stability during your use?
- Did you encounter any technical issues or challenges? If so, could you elaborate?
- How well do you think the system performs its intended functions?

3. Usability Feedback:

- How easy or difficult did you find it to navigate and use the system?
- Were there any specific features or tasks that you found particularly intuitive or confusing?
- Did the system layout and interface meet your expectations for ease of use?

4. User Experience and Satisfaction:

- How satisfied are you with your experience using XIAOXI?
- What aspects of the system did you find most and least helpful?
- Would you recommend the system to others? Why or why not?

5. Specific Comparison Questions (for HCPs and Patients):

- For HCPs: How do you think the XIAOXI system impacts your patients' ability to manage their condition?
- For Patients: How did the system support your understanding and management of your condition?

6. Open Feedback:

- Is there anything else you would like to add about your experience with the XIAOXI system?
- Do you have any suggestions for improvements or features you would like to see added?

Appendix 7D: Interview Protocol for Qualitative Feedback on XIAOXI Effectiveness

Protocol Structure by Dimension (Experimental Group):

1. Person Dimension:

- How has XIAOXI influenced your personal management of your condition?
- Did you feel that the system supported your individual health goals and needs?
- Were there any emotional or psychological impacts from using the system?

2. Task Dimension:

- How did XIAOXI affect your daily routines related to inhaler usage or treatment adherence?
- Did the system make completing necessary tasks easier or more challenging?
- How effectively did XIAOXI provide task-specific guidance or support?

3. Tool Dimension:

- What aspects of the XIAOXI system's tools (e.g., interface, chatbot, feedback mechanisms) did you find most effective?
- Were there any tool features that stood out as particularly useful or lacking?
- Did the system's features align well with your expectations for usability and functionality?

4. Physical Environment Dimension:

- Did the physical context (e.g., where and how you used XIAOXI) affect its effectiveness?
- Did you face any difficulties using the system in specific environments?
- How did XIAOXI help you monitor and respond to environmental conditions that affect your condition?

5. Culture and Social Dimension:

- Did XIAOXI help address any cultural beliefs or attitudes you held about your treatment?
- Did the system help you navigate any social pressures or norms related to managing your condition?

Protocol Structure by Dimension (Control Group):

1. Person Dimension:

- What challenges did you face in managing your condition personally?
- Did you feel adequately supported in meeting your health goals and needs?
- How did your emotional and psychological state affect your adherence to treatment?

2. Task Dimension:

- What difficulties did you encounter in your daily routines related to inhaler usage or treatment adherence?
- Were there any specific tasks you found particularly hard to complete?

3. Tool Dimension:

- What tools or resources (e.g., apps, reminders, physical tools) did you use to support your adherence?

- Did you feel that you lacked any tool that could have helped improve your treatment adherence?

4. Physical Environment Dimension:

- How did your physical environment impact your ability to manage your condition?

- Were there specific places or situations where it was harder to follow your treatment plan?

5. Culture and Social Dimension:

- How did social interactions (e.g., family, peers, HCPs) influence your adherence to treatment?

- Did cultural beliefs or social norms impact your management of your condition?