



HAL
open science

Patient-centric approach to maximize CPAP therapy acceptance: AI-driven design, delivery, and monitoring of interventions

Jensen Joymangul

► **To cite this version:**

Jensen Joymangul. Patient-centric approach to maximize CPAP therapy acceptance: AI-driven design, delivery, and monitoring of interventions. Other [cs.OH]. Université Lumière - Lyon II, 2022. English. NNT: 2022LYO20013 . tel-04061445

HAL Id: tel-04061445

<https://theses.hal.science/tel-04061445>

Submitted on 6 Apr 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

N° d'ordre NNT : 2022LYO20013

THÈSE de DOCTORAT DE L'UNIVERSITÉ LUMIÈRE LYON 2

**École Doctorale : ED 512
Informatique et Mathématiques**

Discipline : Informatique

Soutenue publiquement le 11 octobre 2022, par :

Jensen JOYMANGUL

Patient-centric approach to maximize CPAP therapy acceptance.

***AI-driven design, delivery, and monitoring of
interventions.***

Devant le jury composé de :

Hervé PINGAUD, Professeur des Universités, Université de Toulouse, Président

Lina SOUALMIA, Maîtresse de conférences HDR, Université Étienne du Rouvray, Rapporteur

Hind BRIL-EL-HAOUZI, Professeure des Universités, Université de Lorraine, Examinatrice

Ricardo JARDIM-GONCALVES, Professeur d'université, Nouvelle Université de Lisbonne, Examineur

Aïcha SEKHARI, Maîtresse de conférences, Université Lumière Lyon 2, Examinatrice

Olivier GRASSET, Responsable Routing Respiratoire, Linde Homecare France, Examineur

Nejib MOALLA, Professeur des Universités, Université Lumière Lyon 2, Directeur de thèse

Contrat de diffusion

Ce document est diffusé sous le contrat *Creative Commons* « [Paternité – pas d'utilisation commerciale - pas de modification](#) » : vous êtes libre de le reproduire, de le distribuer et de le communiquer au public à condition d'en mentionner le nom de l'auteur et de ne pas le modifier, le transformer, l'adapter ni l'utiliser à des fins commerciales.



THESE de DOCTORAT DE L'UNIVERSITÉ DE LYON

Opérée au sein de

L'UNIVERSITÉ LUMIÈRE LYON 2

École Doctorale : ED 512 Informatique et Mathématiques

Discipline : Informatique

Soutenue publiquement le 11 octobre 2022, par :

Jensen Selwyn JOYMANGUL

Patient-centric approach to maximize CPAP therapy acceptance: AI-driven design, delivery, and monitoring of interventions

Devant le jury composé de :

M. Hervé Pingaud, Professeur des Universités à l'Université de Toulouse, Rapporteur

Mme Lina Soualmia, Maître de Conférences – HDR à l'Université Saint-Étienne du Rouvray, Rapporteur

Mme Hind Bril El Haouzi, Professeur des Universités à l'Université de Lorraine, Examineur

M. Ricardo Jardim Gonçalves, Professeur d'Université à l'Universidade NOVA de Lisboa (Portugal), Examineur

Mme Aïcha Sekhari, Maître de Conférences à l'Université Lumière Lyon 2, Co-encadrant

M. Olivier Grasset, Manager chez Linde Home Care France, Référent entreprise

M. Néjib Moalla, Professeur des Universités à l'Université Lumière Lyon 2, Directeur de thèse

Declaration of Authorship

I, Jensen Selwyn JOYMANGUL, declare that this thesis titled, "Patient-centric approach to maximize CPAP therapy acceptance: AI-driven design, delivery, and monitoring of interventions." and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

Date:

“Science knows no country, because knowledge belongs to humanity, and is the torch which illuminates the world.”

Louis Pasteur

Abstract

Patient-centric approach to maximize CPAP therapy acceptance: AI-driven design, delivery, and monitoring of interventions.

by Jensen Selwyn JOYMANGUL

Obstructive Sleep Apnea (OSA) is a sleeping disorder that manifests itself in various ways. In the absence of treatment, it has a detrimental effect on the cardiovascular system, causes excessive daytime sleepiness, and increases motor vehicle accidents. It is characterised by repeated narrowing (hypopnea) and closure (apnea) of the upper airway during sleep. In adults with OSA, continuous positive airway pressure (CPAP) therapy is the first-line medical treatment. The primary requirement for CPAP therapy to be practical is that the patient adheres to the therapy. The patient must utilise the CPAP equipment for at least 4 hours per night to see clinical improvement. However, according to research assessing this level of adherence, CPAP therapy has the lowest amount of compliance when compared to 17 other therapies such as HIV, cancer...

With the advent of big data and highly accurate monitoring data in-homecare, new opportunities are open to tackle these ongoing issues. One of these opportunities is a complete understanding of the patient to give targeted interventions that empower the patient in the CPAP therapy. This research project, which is being conducted in conjunction with the homecare provider Linde Homecare France, falls within the scope of these new opportunities. In this research project, we have four core objectives, namely: 1) patient characterisation, 2) personalised intervention design and delivery, 3) verification, validation and monitoring of the interventions, and 4) automatic models readjustment based on experts feedback.

To fully comply with these four objectives, we address the following question: "How to leverage CPAP monitoring data with telemedicine to deliver patient-centric interventions to increase the CPAP therapy adherence level in the long-term and how

should an expert-assisted system be developed and deployed on a wide range of patients for a personalised patient management?"

To address this research question, we developed the novel framework Homecare Intervention as a Service (HIaaS). The HIaaS framework defines the patient by modelling multiple patient profiles and introducing a patient pathway concept tailored to homecare. We determine the most effective interventions based on the patients' compliance barriers. To deepen the patient-centric approach, we add a level of personalisation to each intervention. The system keeps track of both intervention use and patient perceptions of the interventions.

Finally, throughout the entire process beforehand, the HIaaS framework proposes a verification mechanism and a validation mechanism for the intermediate results. Three types of experts are responsible for these mechanisms: sleep experts, homecare managers, and homecare providers. As a result, each expert is bounded to their field of expertise. We solicit expert feedback throughout the verification and validation process. We then propagate this feedback to the various models in the appropriate manner.

The implementation of the HIaaS framework is made up of 2 novel mHealth solutions namely Sleep.py Experts and Sleep.py. Sleep.py Experts, the first application, provides a variety of decision support tools to enable personalised CPAP patient management. This application contributes significantly to the verification and validation processes. The second application, Sleep.py, directly addresses the patient suffering from OSA with motivational, educational, diet, physical activity, and stress management interventions. We incorporate an innovative serious game into the application to help patients improve their adherence. Sleep.py is the most comprehensive collection of personalised CPAP therapy interventions available.

Additionally, these two applications are fuelled by patient profiles and patient pathways. We identify six distinct patient profiles for the first three days of therapy and three distinct patient profiles for the subsequent seven days. We simulated patient pathways by combining this patient profiling with a CPAP adherence prediction model. This is the first study in the field of CPAP therapy to formalise converting

raw data into effective interventions for patients through the use of an automatic feedback propagation model based on expert assessment. Additionally, the HIaaS framework is adaptable to other forms of homecare therapy.

Acknowledgements

This paper presents results that are developed in collaboration between the Linde Homecare France company and the University Lumiere Lyon 2, DISP Lab. This research is established under a CIFRE contract (2018/1575). The content of this thesis reflects an R&D initiative promoted by Linde Homecare France. Responsibility for the information and views expressed in this thesis lies entirely with the authors.

Contents

Declaration of Authorship	iii
Abstract	vii
Acknowledgements	xi
1 Introduction	1
1.1 Research Context	1
1.1.1 Linde Homecare France	3
1.1.2 Our data collections	5
1.2 Research Objectives	6
1.3 Research Questions	7
1.4 Research Problems	8
1.5 HIaaS Framework	9
1.6 Contributions	10
1.7 Organisation of chapters	11
2 State of Art	13
2.1 Patient characterisation	17
2.1.1 Data Analytics in healthcare	17
2.1.2 Patient Pathway	23
2.1.3 Patient Profile in OSA	26
2.2 Personalised intervention design and delivery	32
2.2.1 Interventions for improving CPAP therapy adherence	32
2.2.2 mHealth solutions for CPAP therapy	36
2.3 Feedback collection	39
2.3.1 OSA patient feedback	39

2.3.2	Experts feedback	43
2.4	Automatic feedback propagation	45
3	Homecare Intervention as a Service (HIaaS) Framework	51
3.1	Main Concepts	51
3.1.1	Patient Profile	52
3.1.2	Patient Pathway	53
3.1.3	Homecare Interventions and consumption	53
3.2	HIaaS overview	54
3.2.1	Patient Characterisation	54
3.2.2	Personalised Interventions Buildup and Delivery	56
3.2.3	Intervention Consumption and Evaluation	56
3.2.4	Feedback Propagation	57
3.3	Patient Characterisation	58
3.3.1	Data Exploration	59
3.3.2	Patient Profile	59
3.3.3	Patient Pathway	60
3.3.4	Vulnerabilities detection	61
3.4	Personalised Interventions Buildup and Delivery	61
3.4.1	Personalised interventions	62
3.4.2	Intervention delivery	62
3.5	Intervention Consumption and Evaluation	63
3.5.1	Intervention monitoring	63
3.5.2	Intervention evaluation and validation	64
3.6	Verification and Validation mechanisms	65
3.6.1	Analytic layer	65
3.6.2	Stakeholders	66
Patient	66
Sleep expert	66
Homecare managers	66
Homecare givers	67
3.6.3	Verification mechanism	67

3.6.4	Validation mechanism	68
3.7	Feedback Propagation	69
3.7.1	Feedback build-up	70
3.7.2	Feedback Classifications	70
3.7.3	Feedback Propagation	71
3.8	HIaaS Meta-model	71
3.8.1	Events	72
3.8.2	Abnormalities & Deficiencies	74
3.8.3	Interventions	75
3.8.4	Monitoring & Validations	77
3.8.5	Feedback & Continual Learning	79
4	Implementations & Results	81
4.1	Technologies	81
4.1.1	Data storage	82
4.1.2	Data analytics	83
4.1.3	Back-end	84
4.1.4	Front-end	84
4.2	Architecture	85
4.3	Events	86
4.3.1	Use case	86
4.3.2	Event detections	87
4.3.3	Event profile - Patient Profile	88
4.3.4	Event traces	90
4.3.5	Lifestyle - Real Patient Pathway	90
4.3.6	Discussions	91
4.4	Abnormalities & Deficiencies	91
4.4.1	Vulnerabilities	92
4.4.2	Abnormality	93
4.4.3	Discussions	95
4.5	Interventions	96
4.5.1	Intervention Repository	96

4.5.2	Motivational and educational interventions	96
4.5.3	Food intake monitoring	97
4.5.4	Step Count	98
4.5.5	Smart alarm	98
4.5.6	Meditations	98
4.5.7	Discussions	99
4.6	Monitoring & Validations	99
4.6.1	Patient monitoring	99
4.6.2	Expert validation	101
4.6.3	Discussions	103
4.7	Preliminary tests on the patient	104
5	Discussions & Future Works	107
6	Conclusions	113
A	The Epworth Sleepiness Scale	115
B	The Berlin questionnaire	117
C	Example of clinical lifecycle	121
D	Monash Partners Learning Health System framework	123
E	ESS stored in MongoDB	125
F	"Know My CPAP" game	131
	Bibliography	133

List of Figures

1.1	Sketch of how CPAP works, from [3]. The positive airway pressure prevents the upper airway from collapsing.	2
1.2	CPAP therapy pricing set by Franch Welfare System [16]	4
1.3	The HIaaS framework overview	9
2.1	General procedure for conducting literature reviews proposed by <i>Templier et al.</i> [20]	14
2.2	Information System Research Framework by <i>Hevner et al.</i> [21]	15
2.3	Classifications of paper	17
2.4	The data characterizations for process mining [73]	24
2.5	Hypothesized patient pathway for evaluating the impact of CPAP in intimate relationship [80]	25
2.6	Classification of the questionnaire for collecting the patient feedback	43
2.7	The rules extraction process in the EAML framework proposed by <i>Gennatas et al.</i> [201]	48
3.1	Patient timeline for the first 90 days of the CPAP therapy	52
3.2	The HIaaS framework overview	55
3.3	BPMN for the characterising the patient based on different data collection	58
3.4	BPMN for the selecting, personalising and deliver interventions	61
3.5	BPMN to monitor and evaluate the personalised interventions	63
3.6	Verification (blue) and validation (green) mechanism for the HIaaS framework	66
3.7	Patient timeline for the first 90 days of the CPAP therapy	69
3.8	HIaaS meta-model	73

4.1	The architecture for implementing HIaaS framework	85
4.2	Inertia intra-class for K -means algorithm for the first model	89
4.3	SSE for K -means algorithm for the second model	90
4.4	Vulnerability Detection: Adherence Thresholds	92
4.5	Vulnerability Detection: Mask Leakage Thresholds	92
4.6	Vulnerability Detection: AHI Thresholds	92
4.7	Adherence prediction model prediction based on Machine Learning	93
4.8	"Reveal the image" game	97
4.9	Find the wordgame	97
4.10	Maximum daily calorie intakes	97
4.11	Food scanning	97
4.12	Daily Step counts	98
4.13	Smart alarms	98
4.14	Meditation Playlist	98
4.15	The ESS in the Sleep.py application	100
4.16	Patient's dashboard	102
4.17	Predict the appropriate mask	102
4.18	Mask validation	102
4.19	Predict the appropriate CPAP device settings	102
4.20	Interaction between the mobile application and the stakeholders	103
A.1	The ESS test proposed by <i>M. W. Johns</i> . [154]	115
C.1	Example of clinical lifecycle from [191]	121
D.1	The learning health system framework proposed by Monash University [194]	124
F.1	Game scenario for the "Know My CPAP" game	132

List of Tables

1.1	Characterisation of the CPAP monitoring dataset	5
1.2	Characterisation of the patients reported information dataset	6
2.1	Number of analysed papers related to our topics	17
2.2	Technologies used for data analytics application.	21
2.3	Summary of studies that use unsupervised learning for OSA patients .	31
2.4	Evaluation of studies that include interventions for the CPAP therapy	35
2.5	mHealth solutions for the CPAP therapy	38
2.6	DASS-21 results classification	42
4.1	Primitive Events for the first 3 days of therapy for patient 54892	88
4.2	Lifestyles and interpretations for event traces (Patient Pathway)	91
4.3	Comparison of different Machine Learning Algorithm	94
4.4	Adherence for personalised phone interventions	104

List of Abbreviations

OSA	Obstructive Sleep Apnea
AHI	Apnea Hypopnea Index
CPAP	Continuous Positive Airway Pressure
CL	Continuous Learning
HIaaS	Homecare Intervention as a Service
SoA	State of Art
ISR	Information System Research
PM	Personalized Medicine
EHR	Electronic Health Record
GDPR	General Data Protection Regulation
PP	Patient Profile
ESS	Epworth Sleepiness Scale
LCA	Latent Class Analysis
BMI	Body Mass Index
SaO₂	Oxygen Saturation
SpO₂	Peripheral Oxygen Saturation
AHI	Apnea-Hypopnea Index
PCA	Principal Component Analysis
MCA	Multiple Correspondence Analysis
CBT	Cognitive Behavioural Therapy
MET	Motivational Enhancement Therapy
CPAP-FAAS	CPAP-Fear And Avoidance Scale
BPMN	Business Process Model and NNotation
SSE	Error Sum of Squares
EAML	Expert Augmented Machine Learning
LHF	Linde Homecare France
OASIS	Outcome and Assessment Information Set
MSSQL	MicroSoft SQL
PoC	Proof of Concept
API	Application Programming Interface

Chapter 1

Introduction

1.1 Research Context

The discovery of sleep apnea in 1965 was likely the most significant achievement in the history of sleep medicine [1]. Repetitive episodes of nocturnal breathing cessation characterise obstructive Sleep Apnea (OSA) due to a partial (hypopnea) or complete (apnea) collapse of the upper airway. This pattern can occur hundreds of times in a single night. The result is an increase in cardiovascular morbidity and mortality, as well as severe symptoms such as increased daytime somnolence [2].

Currently, polysomnography is the gold standard for diagnosing OSA. During the diagnosis, polysomnography records the patients' brain waves, the oxygen level in the blood, heart rate and breathing, and eyes and leg movements. Patients perform this diagnosis either at a sleep clinic or hospital. To measure the severity of the OSA, we calculate the Apnea-Hypopnea Index (AHI). This is an average of the number of apneas and hypopnea per hour of sleep. Apneas and hypopnea, referred to as events, must persist for at least 10 seconds to be counted as events.

Prior to 1981, the only successful therapy for OSA was a tracheostomy, which bypassed the blockage in the upper airway. In 1981, *Sullivan et al.* introduced the Continuous Positive Airway Pressure (CPAP) device which maintains a constant pressure in the airways throughout the breathing cycle, during both inspiration and expiration [3]. Figure 1.1 shows the principle of having a continuous positive airway to prevent OSA. Despite multiple treatments like tongue retaining devices and

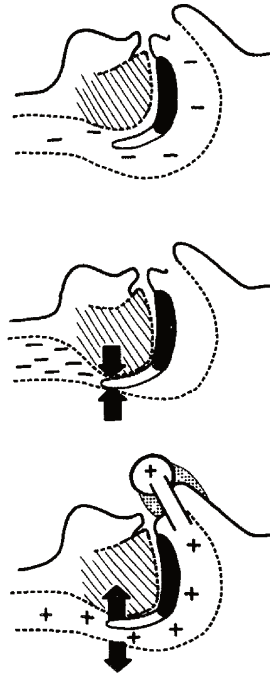


FIGURE 1.1: Sketch of how CPAP works, from [3]. The positive airway pressure prevents the upper airway from collapsing.

orofacial therapy, the CPAP is the first-line therapy for OSA. The main reason is that CPAP therapy is the most effective therapy for all types and severities of OSA [4].

The prime condition for efficient CPAP therapy is the adherence level of the patients. The patient must use the CPAP device for at least 4h/night to see any clinical improvement [5]. However, when compared to 17 other chronic diseases, CPAP therapy has the lowest adherence level [6]. This compliance problem is a well-known issue, and over the past 20 years, researchers tried to solve it. Unfortunately, there were no convincing results [7].

With the advent of big data and highly accurate monitoring data in-homecare, new opportunities are open to tackle these ongoing issues [8]. One of these opportunities is a complete understanding of the patient to give targeted interventions that empower the patient in the CPAP therapy [9]. Studies that fit in these opportunities obtained encouraging results; however, these results were performed on a small cohort and on short-term [10].

Alismail et al. proposed a framework for building, delivering and validating motivational messages for mHealth solutions for CPAP therapy ???. They proposed an

elaborate validation and testing mechanism for constructing a message library deployed in a mHealth solution. The authors emphasize the significance of developing and validating the patient-facing content. However, the study focuses solely on motivational messages and is strongly dependent on patient perception. The proposed framework does not include a layer for patient-specific customization.

Suarez-Giron et al. also implemented a CPAP therapy-specific framework [11]. Moreover, the solution includes a questionnaire for self-reporting and educational interventions. In addition, they proposed a web application for professionals in the homecare industry. The proposed CPAP therapy solutions are among the most comprehensive. The authors, however, do not include any patient-specific customization. Given that homecare providers have already established activity processes from a systemic perspective, integrating personalized interventions is a very complex endeavour. These activity processes are entangled with healthcare, which considers complex variables such as well-being, comfort, and psychological outcomes [12].

Our primary objective is to improve CPAP therapy adherence by capitalizing on these opportunities heavily linked to big data analytics. Furthermore, the project should develop a comprehensive solution that includes knowledge extraction from data, the development and delivery of personalized interventions, and a validation mechanism. Unlike other frameworks that include either a purely data analytics approach [13], [14] or a health-oriented approach without a systemic point of view [14], [15]. Our approach is to combine these two core aspects of homecare to provide the most appropriate and best-fitting interventions through an automated, scalable process. In regards, because CPAP therapy is a long-term treatment, interventions must be administered over an extended period of time to ensure long-term adherence [15]. The scope of this thesis, which is being conducted in collaboration with the homecare provider *Linde Homecare France*, is encompassed by these dimensions.

1.1.1 Linde Homecare France

Linde Homecare France (LHF) has brought together health professionals who have chosen to support patients with chronic diseases in their home treatment for more

than 25 years. LHF is a subsidiary of Linde plc, which supports over 2.4 million patients globally. LHF provides six distinct types of in-home care: CPAP, respiratory assistance, oxygen therapy, home infusion, insulin pump, and cluster headache therapy.

The core therapy of LHF is CPAP therapy with more than 50 000 patients in France. Consequently, CPAP therapy has an important business impact on LHF. The solution proposed in this thesis takes into consideration this impact and the capacity to deliver the interventions on all the patients LHF works closely with sleep clinicians and these clinicians make the diagnosis of OSA and prescribe CPAP therapy. With these prescriptions, LHF delivers the CPAP therapy to the patients' home and provide educational interventions on the therapy.

The business model for CPAP therapies is very specifically for France. As the therapy is fully funded by the France health welfare system (sécurité sociale) and not by the patients. Consequently, in most cases, the patients do not spend any money on CPAP therapy. The Welfare system remunerates homecare providers on a weekly basis to compensate for the CPAP device delivery and patient management. However, these remunerations are based on the adherence level of the patient to the CPAP therapy.

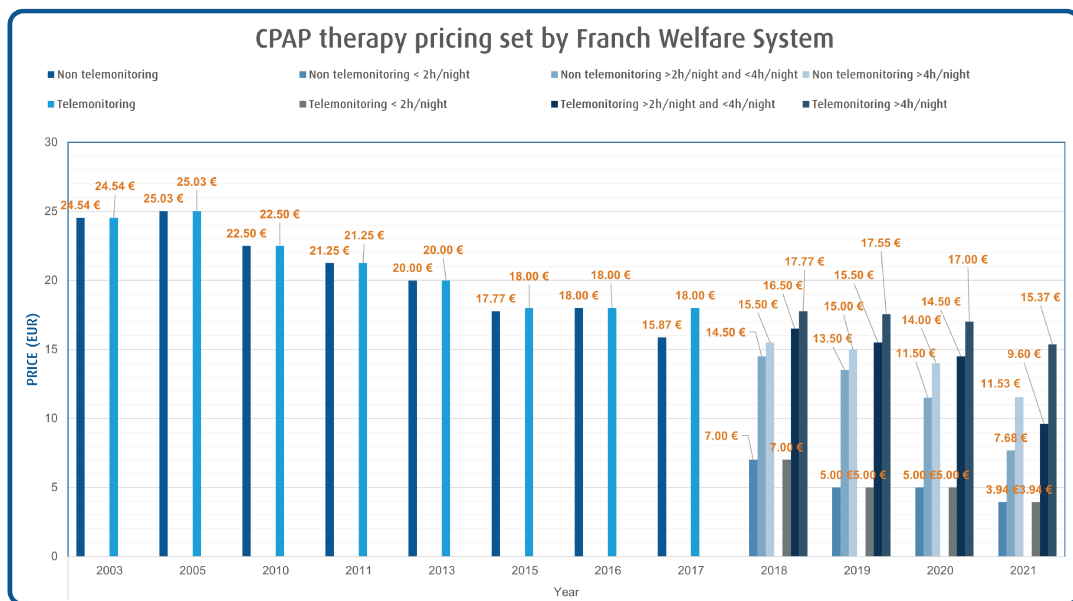


FIGURE 1.2: CPAP therapy pricing set by Franch Welfare System [16]

Figure 1.2 illustrates the evolution of the French welfare system's pricing policy.

The figure shows the weekly pay by the welfare system to the different homecare providers for compensation. As of 2018, these prices are conditional on the level of adherence. Prices have decreased significantly over the years, particularly for non-adherent patients. As a result, these successive decreases have an adverse effect on homecare providers' business models.

1.1.2 Our data collections

We used a data-driven strategy for this thesis topic, as LHF has made numerous data collections available. The most significant dataset is the CPAP monitoring data, which includes approximately 120 000 patients' monitoring data over seven years. This dataset contains only quantitative data collected only through the use of the CPAP equipment. Table 1.1 provide additional information about this dataset. The primary disadvantages of this dataset are its variety and variability. Indeed, the dataset comprises just three quantitative data related to the CPAP device. Additionally, the variability is modest, as the patients exhibit a consistent pattern throughout the months. For example, patients with a poor level of adherence typically continue to be non-adherent.

Characterisation	Dataset description
Volume	High - CPAP monitoring data on 120 000 patients
Variety	Low - 3 variables: CPAP usage, mask leakage, AHI
Velocity	High - Data generated daily for each night
Veracity	Mid - Describe only the CPAP therapy but no data on the patients themselves
Variability	Low - Almost no variation from day to day monitoring

TABLE 1.1: Characterisation of the CPAP monitoring dataset

LHF maintains a dataset containing qualitative data on patients in an attempt to close these gaps. In table 1.2, we summarise the characterisation of this dataset. These statistics are gathered directly from patients' homes by homecare givers. These data, however, are given to technicians by patients who lack the ability to check their accuracy. As a result, the accuracy of these data points may vary significantly.

Despite this addition to the dataset, based on our preliminary analysis we were unable to define the full spectrum of patients receiving CPAP therapy. This is primarily owing to the low velocity and variety of patient-reported data. To address this gap, LHF is currently working on developing a collection of sensors that may be deployed in patients' homes. This solution will significantly increase data velocity and the volume of data measured. As a result, this thesis considers this novel solution when developing our proposed solution in light of this additional dataset.

However, large-scale deployment of these new sensors is not feasible. As a result, this thesis must propose a solution capable of identifying instances in which the CPAP monitoring and patient-reported information datasets are insufficient to empower the patient in his therapy. LHF can then deploy the set of sensors on this subset of patients.

Characterisation	Dataset description
Volume	Low - Data collected on 5000 patients
Variety	Low - 6 reported data: AHI before CPAP therapy, BMI, Epworth, Knowledge of therapy, Motivation, Patient-reported adherence
Velocity	Low - data generated at most 2 times/year
Veracity	Mid - Include information that described the patient on a larger scope compared to CPAP monitoring data but cannot get the whole scope
Variability	Irrelevant - There were a high variability but the velocity is too low to draw any conclusion

TABLE 1.2: Characterisation of the patients reported information dataset

1.2 Research Objectives

With reference to the context presented in the previous section, this research aims at developing a holistic solution to increase the CPAP therapy adherence level. The overall study not only includes data analytics. Instead, we develop a comprehensive system that relies on the data models to provide personalized services to the different stakeholders for home care. While considering the desired functionalities and constraints, our research objectives are:

1. *Patient Characterisations*: Define data models to differentiate patients from others through the CPAP monitoring data. This characterisation allows detecting the needs and vulnerability of each patient to provide personalised interventions.
2. *Personalised Intervention Design and Delivery*: Build a comprehensive repository of interventions that can be delivered directly to the patients. Any interaction between a patient and a healthcare/homecare staff member via any communication channel is considered a homecare intervention. Each intervention should be personalisable to fit the patient's needs.
3. *Verification, validation and monitoring of the interventions*: Define a standardised process to collect the experts' and patients' feedback. We need to provide a set of tools for systematic verification and validation of experts. To perform the validation, we need to determine the efficiency of the interventions through the intervention's consumption.
4. *Automatic models readjustment based on feedback*: The solution developed should integrate experts and patient feedback into a Continuous Learning (CL) process. The automatic CL process readjusts the different data models to stick to the feedback.

1.3 Research Questions

To achieve the goals outlined in section 1.2, we should first address the following fundamental research questions:

1. How can we develop a dynamic patient characterisation using the telemonitoring data? The answer to this question solves the issue of building multiple patient profiles and dynamic patient pathways through raw data.
2. How to build and deliver the patient-centric interventions to increase compliance with the CPAP therapy? It is crucial to answer this question to get the most appropriate interventions to the patient without drawback effects on the CPAP therapy.

3. How to verify the analytic models by different experts? We need to establish the most effective method for involving experts in the verification process before deploying the various models.
4. What are the validation mechanisms to evaluate personalised homecare interventions? There is a need to determine the appropriate mechanism to evaluate the interventions objectively across multiple experts.
5. How to automatically propagate the feedback in the analytic data models and decision support tools? Automatic feedback propagation will allow the solution to be deployed faster and on a large scale.

1.4 Research Problems

Sleep quality has recently gained much attention from researchers and is considered to be an important impact on individual health. As a result, the funding for sleep research has increased by more than 100% from 2013 to 2021, reaching a *470 million U.S. dollars* in the USA [17]. Furthermore, by 2025, the market share for the OSA diagnostic and therapy is expected to reach *7,272.2 million U.S. dollars* worldwide [18].

As expressed in section 1.1.2, the adherence level for the CPAP therapy is a well-known issue. For the past years, researchers are working on this topic with mixed results. However, in recent years new opportunities have opened up and a multi-disciplinary approach can improve the actual condition of the patients with CPAP therapy. In order to provide answers to the identified questions, we formalise our research problem as follow:

How to leverage CPAP monitoring data with telemedicine to deliver patient-centric interventions to increase the CPAP therapy adherence level in the long-term and how should an expert-assisted system be developed and deployed on a wide range of patients for personalised patient management?

1.5 HIaaS Framework

In this research, we create a unique Homecare Interventions as a Service (HIaaS) framework that delivers interventions through various mediums. We develop a framework, as shown in figure 1.3, to solve the identified problems in the section 1.4.

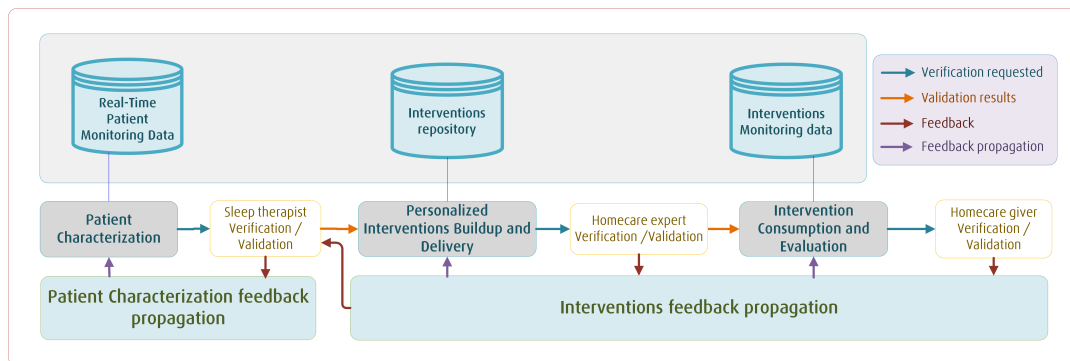


FIGURE 1.3: The HIaaS framework overview

We have three repositories:

- *Real-Time Patient Monitoring Data* containing data collected daily by the CPAP device
- *Interventions Repository* containing a set of personalised interventions
- *Interventions Monitoring Data* containing the intervention consumption monitoring data required in the document.

Before creating and implementing individualised interventions, we must first describe the patient to understand his requirements to comply with CPAP therapy. We create numerous patient profiles based on CPAP monitoring data at various stages of CPAP treatment. We define the exact timeline for intervention delivery according to the patient profiles. As a result, a patient's profile might evolve throughout time, and the variation of the patient profiles gives the patient pathway. With the help of the patient pathway, we can detect patient-specific needs.

We select the most appropriate interventions based on the patients' hurdles to compliance. We choose the intervention in the interventions repository. To deepen the patient-centric approach, we add a level of personalisation to each intervention. Before the interventions are delivered, a home/care professional checks their level

of personalisation. The therapies are subsequently delivered to the patient via the Sleep.Py app, a customised mHealth solution.

The system monitors intervention consumption as well as the patient's perception of the delivered interventions. However, in healthcare, the consumption of interventions is unique since it is dependent on the patient's intention to treat (ITT). When the patient has finished consuming the intervention, the CPAP expert analyses its efficiency using a variety of criteria. During the verification and validation process, we collect feedback from different experts. We then propagate this feedback to the different models accordingly.

1.6 Contributions

The main contribution of this thesis is the HIaaS framework introduced in the previous section. The multiple outputs of the HIaaS framework allow us to fulfil all the objectives set in section 1.2. The originality of our framework is the formal orchestration of multiple artefacts and actors in a delivery system of homecare interventions. This framework is flexible and can be implemented as it is on multiple home care therapies (not only CPAP therapy).

We present the main contributions brought by this research henceforth:

- **Patient Profiling** : A multiple clustering models based on the CPAP monitoring data and qualitative data on the patients collected by the homecare givers. We have multiple clustering models as the cluster is assigned to a patient change over time. As a result, we obtain a patient characterisation based on these multiple clustering also called patient profiles.
- **CPAP adherence predictions** : A set of supervised machine learning models to predict the adherence level of the patients to the CPAP therapy. The models predict adherence at multiple time intervals. Hence, giving an adherence route for each patient. When combining this route with the patient profile, we obtain the patient pathway. For example, one pathway is the combination of the adherence prediction 90 days after the first days of CPAP therapy with the patient profile and the consumption data of 2 interventions.

- **Sleep.py mobile application** : A mHealth solution targeting the patients following the CPAP therapy. This application delivers interventions tailored to its user. Moreover, Sleep.py collects qualitative information on the patient via self-report questionnaires and monitors the intervention consumption by the patient. We use this information in the design of the patient pathway.
- **Sleep.py expert mobile application** : Sleep.py experts are exclusively intended for the different experts in CPAP therapy. The application allows the expert to verify and validate the different interventions. We provide the experts with multiple dashboards and qualitative data related to the patient and collect the experts' feedback.
- **Automatic feedback propagation** : A set of implementation guidelines to propagate the collected feedback into the different data analytic models. This implementation automatically detects the specific data analytic model for an adjustment that sticks to the feedback requirements. Finally, the scheduling for the propagation is automatically built based on multiple criteria like a high risk-to-benefit ratio.

1.7 Organisation of chapters

This document is divided into six chapters. This section elaborates on the introduction (chapter 1). From this point in the document, we organise the contents as follows:

Chapter 2: State of Art

This chapter is dedicated to the literature review. The topics discussed in Chapter 2 were chosen to correspond to the research problem (section 1.4). It discusses the various data analytics techniques used in healthcare and compares them to our objectives. Additionally, we discuss the patient profile and patient pathway concepts as defined and implemented in various studies. We examine the gap in the literature regarding these concepts for homecare.

Recent studies that evaluated and validated interventions for increasing CPAP adherence were identified. Additionally, we present the most well-known CPAP therapy mobile application. For feedback, we conducted an in-depth analysis of multiple methodologies for gathering patient and expert feedback. Finally, we discussed how continuous learning is applied in healthcare, as well as the studies that utilised these techniques.

Chapter 3: Framework

This chapter introduces the HIaaS framework and defines the framework's key concepts. We go into detail with the main processes introduced in section 1.5. To facilitate the implementations and the constraints of this thesis, we also develop the meta-model. This meta-model demonstrates the HIaaS framework's entity-entity relationships.

Chapter 4: Implementations & Results

The implementations and results chapter details the HIaaS framework and mHealth solutions that have been implemented. We began by describing the unique use case for French CPAP therapy providers. We present two clustering models for constructing the patient profile and, by extension, the patient pathway. Additionally, The implementations also include an adherence predictive model based on supervised machine learning. Finally, we demonstrate the Sleep.py intervention delivery app and the Sleep.py expert feedback app.

Chapter 5: Discussions

We discuss the framework's limitations and suggest ways to overcome them. Additionally, this section discusses the prospects for this thesis and future works.

Chapter 6: Conclusions

This chapter summarises the thesis's major contributions and findings.

Chapter 2

State of Art

In this chapter, we present the recent and relevant work to the research topics tackled in this work. This state of art presents objectively the studies that are exclusively related to the identified problems presented in section 1.4. Consequently, we perform a multidisciplinary literature review because, in this thesis, we are dealing with topics related to data analytics, CPAP interventions, homecare and healthcare. To cover all the topics, we divide the state of work into 4 sections:

1. Patient characterisation:

Since the essence of this research project relies on the patient and CPAP monitoring data, we explore the specific and proven data analytic techniques used in the healthcare field. From a caregiver's point of view, we want to explore the concepts of patient pathways to characterise the patients. We examine the definition and building of this patient pathway specifically for homecare.

2. Personalised intervention design and delivery:

The cornerstone of this research is the personalised intervention. To deliver these interventions, we must find the most appropriate medium corresponding to our objectives. Moreover, we review the existing interventions that were purposely designed for OSA patients. There is a need to couple the building and delivery of the personalised data analytic models.

3. Feedback collections:

There are two main stakeholders that are taking a crucial and engaging part in the overall project namely, the patients and experts. We need to identify

the methods to collect the feedback from experts and patients. An important aspect of these methods is to have a systematic approach for evaluations.

4. Automatic feedback propagation:

One of the objectives is to develop an autonomous system that is based on the stakeholders' (detailed in section 3.6.2) feedback. We explore the different implementations of analytic models to assist with expert feedback in healthcare. Importantly, we also explore the impact of this continuous learning process on homecare.

Related work analysis methodology

According to *Card.*, one hurdle to scientific progress is to keep track of previous knowledge, organise them, and synthesise them while keeping up with new scientific developments [19]. To get over these issues, we follow the procedures proposed by *Templier et al.* (figure 2.1) [20]. We combine the proposed approach with an analytic approach to provide a systematic analysis of the different papers.

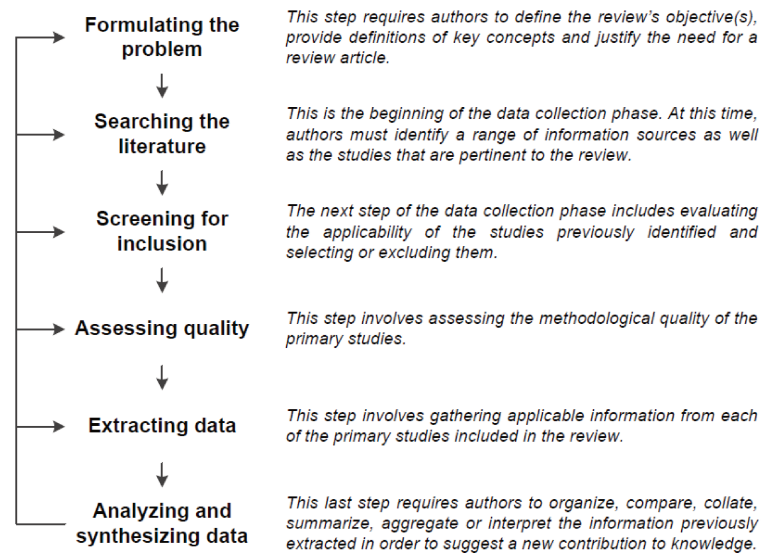


FIGURE 2.1: General procedure for conducting literature reviews proposed by *Templier et al.* [20]

Formulating the problem

To identify the research overall problems and to achieve our goals, we apply the Information System Research (ISR) framework proposed by *Hevner et al.* [21]. The ISR

provide a top-down design that focuses on business needs while constantly assessing the research results via justifications and evaluation activities. As a result, we identify the weaknesses and gaps of the theories and works in the literature.

Figure 2.2 presents the ISR framework which presents the three core pillars namely, environment, research and knowledge. We perform multiple iterations through these 3 ISR components to bring the research rigours to the business needs (section 1.1.1). Consequently, formulating problems that will guarantee at the same time the business relevancy and the scientific rigour. We presented the problems and questions identified through the ISR framework in sections 1.4 and 1.3 respectively.

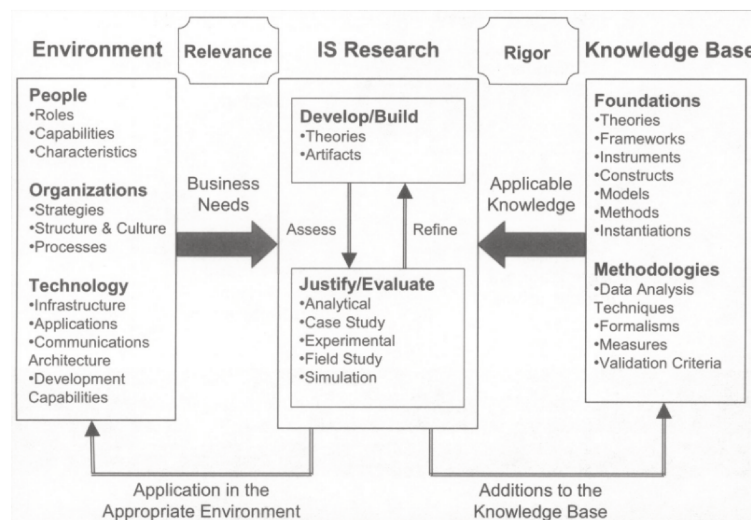


FIGURE 2.2: Information System Research Framework by *Hevner et al.* [21]

Searching the literature

We extract between 2 to 3 keywords for each identified issue. For example, to identify the appropriate interventions for CPAP therapy, we extract the keywords "CPAP" and "interventions". However, before extracting the papers, we search for these keywords on **Scopus**, **Web Of Science Core** and **PubMed**. This step is crucial to validate the interest in the different topics. We assume there is an interest in a topic if there are more than 5000 papers published (in the 3 databases combined) in recent years (between 2010 and 2022).

There is a systematic analysis of the extracted papers using the Natural Language Processing technique provided by KH Coder [22]. As a result, we obtain a map of keywords based on the number of occurrences. These keywords are almost clustered

based according to the contexts in which they were used. Lastly, with these newly detected keywords, we refine our research to retrieve the most relevant papers.

Screening for inclusion

For each of the extracted papers, we assess each of the studies before performing a deeper analysis. We perform the screening process by analysing each paper manually to evaluate specific points that were defined to meet our needs. The evaluating points for the paper screening are:

- Relevancy: the topic of the paper is related to our field of application or issues
- Results quality: results validated either through simulations or through experimentation
- Replicability: capacity to reuse the methodology, process or results in our research

Assessing quality and extracting data

As mentioned previously, we analyze papers that are only referenced by Web of Science Core Collection as part of the Journal Citation Report [23]. For the quality assessment, we also monitor the number of citations of each paper based on the year of publications. We perform the data extraction at the same time as the quality assessment to identify the papers' scopes that fit our study. We extract two main pieces of information for each paper; the methodology or theory proposed by the papers and the results obtained. There is an in-depth analysis of the results in conjunction with the goals set by the studied paper. The table 2.1 presents the number of papers through the different processes for building this SOA.

Analyzing and synthesizing data

Finally, we summarize the papers according to our specific goals. The most important aspect of this SOA is to classify the different papers according to our objectives. The figure 2.3 shows our classification for the papers having the same scopes. This State of the Art follows this classification as well as presents the works according to our identified problems.

Keywords	Searching the literature	Screening for inclusion	Assessing quality and extracting data
"Data Analytics" + "healthcare"	1415	82	42
"Patient Pathway"	1189	32	12
"Patient Profile"	1298	54	25
"OSA Interventions"	1070	53	32
"mHealth"	1399	28	19
"CPAP assessment"	1027	43	34
"Validation" + "Healthcare" + "Risk"	1671	38	11
"Continuous Learning"	766	41	14

TABLE 2.1: Number of analysed papers related to our topics

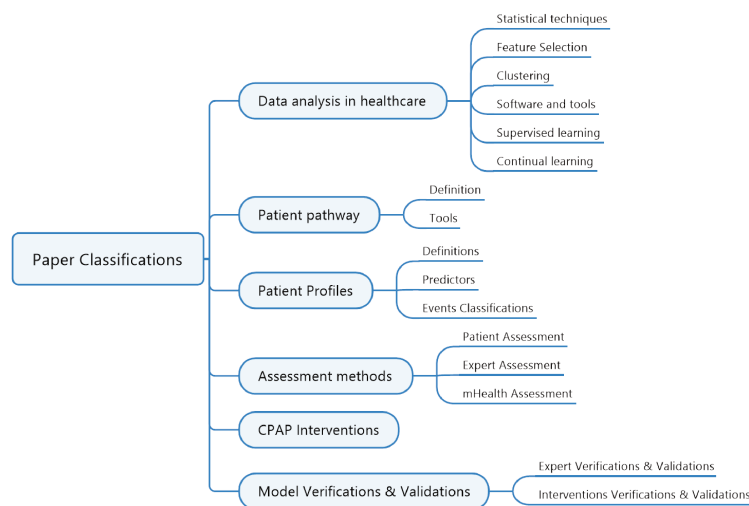


FIGURE 2.3: Classifications of paper

2.1 Patient characterisation

2.1.1 Data Analytics in healthcare

In medicine and healthcare, big data analytics is a very promising approach for integrating, investigating, and analysing massive amounts of complex heterogeneous data of many types: biological data, experimental data, electronic health record data, and social media data.[24]. In their daily operations, healthcare information systems make use of both structured and unstructured data. Structured data follows a pre-defined schema, it is vast, freeform, and available in a number of formats. In comparison, unstructured data, dubbed Big Data, does not conform to standard data

processing formats.[25].

Gandomi et al. define 5 dimensions to define the big data analytics namely Volume, Variety, Velocity, Veracity and Variability (5 V's of big data) [26]. However, *Hare-rimana et al.* identify that volume, velocity and variety as the main innovative resources. As of 2013, data analytics is widely regarded to have the potential to meet healthcare's growing need to improve the quality and efficiency of care delivery [27]. Primarily, research has mostly focused on the role of big data analytics capabilities and its direct impact on business performance i.e. reducing the cost of healthcare [28]. However, in recent researchers are exploiting the data capabilities for having a Personalized Medicine (PM) and have a patient-centric approach to improve the patients' well-being [29].

Simmons et al. refers to PM as "an approach to the practice of medicine where prediction, prevention, intense patient engagement, shared health care decision making, and coordination of cares" [30]. To build this PM using data analytics, *Fatima et al.* give the different steps to implement [31]. This implementation has 5 elements namely data acquisition, data storage, data management, data analytics and data visualisations. Table 2.2 shows the different tools and technologies for the data acquisition, data storage and data analytics applied mostly in OSA data-driven research.

In the study of *Khalifa.*, he identifies 5 types of health data analytics namely [32]:

- **Descriptive analysis** is concerned with characterising circumstances, reporting on them, and making decisions based on their past performance in relation to present and historical data.
- **Predictive analysis**, which is probabilistic in nature, displays the capacity to forecast future occurrences by anticipating what could happen.
- The purpose of **prescriptive analysis** is to provide suitable actions that lead to optimal decision making, in healthcare concerns.
- The primary goal of **diagnostic analysis** is to explain the occurrence of certain events as well as the variables that caused the events to occur.

- In identifying novel pharmaceuticals or alternative therapies, or detecting new symptoms, signs, or diseases, or detecting unknown adverse effects, **discovery analytics** using past knowledge.

Phase	Techniques/Methods	Description	Tools	Study
Data Acquisition	Electronic Health Record (EHR)	An EHR is a digital version of a patient's medical history. There are multiple sets of standards like the Health Level 7 for interoperability of the systems	-	[27], [33]–[35]
	Clinical trials	Main source of data for most prototypes and Proof Of Concept in data-driven approach studies	-	[36]–[39]
	Monitoring data	Qualitative data collected directly on the patients through sensing devices and medical devices like the CPAP device	-	[40], [41]
	Relational Database (SQL)	Relational databases hold data that is "related" having a specified relationship between tables, and these tables are used in relation to other datasets	Microsoft SQL Server	[42], [43]
			PostgreSQL	[44]–[46]
		NoSQL databases store unstructured data. The data can have the document data models, key-value models, column-oriented models or graph models	Apache Hadoop	[47]–[49]
			Apache Cassandra	[50], [51]

Data Storage	Non-Relational Database (NoSQL)		MongoDB	[52], [53]
Data Analytics	Unsupervised Learning	Algorithms seek patterns without any user input. Unsupervised approaches are so exploratory and are used to uncover undefined patterns or clusters that appear within datasets	K-means	[54]–[56]
			Hierarchical Clustering	[57], [58]
			Latent profile analysis	[59]
	Supervised Learning	Supervised ML refers to strategies that train a model on a set of inputs (or features) that are linked with a known output	Support Vector Machine	[14], [60]
			Regressions	[61]–[63]
			k-nearest neighbours	[64], [65]
			Neural Network	[42], [43]

TABLE 2.2: Technologies used for data analytics application.

Discussions

In our case, the data acquisitions phase for the monitoring data and EHR has already been completed. As a result, we apply the 5 V's of big data to give a top-level characterisation of our data collections. The studies that use data analytics in healthcare highlight new opportunities that open up with the advent of big data acquisition and big data analytics. However, all the studies put emphasis on the data characterisation phase to extract the full potential that relies upon the data.

Once, identify the potential in the data, we are able to define the most appropriate type of health data analytics as defined by *Khalifa* [32]. However, when defining this analytic type, we must also consider the analysis's objective of producing meaningful results. As a result, we conduct descriptive analysis, predictive analysis, prescriptive analysis, and discovery analysis in accordance with the research objectives of this project and the already available data.

We exclude the diagnostic analysis as this project is dealing with patients that were already diagnosed with OSA and were prescribed the CPAP therapy. The descriptive analysis is crucial for patient characterisation. The predictive analysis is used to predict future event in the patient's therapy, The prescriptive analysis participates in building and delivering the appropriate interventions. Finally, the discovery analysis is crucial for feedback propagation and relies on past knowledge.

To reach our goal for each type of analytics, there are a plethora of analytics techniques presented in table 2.2. However, there is no guarantee, that an algorithm will be the most accurate. Thus, multiple studies compare multiple algorithms to find the one that fits the data the best [64], [66]. Consequently, we need to assess and select the most appropriate algorithms and techniques according to our usecase and data collection.

The use of data is blooming in recent years in the healthcare domain especially in homecare for optimising the cost of health [67]. At most, the studies presented in this section employ three distinct types of analytics. There is a gap in the literature for providing comprehensive solutions, from data characterisation to care delivery, including a process of continuous learning. Even though researchers believe that

these comprehensive solutions will be capable of resolving 'real-world' healthcare issues.

2.1.2 Patient Pathway

The patient pathway is a well-defined concept in the healthcare system [68]–[70]. In the literature, the patient pathway is also referred to as the "care pathway" and "clinical pathway". *Kinsman et al.* defined the clinical pathway as structured multi-disciplinary care plans for specific clinical conditions, which break down the care process into its essential steps. The term 'clinical pathway' refers to the process of improving and standardizing a specific clinical problem and the path within a clinic or a hospital's 24-hour department [71].

Vanhaecht et al. define the "A complex intervention for the mutual decision making and organization of predictable care for a well-defined group of patients during a well-defined period" [72]. They also express that each patient is unique, however, they have enough similarities to guarantee that care pathways are a beneficial norm. But the pathways must be flexible to allow the patients and physicians make choices that vary from these pathways.

For building the patient pathways, *Mans et al.* use the process mining techniques event logged data [73]. The core idea behind process mining is to extract knowledge from event logs to discover, monitor, and enhance existing processes (rather than assumed processes) [74]. For these event logs, it is critical that each event refers to a well-defined phase in the process (e.g., a lab test) and is associated with a specific case (e.g. the patient). Additionally, extra information such as the event's performer (i.e. the doctor performing the test), the event's timestamp, or data items collected alongside the event (e.g. the patient's gender) may be saved.

Mans et al. also highlight the need to include additional data in the events logs for more optimized results. The figure 2.4 shows the characterization of these additional information according to the level of abstraction, accuracy, granularity, directness and correctness. The level of abstraction is the capacity to extract important information from administrative or clinical data [75]. Data granularity is the level of

detail collected on a specific topic for the event log data it can be referred to the data velocity [76].

	Level of abstraction	Accuracy	Granularity	Directness	Correctness
Administrative systems	High	Low	Low	Low	Average
Clinical support systems	Average	Average	Average	Low	High
Healthcare logistics systems	Average	High/Average	Average/Low	High	High
Medical devices	Low	High/Average	High	High	Average

FIGURE 2.4: The data characterizations for process mining [73]

Durojaiye et al. apply the process for mapping the in-hospital flow of pediatric trauma patients [69]. They build the pathways from event log data generated from the admission, discharge and care transition. For the process mining, they use the ProM 6.6 software [77]. So, the authors revealed 28 different patient pathways where the top 5 patient pathways cover 92.1% of all patient inflow. Furthermore, they also identify 20 care transitions. The top 6 transitions cover 87.5% of all transitions.

In the same vein, *Baker et al.* use the process mining on the EHR for defining patients for the chemotherapy [33]. They collected data on routine clinical care from a large base population over 10 years. To extract the patient pathways from this large data the authors use the Markov chain models [78]. Different healthcare professionals validate each pathway manually, and this is an iterative process for continuous improvement of the pathways.

To detect the patients' behaviours, *Forkan et al.* use the pattern recognition on multiple patient pathways. From simulated data, they were able to validate a model made up of the Hidden Markov model and fuzzy rules [79]. They simulate 4 domains for the event logs: (1) activity start/end time and the type of activity, (2) location information, (3) lifestyle log like sleep time, wakeup time, breakfast time and (4) vital signs log such as blood pressure, heart rate and body temperature. The proposed models are capable to detect the behaviour and anomalies of the patients based on the context. Furthermore, the Hidden Markov model was able to detect abnormal activity according to the different urgency levels.

Based on our literature analysis, we found only one paper that applies the "patient pathway" to the CPAP therapy. *Lai et al.* start from a hypothesis patient pathway from the CPAP adherence to an intimate relationship with multiple steps between

them [80]. There are 2 main sources of data qualitative data from the self-assessment questionnaires and quantitative data of the CPAP usage recorded by the CPAP devices themselves over 1 year on 73 men patients. The authors put a patient pathway hypothesis, this pathway is then validated giving a fully validated pathway and is presented in figure 2.5.

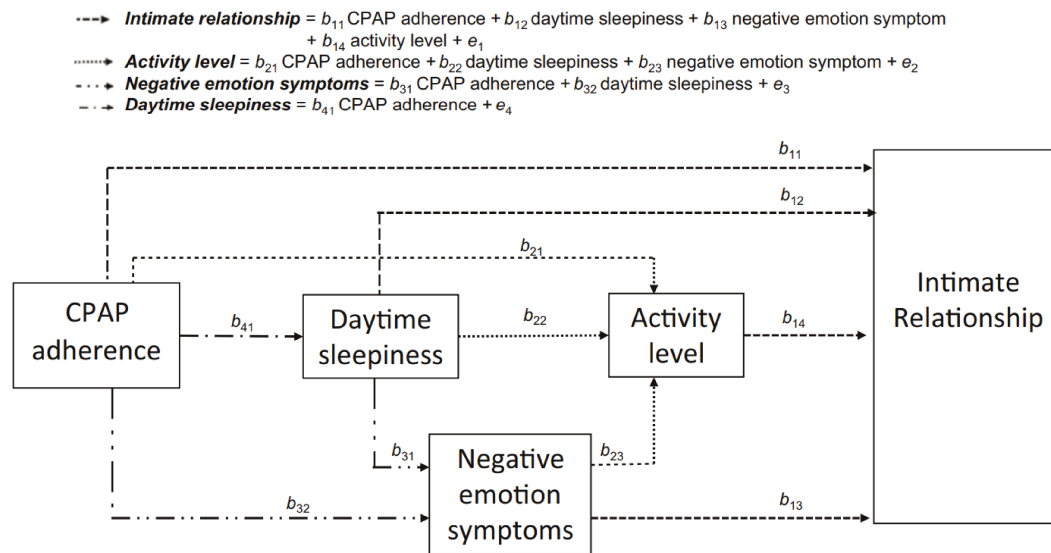


FIGURE 2.5: Hypothesized patient pathway for evaluating the impact of CPAP in intimate relationship [80]

The patient pathway was validated by performing 4 regressions analyses. As a result of these regressions, they obtain a coefficient for each path. The authors use the Sobel test to assess the significance of the intermediate steps [81] Based on empirical analysis, the study highlights direct and indirect predictors for CPAP adherence as well as an optimal pathway to increase CPAP adherence while including the patients' partners. As a result, the proposed framework gave a fully tested and validated patient pathway.

Discussions

The patient pathway, or more precisely, the care pathway leading to homecare, is poorly documented in the literature. However, this concept has been developed and refined over decades for use in in-hospital care, including optimising care delivery, organisation, and cost savings. There is a need to define a patient pathway for

homecare that takes into account the patients' ITT, intervention consumption, real-time monitoring data via sensors, homecare providers, patients' environment, and patients' partners and family.

The patient pathway relies on all the events and outcomes that occur during patient care. As an extension of this assumption, the study that applied the patient pathway for the CPAP therapy uses the event log of the patient. The use of analytic techniques like process mining coupled with the patient pathway revealed hidden pathways which were not yet exploited.

For our use case, the patient pathway is a critical concept because it enables us to track all of the events that occur during a patient's lifecycle. To create the most comprehensive patient pathway, we must consider all factors that influence homecare therapies and patients' lives. As a result, homecare events should not be limited to those directly related to a specific therapy but should have a broader scope.

2.1.3 Patient Profile in OSA

In recent years, there has been growing agreement that improved care of chronic diseases necessitates a patient-centred approach rather than a focus on the originally diagnosed disease [82]–[84]. To implement this patient-centric approach, the studies use patient profiling to consider the patients' personal healthcare needs and preferences [85]. The patient profiles (PP) deepen the relationships, engagement and empathy between the different stakeholders (physicians, caregivers, patients) for better care outcomes [86], [87]. The table 2.3 summarizes the study that uses unsupervised learning techniques to identify multiple clusters for the CPAP therapy.

Study/Year	Population / Data collec- tion period	Features	Clustering Techniques	Results

Joosten et al. / 2012 [88]	N = 1064 T = 24 months (2007 to 2009)	BMI ESS Age Gender Sleep Stage AHI	K-Means	6 clusters
Ye et al. / 2014 [89]	N = 822 (Iceland) T = 24 months	Gender Age BMI AHI Oxygen Saturation Physical component score Mental component score	Latent class analysis (LCA)	3 clusters
Babbin et al. / 2015 [90]	N = 161 (USA) T = 180 days	Demography Education Level Ethnicity Sleep Apnea Severity Sleep Center CPAP device type	Time series analysis	4 clusters
Bailly et al / 2016 [91]	N = 18,263 (France)	Age AHI Oxygen Saturation (SaO2) Self-report Sleep evaluations	Multiple correspondence analysis (MCA) Hierarchical clustering	6 clusters

Gagnadoux et al. /2016 [92]	N = 5,983 (France) T = >6 months	BMI Gender Sleep related information Hypertension Cardiovascular disease Diabetes	LCA	5 clusters
Lacedonia et al. / 2016 [93]	N = 198 (Italia)	BMI ESS AHI SaO2 Comorbidities	Principal Component Analysis (PCA) Hierarchical clustering	3 clusters
Vavougiou et al. /2016 [94]	N = 1472 (Greece)	Gender BMI ESS Arousal Index Charlson Comorbidity Index (CCI) SaO2	PCA Hierarchical clustering	6 Clusters
Turino et al. / 2017 [95]	N = 72,217 T = 12 months (2012 to 2013)	Gender Age Home visits Hospital visits Drugs Most relevant clinic diagnoses	MCA K-means	6 clusters

Ferreira-Santos et al. [96]/ 2018	N = 211 (Portugal)	Gender Age BMI State of the Art Sleepiness	KModes categorical data clustering	3 clusters
Kim et al. / 2018 [97]	N = 422 (South Korea) T = 5 years (2011 to 2015)	Age Gender AHI ESS Comorbidities Sleep analysis data	LCA	3 clusters
Quan et al. / 2018 [98]	N = 2649 (China)	Age Gender Ethnicity BMI AHI 19 clinically relevant indicator	LCA	4 clusters
Zinchuk et al. / 2018 [99]	N = 1247 (USA)	Age Gender Ethnicity Employment BMI ESS AHI Comorbidities	PCA K-means	7 clusters

Mazzotti et al. / 2019 [100]	N = 1207 (USA)	Demography Ethnicity Alcohol use Smoking status Cardiovascular disease	LCA	4 clusters
Nakayama et al. / 2019 [101]	N = 210 (Japan) T = 28 months (2013 to 2015)	Demography ESS Polysomnography data Sleep stages Comorbidities	Hierarchical clustering	3 clusters
Mendelson et al. / 2020 [102]	N = 290 (France) T = 18 months (2015 to 2016)	Demography ESS Polysomnography data Couple related information Sleepiness assessment information	LCA	3 clusters
Bailly et al. / 2021 [103]	N = 23 139 (Multiple European countries and Israel) T = 196 months (2003 to 2019)	Demography ESS Comorbidities SaO2	LCA	8 clusters

Romero-Peralta et al. / 2022 [104]	N = 2050 (Spain) T = 41 months (2014 to 2018)	Demography Comorbidities Sleep symptoms Anthropometric data Physical exam Sleep study results	Hierarchical clustering	4 clusters
Tempaku et al. / 2022 [105]	N = 704 (Brazil) T = 10 months (2015 to 2016)	Demography Comorbidities Sleep assessment Sleep stages Arousal Index	LCA	3 clusters
Testelmans et al. / 2022 [106]	N = 710 (Belgium) T = 24 months (2011 to 2012)	Demography Comorbidities Historic comorbidities	Self Organizing Maps (SOM)	9 clusters

TABLE 2.3: Summary of studies that use unsupervised learning for OSA patients

Discussions

As previously stated, CPAP's low adherence level is a well-known issue. Delivering individualised care via patient clustering is one potential solution to this problem. As shown in table 2.3, numerous studies take advantage of this opportunity to study CPAP therapy. Additionally, we demonstrate that this is a global issue by examining the heterogeneity of the data collections. Furthermore, the dataset evolves over time as additional information is added, such as patients' current and previous comorbidities, physical examinations, and the therapeutic implications of patients' partners.

There were mainly 8 techniques used for the clustering: *K-Means*, *LCA*, *Time-series analysis*, *MCA*, *hierarchical clustering*, *CCI*, *KModes* and *SOM*. All of these techniques

are classified as unsupervised learning because no pre-defined clusters were used, allowing the researchers to highlight hidden profiles. Each cluster is then characterised individually according to the features present in the dataset. This classification enables researchers to ascertain the health condition and needs of patients who reside in these clusters.

However, these studies have a limitation in that the clustering process was carried out in a single instance. There was no tracking of patients to determine whether their profiles changed over time. Additionally, the majority of studies did not specify how the constructed cluster would be used to deliver the intervention and its associated outcomes. *Wohlgemuth et al.* mentioned the strong probability that the patient's profile would change over time but did not investigate this assertion [59].

To address this gap, we apply patient profile concepts from homecare to CPAP therapy in order to construct the dynamic clustering. As mentioned in section 2.1.1, there are no optimal unsupervised learning techniques that fit all datasets; therefore, we will evaluate the multiple techniques presented. We must ensure that the technique used produces converging results and is compatible with our data topology.

2.2 Personalised intervention design and delivery

2.2.1 Interventions for improving CPAP therapy adherence

As expressed before compliance in OSA is a problem known for a long time and PAP therapy has the lowest compliance level for a home care treatment [6]. Multiple studies consider the acceptable adherence level to be 4h/night [92], [107], [108]. To move in that direction, *Weaver et al* show that with 4h/night, there is the highest gain in the Epworth Sleepiness Scale (cf. 2.3), i.e., improvement in daytime sleepiness [9]. Nevertheless, this compliance level of 4h/night is the minimum required for signs of clinical improvement; the more the patient uses the PAP device, the more beneficial for him [109].

In the clinical benchmark presented in this section, the adherence level is confirmed to be 4h/night. *Rotenberg et al.* reviewed 82 papers with the most significant trials to improve compliance in CPAP therapy over the last 20 years [7]. The conclusion of

this study is that compliance levels stagnant to a range of 30% to 60% over all these years despite advances in the PAP device, mask, and the algorithms in CPAP.

However, *Weaver T.E.* one of the most notorious researchers in the sleep apnea topics, highlights those personalised interventions have the potential to change this low adherence tendency for the CPAP therapy [15]. She highlights that there is no "One Size Does Not Fit All" patient management for CPAP therapy. Moreover, she identified four key factors for improving the adherence level namely:

1. **Patient empowerment interventions (I1):** These interventions include educational and supportive interventions [110] to increase the patients' health literacy and Intention to Treat [111]. Educational interventions provide patients with information to help them improve their health and increase their participation in decisions about their ongoing care and treatment [112]. Supportive intervention, on the other hand, focuses on aiding people and their families in coping with diseases and treatments [113]. The primary purpose of these interventions is to provide an individual with an adequate level of health literacy to take responsibility for one's own health as well as the health of one's family and community [114].
2. **Behavioural interventions (I2):** These interventions are associated with the Cognitive Behavioural Therapy (CBT) and Motivational Enhancement Therapy (MET) to have a change in the patients' behaviours in the long term. The CBT model is to lead to changes in emotional distress and problematic behaviours by correcting the patient's beliefs that are incorrect or unfounded [115]. The Motivational Enhancement Intervention (MET) is a brief intervention to resolve the patient's ambivalence regarding their behaviour and has shown efficacy in different populations to increase adherence to a treatment [116].
3. **Real-time monitoring (I3):** CPAP devices objectively record usage data and provides a unique opportunity to assess adherence in real-time [117]. The CPAP device collects the residual apnea-hypopnea index (AHI), and masks leak on a nightly basis. These data can help caregivers and clinicians with early

troubleshooting and decision-making in the patient management [118]. Furthermore, this information can be made available to the patients themselves in a patient empowerment approach [119].

4. **All-inclusive adherence management (I4):** The patient's partner plays an important role in the CPAP adherence level [120]. Consequently, there must be interventions that include different stakeholders like the patients' partners and families. *Donovan et al.* also highlight the importance of extending the interventions not only related to the CPAP therapy but deliver also other disease-related interventions [121].

Based on these definitions of the different interventions for CPAP therapy, we evaluate the different papers that include interventions for improving the CPAP adherence level. We present the results of this evaluation in table 2.4 also including the outcome and impact of these interventions on the adherence level.

Study/Year	Intervention	I1	I2	I3	I4	Outcomes
Cho et al. / 2018 [122]	Activity tracking		X	X		BMI reduced by 2.2 AHI reduced by 4.5/hr
Shapiro et al. / 2021 [123]	Education Patient-support	X				Increase in CPAP literacy Better CPAP acceptance score
Carlier et al. / 2022 [124]	CPAP pressure adjustment			X		Significant increase in CPAP adherence
Merle et al. / 2021 [125]	Peer-Driven interventions		X		X	<i>Did not disclose impact on adherence</i>
Truby et al. / 2019 [126]	Diet intervention		X			<i>Did not disclose results</i>

Hwang et al. / 2018 [127]	Telemedicine Education	X		X		19.7% more patient adherent to the CPAP therapy
Pengo et al./ 2018 [128]	Positive and negative messages delivered to the patients	X	X			Increase in adherence for 2 weeks by a total of 12.9h, No increase in adherence on mid-term
Isetta et al. / 2015 [129]	Telemedecine			X		8% more patient adherent to the CPAP therapy
Kuna et al. / 2015 [130]	Real-time data access			X		Increase of adherence by 1.6h/night for the 1st week Increase of adherence by 1,2h/night for the 3 months
Rudilla et al. / 2021 [131]	Motivation		X			Increase of adherence by 1.6h/night
Luyster et al. / 2019 [120]	Couple education Patient education	X			X	Increase of adherence by 1.4h/night on the short term Not consistant adherence level on long term
Baron et al. / 2020 [132]	Partner inclusion Autonomy support	X			X	Highlights patients' autonomy is a predictor for adherence

TABLE 2.4: Evaluation of studies that include interventions for the CPAP therapy

Discussions

We classified the different studies delivered interventions according to the classification proposed by *Weaver T.E* [15]. As shown in table 2.4, most studies deliver only 2 types of interventions. However, almost all studies observed an increase in adherence and an improvement in the patient's health status in the short term. In the long-term mixed results were obtained. On a long-term basis, these interventions are not feasible because they are delivered by sleep therapists, nurses, and homecare providers. This is primarily due to the fact that these interventions cannot be scaled up to a large cohort of patients, as in our usecase (more than 50 000 patients). However, all the studies come to the conclusion that the interventions and a close patient follow-up must be done on a long go. Hence, we need to find a solution that can deliver personalised intervention on a large scale with a relatively tight cost.

The limits of the studies presented are that they do not cover the complete scope of interventions for the CPAP therapy. They tackle usually one or two issues experienced by the patient, for example, *Rudilla et al.* tackles only the motivation issues [131]. There is a need to develop a comprehensive solution that will include a complete set of interventions for tackling all the issues experienced by the patient in the CPAP therapy.

2.2.2 mHealth solutions for CPAP therapy

The World Health Organisation (WHO) Global Observatory for eHealth defines mHealth as “medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants, and other wireless devices” [133]. The mobility, instantaneous access, and direct communication capabilities of mobile technology enable speedier conveyance of health information, which improves health practices and faster intervention delivery to the patients[134].

The primary uses of mHealth in homecare are remote monitoring of patients' activities and transmission of this information to hospitals and clinicians [135]. As of 2014, *Becker et al.* draw a wider scope for mHealth solutions. A mHealth application can include all the interventions detailed in section 2.2.1 for example diet and exercise

interventions for behavioural interventions [136]. Furthermore, these interventions may be made available to a large public, as there will be 8.9 billion mobile subscriptions by 2027 [137]. Because more individuals are becoming more technologically literate, mHealth therapies can also be helpful among older persons with cognitive impairment [138].

We present the classifications of the mHealth solution for the CPAP therapy in table 2.5. We use the french's "Haute Autorité de Santé" recommendations to classify the solutions [139]. They propose the following classification:

1. **Wellness & prevention (MH1):** exercise and fitness; diet and nutrition; lifestyle and stress; stress management; sleep/insomnia; smoking cessation; alcohol moderation
2. **Symptom onset and seeking care (MH2):** general healthcare information; symptom checking; finding a clinician; managing clinical and financial information; social media
3. **Diagnosis (MH3):** the healthcare professional app recommendations; connected sensors for remote monitoring; apps for any use case across the patient pathway
4. **Condition monitoring (MH4):** self-monitoring; remote patient monitoring; app-enabled rehabilitation programme
5. **Treatment (MH5):** prescription discounts; prescription filling; medication management and adherence

Study/Year	MH1	MH2	MH3	MH4	MH5	Outcomes
Mendelson et al. / 2014 [140]			X	X		No impact on CPAP adherence but the adherence level baseline high
Petrov et al. / 2020 [141]	X		X	X		Higher adherence with the use of the app but no further information disclose

Isetta et al. / 2017 [142]	X					4.4 h/night after 6 weeks 5.0 h/night after 12 weeks
Philips SleepMapper / 2014 [143]				X	X	Increase of adherence level by 1.4h/night
ResMed myAir / 2015 [144]				X	X	Not disclose
Sedkaoui et al. / 2015 [145]	X	X				Increase by 26 minutes/night of adherence level
Alismail et al. / 2020 [146]	X					Not disclose
Berry et al. / 2020 [147]	X	X			X	Increase by 0.8h/night of adherence level
Suarez-Giron et al. / 2020 [11]	X					5.7 h/night adherence level

TABLE 2.5: mHealth solutions for the CPAP therapy

To develop a mHealth solution, *Farao et al.* propose to integrate the ISR framework [21] and the design thinking [148]. The main objective of this framework is to increase the engagement of the end-users towards the mobile application under-resourced context [149]. The authors highlight the role of designing the app with a user-centric approach, and its iterative nature allows for quick improvements to integrate user feedback.

Discussions

mHealth solutions enable mobility, instant access, direct communication, and rapid intervention delivery. These mHealth advantages are critical for delivering interventions on a large scale. The disadvantage of mHealth is that it relies on patient engagement and intervention consumption via mobile applications. Another factor to consider is the long-term retention capacity of mHealth, or the ability of the patient to use the application for an extended period.

Despite these drawbacks, the various studies found that mHealth positively affected adherence levels. It is particularly effective for patients with a low initial level of adherence. More importantly, all studies indicate that the patient uses the CPAP for more than 4 hours per night on average (when information is disclosed). However, these applications were not evaluated in the long run.

Except for Philips SleepMapper and ResMed myAir, our literature review reveals that there are only nine mobile applications with referenced articles. Each application was classified using the "Haute Autorité de Santé" recommendations, and none of the mobile applications fully conform to all the recommendations defined. To facilitate the development of a diverse set of interventions, the mHealth solution must incorporate various features. However, in our use case, the diagnosis characteristics (MH3) are irrelevant, as all of the targeted users have already been diagnosed with OSA.

2.3 Feedback collection

2.3.1 OSA patient feedback

Patient input is shown to be essential for quality improvement and health professional development [150], [151]. Questionnaires are the most common way for patients to provide feedback to physicians and healthcare teams [152]. A questionnaire is a form of written survey that consists of a systematic set of questions. Questionnaires are often designed with highly standardised responses, allowing data to be readily analysed and compared [153].

The Epworth Sleepiness Scale (ESS) questionnaire was proposed back in 1991 by *M. W. Johns.*, this questionnaire itself is presented in appendix A [154]. As shown in table 2.3, the ESS is the more widespread self-administered questionnaire to evaluate the daytime sleepiness of the patients [88], [93], [94], [99], [101]. The goal of the ESS is to determine the level of daytime sleepiness and hence, determine the efficiency of the CPAP therapy. However, the ESS evaluates only one aspect of the patient's life i.e. daytime sleepiness.

The Berlin questionnaire is gaining more and more popularity for the OSA [155]. The Berlin test, in contrast to the ESS, was designed to detect individuals with sleep apnea in the general population. We presented this test in appendix B. The survey addresses the presence and frequency of snoring behaviour, wake-time sleepiness or fatigue, and history of obesity or hypertension [156]. If the patients scored positive in two or more categories, they are classified as high risk; otherwise, they are classified as low risk.

For the OSA screening, *Chung et al.* developed a validated questionnaire called the STOP-BANG questionnaire [157]. The STOP-BANG questionnaire is made up of eight yes or no questions that measure OSA risk based on demographics, comorbidities, and symptoms. The STOP-BANG was designed for surgical patients at pre-operative clinics. However, studies used the survey on different populations with convincing results [158], [159].

To evaluate the nighttime arousal and sleeping quality of patients suffering from OSA, several studies use the Pittsburgh Sleep Quality Index (PSQI) [160]–[162]. The PSQI is a self-reported questionnaire that evaluates sleep quality and disruptions during a one-month period [163]. The PSQI is made up of 19 self-reported questions and five graded by the bed-partner or roommate but the five questions are not included in the score calculation instead are used as clinical information. These 19 items are divided into seven component scores, each of which is weighted equally on a range of 0-3. The seven component values are then added together to get a global PSQI score; higher scores poorer the sleep quality.

Balakrishnan et al. use the Sleep Apnea Quality of Life Index(SAQLI) as predictor

for the CPAP adherence [164]. The SAQLI is a 35-item OSA questionnaire with four key domains: everyday functioning, social interactions, emotional functioning, and symptoms [165]. The SAQLI has the potential to capture the adverse impact of treatment side effects on quality of life.

To assess sleepiness, there are the Functional Outcomes of Sleep Questionnaire (FOSQ), this survey was used in multiple CPAP-related studies [61], [80], [120]. *Weaver et al.* develop the FOSQ to determine if the patient has trouble performing various tasks because they are sleepy or fatigued.[166]. Which was developed to examine the effects of disorders of excessive sleepiness on numerous activities of daily life and the extent to which these skills are improved by successful PAP therapy. in 2009, *Chasens et al.* build a shorter version of the FOSQ with only 10 questions performs similarly to the long version [167].

Another questionnaire directly related to the OSA is the Self-Efficacy Measure for Sleep Apnea (SEMSA) [59]. The SEMSA is a 26-item self-questionnaire that evaluates three factors: OSA risk perception, CPAP benefit, and self-efficacy (the confidence to engage in CPAP compliance) [168]. Moreover, *Micoulaud-Franchi et al.* design the french version of the SEMSA and the survey was validated on 288 patients [169].

Anxiety problems are prevalent in individuals with OSA, and research shows that anxiety disorders and the fear of choking are more common in severe OSA [170], [171]. In the same vein as the Berlin test of developing surveys specific to the OSA, *Edmonds et al.* propose the CPAP-Adapted Fear and Avoidance Scale (CPAP-FAAS) [172]. The CPAP-FAAS assess the agoraphobia and claustrophobia directly related to the CPAP therapy. The outcome of this assessment provides empirical evidence of patient-reported obstacles to CPAP treatment.

In CPAP studies, the Depression, Anxiety, Stress Scale (DASS-21) is also used to measure negative prevalent to the CPAP therapy [80]. The DASS-21 was developed by *Lovibond et al.* [173] and is a well-established tool for determining depression, anxiety, and stress symptoms in clinical and non-clinical populations [174]–[176]. The DASS-21 is divided between 3 axes (Depression, Anxiety, Stress), each question is assigned a score ranging from 0 to 3. As a result, depending on the number of

questions asked, each of the axes displays partial scores ranging from 0 to 18-24. The classification of the results on table 2.6.

Level/Disorder	Depression	Anxiety	Stress
Normal	0 - 4	0 - 3	0 - 7
Mild	5 - 6	4 - 5	8 - 9
Moderate	7 - 10	6 - 7	10 - 12
Severe	11 - 13	8 - 9	13 - 16
Extremely severe	≥ 14	≥ 10	≥ 17

TABLE 2.6: DASS-21 results classification

Yang et al. use the Perceived Stress Scale (PSS) in a mHealth solution to measure the patients' stress like in the DASS-21 [177]. The PSS was developed by *Cohen et al.* to get a factual measurement of the perceived stress by the patient [178]. The questions were created to capture how unexpected, unmanageable, and overburdened respondents' lives are. The scale also contains a number of straightforward questions concerning present stress levels. The survey is composed of 10 questions on a scale of 0 to 4, the higher the score higher the stress level.

Discussions

We organised all the questionnaires presented in the previous section on the figure 2.6. We classified each questionnaire according to its purpose. Each survey has a distinct goal, and there is no such thing as a "one-size-fits-all" questionnaire. To obtain a comprehensive picture of the patient, we must deliver multiple questionnaires. However, there is a possibility that the patient will not complete multiple surveys in a short period of time.

We presented only tested and validated questionnaires; these questionnaires are well-known among experts and can directly interpret these results. These questionnaires may not fit perfectly depending on the patients' needs and barriers to adherence. We could develop our own questionnaire and scale to address this issue, but that is beyond the scope of this research project. As a result, we tackle the issue by dispensing multiple questionnaires to the patient. To determine the most appropriate validated questionnaires, this literature review on patient feedback collection must continue throughout the solution's implementation and utilisation.

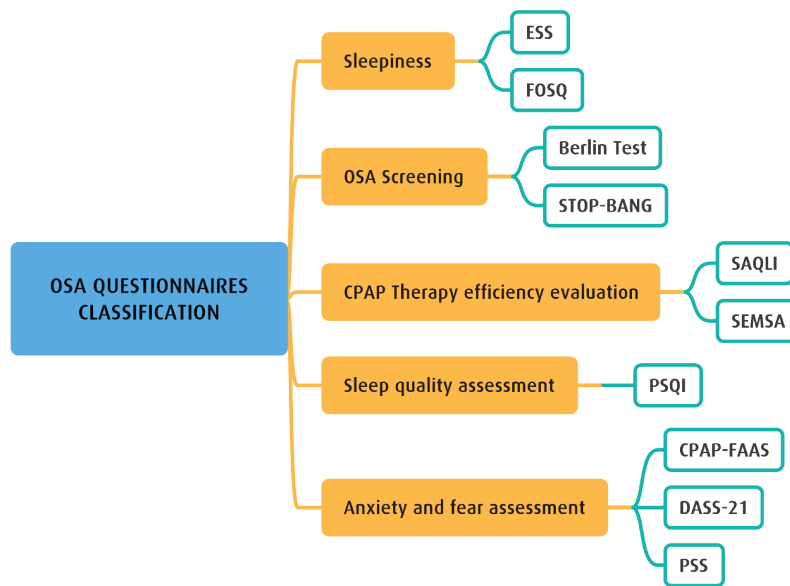


FIGURE 2.6: Classification of the questionnaire for collecting the patient feedback

2.3.2 Experts feedback

The stakeholder other than the patients is the experts in the OSA therapy. The experts include the prescriber (the physician who diagnosed OSA in an individual), nurse, homecare giver and home-care managers. Collecting expert opinion is becoming increasingly important to improve transparency, increase responsibility, enlighten diagnostics, and drive quality improvement in healthcare practice, especially in patient-centric approach [179]. To the best of our knowledge, unlike patient feedback, there is no established and validated questionnaire for expert feedback for the OSA. As a result, in this section, we present frameworks for designing and delivering CPAP interventions in which professionals have a proactive role.

In 2010, *Roecklein et al.* propose one of the first trials where the prescribers provide direct feedback to the patients [180]. Physicians are unaware of their patient's participation in the study, and participants are unaware of their conditions to have unbiased results. However, the limit of this study is that the patients are not provided with the CPAP and there is no evidence that the study encourages the patients to buy a CPAP device due to their low income.

To explore the other factors for defining adherence to the CPAP therapy, in 2014, *Crawford et al.* develop a formalise biopsychosocial model [181]. The model consists

of 3 domains: psychological domain(belief and perceptions about OSA), biomedical domain(OSA severity) and social domain(OSA in the social context). These data are frequently assessed as part of normal clinical treatment by a physician or a respiratory technician. The model facilitates the transmission of this information across these domains by effortlessly integrating them into the patient pathway. Similarly, *Hu et al.* conceptualised the factors of patients living with CPAP and the experts manually record and transmit this information [182].

In 2017, *Pepin, J. L.* highlights the importance of integrating the experts in the patient pathway for delivering personalised interventions for the CPAP therapy [183]. *Swieca et al.* discuss that telemonitoring allows the CPAP therapist and sleep physician to analyse the patient's CPAP usage and assist in determining how well the OSA is treated. However, no acceptable norms or standards exist for practitioners in the sector to follow or avoid while analysing these data [184].

Lim et al. proposed the formalise P4 approach to the OSA; the 4Ps stands for prevention, personalisation, participate and predict [185]. The P4 approach shifts the concept of physicians as gatekeepers of expert advice and sole managers of medical care to one in which people are encouraged to utilise social networking and digital monitoring in addition to consulting with physicians. In this approach, the clinicians are encouraged to take part to generate data and facilitating communication in each of the 4P domains. *Sutherland et al.* also apply the 4P approach to shape personalised CPAP patient management [186]. They highlight an interdisciplinary model for the primary care physicians or nurse practitioners who have access to sleep specialist services. Each of the care given is recorded in the patients' EHR throughout the care pathway.

In the same vein *Hilbert et al.* highlights the need for shared feedback from both the experts and patients [187]. According to the authors, sleep doctors are best regarded as therapeutic partners in the care process, working closely with primary care physicians. This coordinated management might take the shape of a casual dialogue or a formal consultation. However, again there are no standard guidelines for this process, only direct health-related information is recorded in the EHR.

Brostrom et al. develop the questionnaire for the physicians for performing the appropriate interventions on the patients [188]. The questionnaire was built based on feedback from the physicians themselves. The authors determine 38-items to assess each physician and the latter rated each item from "not important" to "very important" on a five-point Likert-type scale. They were able to design a two-factor framework for activities (educational/informational actions and medical actions) based on this feedback. However, further testing is required to confirm this questionnaire-to-action survey.

Discussions

All the studies on personalised medicine put the emphasis that the experts' feedback is crucial as well as the communication with the patients. In the studies presented, the experts give direct feedback to the patients and there is a scarce process to record this information. Furthermore, in a situation where this information is stored, the data are unstructured and require a further process for analysis. To tackle this issue, there can be questionnaires especially targeting the experts.

The methodology outlined by *Brostrom et al.* can be replicated to develop our own questionnaire for OSA and CPAP experts [188]. To develop this questionnaire, we need to involve experts at various stages of the solution and in the questionnaire's development. Additionally, each expert has a specific area of expertise. As a result, a questionnaire tailored to each type of expert stakeholder must be developed. Because the questionnaire will be personalised to our specific needs, we will be able to collect the data we require.

2.4 Automatic feedback propagation

Continuous learning in healthcare is a core and important concept in healthcare [189]. In 2012, during a round table on Value & Science-Driven Health Care, *Institute of Medicine (USA)* and *National Academy of Engineering (USA)* define a learning healthcare system as follows: "A learning health care system is one in which science, informatics, incentives, and culture are aligned for continuous improvement and innovation, with best practices seamlessly embedded in the care process, patients

and families active participants in all elements, and new knowledge captured as an integral by-product of the care experience" [190].

McLachlan et al. propose the Heimdall framework to classify the works in the learning healthcare system domain [191]. This framework is critical because researchers have a limited understanding of learning healthcare. They also introduced the concept of the clinical lifecycle with the framework; the appendix C.1 shows an example of the clinical lifecycle. They proposed a six criteria for the studies namely:

1. Taxonomic consistency – conforms to the taxonomy
2. Patient-focused – ensures personalised healthcare
3. Technology usage – uses health IT with big data, machine learning algorithms and automation
4. Decision support – near real-time support to clinicians, bringing recent scientific advances, and machine learning
5. Application of learning healthcare – goes beyond selecting ‘most likely treatment for a population’, to selecting the ‘most applicable treatment for an individual
6. Barriers and further observations – challenges limiting implementation

Based on this definition, *Smith et al.* highlight the importance of establishing feedback loops for effective continuous learning and system improvement [192]. They also highlight the importance of having a culture of collaboration, adaptability, and teamwork with the primary goal of promoting continuous learning. The authors express the opportunity of continuous learning to engage the patients in the care process to ensure that their needs, goals, and circumstances are met.

Historically, in healthcare, researchers have tested a variety of protocols as a baseline to ensure that patients receive the appropriate care. However, in continuous learning, we adapt this baseline according to multiple goals for example to increase the organisational efficiency. *Smith et al.* identify that the adoption of learning models is critical for the development of self-improving and continuously learning health systems [193].

The *Monash University* proposed a framework for implementing a learning health system [194]. This framework is presented in appendix D.1. The authors organise the framework in a cyclic way where every stakeholder is connected and highlight the importance of an iterative approach. The framework confronts evidence from stakeholders, research, data, and implementations to improve the healthcare systems.

Abernethy et al. implement a rapid learning system apply to the cancer care using patient-reported data [195], [196]. They collect feedback from 178 patients to record the outcomes of the interventions in the clinic routine. The authors were able to validate the collected data and were able to identify successful interventions. Currently, physicians analyse these pieces of information. They intend to reintroduce this data into the system in order to facilitate tailored interventions.

Flynn, A. present the data-driven learning health systems [197]. A data-driven learning system combines real-world data collection, analytics, and decision support to enable the establishment of complete, persistent learning cycles at multiple scales. *Flynn, A.* shows the need for an expert in leading data analyses, interpreting analytic results, and determining whether or not newly acquired knowledge should be integrated into clinical practice.

Patel et al. perform a literature review of the implementation of different data analytic and artificial intelligence solutions in different healthcare domains [198]. In this review, the experts play a significant role in validating the different models. Moreover, they identify expert-aided machine learning solutions are crucial for having pertinent results. *Fruehwirt et al.* identify experts in similar roles and emphasise the importance of automatically inferring expert feedback in analytic models [199].

To go down the road of automation, *Weiss et al.* propose a comprehensive solution to complete "inconsistent, incomplete and inaccurate" labelled data with feedback [200]. They incorporate feedback into their clustering and classification (machine learning) processes. Through clustering, the authors use this feedback to automatically assign labels to the data. Following that, the classification process makes use of the labelled data. They were able to discover new labels while also avoiding the

time-consuming task of manually assigning labels to individual records. This approach is critical for performing rapid analysis of new data.

Relatively, *Gennatas et al.* uses the feedback from 15 different clinicians to implement the expert augmented machine learning (EAML) [201]. They propose a formal process for determining empirical rules that can be reused in other data collection (figure 2.7). The study also compares rules calculated empirically through machine learning and rules extracted from the clinician’s feedback. In most cases, the clinicians agreed with the empirical rules. For the other situations, the authors extracted hidden rules like in [200] and calculate the gap between the experts’ feedback and the empirical results. To summarise, the EAML is a method for automatically acquiring problem-specific rules and incorporating them into various machine learning models. Moreover, the EAML improve performance on out-of-sample data and reduced the amount of data required to train the analytic models.

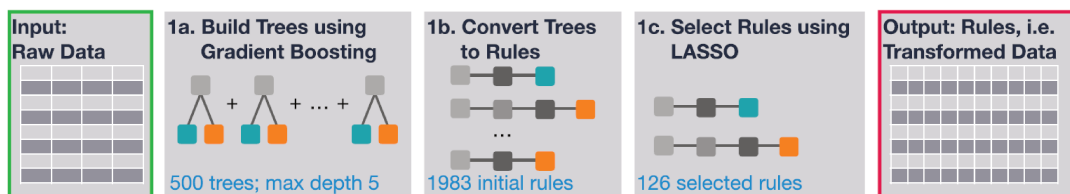


FIGURE 2.7: The rules extraction process in the EAML framework proposed by *Gennatas et al.* [201]

Discussions

The continuous learning process is a relatively new concept for the healthcare more specifically automatising this process. The definition and taxonomic provided by *McLachlan et al.* is important helped us to select the studies including a learning process [191]. However, during our research most of the studies that include this learning process targets the the healthcare at an organisational level for cost reduction.

The different authors in the learning healthcare system agree on the fact that the experts need to validate the data analytic models. To go in that way, machine learning applied in healthcare is assisted by the expert to get meaningful implications. However, the drawback of these solutions is that the experts only validate the results of

the models, The experts are not involved in the process of developing the models or in the verification process.

The alternative is to compare the expert's findings to the analytics findings. This process is described in detail by *Gennatas et al.*; in most cases, analytic models produce results that agree with those of experts [201]. However, the weakness of this approach is that in cases the results diverge, the question of which result is correct arises. To address this question, one strategy is to completely redevelop the whole analytic model to fit the experts validation. This solution is overly constrained; to address this, multiple validation processes can be used, in which experts are asked to evaluate only divergent results directly. Which requires less validation from experts because only divergent results will be re-evaluated.

Chapter 3

Homecare Intervention as a Service (HIaaS) Framework

We analyse the numerous concepts and methodologies existing in the literature to develop the HIaaS framework using the SoA described in the chapter 2. In this chapter, we develop the HIaaS framework as well as all of its related concepts and models. The suggested framework achieves all the goals outlined in section 1.2. This chapter is organised as follows: firstly, we outline the framework's key concepts. Second, we provide an overview of the HIaaS framework. Then, we go over the many processes, models, and workflows that are included in our suggested solution. Finally, we provide a meta-model that specifies one of the models used to create the HIaaS framework.

3.1 Main Concepts

Before enlightening the framework, we introduce the core concepts of HIaaS framework. For an easier understanding, we take the example of a patient timeline during the first 90 days of the CPAP therapy. We take this specific example since it is the most crucial part of the CPAP therapy [202] and also this phase has the highest velocity of intervention delivery and data harvesting.

Figure 3.1 illustrates the patient's timeline during the initial phase of CPAP therapy (the first 90 days of therapy). The patient receives three interventions separated by 30 days in this example. The initial intervention occurs during the therapy's first

days. This intervention is consumed by the patient until the next intervention is delivered. We developed the patient profile for this intervention and the patient pathway throughout the intervention's consumption. These concepts are critical for ensuring that these interventions are tailored to each patient.

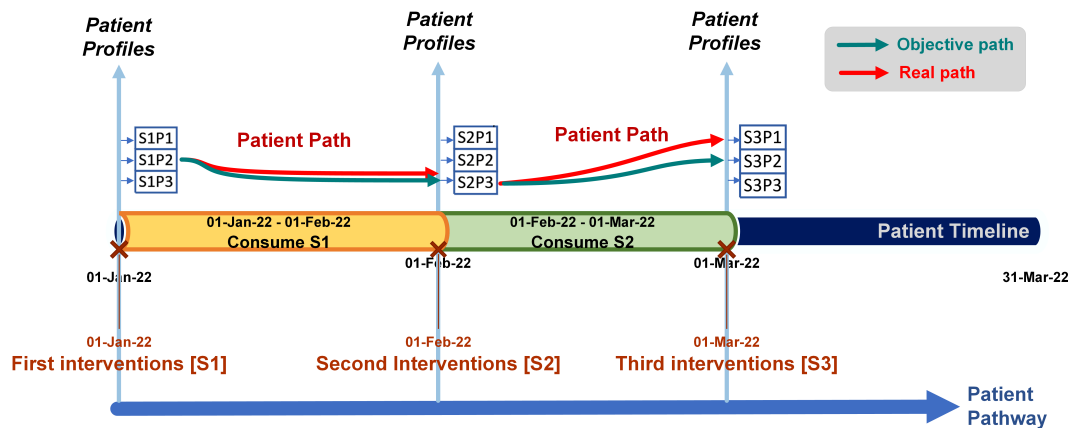


FIGURE 3.1: Patient timeline for the first 90 days of the CPAP therapy

3.1.1 Patient Profile

The first model in the HIaaS framework that directly uses the patients' information is the patient profile. At the beginning of the CPAP therapy, the patient is assigned a profile to get the first glimpse of the patient's phenotyping. To build the model for patient profiling, use the techniques explored by different studies presented in section 2.1.3. In our example, in the beginning, the patient is assigned the profile *S1P2*.

The primary distinction between patient profiles and patient clustering is that the patient profile is dynamic, and the patient can shift from one profile to another over time. We conduct this patient profile assignment at regular intervals, i.e. there are multiple clustering models throughout the CPAP therapy because the patient's situation changes over time. For example, there are three patient profiles assigned throughout the first 90 days of therapy.

Patient Profile

The patient profile for homecare is the dynamic patient characterisation that regards the ever-changing patient's health, environment and lifestyle condition.

Unlike the initial patient profile, the succeeding patient profile models are based on the patient pathway, the previous profile, and the intervention consumption from the previous profile assignment to the current profile. For example, to assign the *S3P1* profile to a patient, we use the patient pathway from the start of therapy, the profile *S2P3*, and the intervention consumption *S2*.

3.1.2 Patient Pathway

The patient pathway is made up of the several patient profiles that the patient possesses throughout his therapy. As a result, for new patients, we rely solely on the first profile assigned to them. As the patient progresses through his therapy, the patient pathway begins to take shape. Consequently, the patient pathway provides a macro-analysis of the patient during therapy.

Patient Pathway

The patient pathway is a collection of patient profiles that gives a macro-analysis of the patient which includes the health condition, intervention delivered and consumption.

With the patient pathway, we can trace the patient's progression throughout the therapy and predict the patient's vulnerabilities to the therapy. With this prediction, we establish an objective path for each patient as well as an objective patient profile. In the figure 3.1, the red pathway represents the patient's actual journey, while the blue line represents the objective path. During the first interval (01-Jan-22 to 01-Feb-22), the patient conforms to the goal. However, during the second period, the real and objective paths diverge, and we conclude that the patient is in danger. As a result, the HlaaS framework readjusts the right models to match the patient's needs for the next period.

3.1.3 Homecare Interventions and consumption

Between each patient profile, we deliver a set of interventions to the patient via multiple channels. Healthcare interventions are usually delivered directly by physicians and nurses and the patient immediately consumes the interventions. This is true because interventions are typically delivered directly to patients by clinicians

or healthcare experts, who thus monitor their consumption. However, intervention delivered via a mHealth solution, the consumption spreads out over a period. In our example, the interventions are spread over 1 month (*Consume S1/S2*). The selection and personalisation of the interventions are based on the specific vulnerabilities of each patient to his therapy.

Homecare Interventions

The homecare interventions are any interaction of the patient with a healthcare/homecare staff or medical-grade services via any communication channel (for example, physical interaction, phone calls and mobile application).

3.2 HIaaS overview

The HIaaS framework is a novel framework that we propose to build, deliver and monitor personalised homecare interventions. As expressed in section 2.2.2, the clinic stakeholders and the patients are urged to have a proactive role in homecare. The HIaaS framework has a complete patient-centric approach where each stakeholder plays an active role in the treatment. The framework includes multiple verifications and validation mechanisms based on the competencies of each expert (physician, sleep therapist, nurse, homecare giver and homecare patient managers) in the homecare.

Additionally, we have a data-driven approach to build the different models as the CPAP device generates a lot of data. Aside from these monitoring data, we include newly generated data (based on the patients' and experts' stakeholders) in the different data analytic models. Including the quantitative data and qualitative in the models and the readjustment of these models just on time gives intelligence to the HIaaS. The figure 3.2 shows the high-level models present in the HIaaS model which we detail in this section.

3.2.1 Patient Characterisation

We depend on three basic principles to characterise the patient: the patient pathway, the patient profile, and automated vulnerability identification. One of the shared

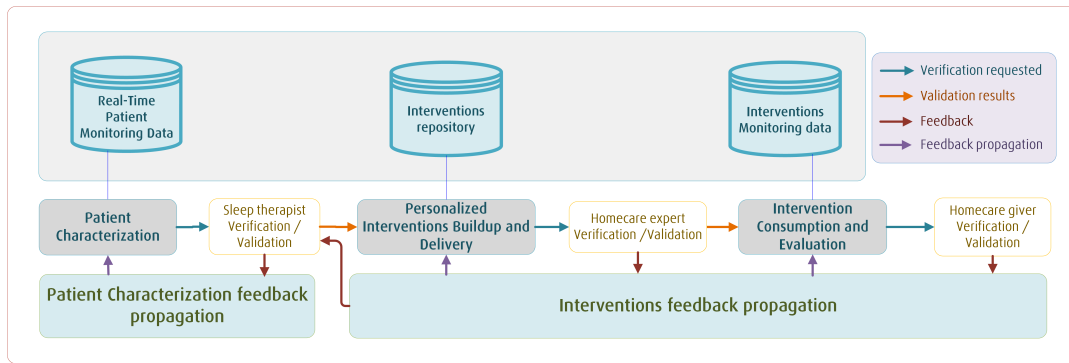


FIGURE 3.2: The HlaaS framework overview

goals of the patient pathway and patient profile is the capacity to distinguish one patient from another based on various criteria, in other words, to characterise each patient. These objectives are outlined in section 2.1.3, where the studies define the phenotype of each patient.

We build the patient pathway from the real-time monitoring data collected by the CPAP devices. The CPAP device record 3 quantitative data: CPAP therapy usage per night (adherence level), AHI and mask leakage. The adherence is measured in *h/night* and it is considered that good adherence is above 4h/night [203]. The AHI is the average number of apneas and hypopneas per hour of sleep. Mask leakage is defined as unintended air leaking from the mouth or around the mask and is typically measured in *l/min* [204]. We automatically collect this data remotely daily.

To create the various patient profiles, we use the same patient monitoring data as well as qualitative data obtained at the patient's home by the homecare giver. The homecare provider assesses the patient's health literacy on CPAP therapy, motivation, and smoking habits. The patient profiles are dynamic for each patient; in other words, the patient's profile may vary over time. We complete the patient profile assignment at the time specified by the patient pathway.

The patient pathway allows us to obtain the patient's complete historical data during the therapy. Patient profiles, on the other hand, provide us with a more extensive study of the patient in the short term than the patient pathway. To determine the patient's full extent, we examine both the patient pathway and the patient profile to identify the patient's weaknesses. All of the difficulties that patients have when undergoing CPAP therapy are referred to as vulnerabilities (not only hurdles to low

adherence). We identify these vulnerabilities automatically based on the diverging patient pathway, and we set thresholds to certain markers based on the patient profile.

The building methodology and data of these 3 models (patient pathway, patient profile and vulnerability detection) are verified by the physicians or sleep therapist. The same specialists validate the findings of these models, and we primarily collect feedback on the automatic vulnerability detection system. Because the results of this model are employed in the next steps and are critical for feedback propagation.

3.2.2 Personalised Interventions Buildup and Delivery

Based on the patients' vulnerability, we select the most appropriate intervention or set of interventions in the intervention repository. The intervention repository consists of a list of interventions designed for CPAP therapy. We build the most comprehensive intervention repository feasible, which contains interventions already tested and validated in previous studies (section 2.2.2). We also include interventions that are entirely novel to CPAP therapy.

However, the selected interventions or set of interventions are common to all patients. To tackle this problem, each intervention has a customisable layer. To personalise the interventions, we rely on the patient pathway and on the patient profile. Hence, the intervention would fit the patient and maximise the intention to treat.

The homecare experts (homecare managers) verify and validate (section 3.6) the intervention selection and personalisation. Finally, the interventions are delivered to the patient directly through our mHealth solution. However, the delivery conforms to a fixed timetable that is established by the patient pathway and the type of vulnerabilities. This scheduling is specific to the homecare and mHealth interventions since the interventions are consumed by the patient over a while. Furthermore, the patient might consume the interventions on his initiative.

3.2.3 Intervention Consumption and Evaluation

Each intervention has its monitoring mechanism to track the patient's consumption. In addition, each patient is allocated a design test protocol to provide an unbiased

assessment of the impact of the therapies on the patient pathway and profile. As previously said, this monitoring is critical because the patient can choose whether or not to consume the interventions. These monitoring data are stored in the interventions monitoring data repository and are used as feedback for the analytic models.

There is constant monitoring and evaluation of these interventions and accordingly, the model can change the delivery schedule. The interventions are evaluated based on the consumption data and the questionnaires and techniques detailed in section 2.3. To some extent, the HIaaS model can stop the intervention delivery and we perform another iteration through the "Patient Characterisation" and "Personalised Interventions Buildup and Delivery" process. Though the homecare giver validated this process to reschedule or stop the intervention delivery.

3.2.4 Feedback Propagation

It is critical to have clear and well-defined boundaries between the various verification and validation jobs, as stated in the section 2.4. The HIaaS framework has 3 levels of verification and validation each impacting the specific model. These 3 levels are:

1. **Physician and sleep therapist feedback:** They verify and validate the patient characterisation. Feedback has an immediate impact on vulnerability identification, patient profile, and patient route models. We use a cascade approach to apply feedback to the vulnerability detection model, and if the model adheres to the feedback, the other model remains unaffected. If the model does not adhere to the feedback, we use the feedback on the patient profile and the same procedure for the patient pathway model.
2. **Homecare managers feedback:** They verify and validate and have an impact on the intervention selection, personalisation and delivery models. As for the physician and sleep therapist feedback, we apply the homecare managers' feedback on these models in a cascade mechanism. However, if at the end of the cascade process, the models do not stick to the feedback, we request the physician and sleep therapist feedback to readjust the patient characterisation models.

3. **Homecare givers feedback:** They verify and validate the intervention consumption and evaluation models and have an impact on them. We use the feedback from homecare givers on these models in a cascade manner, as we did with the prior two. Despite this, we use the cascade technique for intervention selection, personalization, and delivery models without soliciting feedback from homecare managers. This technique is possible since we can collect useful data for intervention selection, personalization, and delivery models.

3.3 Patient Characterisation

We have a data-driven approach for this research project. Consequently, the first step is the data exploration phase as we are dealing with raw data that was collected over more than 5 years on more than 70 000 patients with a prescription for the CPAP therapy. In this section, we give the detailed structure of the patient characterisation, which includes the data exploration, patient profile, patient pathway and the vulnerability detection model. The overall process is presented in the figure 3.3.

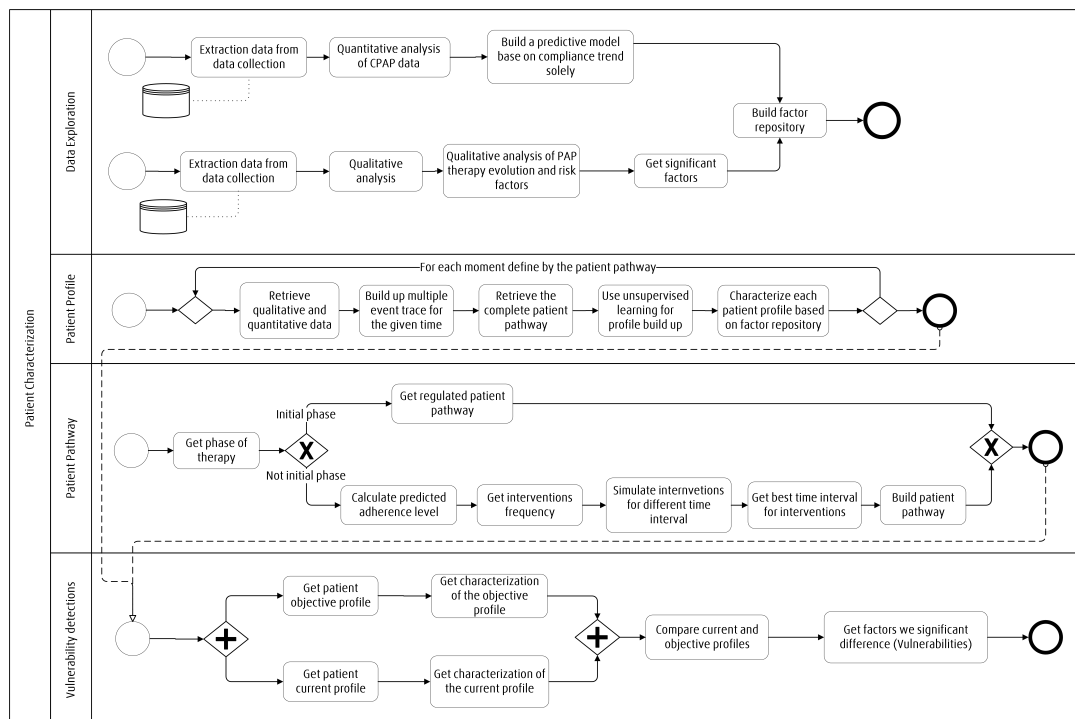


FIGURE 3.3: BPMN for the characterising the patient based on different data collection

3.3.1 Data Exploration

The purpose of the data exploration is to create a factor repository that contains all of the factors affecting CPAP therapy that have been identified in our various data monitoring repositories. There are two types of analysis: quantitative and qualitative. The quantitative analysis is based on CPAP monitoring described in section 3.2. We develop a CPAP adherence prediction model based on the two datasets detailed in section 1.1.2, which is used to construct the patient pathway.

The qualitative analysis focuses on the various assessment points conducted with the patient by the homecare provider. These variables are reported rather than measured, it is critical to assess the reliability of the reported data. We collaborate closely with the homecare provider and manager to conduct this evaluation. We use multivariate regression and correlations to identify all of the factors affecting CPAP therapy using these reliable data. The factor repository contains the complete set of influencing factors.

3.3.2 Patient Profile

We use both quantitative and qualitative data to create the patient profile. Various concepts were identified from related works in order to construct a meta-model for modelling patient profiles, particularly event detection. In the section 3.8, we detailed the process of creating the event trace used in the patient profile. We redraw all of the patient's therapy events in order to infer his lifestyle in relation to the therapy.

As previously stated, the patient profile also employs the complete patient pathway in order to construct the clustering models. However, the initial patient profile is not dependent on the patient pathway, as this pathway is established on the first day of therapy. The unsupervised learning algorithm "ingests" the event trace and patient pathway. We selected K-means unsupervised learning based on the topologies of our data and the table 2.3, which lists the principal clustering methods used in comparable studies. As a result, we obtain multiple clusters at any given time.

We use the impacting factor repository to characterise each cluster. We select only the most influential factors for each cluster, as not all of the different variables have an effect on the therapy for specific patients. Sleep therapists differentiate the process of identifying impact factors. This is the first level of the HIaaS framework's patient-centric analysis. These steps are repeated at various points along the patient pathway in order to generate a multitude of clustering models and thus the dynamic patient profile.

3.3.3 Patient Pathway

PAP therapy is divided into two distinct phases: the initial phase and the follow-up phase. As a result, there are two distinct techniques for developing the patient pathway. The French health authority defines a "one-size-fits-all" patient pathway for the initial phase, [205]. This route entails installing the CPAP at the patient's residence. A homecare giver performs this installation, and three days later, the same expert contacts the patient to obtain the patient's initial feedback. Regarding the installation, there are two additional home visits by a homecare expert 15 and 90 days later. This 90-day visit concludes the initial phase. This predefined patient pathway has been demonstrated to be effective in terms of adherence [206].

There is no predefined patient pathway for the follow-up phase, and thus we must create the optimal pathway for each patient. We use supervised learning to predict the patient's adherence level. Multiple methods outlined in the table 2.2 were evaluated to determine the optimal model for our dataset. The model predicts the level of adherence for the subsequent 90 days based on data collected during the initial phase. The lower the level of adherence, the more frequent interventions are required for optimal patient management. This assumption, however, may not be true for every patient. To this end, we simulate the frequency of calculated interventions using the patient's historical data.

The prediction identifies the optimal intervention frequency and timing for the patient. The simulation accounts for the patient's consumption of previously delivered interventions. As a result, we obtain the patient's 90-day pathway: in other words, the precise timing for delivering the patient's interventions.

3.3.4 Vulnerabilities detection

Prior to selecting the most appropriate interventions, it is necessary to understand the factors that contribute to noncompliance with CPAP therapy. These flaws are caused by the in-depth analysis of patient profiles. To begin, the model retrieves both the current and objective profiles. This objective profile corresponds to the patient's target profile as discovered on his pathway. By analysing the patient's complete path (complete profile sequence), the model automatically establishes the objective profile and deduces the converging profile for a higher level of adherence.

Second, the model compares the current and objective profiles in order to determine the difference between them. This calculation identifies the variables on which we should intervene to ensure that the patient fits the objective profile, which is referred to as the patient's vulnerabilities. Additionally, the models select only those factors that have a significant difference between the objective and current profiles, leaving sufficient room for adherence improvement.

3.4 Personalised Interventions Buildup and Delivery

The core feature of the HlaaS framework is delivering the appropriate personalised intervention directly to the patient. "the process to select, personalize and schudele the interventions..." In this section, we develop the process to select, personalise and schedule the delivery of the interventions as described in figure 3.4.

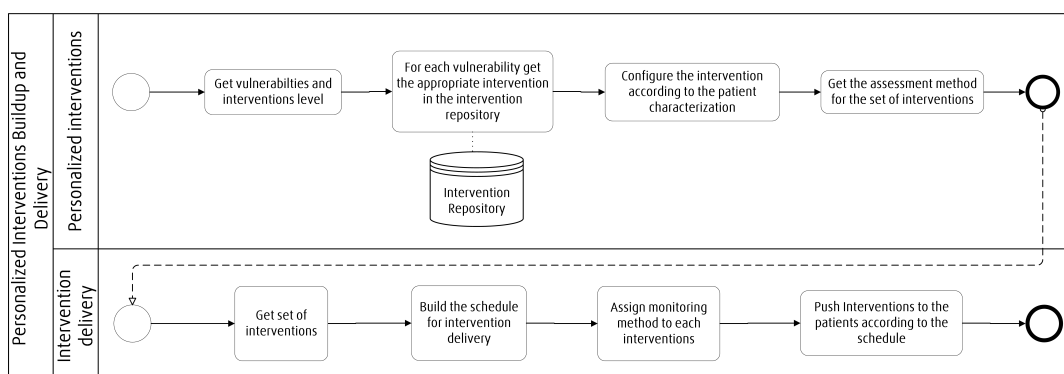


FIGURE 3.4: BPMN for the selecting, personalising and deliver interventions

3.4.1 Personalised interventions

Based on previously detected vulnerabilities, the model automatically retrieves the appropriate interventions from the intervention's repository. We associate each intervention with the vulnerabilities it addresses as we build the interventions repository. For example, the repository contain an intervention that include meditation to tackle the stress of the patient. We add a level of personalisation to the interventions by configuring them according to the patient. In the same sense as the meditation intervention, personalisation entails sending a reminder notification based on the patient's typical sleeping time. The model determines this configuration by analysing the severity of each vulnerability, i.e., for each impacting factor, we apply a dynamic threshold to classify it as low, medium, or high severity.

Additionally, the interventions include a method for assessing their efficacy. The various metrics that are measured prior to and following the delivery of interventions, as well as how these metrics are measured. Patient monitoring via multiple sensors and questionnaires to obtain qualitative data on the patient are the two most frequently used assessment methods. Assessment techniques vary according to these metrics and, thus, according to the interventions.

3.4.2 Intervention delivery

The patient pathway enables the model to schedule the set of interventions to be delivered to the patient automatically. Additionally, scheduling entails planning the assessment methods. This step is critical to avoiding incompatible interventions from overlapping and ensuring that the intervention is delivered in accordance with the patient's pathway.

We assign a monitoring method to each intervention or set of interventions. Since each intervention requires a unique assessment method, the monitoring of the interventions varies. Finally, we schedule the interventions to be sent directly to the *Sleep.Py* application. On the mobile application, the patient will consume the interventions directly. These interventions are in addition to those delivered via phone call by a homecare givers.

3.5 Intervention Consumption and Evaluation

It is unique to deliver homecare interventions via a mobile health solution. Indeed, the patient's Intention-To-Treat determines the consumption of interventions. Due to the dynamic nature of the HlaaS in terms of patient identification, intervention selection/personalization/delivery, the evaluation must be dynamic as well. We perform multiple tests at different moments Figure 3.5 illustrates how we collect and dynamically evaluate intervention consumption.

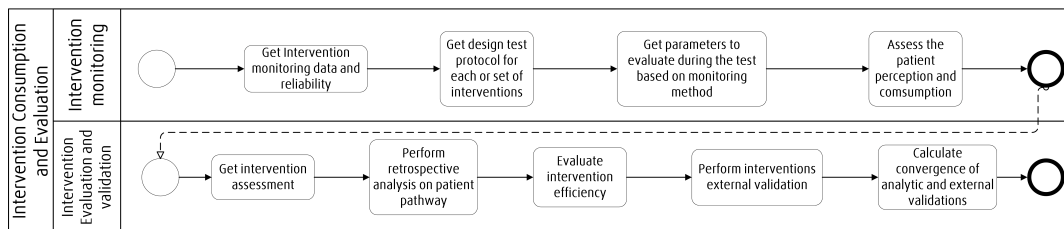


FIGURE 3.5: BPMN to monitor and evaluate the personalised interventions

3.5.1 Intervention monitoring

To collect pertinent feedback, we must first closely monitor the patient's intervention consumption. Each set of interventions is assigned a unique test protocol. We cannot conduct random control trials in this case because we are dealing with ever-adaptive interventions over time. However, we adapt the protocol for continuous evaluation of evolving behavioural intervention design to mHealth interventions [207]. This protocol enables the evaluation of intervention efficacy using a profile of intervention monitoring.

The intervention monitoring profile identifies the indicators that will be used to monitor the patient. For our CPAP therapy application, we have three intervention monitoring profiles:

- *Perception monitoring profile*: monitor the patients' perception of the interventions. We measure the patient through the questionnaires detailed in section 2.3.
- *Consumption monitoring profile*: monitor the patients' intervention consumption. i.e., the type and number of interactions of the patient with the CPAP

interventions. We measure these interactions using different logging levels in the mobile application.

- *Health monitoring profile*: monitor the different clinical indicators directly linked to the CPAP therapy. We have the adherence level. The CPAP device itself measures these data.

Each piece of monitoring data includes a metric for assessing the data's quality. This metric is calculated based on the monitoring's reliability, the variety of data it contains, and the volume of data it contains. For instance, when it comes to patient perception, we ask the patient to complete the same questionnaire at a different time to ensure the information's reliability by verifying data convergence. Monitoring data and quality metrics, on the other hand, are machine-readable data. We convert this data into multiple data visualization figures and dynamic thresholds based on the intervention monitoring profile to allow experts to assess the intervention's effectiveness. Various experts can then interpret the monitoring data to confirm the intervention's effectiveness.

3.5.2 Intervention evaluation and validation

To conduct a thorough evaluation of the interventions, we require a variety of data. The first piece of information is the outcome of the intervention's evaluation. Secondly, the outcome of the retrospective patient pathway analysis i.e. determines the patient's new therapeutic path.

For example, in figure 3.1, the blue path is the calculated patient pathway through multiple interventions consumption. If the patient achieves the goal, we can conclude that the interventions were effective. External validation from home care and CPAP experts is the final step in evaluating the intervention.

However, patient pathways are model-generated metrics that are difficult for experts to interpret. As a result, it is critical converting these metrics into a human-readable format that allows experts to validate the suggested interventions and configurations. We provide a comprehensive decision support tool that presents all relevant data to the expert in a human-readable format, such as line charts.

The results of expert validation can be compared to the results of the analysis. If these two results diverge, the model establishes a mechanism for continuous learning in order to improve the model in the subsequent iteration. In all cases, the model considers the expert validation to be correct, and the analytic models must be adjusted accordingly. As a result, HIaaS undergoes continuous improvement while verification and validation are carried out by integration experts.

3.6 Verification and Validation mechanisms

This section discusses our proposed verification and validation mechanism throughout the HIaaS framework. Multiple stakeholders play a critical role in the management of OSA patients through these processes. Due to the dynamic nature of the HIaaS in terms of patient identification, intervention selection/personalisation/delivery, the evaluation must be dynamic as well. We perform multiple tests at different stages of development to ensure that the system meets the requirements (verifications). The end solutions are also assessed to ensure that these solutions meet the end-users (patients and experts) true needs (Validations).

We firstly introduce the main stakeholders in this mechanism and more importantly the role of each of these stakeholders. Then, we present the verification process and finally, we detail the validation mechanisms. The figure 3.6 illustrated the overall process of the verification and validation collection. In the figure, the process in blue is specific to the verification and the process in green represents the validation process.

3.6.1 Analytic layer

The framework's analytical layer makes use of multiple data analytic models to process a large volume of data automatically. There are two primary data sources: CPAP telemonitoring and intervention monitoring. These processes will be discussed in greater detail later in this section.

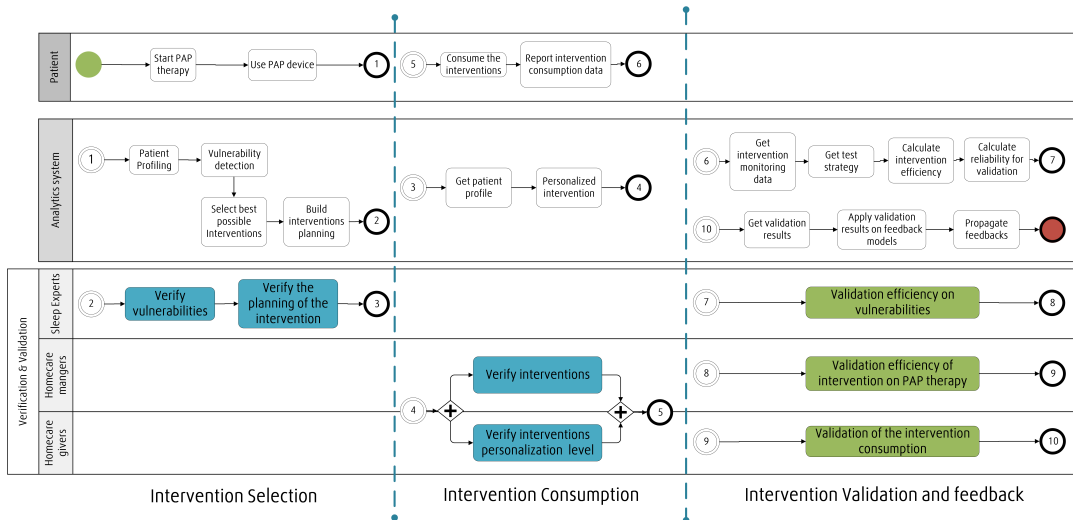


FIGURE 3.6: Verification (blue) and validation (green) mechanism for the HIaaS framework

3.6.2 Stakeholders

Patient

The patient is already diagnosed with OSA and is prescribed CPAP therapy by a sleep expert. During the installation of the CPAP device, the patient receives the mHealth solution.

Sleep expert

The sleep physician's primary responsibilities are twofold. To begin, verifying the analytic layer's intervention selection and scheduling. Second, establishing the intervention's efficacy in addressing the patient's vulnerabilities. This efficacy is validated by the intervention test strategy. Before that, the sleep expert screens the patient for OSA.

Homecare managers

Homecare managers are multi-therapy specialists who are responsible for a variety of homecare patients. This expert has a broad understanding of a diverse range of patient phenotypes. Additionally, the expert will schedule and monitor the interventions that will be delivered. As a result of the intervention monitoring data, the homecare manager verifies intervention scheduling and validates intervention consumption.

Homecare givers

The homecare giver is a homecare technician specialising in CPAP therapy. The homecare givers validate the direct impact of the interventions on the CPAP therapy only. They oversee setting up the CPAP device at the patient place. Moreover, they deliver in-person interventions throughout the therapy. For example, the homecare givers deliver essential information on the CPAP device and adjust the mask correctly during the initial phase.

3.6.3 Verification mechanism

IEEE Std 610.12-1990 defines verification as "The process of evaluating a system or component to determine whether the products of a given development phase satisfy the conditions imposed at the start of that phase" [208]. In other words, verification occurs throughout the development and implementation of the HIaaS framework to ensure that the final solutions meet the objectives specified in 1.2. The verification processes are performed by the sleep experts, homecare managers and homecare givers. Each of these experts verifies specific models according to their field of expertise.

We present the set of influencing factors to the sleep experts. The sleep experts evaluate each factor to verify its impact on CPAP therapy. For example, the sleep experts verify the threshold for the bedroom humidity level. Additionally, these experts verify the correlation between AHI and the patient's age in order to provide a more precise vulnerability detection based on AHI. Besides that, the sleep experts verify the intervention schedule. This verification is accomplished by simulating multiple scheduling scenarios for various patients, which are then verified by sleep experts. We are able to guarantee the scheduling models are optimal as a result of this verification.

The homecare managers and the homecare givers perform the verification in parallel. The managers verify all the interventions present in the intervention repository. According to this verification, we are able to determine if the developed interventions are appropriate for the CPAP patients. For example, for the physical interventions, multiple verification processes were needed to get the adequate end-product

that meets the expectations. There were various changes in the user experience and user interface.

Homecare givers are responsible for verifying the personalisation of the interventions. We present the homecare providers with various scenarios, and they evaluate each scenario to ensure that they are appropriate for the CPAP therapy. To demonstrate this point, homecare providers validate the daily step count objective associated with the physical activity intervention.

3.6.4 Validation mechanism

Validation processes are defined as "the process of evaluating a system or component during or at the end of the development process to determine whether it satisfies specified requirements" [208]. To validate the interventions and the different data analytic models, we must calculate each intervention's efficiency or set of interventions' efficiency. Firstly, the analytic layer retrieves the intervention monitoring data as well as the CPAP telemonitoring data. Secondly, we applied the appropriate intervention test strategy accordingly. As a result, the analytic layer automatically deduces the efficiency of the intervention. Finally, we compute the variety of data and data quality to get the reliability of the previous results.

The different experts use this reliability as decision support to validate the interventions at distinct levels. The sleep expert validates the impact of the interventions on the vulnerabilities detected by the patient profile. In other words, it validates any improvement in the health condition of the patient attributed to the interventions.

The CPAP expert performs the second level of validation. This step incorporates the validation of the impact on CPAP therapy. The CPAP expert uses three different telemonitoring data defined in the previous section, i.e., the adherence level, the residual apnea events, and mask leakage.

Lastly, the homecare expert validates the intervention consumption by the patient. This step is significant; it validates the compliance of the patient to the interventions only. The expert uses the intervention completion percentage and compares patients

in the same profile to validate this intervention consumption. Consequently, we deduce the efficiency of the personalisation for the patient.

The analytic level collects all the validation results from the different experts and uses these validations for feedback. A feedback model confronts the experts' validation with the validation carried out by the analytic layer. Based on these results, the framework will propagate the feedback to the different data models present in the analytic layer to improve the models' accuracy. To implement this propagation, we infer the models' feedback directly by adding weighted variables in the dataset and adjusting the thresholds of the decision support tools. Consequently, increase the efficiency of the personalised interventions to tackle the patients' vulnerabilities.

The presented framework integrates the recent advances in data analytics to validate different healthcare stakeholders. As a result, the HIaaS framework supplies multiple decision support tools to the stakeholders at critical moments in CPAP therapy, and this decision uses the feedback for continuous improvement. The framework can deliver a personalised patient follow-up to a large number of patients.

3.7 Feedback Propagation

We develop automatic feedback propagation in the various data analytic models to develop intelligence for the HIaaS framework. We detail the methodology for implementing this feedback propagation in this section. Additionally, we detail the feedback generation and classification processes that are critical for propagation. The figure 3.7 illustrates these three final steps within the context of the HIaaS framework.

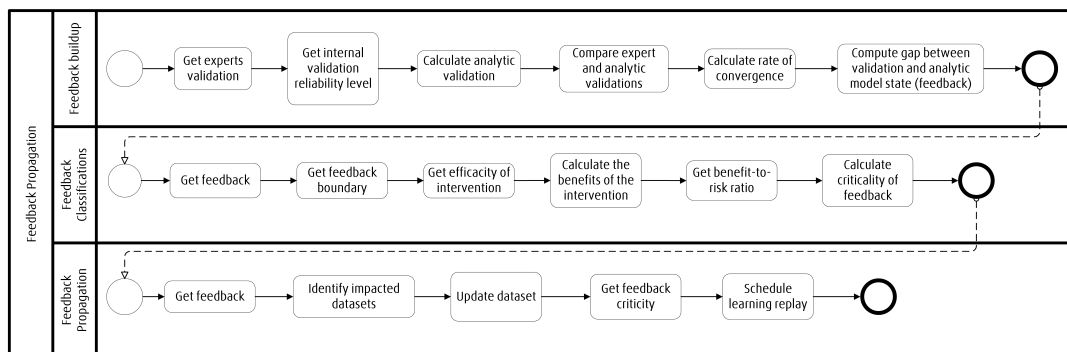


FIGURE 3.7: Patient timeline for the first 90 days of the CPAP therapy

3.7.1 Feedback build-up

Even though experts have validated CPAP interventions, we are unable to propagate this validation directly into the analytic models. For instance, if sleep experts do not validate the vulnerability detection for a particular patient, we must "translate" this validation. This "translation" entails determining which model and dataset are relevant to this validation. To accomplish this, we must develop feedback in the appropriate format for each of our models. We then calculate an empirical validation based on multiple clustering and machine learning models after retrieving the experts' validation. Clustering validates the patient profile (convergent validation), whereas machine learning validates the various predictions made (predictive validation). The machine learning model predicts the multiple clinic indicators that are used in the profile of health intervention monitoring.

The expert validations are then compared to the empirical validations using the rate of convergence of the two validations. If the two validations match, we conclude that the models have been thoroughly trained and tuned. If, however, the validations diverge, we must re-balance the models via feedback propagation. We never cast doubt on expert validation in our approach. We generate feedback by bridging the empirical and expert validation divide. We close this gap through the identification of diverging data.

3.7.2 Feedback Classifications

Prior to propagating the feedback, we must classify it in order to determine its criticality level. We can calculate the benefits of an intervention on health, consumption, or perception indicators by combining feedback and intervention efficiency. We assess the intervention's effectiveness on two fronts: intervention impact on CPAP therapy (e.g., increased adherence level), and patient perception of the intervention. Each intervention in the intervention repository is associated with a risk level. For instance, in an intervention to increase physical activity, the risk is that the patient will find it tedious to meet the daily step count goal.

We calculate the benefit-to-risk ratio for each intervention using the benefit and risk associated with it. The greater the value of this ratio, the greater the level of criticism.

In other words, when the benefits outweigh the risks, the criticality should propagate the feedback in the models. On the other hand, if the risks are low and the benefits are small, the level of criticality is low.

3.7.3 Feedback Propagation

For propagating, we retrieve the feedback that we previously accumulated. Our approach considers the fact that multiple experts will provide validation. Because each expert is an expert in his or her own field, we have a well-defined boundary for feedback propagation. For example, the physician will verify the patient's profile (clustering). As a result, we can easily identify the various models and datasets that influence patient profiling. To ensure proper feedback propagation, the feedback boundary must be clear and well-defined.

As a result, each HIaaS stakeholder plays a unique and explicit role. Sleep experts are constrained by patient profiles, patient pathways, and vulnerability models. Homecare managers have a direct influence on the content of the intervention repository and the scheduling of these interventions. Finally, homecare providers are bounded by the intervention personalisation model, which has as its primary objective maximising intervention consumption.

We can easily identify the impacted datasets using this feedback boundary. We update these datasets in response to feedback and thus align them with expert validation. As a result, a new dataset for training analytic models has been created. To schedule this training session, we retrieve the criticality of the previous section's feedback. The greater the level of criticism, the more rapid the training process. On the other hand, the lower the level of criticism, the shorter the training process. The modified dataset is used to train the appropriate models, which propagates the feedback.

3.8 HIaaS Meta-model

In the previous sections, we discussed the workflows and dynamic aspects of the HIaaS model. This section focuses on the meta-model that defines the structure of

the proposed framework's core components. This meta-model defines the mandatory classes required for HIaaS implementation. The meta-model incorporates the following five components: 1) events, 2) abnormalities & deficiencies, 3) interventions, 4) monitoring & validations, and 5) feedback & continuous learning. These five components are critical for the HIaaS framework's complete implementation and, as a result, for meeting all of our established objectives 1.2).

3.8.1 Events

The "events" package comprises the different statements needed to conceptualise the patient's lifestyle according to the therapy. Consequently, this package plays a crucial role in the patient profile and pathway build-up.

- **Event:** An event is a characteristic quantified at a particular point in the therapy. To be considered an event, certain conditions must exist prior to and following the measured moment. There are two distinct categories of events: primitive and composite events [209]. There are pre-conditions and post-conditions rules that validate the event detections. For example, the pre-requisite for physical activity is increased heart rate and a rapid increase in step count over a brief period. A sustained increase in heart rate over a period is considered the post-condition.

Primitive events are indivisible atomic events that occur at a specific time. Composite events are constructed from a collection of primitive and/or composite events. Additionally, the sequence of these events is recorded, as a different sequence results in another composite event.

- **Event Profile:** An event profile is a description of a collection of events that occur on the same real-world object, like all events linked to the patient's stress. The event profile is used to identify the event assessment processes that are most closely related to the event. Some of the event profiles include the patient's physiology, CPAP therapy monitoring, and home environment monitoring.

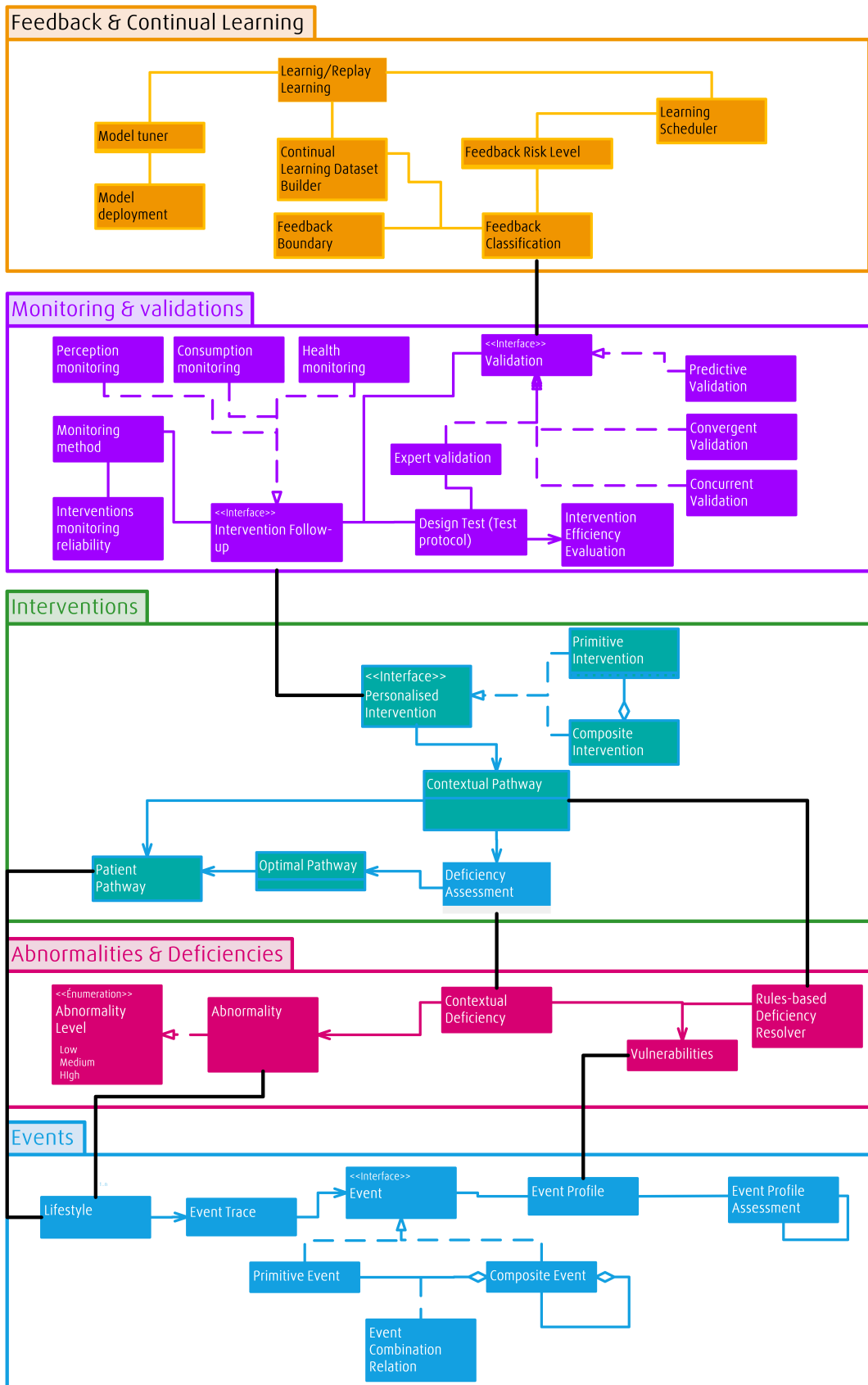


FIGURE 3.8: HlaaS meta-model

- **Event Profile Assessment:** An event profile assessment is a process of quantifying and evaluating an event profile. For instance, questionnaires were used to determine the patient's level of knowledge about the therapy, and sensors were used to monitor the patient's home environment.
- **Event Trace:** An event trace is a collection of events that occur over a specified time. The event trace is used to create clusters for a particular point in time.
- **Lifestyle:** A patient's lifestyle is a collection of his event traces. This collection of traces is critical for modelling the patient's entire scope. Additionally, the patient's lifestyle includes a description of how the patient is progressing with his therapy. The progression of this disease is determined by analysing the patient's various profiles.

The main feature of the "Events" package is the construction of a sequence of events that have an effect on each patient's therapy. Each patient's sequence is unique, and patients with similar sequences are grouped together under the same patient profile. Until now, the evolution of the factors involved in CPAP therapy has been undervalued. By associating a factor with a specific moment (an event), we can analyse evolving factors over time and their effect on the patient's therapy.

3.8.2 Abnormalities & Deficiencies

The "Abnormalities & Deficiencies" package uses the "Events" package's results to identify a single or a collection of abnormal patterns and vulnerabilities in the patient's therapy-related lifestyle. This package is critical for the system's automatic vulnerability detection.

- **Abnormality:** The "Abnormality" feature analyses the sequence of event traces (Lifestyle) for any abnormal behaviour in both the sequence and the individual event traces. As a result, we obtain the abnormal lifestyle and event trace. We employ a pattern recognition system on time-series event traces to detect any abnormal presence. We assign a risk level to each abnormality (low, medium, high). The more frequently an abnormality occurs, the higher the level of risk.

These three levels are already implemented in the different businesses of LHF. Hence, this approach eases the understanding of the stakeholders.

- **Vulnerabilities:** Each event profile (described in detail in the preceding section) is associated with a number of vulnerabilities. The vulnerabilities are directly derived from the factor repository to obtain the list of factors to analyse. Additionally, this ensures that all vulnerabilities discovered are compatible with the deficiency models.
- **Rules-based Deficiency Resolver:** The rules-based deficiency resolver is composed of several factors with associated thresholds. These thresholds are defined in consultation with the experts and data mining results. Each rule corresponds to a vulnerability. These rules are used to detect the vulnerabilities automatically and with minimal human intervention. Before adding a rule to this resolver, a sleep therapist verifies it.
- **Contextual Deficiency:** The contextual deficiency enables us to associate any abnormality with a vulnerability. Indeed, because abnormality detection is purely analytic in nature, we must match the abnormality to an explainable indicator (factor repository) in order to address it. To summarise, Contextual Deficiency encompasses all abnormalities that can be explained by a list of factors that sleep experts can interpret.

The package's results detail all vulnerabilities discovered in the patient's health-related lifestyle. Moreover, it also associated all of these vulnerabilities with factors that we can further analyse using the various data analytic models. Because sleep therapists validated the factor repository, they can interpret and verify the results.

3.8.3 Interventions

The "Interventions" packages enable the HIaaS to tailor interventions to each patient's specific needs. This package has two primary objectives: to contextualise vulnerabilities and to develop appropriate interventions based on that context.

- **Deficiency Assessment:** Each contextual inadequacy is automatically assessed about the vulnerabilities. This assessment thoroughly examines all vulnerabilities and abnormalities discovered in a patient. The assessment's findings provide a quantitative analysis of each patient's barriers to therapy. The result is a list of vulnerabilities, each of which is assigned a score. The higher the score, the more vulnerable the patient is.
- **Optimal Pathway:** We can construct the optimal pathway based on the deficiency assessment's computed score. The optimal pathway's objective is to reduce the deficiency assessment score. The scores are computed based on logistic regression and the constants defined by this regression. If the patient adheres to the optimal pathway strictly, all deficiency assessment scores should be equal to zero.
- **Patient Pathway:** The patient pathway is the relationship between the sequence of events (lifestyle) and the optimal path. The lifestyle is the "real" path the patient took in the past, whereas the optimal path is the "objective" path. We anticipate that the patient will eventually follow the objective pathway. This, however, may not be feasible due to the patient's condition or other factors.
- **Contextual Pathway:** The contextual pathway is the feasible patient pathway that we expect the patient can achieve. To calculate this pathway, we apply the rules present in the Rules-based Deficiency Resolver on the patient pathway and the deficiency assessment scores. We ensure that the contextual pathway is as close to the optimal as possible throughout this pathway construction process. Under perfect conditions, this contextual pathway is equivalent to the optimal path.
- **Personalised Intervention:** The contextual pathway serves as the foundation for personalised interventions. Each configuration of interventions is carried out in accordance with this path. Personalised interventions fall into two distinct categories: primitive and composite interventions (same distribution as

the events). The completed list of personalised interventions is the intervention repository.

As a result of this package, we have a contextual pathway that we anticipate the patient will follow. This pathway is comparable to the optimal pathway but has a higher probability of success. We are able to select, configure, and schedule interventions based on this contextual pathway.

3.8.4 Monitoring & Validations

The "Monitoring & Validations" package's objective was to contain concepts that would be used to monitor all interventions. Additionally, the package provides analytical evaluations of interventions alongside expert validations.

- **Intervention Follow-up:** The intervention follow-up regroups all the techniques of intervention monitoring. It is a generic module and each sub-module is implemented according to the situation. In our case there are 3 types of intervention follow-up:
 1. Consumption monitoring: mHealth solutions include logs for tracking intervention consumption via the mobile application.
 2. Health monitoring: Sensors placed on the patient or in this location to collect health-related data (section 1.1.1)
 3. Perception monitoring: Multiple questionnaires are used to ascertain the patient's perception. This perception monitoring is primarily qualitative in nature.
- **Monitoring Method:** It is not possible to generalise about each intervention. In conjunction with a monitoring method, follow-up is necessary. Sensors, for example, are one type of monitoring method, whereas questionnaires or direct interviews with the homecare provider are another type of monitoring method.
- **Interventions Monitoring reliability:** Each monitoring technique is supported by a reliability indicator. This is critical to ensure the reliability of each piece of

data collected during the analysis process. The manufacturer communicates the reliability of sensors, whereas the reliability of questionnaires is a more complex computation that is dependent on the patient pathway and is related to other assessment techniques.

- **Design Test (Test protocol):** We associate a specific test with each intervention or set of interventions. This test contains all scheduling and configuration information for the various "Intervention Follow-up" procedures. Additionally, the design test includes a schedule for stakeholder interventions as well as a schedule for the validation process for experts.
- **Intervention efficiency Evaluation:** Based on the Design Test, we can assess the efficiency of various interventions. This evaluation makes use of a variety of statistical analysis techniques. This evaluation includes multiple statistical analysis methods. For example, correlation evaluation, t-test, statistical description of variables, etc.
- **Validation:** Each intervention follow-up must be validated. However, due to the wide variety of this follow-up, there is no generic validation process. We describe different types of validation and a single intervention follow-up can be associated with one or more validation processes. For our usecase there are 4 types of validation:
 1. **Expert Validation:** The different experts validates the different process (Section 3.6).
 2. **Predictive Validation:** Validation of various predictive models analytically. The predictive validation process compares forecast data to actual data to determine these models' predictive capability.
 3. **Convergent Validation:** Convergent validation is another type of analytic validation in which two values are measured under identical conditions and the two values are expected to be highly correlated. The greater the correlation between these measures, the more convergent they are.

4. **Concurrent Validation:** The degree of agreement between two distinct assessments is referred to as concurrent validity. In general, one assessment is novel, whereas the other is well-established and has been validated.

The Monitoring & Validation packages result in the establishment of various test protocols that formalise the procedures for monitoring interventions. Furthermore, we have fully validated interventions, which are validated using the most appropriate stakeholder or technique. As a result, we can build feedback around these validations.

3.8.5 Feedback & Continual Learning

The goal of the "Feedback & Continual Learning" package is to develop feedback based on validation. More importantly, to provide guidelines for propagating this feedback across the various analytic models.

- **Feedback Classification:** To convert validation into useful feedback that can be used in analytic models, we must classify it strictly according to multiple criteria. In our case, we have two distinct classification systems. The first classification, which is a micro classification, is the task classification. Modify a record in a table, for example, or fine-tune the hyper-parameters of an algorithm. The other classification is macro. For instance, completely redesigning a model (algorithm change), creating a new analytic model, etc.
- **Feedback Boundary:** When it comes to feedback classification, the feedback boundary is a useful tool. Essentially, the feedback boundary is a set of rules for categorising feedback that has been predefined in advance.
- **Feedback Risk Level:** Each feedback has a risk level assigned to it based on the feedback classification and the nature of the validation that occurred during the feedback. The feedback risk level refers to the degree to which the feedback has an impact on the patient's treatment.
- **Continuous Learning Builder:** This continuous learning builder is responsible for making the connection between the feedback and the record/dataset/-model. This builder also builds a new record, dataset, or model that takes into

account the feedback received.

- **Learning Scheduler:** The learning scheduler determines when feedback should be propagated to the appropriate entity and when it should not. The schedule takes into account the degree to which the feedback is at risk of being incorrect. The feedback with a higher risk will be scheduled more quickly.
- **Learning/Replay Learning:** The Learning and replay learning class is responsible for executing the new entity created by the continual learning builder at the time specified by the learning scheduler.
- **Model Tuner:** The model tuner is responsible for fine-tuning the hyper-parameters of the various models. Besides, this also serves to perform the technical validation of the model in preparation for deployment.
- **Model Deployment:** Deployment of the models that include the feedback in the HIaaS framework.

Chapter 4

Implementations & Results

Following the methodology for developing the HIaaS framework in section 3, this section introduces the HIaaS implementation with its technical aspects and outcomes. The implementation is the instantiation of the meta-model (section 3.8). Consequently, this chapter contains the instances of the five main packages present in the meta-model, namely events, abnormalities & deficiencies, interventions, monitoring & validations, and feedback & continual learning. Before developing these implementations, we outlined the technologies and the overall architecture of this instantiation.

As stated previously, the meta-model provides a comprehensive implementation for personalised homecare intervention based on the optimal 5Vs of the big data. However, this is not optimal for our use case. Based on the available dataset, only a portion of the meta-model could be implemented. Throughout, this chapter we will indicate these unimplemented concepts. Nonetheless, this implementation is one of the most comprehensive within the OSA context (chapter 2). The various sections present validation and findings for future deployment on a large scale, as well as generalisation of the implementations with a more comprehensive dataset.

4.1 Technologies

For the implementation of the HIaaS framework, there are multiple technologies involved each for a specific purpose. We divide this section into four categories namely data storage, data analytics, back-end and front-end.

4.1.1 Data storage

We use 2 types of databases for data storage: SQL database and No-SQL database. SQL database schemas always represent tabular, relational data with rules for consistency and integrity. They consist of tables with columns (attributes) and rows (records), and their keys have constrained logical relationships [210]. On the other hand, the NoSQL databases do not comply with a structured data format [211]. NoSQL databases can be divided into 4 categories namely:

1. **Column-oriented** databases permit the efficient storage of high-dimensional data and individual records with variable attributes.
2. **Key-Value** stores are dictionaries that access diverse objects using a key that is unique to each.
3. **Document** stores contain semi-structured data: objects that contain all their own pertinent information and can be completely distinct from one another.
4. **Graph** databases augment documents with the concept of relationships (direct links between objects), enabling rapid traversal of highly interconnected data sets.

Microsoft SQL Server

Microsoft SQL (MSSQL) Server is a SQL database developed and maintained by Microsoft. We store the structured and relational data in this database. For example, the patient information, the intervention consumption monitoring and the CPAP monitoring data. Finally, MSSQL is already deployed at LHF and the historical monitoring data on the patients and stored in MSSQL databases. Consequently, using the MSSQL database would eliminate any interoperability issues, and we can apply the same security scheme.

MongoDB

MongoDB is a document-oriented NoSQL database. It is the most popular document-based database [212]. Consequently, there is a myriad of well-supported connector that speeds up the development time. The documents are saved in JSON format.

We chose this database in conjunction with MSSQL because we work with semi-structured data. Moreover, the external APIs for the CPAP real-time monitoring are encoded in the JSON format. For instance, MongoDB stores the schema and results of multiple questionnaires (Appendix E demonstrates the ESS in MongoDB). MongoDB also includes the game mechanism described in F.

4.1.2 Data analytics

In the two primary phases of data analytics, prototyping and model building, multiple technologies are employed. During the prototyping phase, we developed multiple proofs-of-concept (POC) to validate the data and model integrity and expected performance for deployment. For example, for regression in this prototype, we verify that the variables are independent. In addition, this phase of prototyping enables us to measure the various model metrics, such as the f1-score. After the prototype, we build multiple final models that are ready for deployment.

R

R is a programming language designed specifically for statistical computing. R contains all the fundamental and even advanced statistical methods, and libraries can be added to meet specific requirements. R is used for the prototyping phase because it enables rapid testing and implementation of multiple statistical methods. As R is a single-threaded programming language, it can be problematic when working with a large volume of data [213].

Python

Python is used for the model building phase and for the deployment of these models. To build these models we rely on multiple tools and libraries that can be an add-on to the base python programming language. We use the *Jupyter Notebook* to build the models. The Jupyter notebook facilitates the model building on a high-performance computer and facilitated the data visualisation when compared to base python scripts. We also use the *Scikit-learn* machine learning library in Python, This library includes the most popular machine algorithm.

4.1.3 Back-end

The back end of our implementation has two major features. At first, expose multiple Application Programming Interfaces (APIs) that will be consumed by the front-end and other information systems that utilised results from the various HIaaS models. Secondly, a workflow automation system that will utilise external APIs. We utilise APIs from multiple CPAP device manufacturers, such as Philips, to retrieve data collected by CPAP devices. We require an automated procedure to retrieve these CPAP monitoring data in "near real-time."

Flask

Flask is a lightweight web application and API development framework. This framework's purpose is to expose various APIs that will consume various resources, such as the results of machine learning models. It is designed to make getting started fast and simple, and it can scale to support complex applications [214]. Flask is constructed using the Python programming language. Since the data analytics models are already incorporated into Python, the integration of these models is seamless.

Apache Airflow

The Apache Airflow platform is utilised for consuming external APIs. Apache Airflow is a platform for authoring, scheduling, and monitoring workflows programmatically.[215]. Apache Airflow, like Flask, uses the Python programming language. Consequently, it also facilitates interoperability among the various technologies. We import numerous workflows into the Apache Airflow that are triggered by various conditions. For example, we automatically retrieve CPAP monitoring from the Philips server twice per day.

4.1.4 Front-end

The front-end is the information system that directly has a direct interaction with the different end-user. For our implementations, the front-end is made up of 2 mobile applications: Sleep.py and Sleep.py Experts. However, despite being a mobile

application, the application needs to be able to be deployed on tablets, especially for the Sleep.py Experts.

Flutter

Flutter is the app development framework developed and maintained by Google [216]. Create, test, and deploy mobile, web, desktop, and embedded applications from a single codebase. In other words, it is unnecessary to redevelop the application from scratch for different platforms such as Android and iOS. Flutter is used to develop both mobile applications (Sleep.py Experts and Sleep.py).

4.2 Architecture

In this section, we provide an overview of the architecture we deployed for the HIaaS meta-model implementation. Figure 4.1 shows the interaction between the different technologies presented in the previous section.

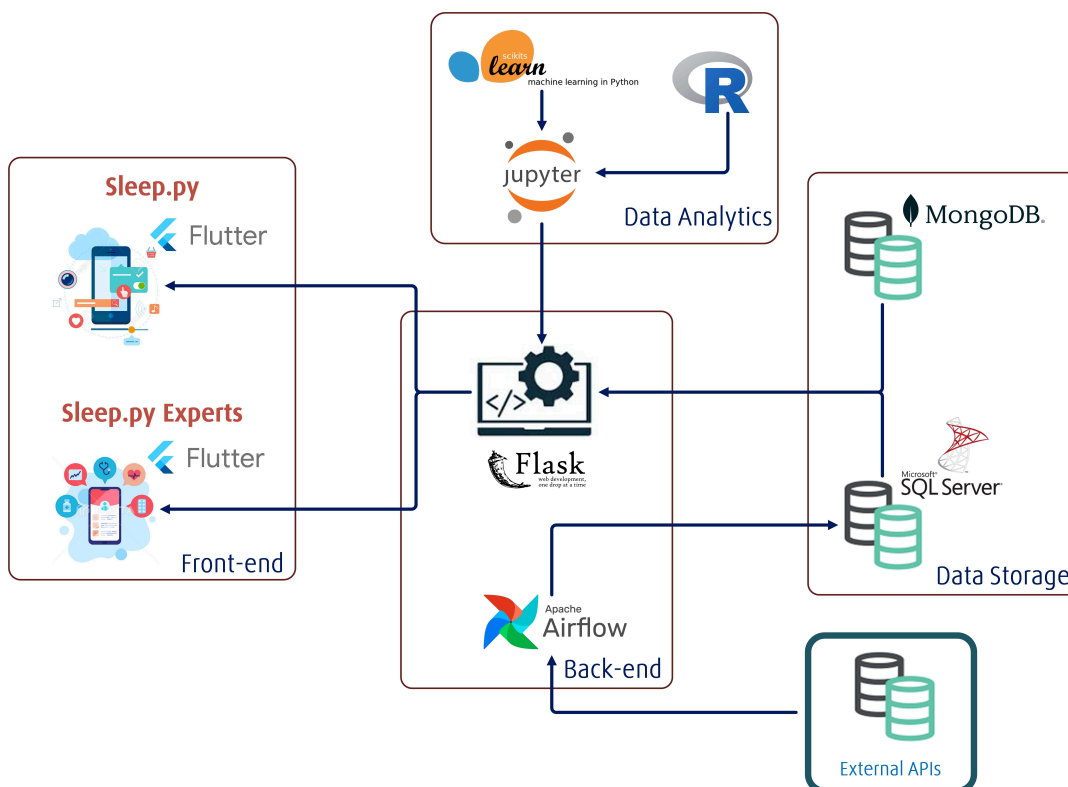


FIGURE 4.1: The architecture for implementing HIaaS framework

The two Flutter mobile applications (*Sleep.py* and *Sleep.py Experts*) consume directly the APIs made available by the Flask server. The Flask server is the master

system of the overall architecture where it contains multiple microservices. There are three microservices implemented:

1. Retrieve data from SQL databases: Connection to the multiple MSSQL databases that contain the Electronic Health Record and the monitoring data of all patients.
2. Retrieve data from NoSQL database: Connection to the MongoDB database that includes the document required for the different questionnaires and the intervention configurations.
3. Consume data analytics model: Consume the data analytics models that are deployed. For example, the Flask server consumes the adherence prediction model that was validated by R and deployed by Jupyter notebook.

The other back-end component is the Apache Airflow server. Multiple Python scripts are implemented on the Apache Airflow server to retrieve data from external APIs and store it in the MSSQL database. We implement an architecture that can be easily scaled up to respond to the 50 000 patients of LHF and include therapies other than CPAP therapy.

4.3 Events

4.3.1 Use case

We concentrate our attention on patients with recent OSA diagnoses. CPAP therapy or any other form of OSA treatment has never been prescribed to the patients in question. Patients are guided through a patient pathway that has been established by the French health authority and is considered somewhat effective [206].

Stratified sampling is used to determine whether 50% of patients meet the compliance requirement and 50% do not. On the basis of a sample of 668 patients, the analysis and implementation were carried out. Throughout the CPAP therapy, compliance data is collected for each patient. Patients who stop taking their medication more than three months after starting the therapy are barred from participating.

Installation of the CPAP device takes place directly at the patient's residence by a homecare giver. A variety of factors are evaluated by the technician prior to installation, including the patients' knowledge of CPAP therapy, their Epworth score, their motivation to use the device, and their AHI. As part of the device installation process, the technician educates the patient on the symptoms of OSA, the CPAP device, and the benefits of using it. Finally, with the assistance of the homecare giver, the patient selects the mask that is most comfortable for him or her. The patient receives a phone call from the same homecare giver three days after the installation was completed. The patient's response to the therapy as well as his or her comfort with the mask is evaluated.

After two weeks, the homecare giver intervenes again at the patient's home to solve any problem that the patient experienced with his therapy, for example, changing the type of mask for better comfort. The patient is again assessed on the same points that were addressed during the installation intervention. 90 days after the installation, the homecare giver visits the patient and reassesses the same points during the previous interventions and the phone call.

4.3.2 Event detections

We construct a new dataset containing primitive events. With the verification of the sleep therapists, the measurements made by the CPAP machine are deemed as an event regardless of any pre-condition or post-condition. There is a timestamp associated with each of these measurements, which are the adherence level, IAH, and mask leakage. There are also other primitive events detected, such as the patient's Epworth score, the results of their knowledge and motivation assessment on CPAP therapy, and their BMI. These primitive events, like the CPAP measurements, are associated with the date and time they were recorded.

Thus, we obtain a time-series dataset from which we can retrieve all events associated with a single patient. Table 4.1 shows an example of all the primitive events for the first 3 days of therapy for one specific patient. This dataset is used to construct event profiles (patient profiles) and event traces (patient pathways). However, due to the limitations of the available data, this implementation lacked composite events.

Patient ID	Event	Timestamp	Value
54892	Compliance	2019-09-06T10:50:27+0000	6.59
54892	Mask Leakage	2019-09-06T10:50:27+0000	2.56
54892	AHI	2019-09-06T10:50:27+0000	7
54892	BMI	2019-09-07T15:38:19+0000	27.6
54892	Initial ESS	2019-09-07T15:44:41+0000	14
54892	Knowledge	2019-09-07T15:44:58+0000	600
54892	Motivation	2019-09-07T15:44:59+0000	400
54892	Compliance	2019-09-07T18:08:06+0000	7.02
54892	Mask Leakage	2019-09-07T18:08:06+0000	3.45
54892	AHI	2019-09-07T18:08:06+0000	7
54892	Compliance	2019-09-08T16:16:15+0000	6.57
54892	Mask Leakage	2019-09-08T16:16:15+0000	2.68
54892	AHI	2019-09-08T16:16:15+0000	7

TABLE 4.1: Primitive Events for the first 3 days of therapy for patient 54892

Nonetheless, the procedure for constructing the primitive event dataset takes composite events from a different dataset into account.

4.3.3 Event profile - Patient Profile

For the usecase defined previously, we build two event profiles and clustering models. The first model interlopes shortly after the patient’s first homecare giver phone call (3 days after the beginning of the therapy). This also marks the beginning of the event trace construction. The second clustering model intervenes three days prior to the second home intervention by the homecare provider (10 days after the beginning of the therapy).

We develop the various models using the R and Python programming languages. We use *Scikit-learn* to build pipelines for automatic model building. After evaluating several unsupervised learning algorithms (section 2.1.3), we cluster the various event traces using the *K*-means algorithm. When compared to other algorithms, *K*-means builds clusters that are more compact and guarantee convergence.

The optimum number of clusters is obtained by running multiple iterations with a different number of clusters as hyperparameters to the *K*-means algorithm. The inertia intra-class and the Error Sum of Squares (SSE) of each cluster were then analysed to get the appropriate number of clusters (Figure 4.2). To find the best compromise

between the number of clusters and the quality of the clustering, we use the Elbow method [217].

Profile analysis for 3-days model

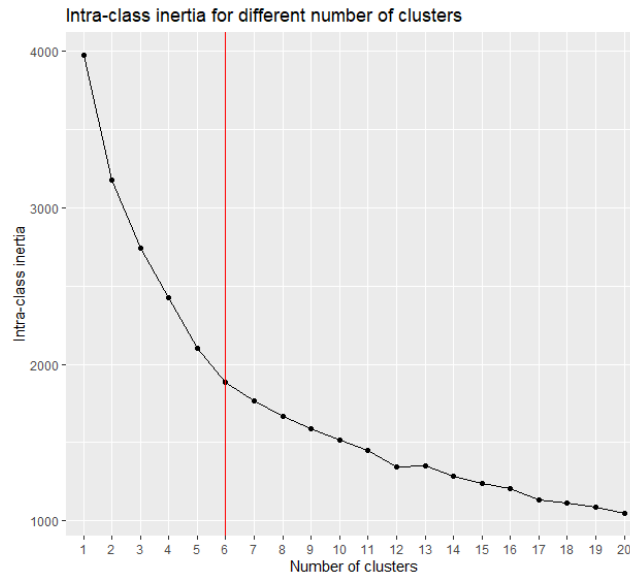


FIGURE 4.2: Inertia intra-class for K -means algorithm for the first model

Following the application of the Elbow method, we were able to identify six distinct patient profiles. Six profiles were found to be the most relevant after we scoured the data for additional profiles. We discovered, however, that the population of patients with a higher profile is far too small, in that these patients cannot be considered outliers and cannot be excluded from the implementation process.

One of the identified profiles has 80.34% of the patient utilising CPAP for more than 4 hours per night. One of the profiles, on the other hand, has 78.61% of the patients falling below the compliance threshold. In contrast, the other profiles are referred to as intermediate profiles because there is a nearly equal number of adherent patients and non-adherent patients who are receiving CPAP therapy.

Profile analysis for 10-days model

The graph 4.3 illustrates the SSE for the ten clusters. The Elbow method returns 3 as the optimal number of profiles. When we compared these profiles to the level of adherence, we discovered three distinct clusters: non-adherent, attempters, and adherent patients. Patients classified as non-adherent have an adherence rate of



FIGURE 4.3: SSE for K-means algorithm for the second model

fewer than 2 hours per night, attempters have an adherence rate of between 2 and 4 hours per night, and adherent patients have an adherence rate greater than 4 hours per night.

4.3.4 Event traces

We use the event profiles built previously for the patient's event trace, which were recorded for the first three days for the first model and for the first ten days for the second model, respectively. When dealing with this situation, we store the results of the first and second clustering in the database in order to obtain the first trace. As a result, we obtain **18** different traces (6×3 clusters). When a new event profile is assigned to a patient, the event trace will be updated as soon as it is assigned. The interpretations of these event profiles and event traces are carried out in the next section.

4.3.5 Lifestyle - Real Patient Pathway

Each event trace and event profile is analysed based on the factors defined in the "factor repository." The "factor repository" is composed of all the distinct events present in the dataset for the purpose of constructing the event profile. This includes adherence, mask leakage, AHI, BMI, initial ESS, knowledge, and motivation. Consequently, as the dataset evolves, so will the "factor repository". The factors present in the repository were presented to sleep therapists for verification before interpretations. However, we were able to interpret only the trace present in the table

Event Trace	Event profile 3 day	Event profile 10 day	Interpretation
1	1	1	All indicators right
2	2	1	Non adherent to adherent
5	5	1	Mask leakage to OK
7	1	2	Adherent to attempters
8	2	2	Constant attempters
11	5	2	Mask leakages with attempters
13	1	3	Adherent to non-adherent
14	2	3	Constant non-adherent
17	5	3	Mask leakages with non adherent

TABLE 4.2: Lifestyles and interpretations for event traces (Patient Pathway)

4.2. The other traces were unrevealed but there was no specific set of factors for interpretations.

4.3.6 Discussions

For the implementation of the event detection models, we were bounded to our data collection. We were able to detect only 3 primitive events namely, compliance, mask leakage and AHI. However, the event detection models can be extended to different events and can be used to detect composite events. We also implemented 2 patient profiling models at 3 and 10 days of CPAP treatment. The first model built 3 profiles and the second model build 6 different profiles. While combining these models, we obtained 18 different and unique event traces. In the initial phase, there are many generated profiles as it is the crucial part of the therapy where the patient pathways are crucial [202]. Despite detecting only 3 primitive events, we were able to generate 18 patient pathways that will be used for the personalisation of the interventions.

4.4 Abnormalities & Deficiencies

The abnormalities & deficiencies consists of using the event profiles and lifestyle interpretations to detect the different hurdles of the patient in the CPAP therapy. There are two main implementations in this section; the vulnerability that analyses the event's profile for short-term analysis and the abnormality detection in the lifestyle interpretations for long-term analysis. The results of these analyses give all the indicators for the interventions.

4.4.1 Vulnerabilities

To identify the patient's vulnerabilities, we define thresholds for each of the three CPAP device measurements (adherence level, mask leakage, and AHI) in collaboration with sleep therapists and homecare managers. These thresholds are used to analyse the various profiles defined in section 4.3.3. The thresholds are described by the following three figures (figure 4.4, figure 4.5 and figure 4.6). Since the latter is defined in collaboration with specialists, we hypothesise that these values have been verified.

Description	Good Adherence	Acceptable Adherence	Low Adherence	Non adherence
Threshold	<2	$\geq 2 \wedge \leq 4$	$> 4 \wedge \leq 6$	>6
Score	0	1	2	3

FIGURE 4.4: Vulnerability Detection: Adherence Thresholds

Description	Good Leakage	Acceptable Leakage	High Leakage	Very High Leakage
Threshold	<6%	$\geq 6\% \wedge \leq 9\%$	$> 9\% \wedge \leq 12\%$	$\geq 12\%$
Score	0	1	2	3

FIGURE 4.5: Vulnerability Detection: Mask Leakage Thresholds

Description	Good AHI	Acceptable AHI	High AHI	Very High adherence
Threshold	<5	$\geq 5 \wedge \leq 10$	$> 10 \wedge \leq 20$	>20
Score	0	1	2	3

FIGURE 4.6: Vulnerability Detection: AHI Thresholds

Each threshold is assigned a score ranging between 0 and 3. The higher the score, the more vulnerable the patients. Consequently, we can perform the analysis of each profile automatically. We developed a Python script that automatically computes the score for each profile and stores it in the SQL database alongside the profile. To determine this score, the script calculates the median value for each CPAP measurement. Each new patient is assigned with an event profile, the script is automatically executed through Apache Airflow.

4.4.2 Abnormality

The abnormality detection implementation primary goal is to detect abnormal lifestyle of the CPAP therapy according to the CPAP therapy. This detection solely relied on the lifestyle interpretations. As a result, we have the analysis of all the event traces and the vulnerability associated with all the the event profiles. To define the abnormality of an event trace, we sums up the score of all the events profile in the trace coupled with the adherence prediction.

Adherence prediction

Adherence prediction is a critical component of the patient pathway discussed in section 3.3.3. In this implementation, we develop a model to forecast adherence levels 30 days, 60 days, and 90 days after initiating CPAP therapy. We predict the patient's adherence level at the end of the initial phase using supervised machine learning algorithms.

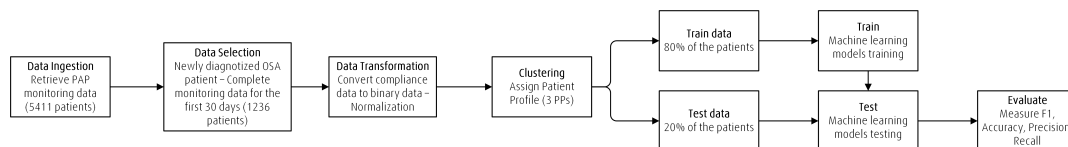


FIGURE 4.7: Adherence prediction model prediction based on Machine Learning

We use the pipeline detailed in the figure 4.7 to train these algorithms. The first step is data ingestion, which involves obtaining data from various data sources. The learning process makes use of both quantitative and qualitative data (CPAP monitoring). We collect quantitative data on the first ten days of adherence, mask leakage, and AHI. Homecare givers collect qualitative data in order to evaluate patients on three dimensions:

1. *Health Literacy* of the patient on CPAP therapy; the patient's level of knowledge on a variety of topics related to CPAP therapy
2. *Motivation* of the patient's compliance with CPAP therapy
3. *Epworth score* (Appendix A) obtained through self-assessment of the patient's OSA severity and the effect of CPAP therapy on OSA and daytime sleepiness

We chose patients who were newly diagnosed with OSA between *01/08/2017 and 30/10/2020*. It is critical to select these "new" patients because this is an essential phase of CPAP therapy. Additionally, we exclude patients whose qualitative and quantitative data are missing for the first 30 days. At the conclusion of the data selection process, the dataset contains **1236** patients.

To improve the data's predictive capacity, we convert it to binary data. When the level of adherence is $<4\text{h/night} = 0$ and $\geq 4\text{h/night} = 1$. Additionally, we normalise the qualitative data to facilitate the use of machine learning algorithms such as logistic regression. First normalising the data, we scale it between 0 and 1. After that, we normalise the data to ensure that they have a normal distribution.

Following data transformation, we create patient profiles for each of the 1236 patients. We use the K-Means model developed in the section ?? to assign the patient profile. We have 333 patients in the non-adherent profile, 629 patients in the adherent profile, and 274 patients in the attempters' profile from the initial dataset. Finally, we divide the training and test datasets in an 80:20 ratio to train the machine learning models.

As demonstrated in section 2.1.1, there is no optimal supervised algorithm for all data. We compare several machine-learning algorithms, including Logistic Regression, K-nearest neighbours, Naive Bayes, Support Vector Machine, and Adaboost. By comparing various algorithms, we can determine which one is the most effective for our dataset.

Algorithm	30 days prediction					60 days prediction					90 days prediction				
	Precision	Recall	F1-score	Accuracy	ROC AUC	Precision	Recall	F1-score	Accuracy	ROC AUC	Precision	Recall	F1-score	Accuracy	ROC AUC
Logistic Regression	0.81	0.88	0.84	0.81	0.87	0.75	0.84	0.79	0.75	0.82	0.73	0.81	0.76	0.72	0.8
K-nearest neighbours	0.75	0.89	0.81	0.75	0.77	0.69	0.84	0.76	0.7	0.72	0.68	0.8	0.73	0.67	0.7
Naive Bayes	0.84	0.83	0.83	0.8	0.87	0.76	0.79	0.78	0.75	0.82	0.75	0.78	0.76	0.73	0.8
Support Vector Machine	0.77	0.91	0.83	0.78	0.86	0.7	0.88	0.78	0.72	0.81	0.69	0.88	0.77	0.71	0.78
Adaboost	0.82	0.85	0.83	0.8	0.85	0.77	0.8	0.78	0.75	0.81	0.74	0.78	0.76	0.73	0.79

TABLE 4.3: Comparison of different Machine Learning Algorithm

Table 4.3 shows the results obtained when comparing these machine learning algorithms. To analyse the results, we use the f1-score [218] and ROC AUC [219]. Especially the ROC AUC gives a metric on how the machine learning model is capable of distinguishing between the patients $<4\text{h/night}$ and $\geq 4\text{h/night}$. The most fitted algorithm in our case is the Logistic Regression classifier.

The Logistic Regression classifier is the best fitting algorithm for predicting the adherence at 30, 60 and 90 days. This result always us to complete the patient pathway with the combination of a patient profile and the adherence prediction. Moreover, these results underline the importance of the initial phase for adherence in the long term since the adherence trend for the first two months gives the adherence trend for almost the rest of the therapy. The goal of the HIaaS model is to have a direct impact on this pathway to help the patient to comply with the CPAP therapy.

Abnormality classification

As stated previously, the overall abnormality score is derived from the vulnerability score and the adherence prediction. For the 30-day forecast, we employ the same threshold shown in figure 4.4. In addition, we apply a 1.5x multiplier to the calculated score. For illustration, if the score determined by the threshold is 2, the final score will be 3 (2×1.5). To compute the global abnormality score, we add the vulnerability of each event profile in the event trace and the adherence prediction score. Then, we can detect and classify the anomalies. The greater the abnormality score, the greater the likelihood of an abnormal lifestyle. However, we were unable to implement the abnormality level because, for instance, our event traces contain only two distinct event profiles. In addition, not every trace was fully characterised.

4.4.3 Discussions

For the 3 primitive events detected, we defined thresholds for each of them to detect the vulnerabilities. These thresholds are fully validated by sleep experts. Throughout the implementation, these values were never changed. However, these thresholds should be dynamic in future implementations. With dynamic thresholds that adapt to each patient, we can obtain a deeper personalisation level for patient management. To classify the detected vulnerabilities, we built an adherence prediction model based on the Logistic Regression classifier. This predictive model, only predicts if a patient will comply or not with the CPAP therapy. Further tweaking to the model can be done in order to predict a more in-detail compliance prediction. For

example, we can predict attempters, non-adherent and adherent patients instead of only adherent and non-adherent.

4.5 Interventions

For the interventions package, we implemented the intervention repository through the Sleep.py mobile application. For instance, we implemented primitive interventions and composite interventions are not yet implemented in this thesis. Despite being primitive interventions, multiple of these primitive interventions are delivered to the patient.

4.5.1 Intervention Repository

The Sleep.py application targets uniquely patients suffering from OSA. The application includes multiple CPAP interventions based on the literature review presented in section 2.2.2. However, Sleep.py has the most CPAP interventions implemented in a single mHealth solution. Furthermore, we can personalise each intervention and its dosing based on the patient profile and the feedback. Our Sleep.py has 5 majors interventions:

1. Motivational and educational interventions through situation game to have seamless interaction with the patients
2. Diet interventions by measuring the daily food intake of the patient
3. Increase physical activity interventions by counting the daily step count
4. Provide regular sleep cycles to the patient through an automatic alarm
5. Help the patient to manages his anxiety through meditational interventions

4.5.2 Motivational and educational interventions

We implement a serious game in the Sleep.py app called the situation game. The application put the patients in different situations allowing us to assess the patients' knowledge. To put the patient in the situation, we implement multiple mechanisms, through text and images. To assess the patient, either the patient has a set

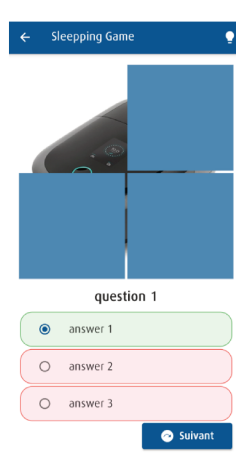


FIGURE 4.8: "Reveal the image" game



FIGURE 4.9: Find the wordgame



FIGURE 4.10: Maximum daily calorie intake



FIGURE 4.11: Food scanning

of multiple-choice questions and in the end reveals an image (figure 4.8) or to find the word that matches an image in an alphabet grid (figure 4.9).

Through this game, we provide educational interventions since all the questions are related to sleep and CPAP therapy. At the end of the assessment, the patients gain points, and these allow the patients to unlock new situations. We detail the education game "Know My CPAP" appendix F. As a result, we have a motivational intervention through this system. For further motivation, we assign more points to the patient based on the adherence level to the CPAP therapy. In addition, we can personalise the situation game by varying the difficulty level and changing the frequency of the delivery of the interventions.

4.5.3 Food intake monitoring

To provide the diet intervention, we set a maximum daily calorie intake for each patient (figure 4.10). We calculate this maximum calorie intake, we use the patient's sex, age, height and weight. Each patient self-reports their height and weight. To help the patient to track the number of calorie intake, we implement a food scanner (figure 4.11). The patient uses Sleep.py to scan the barcode of the product and then the application automatically calculates the number of calories for 1 portion. This intervention gives the patients the convenience to track in real-time their calorie intake to achieve their goals.

4.5.4 Step Count

In the same vein as the food intake monitoring, we provide the patient with a number of steps to perform daily (figure 4.12). The smartwatch measures the step count, physical activity and calorie burning by the patient. Of course, the daily maximum calorie intake varies according to the number of calories burnt. Moreover, the patient can visualise his historical data on the step counts. As part of the situation game and the patient empowerment, the patients receive points if they fulfil the objective step count. The points will allow the patients to unlock new levels in the situation game.

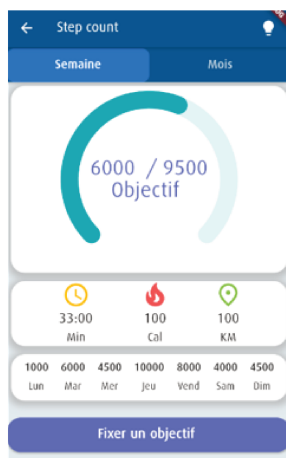


FIGURE 4.12: Daily Step counts



FIGURE 4.13: Smart alarms

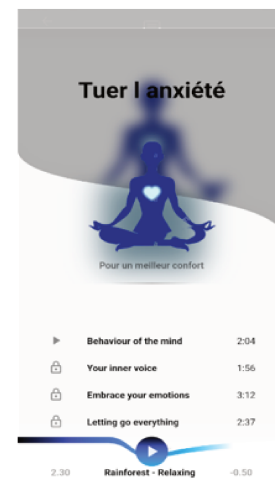


FIGURE 4.14: Meditation Playlist

4.5.5 Smart alarm

The smart alarm allows the patient to select their sleep time or wake-up time based on the sleep cycles of each patient (figure 4.13). We measure the sleep cycles with the smartwatch and the PPC device itself. The patients can select at what time they want to sleep and Sleep.py automatically set the alarm at the appropriate time according to the sleep cycle. On the other hand, the patients can select at the time they want to wake up and the application will send a notification when the patient needs to sleep.

4.5.6 Meditations

To help the patient to sleep and cope with the stress or claustrophobic tendency, Sleep.py provide a meditation playlist. Figure 4.14 shows one of these playlists that

contain a set of relaxing sounds. There are multiple playlists with videos that teach the patient how to meditate according to stressful situations. This intervention focuses on the stress and claustrophobic tendencies towards the CPAP device and the mask they have to wear every night.

4.5.7 Discussions

There are five interventions in the intervention repository, each of which addresses obstacles a patient may face during CPAP therapy. These interventions are geared toward empowering patients in order to increase their adherence to therapy. All of these interventions are delivered through the Sleep.py mHealth solution's serious game. We are continually adding new interventions to the intervention repository, and we anticipate an increase in the number of interventions that can be delivered to patients over time. Consequently, we would be able to further accommodate the lifestyles of our patients. Moreover, each intervention is entirely customisable. Consequently, they can be applied to other homecare therapies.

4.6 Monitoring & Validations

4.6.1 Patient monitoring

We implemented two primary types of monitoring for the patient: monitoring of consumption and monitoring of patient perception. The monitoring of consumption entails tracking how patients interact with the Sleep.py application and the various personalised interventions. Patient perception monitoring involves delivering validated and tested questionnaires to patients.

Consumption monitoring

In the mobile application, we implemented an advanced logging system for consumption. We monitor the amount of time a patient spent using the mobile application. With this period tracking, the start date/time and end date/time are associated.

As part of the intervention consumption monitoring, we record each patient interaction (click and input) with the mobile application. Based on our internal testing, this monitoring enables us to generate data at a high velocity.

Patient perception monitoring

We include a specific questionnaire module in the Sleepy.py to deliver questionnaires. This module interprets the questionnaires JSON document in MongoDB (an example is provided in appendix E) and displays them in Sleep.py. This module is flexible enough that adding new questionnaires to the database does not require programming knowledge. Simply convert the questionnaire into the predefined JSON format and insert it into MongoDB. This flexibility is essential because, as described in section 2.3.1, the Sleep.py application can incorporate a wide variety of questionnaires.

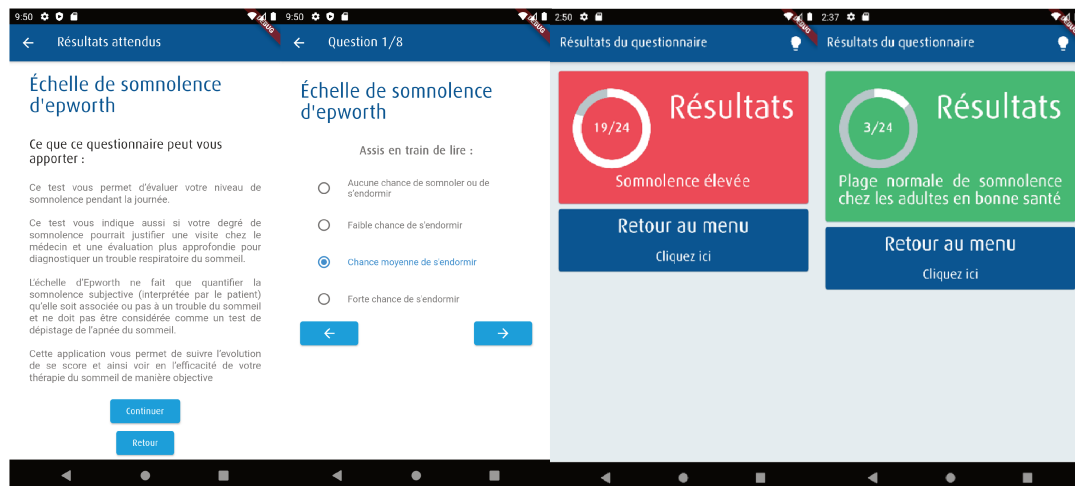


FIGURE 4.15: The ESS in the Sleepy.py application

Figure 4.15 exhibits the questionnaire module interpreting the ESS JSON file and displaying the questionnaire within the Sleepy.py mobile application. At the conclusion of the questionnaire, we provide the patient with a thorough explanation of the questionnaire's results. We not only save the final results of the questionnaire but also the responses to each question. In each questionnaire, we apply the same consumption monitoring principles, which include tracking the patient's interactions and the time spent on each question.

4.6.2 Expert validation

There is a dedicated application for the different experts called Sleep.py Expert. This application firstly helps the experts to provide personalised CPAP patient management. Secondly, we collect the expert's verification and validations through Sleep.py Expert. Consequently, there is a close interaction between the Sleep.py Expert and SLeep.py applications, we detailed this interaction in the section 4.6.2. The Sleep.py Expert app also logs how the expert consumes the application through different logging levels. We develop 2 major features for this application:

1. Monitoring the different data collected on the patient's health and the patient's environment
2. Provide the most appropriate configurations for the CPAP therapy and collect the feedback on this prediction

Monitoring dashboard

To provide personalised CPAP patient management, the Sleep.Py Expert app provides multiple dashboards to monitor the patients. Figure 4.16 show the dashboard homepage. There are 3 main categories of monitoring data:

1. Sleep data: data collected by the CPAP device itself. The expert can visualise the adherence level, mask leakage and AHI
2. Physical activity data: data collected by the smartwatch. The smartwatch measure, the daily step count, number of burnt calories and the training sessions done by the patient
3. Miscellaneous data: data collected by the multiple sensors like the CO2 sensors and information self-reported by the patient. The experts can visualise the patient's indoor environment and patient's weight

PAP therapy configuration prediction and feedback

To go further in personalised patient management, the application supply multiple decision support tools to the experts. These tools focus on the CPAP therapy configuration. The mask selection is crucial for a good CPAP therapy Figure 4.17 shows

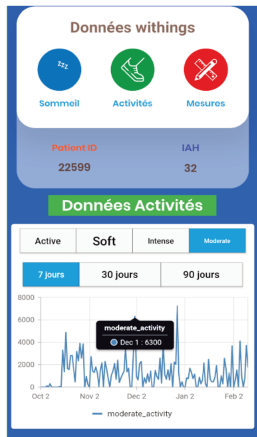


FIGURE 4.16: Patient's dashboard

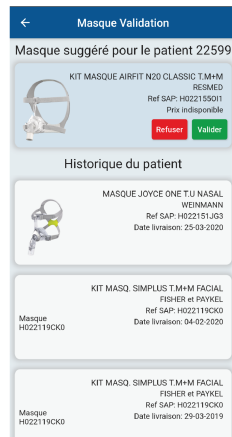


FIGURE 4.17: Predict the appropriate mask

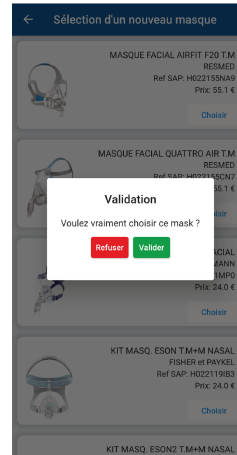


FIGURE 4.18: Mask validation



FIGURE 4.19: Predict the appropriate CPAP device settings

our tool for helping the expert to select the appropriate mask according to the patient profile. However, the application gives the expert the option to accept or reject the suggested mask through the popup shown in figure 4.18. We save the expert choice for this validation. Furthermore, if the expert rejects the suggested mask, the application calls the experts to fill up a questionnaire to build the feedback. Another important component of the CPAP therapy is the comfort settings of the CPAP device. The application suggests the appropriate comfort settings (figure 4.19) for the technician to apply on the CPAP device. Again, the expert can accept or reject the suggested settings. Furthermore, we apply the same mechanism to collect the validation and build the feedback.

Interaction between Sleep.py Expert and Sleep.py

Sleep.py expert and Sleep.py are 2 complimentary applications. The sequence diagram in figure 4.20 shows the detailed interventions between these 2 mobile applications and their end-users. For this authentication, we employ the OAuth 2 protocol [220]. After the authentication, Sleep.py requests the interventions to be delivered to the patient. The sleep expert verifies the set of interventions to deliver and the homecare expert verifies the personalisation level of these interventions based on the patient profile.

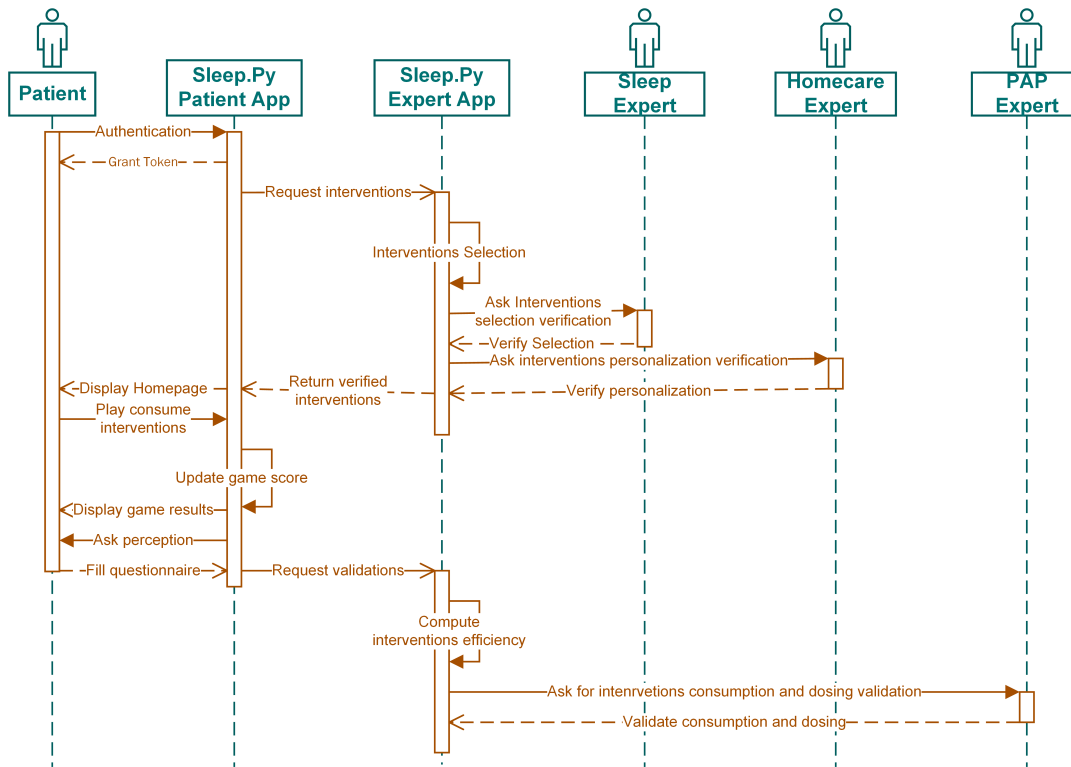


FIGURE 4.20: Interaction between the mobile application and the stakeholders

Sleep.py delivers the interventions for the patient to consume. To monitor the intervention consumption, we log all the patient's interactions with the mobile application. Finally, at regular time intervals, we request the patient to fill up multiple questionnaires to assess the patient's perception. Finally, the CPAP expert validates the impact of the interventions on the patient.

4.6.3 Discussions

In addition, to the Sleep.py application, there is the Sleep.py Experts application which is intended to be used by sleep, homecare and CPAP experts. Sleep.py contains multiple decision-support tools that help the different stakeholders to deliver the appropriate interventions to the patients. Furthermore, both applications (Sleep.py and Sleep.py experts) push forward multiple self-reporting questionnaires. These questionnaires are important for patient monitoring and the validation process. We constantly add new questionnaires to the two mobile applications to collect more accurate data. However, we rely solely on questionnaires and this can induce some bias in some results. To tackle this issue, we expect to deploy the applications on a large scale and we are currently multiple feedback channels.

4.7 Preliminary tests on the patient

Before a full deployment of the different mHealth solution, we carried out a test on patients to test the feasibility deployment of personalised interventions. As this test was performed before the implementation of the mobile application, we deliver personalised phone call interventions to the patients. We analyse the impact of the personalised phone call on the adherence level and impact on the internal processes of LHF.

This implementation concerns only two profiles: non-adherent and attempters patients. Adherent patients were excluded because they already have an efficient adherence level. The interventions consist of a homecare giver who calls the patient; the homecare giver is specially trained to motivate the patient in using CPAP therapy. The expert conducts only one phone call, and if the patient is unreachable, the expert attempts to call the patient three more times. If the patient is still unreachable, then we exclude the patient from this study.

The other selection criteria for this study are that the selected patients are not in the initial phase, and the patients must have CPAP therapy for less than two years. The patients received the personalised phone call at least six weeks after the initial phase, For this study, there are 1680 patients: 717 non-adherent and 963 attempters patients.

	Non-adherent	Attempter
	717	963
Mean compliance 6 weeks before interventions (h/night)	0.95±0.04	2.91±0.05
Mean compliance 1 week after interventions (h/night)	1.90±0.06	3.92±0.05
Mean compliance 6 weeks after interventions (h/night)	1.97±0.06	3.60±0.06
Median compliance 6 weeks before interventions (h/night)	0.55	3.13
Median compliance 1 week after interventions (h/night)	1.39	3.95
Median compliance 6 weeks after interventions (h/night)	1.50	3.62

TABLE 4.4: Adherence for personalised phone interventions

Table 4.4 shows the impact of the phone call on the adherence level at a different time (1 week and six weeks after the interventions). We use the 2-sample t-test to compare the means of the adherence between and after the interventions. The default null

hypothesis for a 2-sample t-test is that the two groups are equal, $\alpha = 0.05$, and if P-value is $< \alpha$ then the null hypothesis is rejected.

For the non-adherent patients, when comparing the adherence six weeks before the interventions to one week and six after the interventions, the adherence level increased by 0.95h/night and 1.02h/night, respectively. For attempters, the adherence level increased by 1.01h/night and 0.69h/night. The t-test reveals that the adherence level before and after are different for both non-adherent and attempters patients. These results show that personalised interventions are useful for increasing the adherence level to CPAP therapy.

Chapter 5

Discussions & Future Works

The benefits and potential of the HIaaS framework and the various implementations detailed in the preceding sections are discussed in this section. The section discusses also its limitations and future work for this thesis. We put the findings of other studies that have addressed the same issue in our context. Finally, we enhance the importance of the benefits of a patient-centric approach for homecare. . .

The HIaaS framework is a data-driven approach. We develop the HIaaS framework while considering the new dataset that LHF is currently deploying. That is to increase the number of sensors at the patient's home, increasing the variety and velocity of the data. As a result, the overall framework's success relies on a high variety, volume, and velocity of the data. It is possible that the HIaaS output would not be optimal if one of these factors were inefficient. To address these concerns, we provide a minimum generic set of interventions available to all patients. The perspectives of this thesis are to develop additional backup scenarios that use "small" data.

Different stakeholders verify and validate our HIaaS framework, which is used as feedback to readjust the other analytic models automatically. However, we never questioned the verification or validation results, even if the experts incorrectly performed the verification or validation. In other words, we incorporate these results directly into the feedback. We can compare the results obtained from stakeholders with the data model's results. When there is a significant divergence between the two results, we can investigate the divergent results in detail rather than using the expert results directly as feedback.

In this research, patients are assessed by various homecare givers and managers. Even though all these experts received the same training, their assessment methods and perceptions vary slightly. As a result, the outcomes of these assessments may vary. For future trials, a standardised questionnaire should be used to target the experts to obtain less expert-dependent results specifically. A cohort of experts must be used to evaluate and validate the questionnaire. In this thesis, we could not validate the questionnaire as we had only one sleep expert included in the study. We plan to perform this evaluation and validation in future work.

Validation, and feedback propagation, in most cases, the different stakeholders perform the validation at different rates. As previously stated, the various stakeholders are mutually dependent. At some point, despite a critical situation, we may not have a complete validation process. We can clearly define specific situations in which the criticality is too high to delay feedback propagation until the validation process is complete. For instance, one of these critical situations may occur when a large number of patients experience a significant drop in CPAP adherence over a short period.

Based on the available dataset, we were unable to implement the meta-model in its entirety. However, based on the LHF new project, the patient's home will be equipped with sensors to collect new patient data. We anticipate that with this new dataset, we will be able to fully implement the metamodel. In addition, the lifestyle interpretation was solely focused on CPAP therapy; with this new dataset, we intend to expand this interpretation to include other patient health issues.

Bailly et al. and *Wang et al.* already use the K-Means clustering algorithms for defining multiple patient patterns [221], [222]. On the clustering model for the second patient profile, we obtained the same results as these two studies. We demonstrate that we can create three patient profiles by analysing CPAP monitoring data: non-adherent, attempters, and adherent. However, our HIaaS model takes the consumption of these patient profiles a step further. Patient profiles are used to construct the patient pathway, determine the most appropriate interventions, and personalise the interventions. Additionally, we intend to develop these patient profiles at various points during CPAP therapy to fine-tune the patient's characteristics. This method of consuming patient profiles is novel for CPAP therapy.

Although the individualised phone call interventions increased adherence, none altered the patient profile. In other words, patients associated with attempters retain their association with attempters, and non-adherent patients keep their association with non-adherent patients despite an increase in adherence level. This result is explicable because there is only one intervention and a requirement to provide intervention at regular intervals for improved patient management. Additionally, phone call interventions are impractical on a large scale. This highlights the importance of developing a comprehensive patient pathway that will accompany the patient throughout his or her therapy.

Various home care experts conducted these phone call interventions and all received the same training on motivating the patient. However, no predefined and standardised process was communicated to the experts. As a result, intervention methodologies vary, and the results are inconsistent among home care experts. As for the validation process, there is a need to develop a standardised method for delivering interventions flexible enough for personalisation.

The models built for predicting the adherence level mainly used the CPAP monitoring data and only three qualitative data. More data should be collected on the patient to increase the models' accuracy. There is a clear need to have more qualitative data from the patients. These data can be collected via a different sensing solution and seize the opportunity of smart home [223].

There are multiple studies that tackle adherence prediction issues [107], [224], [225]. However, it is challenging to crosscheck the results of these studies with our results. The main hurdle for this issue is that there is no open and common dataset for OSA patients. *Rafael-Palou et al.* had excellent results with well-characterised patients. Yet, they had a small cohort of patients (42 patients) [107]. There is a need to build a shared and open dataset on OSA patients alongside CPAP monitoring data. The Outcome and Assessment Information Set (OASIS) initiative for developing an open dataset that contains patient outcomes [226]. The OASIS is a patient-specific, standardised assessment used in Medicare home health care to plan care, decide reimbursement, and monitor quality.

The primary goal of the Sleep.py application is to increase adherence to CPAP therapy. It is possible that patients who are already non-compliant with their CPAP therapy will also be non-compliant with the Sleep.py application. These patients can benefit from additional phone call interventions, which will allow us to provide a more intensive follow-up. We can establish a backup protocol in cases where patients continue to be non-compliant, and we can refer the patients to sleep therapists for their decision in those cases.

Sleep.py's other concern is its lifespan and the patient's long-term adherence to the app. Indeed, patients' interactions with the application can be repetitive. Additionally, there is a possibility that this will have a detrimental effect on adherence to CPAP therapy. There is an urgent need to add new interventions and features to Sleep.py on a continuous basis. Additionally, we can add a new game to the situation game and incorporate a new method of interacting with the mobile application.

The intervention repository's contents were not tested directly on patients. We did not fully validate the effectiveness of all interventions. Nonetheless, we are currently conducting these tests on a select group of patients. We anticipate obtaining the results in the near future and deploying these interventions on a large scale based on these findings. Nonetheless, by implementing various verification mechanisms during the development phase of the HIaaS framework, we maximise the applicability of the various implementations.

From a longer perspective, we expect the HIaaS framework to be deployed in other homecare therapy other than CPAP therapy. For example, for assisted ventilation and oxygen where adherence is not an issue but the HIaaS can be deployed to increase the well-being of the patients, As telemonitoring are are expanding, we expect that the HIaaS framework will find new use cases. To facilitate these implementations, we expect that the HIaaS framework will be incorporated into an already in-place information system and there will be the need to develop connectors to exploit the intervention repository.

Currently, the HIaaS and more specifically the interventions repository is strongly bound to Linde Homecare France. However, the interventions repository can be

made available to other homecare providers where any user can have his own intervention repository. These interventions are developed so that they can be fuelled by other data sources and hence a deployment in other contexts can be achieved.

Other feedback mediums can be included in the HiaaS framework other than the self-reporting questionnaires. For the patients' perception monitoring, we can use the smartphone camera for sentiment analysis of the patients. This sentiment analysis can be coupled with self-reporting questionnaires to detect the tone of the patients during the questionnaire fill-up. This can be taken into consideration during the analysis in order to reduce the bias.

Chapter 6

Conclusions

This research project proposes the novel Homecare Intervention as a Service framework in the context of the CPAP therapy. We developed the framework using a data-driven and patient-centred approach. The HIaaS is composed of four core modules with a distinct purpose each of them:

1. *Patient Characterisations*: This module phenotype each patient using multiple data analytic models. To accomplish this goal, we rely on three fundamental concepts: the patient pathway, the patient profile, and automated vulnerability detection.
2. *Personalised Intervention Design and Delivery*: The HIaaS includes a module for developing and delivering personalised interventions directly to patients. The framework selects the most appropriate interventions from the intervention repository on an automatic basis. We build one of the largest intervention repositories for CPAP therapy for mobile health solutions. The interventions are carried out through the use of the mobile application "Sleep.py."
3. *Verification, validation, and monitoring of the interventions*: The HIaaS provide standardised processes to collect the verification and validation from the experts and the feedback from the patients. The expert's feedback is collected via our dedicated mobile application called "Sleep.py Experts". We assess the patients via tested and validated questionnaires delivered via the Sleep.py application.

4. *Automatic models readjustment-based feedback*: We integrated the collected feedback into a continuous learning process within the HIaaS framework. We automate the process of continuous learning in order to fine-tune the various data analytic models. This module induces intelligence in the HIaaS.

While implying the HIaaS to the CPAP therapy, we build 2 models to build the patient profile at 2 different moments. The first model creates a patient profile after 3 days of therapy and identifies 6 different profiles. The second model intervenes after 10 days of therapy and there are 3 adherence profiles namely non-adherent patients, attempters patients, and adherent patients.

In addition, we demonstrate the impact of a personalised phone call intervention on patient adherence to continuous positive airway pressure (CPAP) therapy. This implementation makes use of the patient profile that has been defined. Patients' compliance increased, but their profiles remained unchanged.

We also discussed the implementation of the Sleep.py experts and the Sleep.py mobile application, which were both designed to collect feedback from experts and patients. Experts from Sleep.py also provide a variety of decision support tools to help patients manage their CPAP therapy in a more personalised fashion. Patients undergoing CPAP therapy are evaluated by Sleep.py, and their perceptions are recorded. Through this application, we are able to provide interventions in the areas of motivation, education, diet, physical activity, and stress management. Sleep.py provides one of the most comprehensive sets of individualised interventions for CPAP therapy available.

Appendix A

The Epworth Sleepiness Scale

Take the Test.....

Epworth Sleepiness Scale

The Epworth Sleepiness Scale is used by sleep professionals to measure sleepiness. Choose the most appropriate number for each situation and total your score. How likely are you to doze off or fall asleep in the following situations, in contrast to feeling just tired?

Use the following scale to choose the **most appropriate number** for each situation:

- 0 = would **never** doze
- 1 = **slight chance** of dozing
- 2 = **moderate chance** of dozing
- 3 = **high chance** of dozing

It is important that you answer each question as best you can.

Situation Chance of Dozing (0-3)

- Sitting and reading ____
- Watching TV ____
- Sitting, inactive in a public place (e.g. a theatre or a meeting) ____
- As a passenger in a car for an hour without a break ____
- Lying down to rest in the afternoon when circumstances permit ____
- Sitting and talking to someone ____
- Sitting quietly after a lunch without alcohol ____
- In a car, while stopped for a few minutes in the traffic ____

TOTAL = ____

IF YOUR SCORE IS :

LESS THAN 8: Normal sleep function

8 to 10: Mild sleepiness

11 to 15: Moderate Sleepiness

16 to 20: Severe Sleepiness

21 to 24: Excessive Sleepiness

If your score is above 10, you should contact your physician to see if you may benefit from a sleep disorder evaluation. He or she may refer you to our center.

FIGURE A.1: The ESS test proposed by M. W. Johns. [154]

Appendix B

The Berlin questionnaire

Berlin Questionnaire® Sleep Apnea

Height (m) _____ Weight (kg) _____ Age _____ Male / Female

Please choose the correct response to each question.

Category 1

1. Do you snore?

- a. Yes
- b. No
- c. Don't know

If you answered 'yes':

2. You snoring is:

- a. Slightly louder than breathing
- b. As loud as talking
- c. Louder than talking

3. How often do you snore?

- a. Almost every day
- b. 3-4 times per week
- c. 1-2 times per week
- d. 1-2 times per month
- e. Rarely or never

4. Has your snoring ever bothered other people?

- a. Yes
- b. No
- c. Don't know

5. Has anyone noticed that you stop breathing during your sleep?

- a. Almost every day
- b. 3-4 times per week
- c. 1-2 times per week
- d. 1-2 times per month
- e. Rarely or never

Category 2

6. How often do you feel tired or fatigued after your sleep?

- a. Almost every day
- b. 3-4 times per week
- c. 1-2 times per week
- d. 1-2 times per month
- e. Rarely or never

7. During your waking time, do you feel tired, fatigued or not up to par?

- a. Almost every day
- b. 3-4 times per week
- c. 1-2 times per week
- d. 1-2 times per month
- e. Rarely or never

8. Have you ever nodded off or fallen asleep while driving a vehicle?

- a. Yes
- b. No

If you answered 'yes':

9. How often does this occur?

- a. Almost every day
- b. 3-4 times per week
- c. 1-2 times per week
- d. 1-2 times per month
- e. Rarely or never

Category 3

10. Do you have high blood pressure?

- Yes
- No
- Don't know

Scoring Berlin Questionnaire

The questionnaire consists of 3 categories related to the risk of having sleep apnea. Patients can be classified into High Risk or Low Risk based on their responses to the individual items and their overall scores in the symptom categories.

Categories and Scoring:

Category 1: items 1, 2, 3, 4, and 5;

Item 1: if **'Yes'**, assign **1 point**

Item 2: if **'c'** or **'d'** is the response, assign **1 point**

Item 3: if **'a'** or **'b'** is the response, assign **1 point**

Item 4: if **'a'** is the response, assign **1 point**

Item 5: if **'a'** or **'b'** is the response, assign **2 points**

Add points. *Category 1 is positive if the total score is 2 or more points.*

Category 2: items 6, 7, 8 (item 9 should be noted separately).

Item 6: if **'a'** or **'b'** is the response, assign **1 point**

Item 7: if **'a'** or **'b'** is the response, assign **1 point**

Item 8: if **'a'** is the response, assign **1 point**

Add points. *Category 2 is positive if the total score is 2 or more points.*

Category 3 is positive if the answer to item 10 is **'Yes'** or if the BMI of the patient is greater than 30kg/m².

(BMI is defined as weight (kg) divided by height (m) squared, i.e., kg/m²).

High Risk: if there are 2 or more categories where the score is positive.

Low Risk: if there is only 1 or no categories where the score is positive.

Additional Question: item 9 should be noted separately.

Appendix C

Example of clinical lifecycle

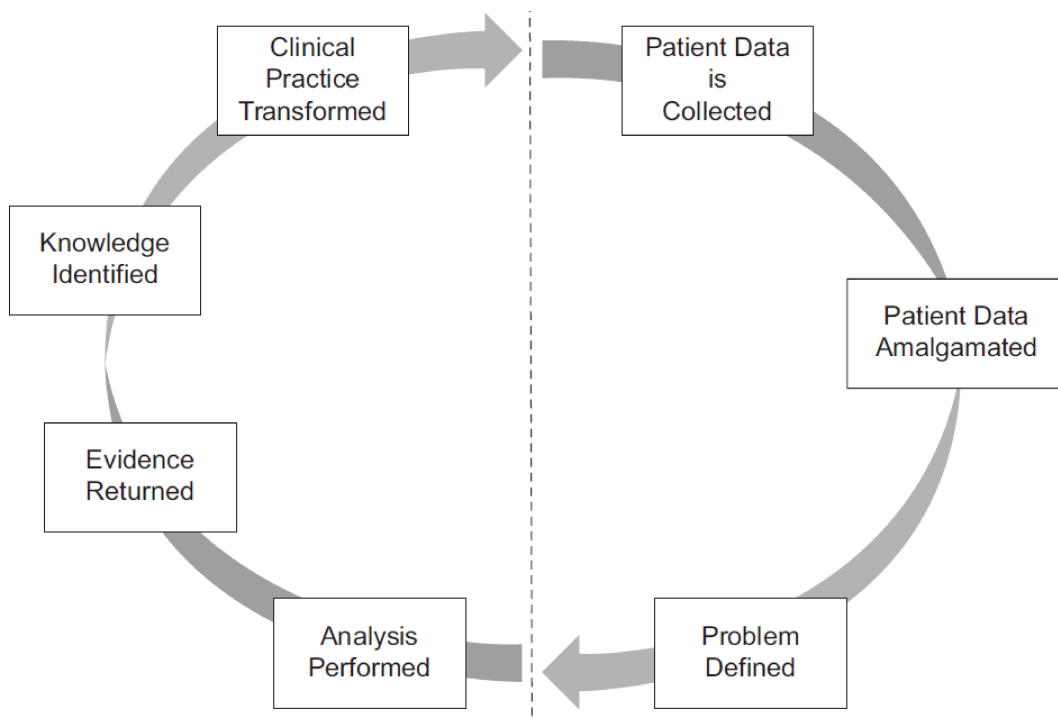
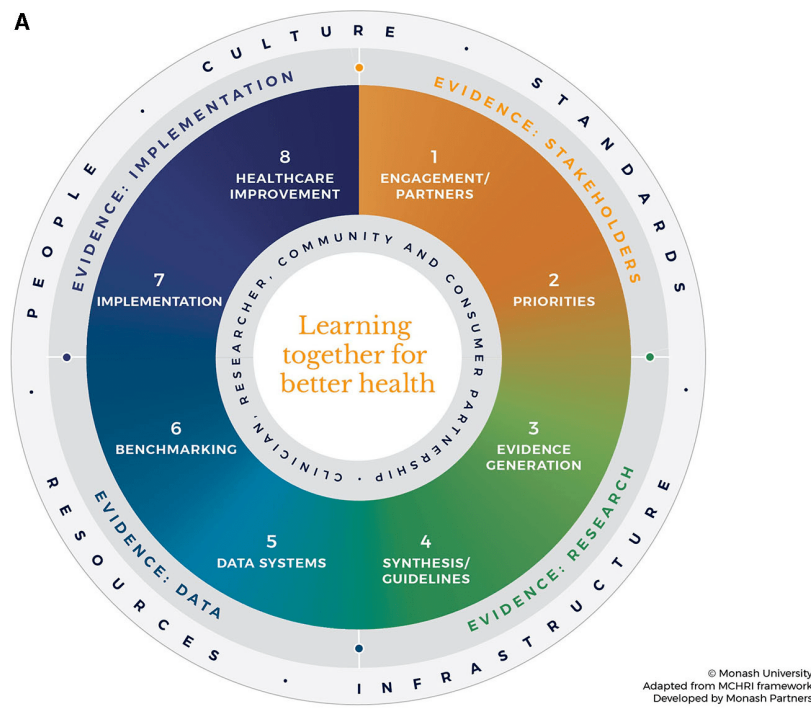


FIGURE C.1: Example of clinical lifecycle from [191]

Appendix D

Monash Partners Learning Health System framework



B COMPONENTS

- | | | |
|---|---|--|
| <p>STAKEHOLDER DERIVED EVIDENCE</p> <p>1 ENGAGEMENT OF PEOPLE</p> <ul style="list-style-type: none"> • Consult • Engage • Involve • Collaborate • Empower • Inform <p>2 IDENTIFYING PRIORITIES</p> <ul style="list-style-type: none"> • Formal engagement • Agreed priorities • Ranked priorities • Prioritised outcome measures | <p>DATA DERIVED EVIDENCE</p> <p>5 DATA AND INFORMATION SYSTEMS</p> <ul style="list-style-type: none"> • Quality, timely, harmonised, meaningful and actionable data • Data from health care and other sources • Patient reported experience and outcome measures • Compliance with 5 safes*, FAIR data principles** and legislative and privacy requirements • Governance, data sharing, linkage, analysis and interpretation • Big data analytics, machine learning • Technology and infrastructure <p>6 BENCHMARKING</p> <ul style="list-style-type: none"> • Transparency and equity • Adjustments for service variation • Real time visual representation at individual, service and organisational levels • Measurement to iteratively and continuously drive improvement • Evaluation • Learning feedback | <p>IMPLEMENTATION EVIDENCE</p> <p>7 IMPLEMENTATION</p> <ul style="list-style-type: none"> • Leadership • Theory driven • Economically sound • Methodologically rigorous • Addressing barriers and enablers • Capability in change management • Consideration of the Burden of data collection • Sustainable and scalable • Demonstrating healthcare improvement <p>8 HEALTHCARE IMPROVEMENT</p> <ul style="list-style-type: none"> • Leadership • Pragmatism • Contextual/ local • Outcome improvement • Quality improvement • Change management • Evaluation |
| <p>RESEARCH DERIVED EVIDENCE</p> <p>3 EVIDENCE BASED INFORMATION</p> <ul style="list-style-type: none"> • Cohort trials • Randomised and pragmatic clinical trials • Epidemiology based research • Economic analysis • Qualitative and Quantitative research <p>4 EVIDENCE SYNTHESIS AND GUIDELINES</p> <ul style="list-style-type: none"> • Systematic reviews • Meta- analysis: aggregate and individual data • Secondary research • Consideration of stakeholder and evidence based priorities • Guidelines, standards and policies | | |

FIGURE D.1: The learning health system framework proposed by Monash University [194]

Appendix E

ESS stored in MongoDB

```
{
  "_id": {
    "$oid": "5f22eebf46c4adcdb1c98e99"
  },
  "description": {
    "game_name": "Questionnaires",
    "short_description": "Etes-vous fatigué ?",
  },
  "information": {
    "name": "Epworth Sleepiness Scale",
    "Abbreviation": "ESS",
    "name_fr": "Échelle de somnolence d'epworth",
    "description_fr": "Mesurer une éventuelle somnolence dans la journée",
    "expected_results": []
  },
  "instruction": {
    "description": ""
  },
  "questions": [{
    "order": 1,
    "title": "Situation",
    "value": "Assis en train de lire",
    "answer_type": "Scale",
    "answer_title": "Chance de s'endormir",
    "answers": [{
      "order": 1,
      "value": "Aucune chance de somnoler ou de s'endormir",
      "score": 0
    }, {
      "order": 2,
      "value": "Faible chance de s'endormir",
      "score": 1
    }, {
      "order": 3,
      "value": "Chance moyenne de s'endormir",
      "score": 2
    }
  ]
}
```

```

    }, {
      "order": 4,
      "value": "Forte chance de s'endormir",
      "score": 3
    }
  ]
}, {
  "order": 2,
  "title": "Situation",
  "value": "En train de regarder la télévision",
  "answer_type": "Scale",
  "answer_title": "Chance de s'endormir",
  "answers": [{
    "order": 1,
    "value": "Aucune chance de somnoler ou de s'endormir",
    "score": 0
  }, {
    "order": 2,
    "value": "Faible chance de s'endormir",
    "score": 1
  }, {
    "order": 3,
    "value": "Chance moyenne de s'endormir",
    "score": 2
  }, {
    "order": 4,
    "value": "Forte chance de s'endormir",
    "score": 3
  }
]
}, {
  "order": 3,
  "title": "Situation",
  "value": "Assis, inactif dans un lieu public (cinéma, théâtre, réunion)",
  "answer_type": "Scale",
  "answer_title": "Chance de s'endormir",
  "answers": [{
    "order": 1,
    "value": "Aucune chance de somnoler ou de s'endormir",
    "score": 0
  }, {
    "order": 2,
    "value": "Faible chance de s'endormir",
    "score": 1
  }, {
    "order": 3,
    "value": "Chance moyenne de s'endormir",
    "score": 2
  }, {
    "order": 4,
    "value": "Forte chance de s'endormir",
    "score": 3
  }
]
}

```

```
  }, {
    "order": 4,
    "title": "Situation",
    "value": "Comme passager d'une voiture (ou transport en commun)... ",
    "answer_type": "Scale",
    "answer_title": "Chance de s'endormir",
    "answers": [{
      "order": 1,
      "value": "Aucune chance de somnoler ou de s'endormir",
      "score": 0
    }, {
      "order": 2,
      "value": "Faible chance de s'endormir",
      "score": 1
    }, {
      "order": 3,
      "value": "Chance moyenne de s'endormir",
      "score": 2
    }, {
      "order": 4,
      "value": "Forte chance de s'endormir",
      "score": 3
    }
  ]
}, {
  "order": 5,
  "title": "Situation",
  "value": "Allongé l'après-midi lorsque les circonstances le permettent",
  "answer_type": "Scale",
  "answer_title": "Chance de s'endormir",
  "answers": [{
    "order": 1,
    "value": "Aucune chance de somnoler ou de s'endormir",
    "score": 0
  }, {
    "order": 2,
    "value": "Faible chance de s'endormir",
    "score": 1
  }, {
    "order": 3,
    "value": "Chance moyenne de s'endormir",
    "score": 2
  }, {
    "order": 4,
    "value": "Forte chance de s'endormir",
    "score": 3
  }
]
}, {
  "order": 6,
  "title": "Situation",
  "value": "Étant assis en parlant avec quelqu'un ",
  "answer_type": "Scale",
```

```

    "answer_title": "Chance de s'endormir",
    "answers": [{
      "order": 1,
      "value": "Aucune chance de somnoler ou de s'endormir",
      "score": 0
    }, {
      "order": 2,
      "value": "Faible chance de s'endormir",
      "score": 1
    }, {
      "order": 3,
      "value": "Chance moyenne de s'endormir",
      "score": 2
    }, {
      "order": 4,
      "value": "Forte chance de s'endormir",
      "score": 3
    }
  ]
}, {
  "order": 7,
  "title": "Situation",
  "value": "Assis au calme après un déjeuner sans alcool",
  "answer_type": "Scale",
  "answer_title": "Chance de s'endormir",
  "answers": [{
    "order": 1,
    "value": "Aucune chance de somnoler ou de s'endormir",
    "score": 0
  }, {
    "order": 2,
    "value": "Faible chance de s'endormir",
    "score": 1
  }, {
    "order": 3,
    "value": "Chance moyenne de s'endormir",
    "score": 2
  }, {
    "order": 4,
    "value": "Forte chance de s'endormir",
    "score": 3
  }
  ]
}, {
  "order": 8,
  "title": "Situation",
  "value": "Dans une voiture immobilisée depuis quelques minutes",
  "answer_type": "Scale",
  "answer_title": "Chance de s'endormir",
  "answers": [{
    "order": 1,
    "value": "Aucune chance de somnoler ou de s'endormir",
    "score": 0
  }
  ]
}

```

```
    }, {
      "order": 2,
      "value": "Faible chance de s'endormir",
      "score": 1
    }, {
      "order": 3,
      "value": "Chance moyenne de s'endormir",
      "score": 2
    }, {
      "order": 4,
      "value": "Forte chance de s'endormir",
      "score": 3
    }
  ]
}
```


Appendix F

"Know My CPAP" game

We develop a sub-game within the situation game to convey information about CPAP therapy to the patient in the Sleep.py app. This sub-game, titled "Know My CPAP," consists of three levels of increasing difficulty. The figure F.1 depicts the "Know My CPAP" scenario. The scenario describes various levels and also considers the various ways in which the patient can interact with the game.

Prior to beginning the game, we conduct a questionnaire to determine the patient's level of knowledge. If the questionnaire results are favourable, the patient advances directly to level 2, otherwise, the patient begins at level 1. Level 1 consists of an educational video explaining how the CPAP works, followed by an in-house ten-question questionnaire. If the patient has more than 70% correct answers, he or she advances to the next trial; otherwise, the patient has three additional trials. If the patient did not improve following these three trials, the HIIaS discontinued the intervention and provided another to the patient, as the framework determined that "Know My CPAP" was not appropriate for the patient.

Level 2 consists of mini-articles (images + text) that provide information about the CPAP's various parameters. As with level 1, the patient is immediately assessed via a seven-question questionnaire, with the same 70% cutoff applied. However, the patient has only two trials at level 2. If the patient successfully completes this level, he or she gains access to additional information about his or her CPAP parameters.

In the same vein, level 3 shows a video with more in-detail information on the functioning of the CPAP device.

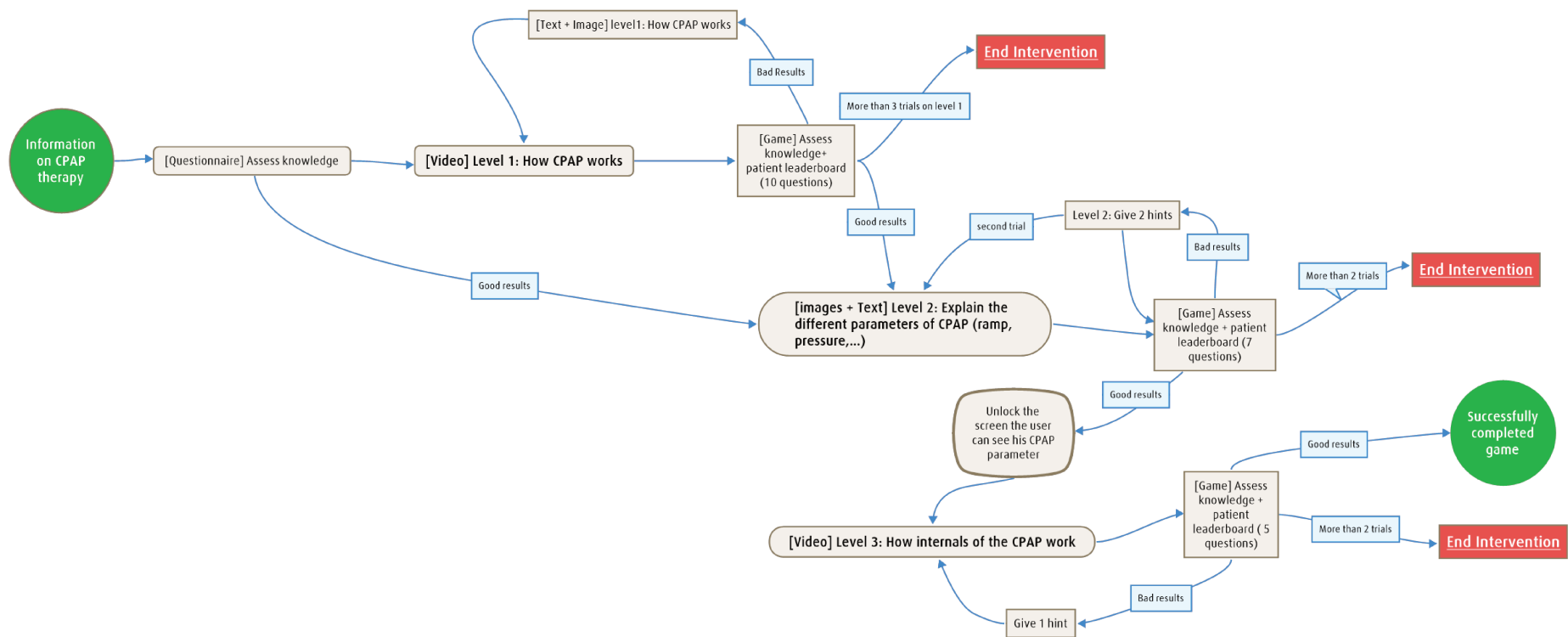


FIGURE F.1: Game scenario for the "Know My CPAP" game

Additionally, the patient has two trials to complete this level successfully. To pass this level, the patient must have at least 80% of the questionnaire responses correct. As with the previous two levels, the HlaaS intervention is terminated if the patient does not successfully complete the level. If patients complete the "Know My CPAP" game completely, the HlaaS considers the patient to have a high level of health literacy regarding the CPAP device.

Bibliography

- [1] R. Jung and W. Kuhlo. "Neurophysiological Studies of Abnormal Night Sleep and the Pickwickian Syndrome". In: *Prog Brain Res* 18 (1965), pp. 140–59. ISSN: 0079-6123 (Print) 0079-6123 (Linking). DOI: [10.1016/s0079-6123\(08\)63590-6](https://doi.org/10.1016/s0079-6123(08)63590-6). URL: <https://www.ncbi.nlm.nih.gov/pubmed/14329033>.
- [2] J. G. Park, K. Ramar, and E. J. Olson. "Updates on definition, consequences, and management of obstructive sleep apnea". In: *Mayo Clin Proc* 86.6 (2011), 549–54, quiz 554–5. ISSN: 1942-5546 (Electronic) 0025-6196 (Linking). DOI: [10.4065/mcp.2010.0810](https://doi.org/10.4065/mcp.2010.0810). URL: <https://www.ncbi.nlm.nih.gov/pubmed/21628617>.
- [3] C. E. Sullivan, F. G. Issa, M. Berthon-Jones, et al. "Reversal of obstructive sleep apnoea by continuous positive airway pressure applied through the nares". In: *Lancet* 1.8225 (1981), pp. 862–5. ISSN: 0140-6736 (Print) 0140-6736 (Linking). DOI: [10.1016/s0140-6736\(81\)92140-1](https://doi.org/10.1016/s0140-6736(81)92140-1). URL: <https://www.ncbi.nlm.nih.gov/pubmed/6112294>.
- [4] A. M. Osman, S. G. Carter, J. C. Carberry, et al. "Obstructive sleep apnea: current perspectives". In: *Nat Sci Sleep* 10 (2018), pp. 21–34. ISSN: 1179-1608 (Print) 1179-1608 (Linking). DOI: [10.2147/NSS.S124657](https://doi.org/10.2147/NSS.S124657). URL: <https://www.ncbi.nlm.nih.gov/pubmed/29416383>.
- [5] Manvir Bhatia and Yogendra Singh. "CPAP Compliance in Obstructive Sleep Apnea". In: *Sleep and Vigilance* 3.2 (2019), pp. 113–118. ISSN: 2510-2265. DOI: [10.1007/s41782-019-00070-8](https://doi.org/10.1007/s41782-019-00070-8).
- [6] M. R. DiMatteo. "Variations in patients' adherence to medical recommendations: a quantitative review of 50 years of research". In: *Med Care* 42.3 (2004), pp. 200–9. ISSN: 0025-7079 (Print) 0025-7079 (Linking). DOI: [10.1097/01.mlr.0000114908.90348.f9](https://doi.org/10.1097/01.mlr.0000114908.90348.f9). URL: <https://www.ncbi.nlm.nih.gov/pubmed/15076819>.
- [7] B. W. Rotenberg, D. Murariu, and K. P. Pang. "Trends in CPAP adherence over twenty years of data collection: a flattened curve". In: *J Otolaryngol Head Neck Surg* 45.1 (2016), p. 43. ISSN: 1916-0216 (Electronic) 1916-0208 (Linking). DOI: [10.1186/s40463-016-0156-0](https://doi.org/10.1186/s40463-016-0156-0). URL: <https://www.ncbi.nlm.nih.gov/pubmed/27542595>.
- [8] J. L. Pepin, S. Bailly, and R. Tamisier. "Big Data in sleep apnoea: Opportunities and challenges". In: *Respirology* 25.5 (2020), pp. 486–494. ISSN: 1440-1843 (Electronic) 1323-7799 (Linking). DOI: [10.1111/resp.13669](https://doi.org/10.1111/resp.13669). URL: <https://www.ncbi.nlm.nih.gov/pubmed/31411796>.
- [9] T. E. Weaver and A. M. Sawyer. "Adherence to continuous positive airway pressure treatment for obstructive sleep apnoea: implications for future interventions". In: *Indian J Med Res* 131 (2010), pp. 245–58. ISSN: 0971-5916 (Print) 0971-5916 (Linking). URL: <https://www.ncbi.nlm.nih.gov/pubmed/20308750>.

- [10] O. Garmendia, R. Farre, C. Ruiz, et al. "Telemedicine Strategy to Rescue CPAP Therapy in Sleep Apnea Patients with Low Treatment Adherence: A Pilot Study". In: *J Clin Med* 10.18 (2021), p. 4123. ISSN: 2077-0383 (Print) 2077-0383 (Linking). DOI: 10.3390/jcm10184123. URL: <https://www.ncbi.nlm.nih.gov/pubmed/34575234>.
- [11] M. Suarez-Giron, O. Garmendia, V. Lugo, et al. "Mobile health application to support CPAP therapy in obstructive sleep apnoea: design, feasibility and perspectives". In: *ERJ Open Res* 6.1 (2020). ISSN: 2312-0541 (Print) 2312-0541 (Linking). DOI: 10.1183/23120541.00220-2019. URL: <https://www.ncbi.nlm.nih.gov/pubmed/32055630>.
- [12] K. E. Lewis, L. Seale, I. E. Bartle, et al. "Early predictors of CPAP use for the treatment of obstructive sleep apnea". In: *Sleep* 27.1 (2004), pp. 134–8. ISSN: 0161-8105 (Print) 0161-8105 (Linking). DOI: 10.1093/sleep/27.1.134. URL: <https://www.ncbi.nlm.nih.gov/pubmed/14998250>.
- [13] M. Araujo, L. Kazaglis, C. Iber, et al. "A Data-Driven Approach for Continuous Adherence Predictions in Sleep Apnea Therapy Management". In: *2019 Ieee International Conference on Big Data (Big Data)* (2019), pp. 2716–2725. ISSN: 2639-1589. URL: <https://doi.org/10.1109/BigData4714376.2019.9014376>.
- [14] G. Scioscia, P. Tondo, M. P. Foschino Barbaro, et al. "Machine learning-based prediction of adherence to continuous positive airway pressure (CPAP) in obstructive sleep apnea (OSA)". In: *Inform Health Soc Care* (2021), pp. 1–9. ISSN: 1753-8165 (Electronic) 1753-8157 (Linking). DOI: 10.1080/17538157.2021.1990300. URL: <https://www.ncbi.nlm.nih.gov/pubmed/34748437>.
- [15] T. E. Weaver. "Novel Aspects of CPAP Treatment and Interventions to Improve CPAP Adherence". In: *J Clin Med* 8.12 (2019). ISSN: 2077-0383 (Print) 2077-0383 (Linking). DOI: 10.3390/jcm8122220. URL: <https://www.ncbi.nlm.nih.gov/pubmed/31888148>.
- [16] Ameli Santé. *Remboursement Assurance Maladie*. URL: http://www.codage.ext.cnamts.fr/codif/tips//chapitre/index_chap.php?p_ref_menu_code=188&p_site=AMELI.
- [17] *Sleep research funding by US National Institutes for Health 2013-2021*. en. <https://www.statista.com/statistics/713336/sleep-research-funding-by-the-national-institutes-for-health/>. Accessed: 2022-2-22.
- [18] *Sleep apnea therapeutics and diagnostics market by world region 2028*. en. <https://www.statista.com/statistics/1261137/sleep-apnea-therapeutics-and-diagnostics-market-by-world-region/>. Accessed: 2022-2-22.
- [19] N.A. Card. *Applied Meta-analysis for Social Science Research*. Guilford Publications, 2012. ISBN: 9781609184995. URL: <https://www.guilford.com/books/Applied-Meta-Analysis-for-Social-Science-Research/Noel-Card/9781462525003>.
- [20] M. Templier and G. Pare. "A Framework for Guiding and Evaluating Literature Reviews". In: *Communications of the Association for Information Systems* 37 (2015), pp. 112–137. ISSN: 1529-3181. DOI: 10.17705/1CAIS.03706. URL: <https://aisel.aisnet.org/cais/vol37/iss1/6/>.
- [21] Alan R. Hevner, Salvatore T. March, Jinsoo Park, et al. "Design Science in Information Systems Research". In: *MIS Q.* 28.1 (Mar. 2004), pp. 75–105. ISSN: 0276-7783.
- [22] Koichi Higuchi. *KH Coder*. URL: <https://kncoder.net/en>.

- [23] *Journal Citation Reports*. en. <https://jcr.clarivate.com/jcr/home>. Accessed: 2022-3-8.
- [24] B. Ristevski and M. Chen. "Big Data Analytics in Medicine and Healthcare". In: *J Integr Bioinform* 15.3 (2018), p. 20170030. ISSN: 1613-4516 (Electronic) 1613-4516 (Linking). DOI: 10.1515/jib-2017-0030. URL: <https://www.ncbi.nlm.nih.gov/pubmed/29746254>.
- [25] K. Batko and A. Slezak. "The use of Big Data Analytics in healthcare". In: *J Big Data* 9.1 (2022), p. 3. ISSN: 2196-1115 (Print) 2196-1115 (Linking). DOI: 10.1186/s40537-021-00553-4. URL: <https://www.ncbi.nlm.nih.gov/pubmed/35013701>.
- [26] A. Gandomi and M. Haider. "Beyond the hype: Big data concepts, methods, and analytics". In: *International Journal of Information Management* 35.2 (2015), pp. 137–144. ISSN: 0268-4012. DOI: 10.1016/j.ijinfomgt.2014.10.007. URL: <https://www.sciencedirect.com/science/article/pii/S0169260712002805>.
- [27] T. B. Murdoch and A. S. Detsky. "The inevitable application of big data to health care". In: *JAMA* 309.13 (2013), pp. 1351–2. ISSN: 1538-3598 (Electronic) 0098-7484 (Linking). DOI: 10.1001/jama.2013.393. URL: <https://www.ncbi.nlm.nih.gov/pubmed/23549579>.
- [28] D. W. Bates, S. Saria, L. Ohno-Machado, et al. "Big data in health care: using analytics to identify and manage high-risk and high-cost patients". In: *Health Aff (Millwood)* 33.7 (2014), pp. 1123–31. ISSN: 1544-5208 (Electronic) 0278-2715 (Linking). DOI: 10.1377/hlthaff.2014.0041. URL: <https://www.ncbi.nlm.nih.gov/pubmed/25006137>.
- [29] D. Cirillo and A. Valencia. "Big data analytics for personalized medicine". In: *Curr Opin Biotechnol* 58 (2019), pp. 161–167. ISSN: 1879-0429 (Electronic) 0958-1669 (Linking). DOI: 10.1016/j.copbio.2019.03.004. URL: <https://www.ncbi.nlm.nih.gov/pubmed/30965188>.
- [30] L. A. Simmons, C. D. Drake, T. W. Gaudet, et al. "Personalized Health Planning in Primary Care Settings". In: *Fed Pract* 33.1 (2016), pp. 27–34. ISSN: 1945-337X (Electronic) 1078-4497 (Linking). URL: <https://www.ncbi.nlm.nih.gov/pubmed/30766135>.
- [31] T. Fatima and S. Jyothi. "Big Data Analytics in Health Care". In: *Emerging Research in Data Engineering Systems and Computer Communications, Ccode 2019* 1054 (2020), pp. 377–387. ISSN: 2194-5357. DOI: 10.1007/978-981-15-0135-7_36. URL: https://link.springer.com/chapter/10.1007/978-981-15-0135-7_36.
- [32] M. Khalifa. "Health Analytics Types, Functions and Levels: A Review of Literature". In: *Stud Health Technol Inform* 251 (2018), pp. 137–140. ISSN: 1879-8365 (Electronic) 0926-9630 (Linking). URL: <https://www.ncbi.nlm.nih.gov/pubmed/29968621>.
- [33] K. Baker, E. Dunwoodie, R. G. Jones, et al. "Process mining routinely collected electronic health records to define real-life clinical pathways during chemotherapy". In: *Int J Med Inform* 103 (2017), pp. 32–41. ISSN: 1872-8243 (Electronic) 1386-5056 (Linking). DOI: 10.1016/j.ijmedinf.2017.03.011. URL: <https://www.ncbi.nlm.nih.gov/pubmed/28550999>.

- [34] T. Jackson. "Building the 'continuous learning' healthcare system". In: *Health Information Management Journal* 43.1 (2014), pp. 4–5. ISSN: 1833-3583. URL: <https://doi.org/10.1177/1078155213500001>.
- [35] Montserrat Batet, David Isern, Lucas Marin, et al. "Knowledge-driven delivery of home care services". In: *Journal of Intelligent Information Systems* 38.1 (2012), pp. 95–130. DOI: [10.1007/s10844-010-0145-0](https://doi.org/10.1007/s10844-010-0145-0).
- [36] M. A. Martinez-Garcia, F. Capote, F. Campos-Rodriguez, et al. "Effect of CPAP on blood pressure in patients with obstructive sleep apnea and resistant hypertension: the HIPARCO randomized clinical trial". In: *JAMA* 310.22 (2013), pp. 2407–15. ISSN: 1538-3598 (Electronic) 0098-7484 (Linking). DOI: [10.1001/jama.2013.281250](https://doi.org/10.1001/jama.2013.281250). URL: <https://www.ncbi.nlm.nih.gov/pubmed/24327037>.
- [37] G. M. Schmolzer, M. Kumar, G. Pichler, et al. "Non-invasive versus invasive respiratory support in preterm infants at birth: systematic review and meta-analysis". In: *BMJ* 347.oct17 3 (2013), f5980. ISSN: 1756-1833 (Electronic) 0959-8138 (Linking). DOI: [10.1136/bmj.f5980](https://doi.org/10.1136/bmj.f5980). URL: <https://www.ncbi.nlm.nih.gov/pubmed/24136633>.
- [38] K. Sutherland, O. M. Vanderveken, H. Tsuda, et al. "Oral appliance treatment for obstructive sleep apnea: an update". In: *J Clin Sleep Med* 10.2 (2014), pp. 215–27. ISSN: 1550-9397 (Electronic) 1550-9389 (Linking). DOI: [10.5664/jcsm.3460](https://doi.org/10.5664/jcsm.3460). URL: <https://www.ncbi.nlm.nih.gov/pubmed/24533007>.
- [39] D. J. Gottlieb, N. M. Punjabi, R. Mehra, et al. "CPAP versus oxygen in obstructive sleep apnea". In: *N Engl J Med* 370.24 (2014), pp. 2276–85. ISSN: 1533-4406 (Electronic) 0028-4793 (Linking). DOI: [10.1056/NEJMoa1306766](https://doi.org/10.1056/NEJMoa1306766). URL: <https://www.ncbi.nlm.nih.gov/pubmed/24918372>.
- [40] M. R. Bonsignore, J. L. Pepin, F. Cibella, et al. "Excessive Daytime Sleepiness in Obstructive Sleep Apnea Patients Treated With Continuous Positive Airway Pressure: Data From the European Sleep Apnea Database". In: *Front Neurol* 12 (2021), p. 690008. ISSN: 1664-2295 (Print) 1664-2295 (Linking). DOI: [10.3389/fneur.2021.690008](https://doi.org/10.3389/fneur.2021.690008). URL: <https://www.ncbi.nlm.nih.gov/pubmed/34434158>.
- [41] K. Saito and Y. Takamatsu. "Periodic breathing in patients with stable obstructive sleep apnea on long-term continuous positive airway pressure treatment: a retrospective study using CPAP remote monitoring data". In: *Sleep Breath* (2021). ISSN: 1522-1709 (Electronic) 1520-9512 (Linking). DOI: [10.1007/s11325-021-02510-0](https://doi.org/10.1007/s11325-021-02510-0). URL: <https://www.ncbi.nlm.nih.gov/pubmed/34651259>.
- [42] B. Battis, L. Clifford, M. Huq, et al. "The impacts of a pharmacist-managed outpatient clinic and chemotherapy-directed electronic order sets for monitoring oral chemotherapy". In: *J Oncol Pharm Pract* 23.8 (2017), pp. 582–590. ISSN: 1477-092X (Electronic) 1078-1552 (Linking). DOI: [10.1177/1078155216672314](https://doi.org/10.1177/1078155216672314). URL: <https://www.ncbi.nlm.nih.gov/pubmed/27733666>.
- [43] M. Bowya and V. Karthikeyan. "A Novel Secure IoT Based Optimizing Sensor Network for Automatic Medicine Composition Prescribe System". In: *Inventive Communication and Computational Technologies*. Ed. by G. Ranganathan, Joy Chen, and Álvaro Rocha. Springer Singapore, pp. 1109–1118. ISBN: 978-981-15-0146-3.

- [44] T. Austin, S. Sun, Y. S. Lim, et al. "An Electronic Healthcare Record Server Implemented in PostgreSQL". In: *J Healthc Eng* 6.3 (2015), pp. 325–44. ISSN: 2040-2295 (Print) 2040-2295 (Linking). DOI: 10.1260/2040-2295.6.3.325. URL: <https://www.ncbi.nlm.nih.gov/pubmed/26753438>.
- [45] J. Gruendner, C. Gulden, M. Kampf, et al. "A Framework for Criteria-Based Selection and Processing of Fast Healthcare Interoperability Resources (FHIR) Data for Statistical Analysis: Design and Implementation Study". In: *JMIR Med Inform* 9.4 (2021), e25645. ISSN: 2291-9694 (Print). DOI: 10.2196/25645. URL: <https://www.ncbi.nlm.nih.gov/pubmed/33792554>.
- [46] Mohammad Monirujaman Khan and Rezaul Karim. "Development of Smart e-Health System for Covid-19 Pandemic". In: *2020 23rd International Conference on Computer and Information Technology (ICCIT)*. IEEE. DOI: 10.1109/iccit51783.2020.9392743.
- [47] Q. Yao, Y. Tian, P. F. Li, et al. "Design and development of a medical big data processing system based on Hadoop". In: *J Med Syst* 39.3 (2015), p. 23. ISSN: 1573-689X (Electronic) 0148-5598 (Linking). DOI: 10.1007/s10916-015-0220-8. URL: <https://www.ncbi.nlm.nih.gov/pubmed/25666927>.
- [48] M. M. Rathore, A. Paul, A. Ahmad, et al. "Hadoop-Based Intelligent Care System (HICS): Analytical Approach for Big Data in IoT". In: *Acm Transactions on Internet Technology* 18.1 (2017), pp. 1–24. ISSN: 1533-5399. DOI: Artn810.1145/3108936. URL: %3CGo%20to%20ISI%3E://WOS:000419034400008.
- [49] N. Mehta and A. Pandit. "Concurrence of big data analytics and healthcare: A systematic review". In: *Int J Med Inform* 114 (2018), pp. 57–65. ISSN: 1872-8243 (Electronic) 1386-5056 (Linking). DOI: 10.1016/j.ijmedinf.2018.03.013. URL: <https://www.ncbi.nlm.nih.gov/pubmed/29673604>.
- [50] Haridimos Kondylakis, Anca Bucur, Feng Dong, et al. "IManageCancer: Developing a Platform for Empowering Patients and Strengthening Self-Management in Cancer Diseases". In: *Proceedings - IEEE Symposium on Computer-Based Medical Systems 2017-June/November* (2017), pp. 755–760. ISSN: 9781538617106. DOI: 10.1109/CBMS.2017.62.
- [51] J. Kaur and K. S. Mann. "AI based HealthCare Platform for Real Time, Predictive and Prescriptive Analytics using Reactive Programming". In: *10th International Conference on Computer and Electrical Engineering* 933 (2018). ISSN: 1742-6588. DOI: Artn01201010.1088/1742-6596/933/1/012010. URL: <https://iopscience.iop.org/article/10.1088/1742-6596/933/1/012010>.
- [52] G. Alfian, M. Syafrudin, M. F. Ijaz, et al. "A Personalized Healthcare Monitoring System for Diabetic Patients by Utilizing BLE-Based Sensors and Real-Time Data Processing". In: *Sensors (Basel)* 18.7 (2018). ISSN: 1424-8220 (Electronic) 1424-8220 (Linking). DOI: 10.3390/s18072183. URL: <https://www.ncbi.nlm.nih.gov/pubmed/29986473>.
- [53] A. Baldominos, F. De Rada, and Y. Saez. "DataCare: Big Data Analytics Solution for Intelligent Healthcare Management". In: *International Journal of Interactive Multimedia and Artificial Intelligence* 4.7 (2018), pp. 13–20. ISSN: 1989-1660. DOI: 10.9781/ijimai.2017.03.002. URL: <https://www.ijimai.org/journal/bibcite/reference/2614>.
- [54] E. Bose and K. Radhakrishnan. "Using Unsupervised Machine Learning to Identify Subgroups Among Home Health Patients With Heart Failure Using Telehealth". In: *Comput Inform Nurs* 36.5 (2018), pp. 242–248. ISSN: 1538-9774

- (Electronic) 1538-2931 (Linking). DOI: [10.1097/CIN.0000000000000423](https://doi.org/10.1097/CIN.0000000000000423). URL: <https://www.ncbi.nlm.nih.gov/pubmed/29494361>.
- [55] C. Veneroni, D. Mercadante, A. Lavizzari, et al. "Changes in respiratory mechanics at birth in preterm infants: A pilot study". In: *Pediatr Pulmonol* 55.7 (2020), pp. 1640–1645. ISSN: 1099-0496 (Electronic) 1099-0496 (Linking). DOI: [10.1002/ppul.24772](https://doi.org/10.1002/ppul.24772). URL: <https://www.ncbi.nlm.nih.gov/pubmed/32311845>.
- [56] Y. Wang, A. F. Geater, Y. Chai, et al. "Pre- and in-therapy predictive score models of adult OSAS patients with poor adherence pattern on nCPAP therapy". In: *Patient Prefer Adherence* 9 (2015), pp. 715–23. ISSN: 1177-889X (Print) 1177-889X (Linking). DOI: [10.2147/PPA.S83105](https://doi.org/10.2147/PPA.S83105). URL: <https://www.ncbi.nlm.nih.gov/pubmed/26064041>.
- [57] K. Sutherland, F. R. Almeida, T. Kim, et al. "Treatment usage patterns of oral appliances for obstructive sleep apnea over the first 60 days: a cluster analysis". In: *Journal of Clinical Sleep Medicine* 17.9 (2021), pp. 1785–1792. ISSN: 1550-9389. DOI: [10.5664/jcsm.9288](https://doi.org/10.5664/jcsm.9288). URL: <https://www.ncbi.nlm.nih.gov/pubmed/34300006>.
- [58] S. Romero-Peralta, F. Garcia-Rio, P. Resano Barrio, et al. "Defining the Heterogeneity of Sleep Apnea Syndrome: A Cluster Analysis With Implications for Patient Management". In: *Arch Bronconeumol* 58.2 (2022), pp. 125–134. ISSN: 1579-2129 (Electronic) 0300-2896 (Linking). DOI: [10.1016/j.arbres.2021.02.022](https://doi.org/10.1016/j.arbres.2021.02.022). URL: <https://www.ncbi.nlm.nih.gov/pubmed/33820676>.
- [59] W. K. Wohlgemuth, D. A. Chirinos, S. Domingo, et al. "Attempters, adherers, and non-adherers: latent profile analysis of CPAP use with correlates". In: *Sleep Med* 16.3 (2015), pp. 336–42. ISSN: 1878-5506 (Electronic) 1389-9457 (Linking). DOI: [10.1016/j.sleep.2014.08.013](https://doi.org/10.1016/j.sleep.2014.08.013). URL: <https://www.ncbi.nlm.nih.gov/pubmed/25441752>.
- [60] J. U. Park, U. Erdenebayar, E. Y. Joo, et al. "Estimating sleep parameters using nasal pressure signals applicable to continuous positive airway pressure devices". In: *Physiol Meas* 38.7 (2017), pp. 1441–1455. ISSN: 1361-6579 (Electronic) 0967-3334 (Linking). DOI: [10.1088/1361-6579/aa723e](https://doi.org/10.1088/1361-6579/aa723e). URL: <https://www.ncbi.nlm.nih.gov/pubmed/28489018>.
- [61] T. E. Weaver, G. Maislin, D. F. Dinges, et al. "Relationship between hours of CPAP use and achieving normal levels of sleepiness and daily functioning". In: *Sleep* 30.6 (2007), pp. 711–9. ISSN: 0161-8105 (Print) 0161-8105 (Linking). DOI: [10.1093/sleep/30.6.711](https://doi.org/10.1093/sleep/30.6.711). URL: <https://www.ncbi.nlm.nih.gov/pubmed/17580592>.
- [62] M. E. Billings, D. Auckley, R. Benca, et al. "Race and residential socioeconomics as predictors of CPAP adherence". In: *Sleep* 34.12 (2011), pp. 1653–8. ISSN: 1550-9109 (Electronic) 0161-8105 (Linking). DOI: [10.5665/sleep.1428](https://doi.org/10.5665/sleep.1428). URL: <https://www.ncbi.nlm.nih.gov/pubmed/22131602>.
- [63] D. D. Sin, I. Mayers, G. C. Man, et al. "Long-term compliance rates to continuous positive airway pressure in obstructive sleep apnea: a population-based study". In: *Chest* 121.2 (2002), pp. 430–5. ISSN: 0012-3692 (Print) 0012-3692 (Linking). DOI: [10.1378/chest.121.2.430](https://doi.org/10.1378/chest.121.2.430). URL: <https://www.ncbi.nlm.nih.gov/pubmed/11834653>.
- [64] P. Chriskos, D. S. Kaitalidou, G. Karakasis, et al. "Automatic Sleep Stage Classification Applying Machine Learning Algorithms on EEG Recordings". In:

- 2017 IEEE 30th International Symposium on Computer-Based Medical Systems (CBMS), pp. 435–439. ISBN: 2372-9198. DOI: [10.1109/CBMS.2017.83](https://doi.org/10.1109/CBMS.2017.83).
- [65] J. A. Rodger. “Advances in multisensor information fusion: A Markov-Kalman viscosity fuzzy statistical predictor for analysis of oxygen flow, diffusion, speed, temperature, and time metrics in CPAP”. In: *Expert Systems* 35.4 (2018), e12270. ISSN: 0266-4720. DOI: [ARTNe1227010.1111/exsy.12270](https://doi.org/10.1111/exsy.12270). URL: [%3CGo%20to%20ISI%3E://WOS:000442211200005](https://www.wos.com/doi/10.1111/exsy.12270).
- [66] G. Harerimana, B. Jang, J. W. Kim, et al. “Health Big Data Analytics: A Technology Survey”. In: *Ieee Access* 6 (2018), pp. 65661–65678. ISSN: 2169-3536. DOI: [10.1109/Access.2018.2878254](https://doi.org/10.1109/Access.2018.2878254). URL: [%3CGo%20to%20ISI%3E://WOS:000451556100001](https://www.wos.com/doi/10.1109/Access.2018.2878254).
- [67] M. S. Islam, M. M. Hasan, X. Wang, et al. “A Systematic Review on Healthcare Analytics: Application and Theoretical Perspective of Data Mining”. In: *Healthcare (Basel)* 6.2 (2018). ISSN: 2227-9032 (Print) 2227-9032 (Linking). DOI: [10.3390/healthcare6020054](https://doi.org/10.3390/healthcare6020054). URL: <https://www.ncbi.nlm.nih.gov/pubmed/29882866>.
- [68] K. Kaptain, M. L. Ulsoe, and P. Dreyer. “Surgical perioperative pathways—Patient experiences of unmet needs show that a person-centred approach is needed”. In: *J Clin Nurs* 28.11-12 (2019), pp. 2214–2224. ISSN: 1365-2702 (Electronic) 0962-1067 (Linking). DOI: [10.1111/jocn.14817](https://doi.org/10.1111/jocn.14817). URL: <https://www.ncbi.nlm.nih.gov/pubmed/30786078>.
- [69] A. B. Durojaiye, N. M. McGeorge, L. L. Puett, et al. “Mapping the Flow of Pediatric Trauma Patients Using Process Mining”. In: *Appl Clin Inform* 9.3 (2018), pp. 654–666. ISSN: 1869-0327 (Electronic) 1869-0327 (Linking). DOI: [10.1055/s-0038-1668089](https://doi.org/10.1055/s-0038-1668089). URL: <https://www.ncbi.nlm.nih.gov/pubmed/30134474>.
- [70] J. Lismont, A. S. Janssens, I. Odnoletkova, et al. “A guide for the application of analytics on healthcare processes: A dynamic view on patient pathways”. In: *Comput Biol Med* 77 (2016), pp. 125–34. ISSN: 1879-0534 (Electronic) 0010-4825 (Linking). DOI: [10.1016/j.combiomed.2016.08.007](https://doi.org/10.1016/j.combiomed.2016.08.007). URL: <https://www.ncbi.nlm.nih.gov/pubmed/27544069>.
- [71] L. Kinsman, T. Rotter, E. James, et al. “What is a clinical pathway? Development of a definition to inform the debate”. In: *BMC Med* 8.1 (2010), p. 31. ISSN: 1741-7015 (Electronic) 1741-7015 (Linking). DOI: [10.1186/1741-7015-8-31](https://doi.org/10.1186/1741-7015-8-31). URL: <https://www.ncbi.nlm.nih.gov/pubmed/20507550>.
- [72] Kris Vanhaecht, Massimiliano Panella, Ruben van Zelm, et al. “An overview on the history and concept of care pathways as complex interventions”. In: *International Journal of Care Pathways* 14.3 (2010), pp. 117–123. ISSN: 2040-4034. DOI: [10.1258/jicp.2010.010019](https://doi.org/10.1258/jicp.2010.010019). URL: <https://journals.sagepub.com/doi/abs/10.1258/jicp.2010.010019>.
- [73] Ronny S. Mans, Wil M. P. Van Der Aalst, Rob J. B. Vanwersch, et al. “Process Mining in Healthcare: Data Challenges When Answering Frequently Posed Questions”. In: *Lecture Notes in Computer Science*. Springer Berlin Heidelberg, 2013, pp. 140–153. ISBN: 0302-9743. DOI: [10.1007/978-3-642-36438-9_10](https://doi.org/10.1007/978-3-642-36438-9_10). URL: <http://wwwis.win.tue.nl/~wvdaalst/publications/p707.pdf>.
- [74] Wil M. P. van der Aalst. *Process Mining*. Process Mining: Discovery, Conformance and Enhancement of Business Processes. van der Aalst, Wil M. P. van der Aalst, Wil/G-1248-2011 van der Aalst, Wil/0000-0002-0955-6940. 2011,

- p. 1. ISBN: 978-3-642-19344-6/978-3-642-19345-3. DOI: 10.1007/978-3-642-19345-3. URL: <https://www.ncbi.nlm.nih.gov/pubmed/34035789>.
- [75] V. J. M. Watzlaf, P. T. Sheridan, A. A. Alzu'bi, et al. "Clinical Data Abstraction: A Research Study". In: *Perspect Health Inf Manag* 18.Spring (2021), 1g. ISSN: 1559-4122 (Electronic) 1559-4122 (Linking). URL: <https://www.ncbi.nlm.nih.gov/pubmed/34035789>.
- [76] Chunhua Weng. "Clinical data quality: a data life cycle perspective". In: *Bio-statistics & Epidemiology* 4.1 (2020), pp. 6–14. ISSN: 2470-9360. DOI: 10.1080/24709360.2019.1572344.
- [77] H. M. W. Verbeek, J. C. A. M. Buijs, B. F. van Dongen, et al. "XES, XESame, and ProM 6". In: *Information Systems Evolution* 72 (2011), pp. 60–75. ISSN: 1865-1348. URL: <https://www.ncbi.nlm.nih.gov/pubmed/22517736>.
- [78] Y. G. Lei, N. P. Li, L. Guo, et al. "Machinery health prognostics: A systematic review from data acquisition to RUL prediction". In: *Mechanical Systems and Signal Processing* 104 (2018), pp. 799–834. ISSN: 0888-3270. DOI: 10.1016/j.ymsp.2017.11.016. URL: <https://www.ncbi.nlm.nih.gov/pubmed/28841264>.
- [79] A. R. M. Forkan, I. Khalil, Z. Tari, et al. "A context-aware approach for long-term behavioural change detection and abnormality prediction in ambient assisted living". In: *Pattern Recognition* 48.3 (2015), pp. 628–641. ISSN: 0031-3203. DOI: 10.1016/j.patcog.2014.07.007. URL: <https://www.ncbi.nlm.nih.gov/pubmed/26265560>.
- [80] A. Y. Lai, M. S. Ip, J. C. Lam, et al. "A pathway underlying the impact of CPAP adherence on intimate relationship with bed partner in men with obstructive sleep apnea". In: *Sleep Breath* 20.2 (2016), pp. 543–551. ISSN: 1522-1709 (Electronic) 1520-9512 (Linking). DOI: 10.1007/s11325-015-1235-6. URL: <https://www.ncbi.nlm.nih.gov/pubmed/26265560>.
- [81] Michael E. Sobel. "Asymptotic Confidence Intervals for Indirect Effects in Structural Equation Models". In: *Sociological Methodology* 13 (1982), pp. 290–312. ISSN: 00811750. DOI: 10.2307/270723. URL: <http://www.jstor.org/stable/270723>.
- [82] S. E. Inzucchi, R. M. Bergenstal, J. B. Buse, et al. "Management of hyperglycemia in type 2 diabetes: a patient-centered approach: position statement of the American Diabetes Association (ADA) and the European Association for the Study of Diabetes (EASD)". In: *Diabetes Care* 35.6 (2012), pp. 1364–79. ISSN: 1935-5548 (Electronic) 0149-5992 (Linking). DOI: 10.2337/dc12-0413. URL: <https://www.ncbi.nlm.nih.gov/pubmed/22517736>.
- [83] G. M. Fix, C. VanDeusen Lukas, R. E. Bolton, et al. "Patient-centred care is a way of doing things: How healthcare employees conceptualize patient-centred care". In: *Health Expect* 21.1 (2018), pp. 300–307. ISSN: 1369-7625 (Electronic) 1369-6513 (Linking). DOI: 10.1111/hex.12615. URL: <https://www.ncbi.nlm.nih.gov/pubmed/28841264>.
- [84] G. M. Fix, C. VanDeusen Lukas, R. E. Bolton, et al. "Patient-centred care is a way of doing things: How healthcare employees conceptualize patient-centred care". In: *Health Expect* 21.1 (2018), pp. 300–307. ISSN: 1369-7625 (Electronic) 1369-6513 (Linking). DOI: 10.1111/hex.12615. URL: <https://www.ncbi.nlm.nih.gov/pubmed/28841264>.
- [85] A. M. Elissen, D. F. Hertroijs, N. C. Schaper, et al. "Profiling Patients' Healthcare Needs to Support Integrated, Person-Centered Models for Long-Term

- Disease Management (Profile): Research Design". In: *Int J Integr Care* 16.2 (2016), p. 1. ISSN: 1568-4156 (Print). DOI: [10.5334/ijic.2208](https://doi.org/10.5334/ijic.2208). URL: <https://www.ncbi.nlm.nih.gov/pubmed/27616957>.
- [86] C. Barba, S. Hammond, and R. S. Hammond. "The Patient Profile: Improving Treatment Adherence". In: *Ann Fam Med* 16.3 (2018), p. 271. ISSN: 1544-1717 (Electronic) 1544-1709 (Linking). DOI: [10.1370/afm.2239](https://doi.org/10.1370/afm.2239). URL: <https://www.ncbi.nlm.nih.gov/pubmed/29760035>.
- [87] J. Hakansson Eklund, I. K. Holmstrom, T. Kumlin, et al. "'Same same or different?' A review of reviews of person-centered and patient-centered care". In: *Patient Educ Couns* 102.1 (2019), pp. 3–11. ISSN: 1873-5134 (Electronic) 0738-3991 (Linking). DOI: [10.1016/j.pec.2018.08.029](https://doi.org/10.1016/j.pec.2018.08.029). URL: <https://www.ncbi.nlm.nih.gov/pubmed/30201221>.
- [88] S. A. Joosten, K. Hamza, S. Sands, et al. "Phenotypes of patients with mild to moderate obstructive sleep apnoea as confirmed by cluster analysis". In: *Respirology* 17.1 (2012), pp. 99–107. ISSN: 1440-1843 (Electronic) 1323-7799 (Linking). DOI: [10.1111/j.1440-1843.2011.02037.x](https://doi.org/10.1111/j.1440-1843.2011.02037.x). URL: <https://www.ncbi.nlm.nih.gov/pubmed/21848707>.
- [89] L. Ye, G. W. Pien, S. J. Ratcliffe, et al. "The different clinical faces of obstructive sleep apnoea: a cluster analysis". In: *Eur Respir J* 44.6 (2014), pp. 1600–7. ISSN: 1399-3003 (Electronic) 0903-1936 (Linking). DOI: [10.1183/09031936.00032314](https://doi.org/10.1183/09031936.00032314). URL: <https://www.ncbi.nlm.nih.gov/pubmed/25186268>.
- [90] S. F. Babbin, W. F. Velicer, M. S. Aloia, et al. "Identifying Longitudinal Patterns for Individuals and Subgroups: An Example with Adherence to Treatment for Obstructive Sleep Apnea". In: *Multivariate Behav Res* 50.1 (2015), pp. 91–108. ISSN: 1532-7906 (Electronic) 0027-3171 (Linking). DOI: [10.1080/00273171.2014.958211](https://doi.org/10.1080/00273171.2014.958211). URL: <https://www.ncbi.nlm.nih.gov/pubmed/26609745>.
- [91] S. Bailly, M. Destors, Y. Grillet, et al. "Obstructive Sleep Apnea: A Cluster Analysis at Time of Diagnosis". In: *PLoS One* 11.6 (2016), e0157318. ISSN: 1932-6203 (Electronic) 1932-6203 (Linking). DOI: [10.1371/journal.pone.0157318](https://doi.org/10.1371/journal.pone.0157318). URL: <https://www.ncbi.nlm.nih.gov/pubmed/27314230>.
- [92] F. Gagnadoux, M. Le Vaillant, A. Paris, et al. "Relationship Between OSA Clinical Phenotypes and CPAP Treatment Outcomes". In: *Chest* 149.1 (2016), pp. 288–90. ISSN: 1931-3543 (Electronic) 0012-3692 (Linking). DOI: [10.1016/j.chest.2015.09.032](https://doi.org/10.1016/j.chest.2015.09.032). URL: <https://www.ncbi.nlm.nih.gov/pubmed/26757296>.
- [93] D. Lacedonia, G. E. Carpagnano, R. Sabato, et al. "Characterization of obstructive sleep apnea-hypopnea syndrome (OSA) population by means of cluster analysis". In: *J Sleep Res* 25.6 (2016), pp. 724–730. ISSN: 1365-2869 (Electronic) 0962-1105 (Linking). DOI: [10.1111/jsr.12429](https://doi.org/10.1111/jsr.12429). URL: <https://www.ncbi.nlm.nih.gov/pubmed/27191534>.
- [94] G. D. Vavougiou, D. G. George, C. Pastaka, et al. "Phenotypes of comorbidity in OSAS patients: combining categorical principal component analysis with cluster analysis". In: *J Sleep Res* 25.1 (2016), pp. 31–8. ISSN: 1365-2869 (Electronic) 0962-1105 (Linking). DOI: [10.1111/jsr.12344](https://doi.org/10.1111/jsr.12344). URL: <https://www.ncbi.nlm.nih.gov/pubmed/26365653>.
- [95] C. Turino, S. Bertran, R. Gavalda, et al. "Characterization of the CPAP-treated patient population in Catalonia". In: *PLoS One* 12.9 (2017), e0185191. ISSN:

- 1932-6203 (Electronic) 1932-6203 (Linking). DOI: [10.1371/journal.pone.0185191](https://doi.org/10.1371/journal.pone.0185191). URL: <https://www.ncbi.nlm.nih.gov/pubmed/28934303>.
- [96] D. Ferreira-Santos and P. Pereira Rodrigues. "Phenotyping Obstructive Sleep Apnea Patients: A First Approach to Cluster Visualization". In: *Stud Health Technol Inform* 255 (2018), pp. 75–79. ISSN: 1879-8365 (Electronic) 0926-9630 (Linking). URL: <https://www.ncbi.nlm.nih.gov/pubmed/30306910>.
- [97] J. Kim, B. T. Keenan, D. C. Lim, et al. "Symptom-Based Subgroups of Koreans With Obstructive Sleep Apnea". In: *J Clin Sleep Med* 14.3 (2018), pp. 437–443. ISSN: 1550-9397 (Electronic) 1550-9389 (Linking). DOI: [10.5664/jcsm.6994](https://doi.org/10.5664/jcsm.6994). URL: <https://www.ncbi.nlm.nih.gov/pubmed/29510793>.
- [98] W. Quan, D. Zheng, R. Douglas McEvoy, et al. "High Risk Characteristics for Recurrent Cardiovascular Events among Patients with Obstructive Sleep Apnoea in the SAVE Study". In: *EClinicalMedicine* 2-3 (2018), pp. 59–65. ISSN: 2589-5370 (Electronic) 2589-5370 (Linking). DOI: [10.1016/j.eclinm.2018.09.002](https://doi.org/10.1016/j.eclinm.2018.09.002). URL: <https://www.ncbi.nlm.nih.gov/pubmed/31193555>.
- [99] A. V. Zinchuk, S. Jeon, B. B. Koo, et al. "Polysomnographic phenotypes and their cardiovascular implications in obstructive sleep apnoea". In: *Thorax* 73.5 (2018), pp. 472–480. ISSN: 1468-3296 (Electronic) 0040-6376 (Linking). DOI: [10.1136/thoraxjnl-2017-210431](https://doi.org/10.1136/thoraxjnl-2017-210431). URL: <https://www.ncbi.nlm.nih.gov/pubmed/28935698>.
- [100] D. R. Mazzotti, B. T. Keenan, D. C. Lim, et al. "Symptom Subtypes of Obstructive Sleep Apnea Predict Incidence of Cardiovascular Outcomes". In: *Am J Respir Crit Care Med* 200.4 (2019), pp. 493–506. ISSN: 1535-4970 (Electronic) 1073-449X (Linking). DOI: [10.1164/rccm.201808-15090C](https://doi.org/10.1164/rccm.201808-15090C). URL: <https://www.ncbi.nlm.nih.gov/pubmed/30764637>.
- [101] H. Nakayama, M. Kobayashi, S. Tsuiki, et al. "Obstructive sleep apnea phenotypes in men based on characteristics of respiratory events during polysomnography". In: *Sleep Breath* 23.4 (2019), pp. 1087–1094. ISSN: 1522-1709 (Electronic) 1520-9512 (Linking). DOI: [10.1007/s11325-019-01785-8](https://doi.org/10.1007/s11325-019-01785-8). URL: <https://www.ncbi.nlm.nih.gov/pubmed/30693418>.
- [102] M. Mendelson, T. Gentina, E. Gentina, et al. "Multidimensional Evaluation of Continuous Positive Airway Pressure (CPAP) Treatment for Sleep Apnea in Different Clusters of Couples". In: *J Clin Med* 9.6 (2020), p. 1658. ISSN: 2077-0383 (Print) 2077-0383 (Linking). DOI: [10.3390/jcm9061658](https://doi.org/10.3390/jcm9061658). URL: <https://www.ncbi.nlm.nih.gov/pubmed/32492820>.
- [103] S. Bailly, L. Grote, J. Hedner, et al. "Clusters of sleep apnoea phenotypes: A large pan-European study from the European Sleep Apnoea Database (ESADA)". In: *Respirology* 26.4 (2021), pp. 378–387. ISSN: 1440-1843 (Electronic) 1323-7799 (Linking). DOI: [10.1111/resp.13969](https://doi.org/10.1111/resp.13969). URL: <https://www.ncbi.nlm.nih.gov/pubmed/33140467>.
- [104] S. Romero-Peralta, F. Garcia-Rio, P. Resano Barrio, et al. "Defining the Heterogeneity of Sleep Apnea Syndrome: A Cluster Analysis With Implications for Patient Management". In: *Arch Bronconeumol* 58.2 (2022), pp. 125–134. ISSN: 1579-2129 (Electronic) 0300-2896 (Linking). DOI: [10.1016/j.arbres.2021.02.022](https://doi.org/10.1016/j.arbres.2021.02.022). URL: <https://www.ncbi.nlm.nih.gov/pubmed/33820676>.
- [105] P. F. Tempaku, E. Silva L. Oliveira, T. M. Guimaraes, et al. "The reproducibility of clinical OSA subtypes: a population-based longitudinal study". In: *Sleep Breath* (2022). ISSN: 1522-1709 (Electronic) 1520-9512 (Linking). DOI: [10.1007/](https://doi.org/10.1007/)

- s11325-021-02470-5. URL: <https://www.ncbi.nlm.nih.gov/pubmed/34984643>.
- [106] D. Testelmans, M. A. Spruit, B. Vrijsen, et al. "Comorbidity clusters in patients with moderate-to-severe OSA". In: *Sleep Breath* 26.1 (2022), pp. 195–204. ISSN: 1522-1709 (Electronic) 1520-9512 (Linking). DOI: [10.1007/s11325-021-02390-4](https://doi.org/10.1007/s11325-021-02390-4). URL: <https://www.ncbi.nlm.nih.gov/pubmed/33942208>.
- [107] F. Baratta, D. Pastori, T. Bucci, et al. "Long-term prediction of adherence to continuous positive air pressure therapy for the treatment of moderate/severe obstructive sleep apnea syndrome". In: *Sleep Medicine* 43 (2018), pp. 66–70. ISSN: 1389-9457. DOI: [10.1016/j.sleep.2017.09.032](https://doi.org/10.1016/j.sleep.2017.09.032). URL: [%3CGo%20to%20ISI%3E://WOS:000425976300013](https://www.ncbi.nlm.nih.gov/pubmed/300425976300013).
- [108] P. E. Zink A. N. Holm A. A. Billington C. J. Bunney and C. M. Kotz. "Claustrophobic Tendencies and Continuous Positive Airway Pressure Therapy Non-adherence in Adults with Obstructive Sleep Apnea". In: *Physiology & behavior* 176.2 (2017), pp. 139–148. DOI: [10.1016/j.physbeh.2017.03.040](https://doi.org/10.1016/j.physbeh.2017.03.040).
- [109] A. M. Sawyer, N. Gooneratne, C. L. Marcus, et al. "A Systematic Review of CPAP Adherence Across Age Groups: Clinical and Empiric Insights for Developing CPAP Adherence Interventions". In: *Sleep Medicine* 15.6 (2011), pp. 343–356. DOI: [10.1016/j.smr.2011.01.003](https://doi.org/10.1016/j.smr.2011.01.003).
- [110] C. Turino, I. D. Benitez, X. Rafael-Palou, et al. "Management and Treatment of Patients With Obstructive Sleep Apnea Using an Intelligent Monitoring System Based on Machine Learning Aiming to Improve Continuous Positive Airway Pressure Treatment Compliance: Randomized Controlled Trial". In: *J Med Internet Res* 23.10 (2021), e24072. ISSN: 1438-8871 (Electronic) 1438-8871 (Linking). DOI: [10.2196/24072](https://doi.org/10.2196/24072). URL: <https://www.ncbi.nlm.nih.gov/pubmed/34661550>.
- [111] B. A. Edwards, C. Bristow, D. M. O'Driscoll, et al. "Assessing the impact of diet, exercise and the combination of the two as a treatment for OSA: A systematic review and meta-analysis". In: *Respirology* 24.8 (2019), pp. 740–751. ISSN: 1440-1843 (Electronic) 1323-7799 (Linking). DOI: [10.1111/resp.13580](https://doi.org/10.1111/resp.13580). URL: <https://www.ncbi.nlm.nih.gov/pubmed/31116901>.
- [112] Z. Fereidouni, R. Sabet Sarvestani, G. Hariri, et al. "Moving Into Action: The Master Key to Patient Education". In: *Journal of Nursing Research* 27.1 (2019). ISSN: 1682-3141. DOI: [ARTNe610.1097/jnr.000000000000280](https://doi.org/10.1097/jnr.000000000000280). URL: [%3CGo%20to%20ISI%3E://WOS:000458244700007](https://www.ncbi.nlm.nih.gov/pubmed/300458244700007).
- [113] M. Marthick, D. McGregor, J. Alison, et al. "Supportive Care Interventions for People With Cancer Assisted by Digital Technology: Systematic Review". In: *J Med Internet Res* 23.10 (2021), e24722. ISSN: 1438-8871 (Electronic) 1438-8871 (Linking). DOI: [10.2196/24722](https://doi.org/10.2196/24722). URL: <https://www.ncbi.nlm.nih.gov/pubmed/34714246>.
- [114] K. Sorensen, S. Van den Broucke, J. Fullam, et al. "Health literacy and public health: a systematic review and integration of definitions and models". In: *BMC Public Health* 12 (2012), p. 80. ISSN: 1471-2458 (Electronic) 1471-2458 (Linking). DOI: [10.1186/1471-2458-12-80](https://doi.org/10.1186/1471-2458-12-80). URL: <https://www.ncbi.nlm.nih.gov/pubmed/22276600>.
- [115] S. G. Hofmann, A. Asnaani, I. J. Vonk, et al. "The Efficacy of Cognitive Behavioral Therapy: A Review of Meta-analyses". In: *Cognit Ther Res* 36.5 (2012),

- pp. 427–440. ISSN: 0147-5916 (Print) 0147-5916 (Linking). DOI: [10.1007/s10608-012-9476-1](https://doi.org/10.1007/s10608-012-9476-1). URL: <https://www.ncbi.nlm.nih.gov/pubmed/23459093>.
- [116] R. Marin-Navarrete, V. E. Horigian, M. E. Medina-Mora, et al. “Motivational enhancement treatment in outpatient addiction centers: A multisite randomized trial”. In: *Int J Clin Health Psychol* 17.1 (2017), pp. 9–19. ISSN: 2174-0852 (Electronic) 1697-2600 (Linking). DOI: [10.1016/j.ijchp.2016.05.001](https://doi.org/10.1016/j.ijchp.2016.05.001). URL: <https://www.ncbi.nlm.nih.gov/pubmed/30487876>.
- [117] P. A. Cistulli, J. Armitstead, J. L. Pepin, et al. “Short-term CPAP adherence in obstructive sleep apnea: a big data analysis using real world data”. In: *Sleep Med* 59 (2019), pp. 114–116. ISSN: 1878-5506 (Electronic) 1389-9457 (Linking). DOI: [10.1016/j.sleep.2019.01.004](https://doi.org/10.1016/j.sleep.2019.01.004). URL: <https://www.ncbi.nlm.nih.gov/pubmed/30799254>.
- [118] R. J. Schwab, S. M. Badr, L. J. Epstein, et al. “An official American Thoracic Society statement: continuous positive airway pressure adherence tracking systems. The optimal monitoring strategies and outcome measures in adults”. In: *Am J Respir Crit Care Med* 188.5 (2013), pp. 613–20. ISSN: 1535-4970 (Electronic) 1073-449X (Linking). DOI: [10.1164/rccm.201307-1282ST](https://doi.org/10.1164/rccm.201307-1282ST). URL: <https://www.ncbi.nlm.nih.gov/pubmed/23992588>.
- [119] X. Rafael-Palou, A. Steblin, and E. Vargiu. “Remotely Supporting Patients with Obstructive Sleep Apnea at Home”. In: *Internet of Things Technologies for Healthcare, Healthycare 2016* 187 (2016), pp. 119–124. ISSN: 1867-8211. DOI: [10.1007/978-3-319-51234-1_19](https://doi.org/10.1007/978-3-319-51234-1_19). URL: https://www.wos.org/doi/10.1007/978-3-319-51234-1_19.
- [120] F. S. Luyster, M. S. Aloia, D. J. Buysse, et al. “A Couples-Oriented Intervention for Positive Airway Pressure Therapy Adherence: A Pilot Study of Obstructive Sleep Apnea Patients and Their Partners”. In: *Behav Sleep Med* 17.5 (2019), pp. 561–572. ISSN: 1540-2010 (Electronic) 1540-2002 (Linking). DOI: [10.1080/15402002.2018.1425871](https://doi.org/10.1080/15402002.2018.1425871). URL: <https://www.ncbi.nlm.nih.gov/pubmed/29388827>.
- [121] L. M. Donovan, A. Shah, C. L. Chai-Coetzer, et al. “Redesigning Care for OSA”. In: *Chest* 157.4 (2020), pp. 966–976. ISSN: 1931-3543 (Electronic) 0012-3692 (Linking). DOI: [10.1016/j.chest.2019.10.002](https://doi.org/10.1016/j.chest.2019.10.002). URL: <https://www.ncbi.nlm.nih.gov/pubmed/31639334>.
- [122] S. W. Cho, J. H. Wee, S. Yoo, et al. “Effect of Lifestyle Modification Using a Smartphone Application on Obesity With Obstructive Sleep Apnea: A Short-term, Randomized Controlled Study”. In: *Clin Exp Otorhinolaryngol* 11.3 (2018), pp. 192–198. ISSN: 1976-8710 (Print) 1976-8710 (Linking). DOI: [10.21053/ceo.2017.01284](https://doi.org/10.21053/ceo.2017.01284). URL: <https://www.ncbi.nlm.nih.gov/pubmed/29374961>.
- [123] A. L. Shapiro. “Effect of the CPAP-SAVER Intervention on Adherence”. In: *Clin Nurs Res* 30.2 (2021), pp. 110–119. ISSN: 1552-3799 (Electronic) 1054-7738 (Linking). DOI: [10.1177/1054773819865875](https://doi.org/10.1177/1054773819865875). URL: <https://www.ncbi.nlm.nih.gov/pubmed/31387377>.
- [124] S. Carlier, A. V. Bruyneel, and M. Bruyneel. “Pressure adjustment is the most useful intervention for improving compliance in telemonitored patients treated with CPAP in the first 6 months of treatment”. In: *Sleep Breath* 26.1 (2022), pp. 125–132. ISSN: 1522-1709 (Electronic) 1520-9512 (Linking). DOI: [10.1007/s11325-021-02367-3](https://doi.org/10.1007/s11325-021-02367-3). URL: <https://www.ncbi.nlm.nih.gov/pubmed/33846930>.

- [125] R. Merle, C. Pison, S. Logerot, et al. "Peer-driven intervention to help patients resume CPAP therapy following discontinuation: a multicentre, randomised clinical trial with patient involvement". In: *BMJ Open* 11.10 (2021), e053996. ISSN: 2044-6055 (Electronic) 2044-6055 (Linking). DOI: [10.1136/bmjopen-2021-053996](https://doi.org/10.1136/bmjopen-2021-053996). URL: <https://www.ncbi.nlm.nih.gov/pubmed/34649850>.
- [126] H. Truby, B. A. Edwards, D. M. O'Driscoll, et al. "Sleeping Well Trial: Increasing the effectiveness of treatment with continuous positive airway pressure using a weight management program in overweight adults with obstructive sleep apnoea-A stepped wedge randomised trial protocol". In: *Nutr Diet* 76.1 (2019), pp. 110–117. ISSN: 1747-0080 (Electronic) 1446-6368 (Linking). DOI: [10.1111/1747-0080.12435](https://doi.org/10.1111/1747-0080.12435). URL: <https://www.ncbi.nlm.nih.gov/pubmed/29797800>.
- [127] D. Hwang, J. W. Chang, A. V. Benjafield, et al. "Effect of Telemedicine Education and Telemonitoring on Continuous Positive Airway Pressure Adherence. The Tele-Osa Randomized Trial". In: *Am J Respir Crit Care Med* 197.1 (2018), pp. 117–126. ISSN: 1535-4970 (Electronic) 1073-449X (Linking). DOI: [10.1164/rccm.201703-05820C](https://doi.org/10.1164/rccm.201703-05820C). URL: <https://www.ncbi.nlm.nih.gov/pubmed/28858567>.
- [128] M. F. Pengo, M. Czaban, M. P. Berry, et al. "The effect of positive and negative message framing on short term continuous positive airway pressure compliance in patients with obstructive sleep apnea". In: *J Thorac Dis* 10.Suppl 1 (2018), S160–S169. ISSN: 2072-1439 (Print) 2072-1439 (Linking). DOI: [10.21037/jtd.2017.07.110](https://doi.org/10.21037/jtd.2017.07.110). URL: <https://www.ncbi.nlm.nih.gov/pubmed/29445540>.
- [129] V. Isetta, M. A. Negrin, C. Monasterio, et al. "A Bayesian cost-effectiveness analysis of a telemedicine-based strategy for the management of sleep apnoea: a multicentre randomised controlled trial". In: *Thorax* 70.11 (2015), pp. 1054–61. ISSN: 1468-3296 (Electronic) 0040-6376 (Linking). DOI: [10.1136/thoraxjnl-2015-207032](https://doi.org/10.1136/thoraxjnl-2015-207032). URL: <https://www.ncbi.nlm.nih.gov/pubmed/26310452>.
- [130] Samuel T. Kuna, David Shuttleworth, Luqi Chi, et al. *Web-Based Access to Positive Airway Pressure Usage with or without an Initial Financial Incentive Improves Treatment Use in Patients with Obstructive Sleep Apnea*. Electronic Article. Aug. 2015. DOI: [10.5665/sleep.4898](https://doi.org/10.5665/sleep.4898). URL: <http://europepmc.org/abstract/MED/25581921%20https://doi.org/10.5665/sleep.4898%20https://europepmc.org/articles/PMC4507728%20https://europepmc.org/articles/PMC4507728?pdf=render>.
- [131] David Rudilla, Pedro Landete, Enrique Zamora, et al. "MEntA Program Based on Motivational Interview to Improve Adherence to Treatment of Obstructive Sleep Apnea With Continuous Positive Airway Pressure (CPAP): A Randomized Controlled Trial". In: *Open Respiratory Archives* 3.2 (2021), p. 100088. ISSN: 26596636. DOI: [10.1016/j.opresp.2021.100088](https://doi.org/10.1016/j.opresp.2021.100088). URL: <https://www.sciencedirect.com/science/article/pii/S2659663621000072>.
- [132] C. E. Baron, T. W. Smith, B. R. Baucom, et al. "Relationship partner social behavior and continuous positive airway pressure adherence: The role of autonomy support". In: *Health Psychol* 39.4 (2020), pp. 325–334. ISSN: 1930-7810 (Electronic) 0278-6133 (Linking). DOI: [10.1037/hea0000827](https://doi.org/10.1037/hea0000827). URL: <https://www.ncbi.nlm.nih.gov/pubmed/31841020>.

- [133] World Health Organization. "mHealth: new horizons for health through mobile technologies". In: *mHealth: new horizons for health through mobile technologies*. (2011). ISSN: 9241564253. URL: https://www.who.int/goe/publications/goe_mhealth_web.pdf.
- [134] M. S. Marcolino, J. A. Q. Oliveira, M. D'Agostino, et al. "The Impact of mHealth Interventions: Systematic Review of Systematic Reviews". In: *JMIR Mhealth Uhealth* 6.1 (2018), e23. ISSN: 2291-5222 (Print) 2291-5222 (Linking). DOI: 10.2196/mhealth.8873. URL: <https://www.ncbi.nlm.nih.gov/pubmed/29343463>.
- [135] L. V. Araújo, B. C. Letti, F. T. Cantagalli, et al. "A Health Mobile Application and Architecture to Support and Automate In-home Consultation". In: *2015 IEEE 28th International Symposium on Computer-Based Medical Systems*, pp. 151–156. ISBN: 2372-9198. DOI: 10.1109/CBMS.2015.66. URL: <https://ieeexplore.ieee.org/document/7167476/>.
- [136] S. Becker, T. Miron-Shatz, N. Schumacher, et al. "mHealth 2.0: Experiences, Possibilities, and Perspectives". In: *JMIR Mhealth Uhealth* 2.2 (2014), e24. ISSN: 2291-5222 (Print) 2291-5222 (Linking). DOI: 10.2196/mhealth.3328. URL: <https://www.ncbi.nlm.nih.gov/pubmed/25099752>.
- [137] *Ericsson Mobility Report*. en. <https://www.ericsson.com/en/reports-and-papers/mobility-report/reports/november-2021/>. Accessed: 2022-3-22.
- [138] L. Christiansen, C. Lindberg, J. Sanmartin Berglund, et al. "Using Mobile Health and the Impact on Health-Related Quality of Life: Perceptions of Older Adults with Cognitive Impairment". In: *Int J Environ Res Public Health* 17.8 (2020), p. 2650. ISSN: 1660-4601 (Electronic) 1660-4601 (Linking). DOI: 10.3390/ijerph17082650. URL: <https://www.ncbi.nlm.nih.gov/pubmed/32294911>.
- [139] Haute Autorité de Santé (HAS). *Assessment of apps in the mobile health (mHealth) sector -Overview and quality criteria of medical content for referencing digital services in the digital health space and the professional service package*. en. https://www.has-sante.fr/upload/docs/application/pdf/2021-09/assessment_of_apps_in_the_mobile_health_mhealth_sector._overview_and_quality_criteria_of_medical_content.pdf. Accessed: 2022-3-22.
- [140] M. Mendelson, I. Vivodtzev, R. Tamisier, et al. "CPAP treatment supported by telemedicine does not improve blood pressure in high cardiovascular risk OSA patients: a randomized, controlled trial". In: *Sleep* 37.11 (2014), pp. 1863–70. ISSN: 1550-9109 (Electronic) 0161-8105 (Linking). DOI: 10.5665/sleep.4186. URL: <https://www.ncbi.nlm.nih.gov/pubmed/25364081>.
- [141] M. E. Petrov, K. Hasanaj, C. M. Hoffmann, et al. "Rationale, design, and development of SleepWell24: A smartphone application to promote adherence to positive airway pressure therapy among patients with obstructive sleep apnea". In: *Contemp Clin Trials* 89 (2020), p. 105908. ISSN: 1559-2030 (Electronic) 1551-7144 (Linking). DOI: 10.1016/j.cct.2019.105908. URL: <https://www.ncbi.nlm.nih.gov/pubmed/31843639>.
- [142] V. Isetta, M. Torres, K. Gonzalez, et al. "A New mHealth application to support treatment of sleep apnoea patients". In: *J Telemed Telecare* 23.1 (2017), pp. 14–18. ISSN: 1758-1109 (Electronic) 1357-633X (Linking). DOI: 10.1177/1357633X15621848. URL: <https://www.ncbi.nlm.nih.gov/pubmed/26672606>.

- [143] Philips Respironics. *Sleepmapper adherence White Paper - Sleep Review*. en. <http://cdn.sleepreviewmag.com/sleeprev/2014/06/SleepMapper-Adherence-White-Paper.pdf>, journal=Sleepmapper. Accessed: 2022-3-23.
- [144] S. Lynch, A. Blase, A. W. MScMed, et al. en. Accessed: 2022-3-23. 2015. URL: https://document.resmed.com/en-us/documents/products/data-management/myair/1018839_myair_white-paper_amer_eng.pdf.
- [145] K. Sedkaoui, L. Leseux, S. Pontier, et al. "Efficiency of a phone coaching program on adherence to continuous positive airway pressure in sleep apnea hypopnea syndrome: a randomized trial". In: *BMC Pulm Med* 15.1 (2015), p. 102. ISSN: 1471-2466 (Electronic) 1471-2466 (Linking). DOI: [10.1186/s12890-015-0099-7](https://doi.org/10.1186/s12890-015-0099-7). URL: <https://www.ncbi.nlm.nih.gov/pubmed/26370444>.
- [146] S. Alismail and L. Olfman. "A Tailored Motivational Messages Library for a Mobile Health Sleep Behavior Change Support System to Promote Continuous Positive Airway Pressure Use Among Patients With Obstructive Sleep Apnea: Development, Content Validation, and Testing". In: *JMIR Mhealth Uhealth* 8.8 (2020), e18793. ISSN: 2291-5222 (Electronic) 2291-5222 (Linking). DOI: [10.2196/18793](https://doi.org/10.2196/18793). URL: <https://www.ncbi.nlm.nih.gov/pubmed/32784176>.
- [147] R. B. Berry, E. Beck, and J. G. Jasko. "Effect of cloud-based sleep coaches on positive airway pressure adherence". In: *J Clin Sleep Med* 16.4 (2020), pp. 553–562. ISSN: 1550-9397 (Electronic) 1550-9389 (Linking). DOI: [10.5664/jcsm.8276](https://doi.org/10.5664/jcsm.8276). URL: <https://www.ncbi.nlm.nih.gov/pubmed/32022679>.
- [148] J. P. Roberts, T. R. Fisher, M. J. Trowbridge, et al. "A design thinking framework for healthcare management and innovation". In: *Healthc (Amst)* 4.1 (2016), pp. 11–4. ISSN: 2213-0772 (Electronic) 2213-0764 (Linking). DOI: [10.1016/j.hjdsi.2015.12.002](https://doi.org/10.1016/j.hjdsi.2015.12.002). URL: <https://www.ncbi.nlm.nih.gov/pubmed/27001093>.
- [149] J. Farao, B. Malila, N. Conrad, et al. "A user-centred design framework for mHealth". In: *PLoS One* 15.8 (2020), e0237910. ISSN: 1932-6203 (Electronic) 1932-6203 (Linking). DOI: [10.1371/journal.pone.0237910](https://doi.org/10.1371/journal.pone.0237910). URL: <https://www.ncbi.nlm.nih.gov/pubmed/32813711>.
- [150] B. Burford, M. Greco, A. Bedi, et al. "Does questionnaire-based patient feedback reflect the important qualities of clinical consultations? Context, benefits and risks". In: *Patient Educ Couns* 84.2 (2011), e28–36. ISSN: 1873-5134 (Electronic) 0738-3991 (Linking). DOI: [10.1016/j.pec.2010.07.044](https://doi.org/10.1016/j.pec.2010.07.044). URL: <https://www.ncbi.nlm.nih.gov/pubmed/20943343>.
- [151] A. Griffiths and M. P. Leaver. "Wisdom of patients: predicting the quality of care using aggregated patient feedback". In: *BMJ Qual Saf* 27.2 (2018), pp. 110–118. ISSN: 2044-5423 (Electronic) 2044-5415 (Linking). DOI: [10.1136/bmjqs-2017-006847](https://doi.org/10.1136/bmjqs-2017-006847). URL: <https://www.ncbi.nlm.nih.gov/pubmed/28971881>.
- [152] D. J. Baldie, B. Guthrie, V. Entwistle, et al. "Exploring the impact and use of patients' feedback about their care experiences in general practice settings-a realist synthesis". In: *Fam Pract* 35.1 (2018), pp. 13–21. ISSN: 1460-2229 (Electronic) 0263-2136 (Linking). DOI: [10.1093/fampra/cmz067](https://doi.org/10.1093/fampra/cmz067). URL: <https://www.ncbi.nlm.nih.gov/pubmed/28985368>.

- [153] M. Schofield and C. Forrester-Knauss. "Surveys and questionnaires in health research". In: *Research methods in health: Foundations for evidence-based practice*. Ed. by Pranee Liamputtong. 2nd ed. Oxford University Press, Jan. 2013, pp. 198–218. ISBN: 9780195520064.
- [154] M. W. Johns. "A new method for measuring daytime sleepiness: the Epworth sleepiness scale". In: *Sleep* 14.6 (1991), pp. 540–5. ISSN: 0161-8105 (Print) 0161-8105 (Linking). DOI: [10.1093/sleep/14.6.540](https://doi.org/10.1093/sleep/14.6.540). URL: <https://www.ncbi.nlm.nih.gov/pubmed/1798888>.
- [155] A. Tan, J. D. Yin, L. W. Tan, et al. "Using the Berlin Questionnaire to Predict Obstructive Sleep Apnea in the General Population". In: *J Clin Sleep Med* 13.3 (2017), pp. 427–432. ISSN: 1550-9397 (Electronic) 1550-9389 (Linking). DOI: [10.5664/jcsm.6496](https://doi.org/10.5664/jcsm.6496). URL: <https://www.ncbi.nlm.nih.gov/pubmed/27855742>.
- [156] M. J. Thurtell, B. B. Bruce, D. B. Rye, et al. "The Berlin questionnaire screens for obstructive sleep apnea in idiopathic intracranial hypertension". In: *J Neuroophthalmol* 31.4 (2011), pp. 316–9. ISSN: 1536-5166 (Electronic) 1070-8022 (Linking). DOI: [10.1097/WNO.0b013e31821a4d54](https://doi.org/10.1097/WNO.0b013e31821a4d54). URL: <https://www.ncbi.nlm.nih.gov/pubmed/21537196>.
- [157] F. Chung, B. Yegneswaran, P. Liao, et al. "STOP questionnaire: a tool to screen patients for obstructive sleep apnea". In: *Anesthesiology* 108.5 (2008), pp. 812–21. ISSN: 1528-1175 (Electronic) 0003-3022 (Linking). DOI: [10.1097/ALN.0b013e31816d83e4](https://doi.org/10.1097/ALN.0b013e31816d83e4). URL: <https://www.ncbi.nlm.nih.gov/pubmed/18431116>.
- [158] L. M. Donovan, M. Rueschman, J. Weng, et al. "The effectiveness of an obstructive sleep apnea screening and treatment program in patients with type 2 diabetes". In: *Diabetes Res Clin Pract* 134 (2017), pp. 145–152. ISSN: 1872-8227 (Electronic) 0168-8227 (Linking). DOI: [10.1016/j.diabres.2017.10.013](https://doi.org/10.1016/j.diabres.2017.10.013). URL: <https://www.ncbi.nlm.nih.gov/pubmed/29054482>.
- [159] L. Trenaman, S. Munro, F. Almeida, et al. "Development of a patient decision aid prototype for adults with obstructive sleep apnea". In: *Sleep Breath* 20.2 (2016), pp. 653–61. ISSN: 1522-1709 (Electronic) 1520-9512 (Linking). DOI: [10.1007/s11325-015-1269-9](https://doi.org/10.1007/s11325-015-1269-9). URL: <https://www.ncbi.nlm.nih.gov/pubmed/26449553>.
- [160] J. R. Vranish and E. F. Bailey. "Inspiratory Muscle Training Improves Sleep and Mitigates Cardiovascular Dysfunction in Obstructive Sleep Apnea". In: *Sleep* 39.6 (2016), pp. 1179–85. ISSN: 1550-9109 (Electronic) 0161-8105 (Linking). DOI: [10.5665/sleep.5826](https://doi.org/10.5665/sleep.5826). URL: <https://www.ncbi.nlm.nih.gov/pubmed/27091540>.
- [161] A. A. El-Solh, G. G. Homish, G. Ditursi, et al. "A Randomized Crossover Trial Evaluating Continuous Positive Airway Pressure Versus Mandibular Advancement Device on Health Outcomes in Veterans With Posttraumatic Stress Disorder". In: *J Clin Sleep Med* 13.11 (2017), pp. 1327–1335. ISSN: 1550-9397 (Electronic) 1550-9389 (Linking). DOI: [10.5664/jcsm.6808](https://doi.org/10.5664/jcsm.6808). URL: <https://www.ncbi.nlm.nih.gov/pubmed/29065960>.
- [162] Y. Wang, L. Ai, J. Luo, et al. "Effect of adherence on daytime sleepiness, fatigue, depression and sleep quality in the obstructive sleep apnea/hypopnea syndrome patients undertaking nasal continuous positive airway pressure therapy". In: *Patient Prefer Adherence* 11 (2017), pp. 769–779. ISSN: 1177-889X (Print) 1177-889X (Linking). DOI: [10.2147/PPA.S128217](https://doi.org/10.2147/PPA.S128217). URL: <https://www.ncbi.nlm.nih.gov/pubmed/28442894>.

- [163] D. J. Buysse, 3rd Reynolds C. F., T. H. Monk, et al. "The Pittsburgh Sleep Quality Index: a new instrument for psychiatric practice and research". In: *Psychiatry Res* 28.2 (1989), pp. 193–213. ISSN: 0165-1781 (Print) 0165-1781 (Linking). DOI: [10.1016/0165-1781\(89\)90047-4](https://doi.org/10.1016/0165-1781(89)90047-4). URL: <https://www.ncbi.nlm.nih.gov/pubmed/2748771>.
- [164] K. Balakrishnan, K. T. James, and E. M. Weaver. "Predicting CPAP Use and Treatment Outcomes Using Composite Indices of Sleep Apnea Severity". In: *J Clin Sleep Med* 12.6 (2016), pp. 849–54. ISSN: 1550-9397 (Electronic) 1550-9389 (Linking). DOI: [10.5664/jcsm.5884](https://doi.org/10.5664/jcsm.5884). URL: <https://www.ncbi.nlm.nih.gov/pubmed/26857052>.
- [165] Y. Lacasse, C. Godbout, and F. Series. "Independent validation of the Sleep Apnoea Quality of Life Index". In: *Thorax* 57.6 (2002), pp. 483–8. ISSN: 0040-6376 (Print) 0040-6376 (Linking). DOI: [10.1136/thorax.57.6.483](https://doi.org/10.1136/thorax.57.6.483). URL: <https://www.ncbi.nlm.nih.gov/pubmed/12037222>.
- [166] T. E. Weaver, A. M. Laizner, L. K. Evans, et al. "An instrument to measure functional status outcomes for disorders of excessive sleepiness". In: *Sleep* 20.10 (1997), pp. 835–43. ISSN: 0161-8105 (Print) 0161-8105 (Linking). URL: <https://www.ncbi.nlm.nih.gov/pubmed/9415942>.
- [167] E. R. Chasens, S. J. Ratcliffe, and T. E. Weaver. "Development of the FOSQ-10: a short version of the Functional Outcomes of Sleep Questionnaire". In: *Sleep* 32.7 (2009), pp. 915–9. ISSN: 0161-8105 (Print) 0161-8105 (Linking). DOI: [10.1093/sleep/32.7.915](https://doi.org/10.1093/sleep/32.7.915). URL: <https://www.ncbi.nlm.nih.gov/pubmed/19639754>.
- [168] T. E. Weaver, G. Maislin, D. F. Dinges, et al. "Self-efficacy in sleep apnea: instrument development and patient perceptions of obstructive sleep apnea risk, treatment benefit, and volition to use continuous positive airway pressure". In: *Sleep* 26.6 (2003), pp. 727–32. ISSN: 0161-8105 (Print) 0161-8105 (Linking). DOI: [10.1093/sleep/26.6.727](https://doi.org/10.1093/sleep/26.6.727). URL: <https://www.ncbi.nlm.nih.gov/pubmed/14572127>.
- [169] J. A. Micoulaud-Franchi, O. Coste, S. Bioulac, et al. "A French update on the Self-Efficacy Measure for Sleep Apnea (SEMSA) to assess continuous positive airway pressure (CPAP) use". In: *Sleep Breath* 23.1 (2019), pp. 217–226. ISSN: 1522-1709 (Electronic) 1520-9512 (Linking). DOI: [10.1007/s11325-018-1686-7](https://doi.org/10.1007/s11325-018-1686-7). URL: <https://www.ncbi.nlm.nih.gov/pubmed/29946945>.
- [170] F. Rezaeitalab, F. Moharrari, S. Saberi, et al. "The correlation of anxiety and depression with obstructive sleep apnea syndrome". In: *J Res Med Sci* 19.3 (2014), pp. 205–10. ISSN: 1735-1995 (Print) 1735-1995 (Linking). URL: <https://www.ncbi.nlm.nih.gov/pubmed/24949026>.
- [171] K. A. Babson, A. C. Del Re, M. O. Bonn-Miller, et al. "The comorbidity of sleep apnea and mood, anxiety, and substance use disorders among obese military veterans within the Veterans Health Administration". In: *J Clin Sleep Med* 9.12 (2013), pp. 1253–8. ISSN: 1550-9397 (Electronic) 1550-9389 (Linking). DOI: [10.5664/jcsm.3262](https://doi.org/10.5664/jcsm.3262). URL: <https://www.ncbi.nlm.nih.gov/pubmed/24340286>.
- [172] J. C. Edmonds, H. Yang, T. S. King, et al. "Claustrophobic tendencies and continuous positive airway pressure therapy non-adherence in adults with obstructive sleep apnea". In: *Heart Lung* 44.2 (2015), pp. 100–6. ISSN: 1527-3288 (Electronic) 0147-9563 (Linking). DOI: [10.1016/j.hrtlng.2015.01.002](https://doi.org/10.1016/j.hrtlng.2015.01.002). URL: <https://www.ncbi.nlm.nih.gov/pubmed/25744632>.

- [173] S.H. Lovibond and P.F. Lovibond. *Manual for the Depression Anxiety Stress Scales*. Psychology Foundation of Australia, 1996. ISBN: 9780733414237. URL: <https://books.google.fr/books?id=mXoQHAAACAAJ>.
- [174] J. Vasconcelos-Raposo, H. M. Fernandes, and C. M. Teixeira. "Factor structure and reliability of the depression, anxiety and stress scales in a large Portuguese community sample". In: *Span J Psychol* 16 (2013), E10. ISSN: 1988-2904 (Electronic) 1138-7416 (Linking). DOI: 10.1017/sjp.2013.15. URL: <https://www.ncbi.nlm.nih.gov/pubmed/23866203>.
- [175] S. J. Sinclair, C. J. Siefert, J. M. Slavin-Mulford, et al. "Psychometric evaluation and normative data for the depression, anxiety, and stress scales-21 (DASS-21) in a nonclinical sample of U.S. adults". In: *Eval Health Prof* 35.3 (2012), pp. 259–79. ISSN: 1552-3918 (Electronic) 0163-2787 (Linking). DOI: 10.1177/0163278711424282. URL: <https://www.ncbi.nlm.nih.gov/pubmed/22008979>.
- [176] S. Nahaboo. "Validation of the French Depression Anxiety Stress Scales (DASS-21) and predictors of depression in an adolescent Mauritian population". Book. 2015. DOI: 10.13140/RG.2.1.1321.5203.
- [177] E. Yang, E. Schamber, R. M. L. Meyer, et al. "Happier Healers: Randomized Controlled Trial of Mobile Mindfulness for Stress Management". In: *J Altern Complement Med* 24.5 (2018), pp. 505–513. ISSN: 1557-7708 (Electronic) 1075-5535 (Linking). DOI: 10.1089/acm.2015.0301. URL: <https://www.ncbi.nlm.nih.gov/pubmed/29420050>.
- [178] S. Cohen, T. Kamarck, and R. Mermelstein. "A global measure of perceived stress". In: *J Health Soc Behav* 24.4 (1983), pp. 385–96. ISSN: 0022-1465 (Print) 0022-1465 (Linking). DOI: 10.2307/2136404. URL: <https://www.ncbi.nlm.nih.gov/pubmed/6668417>.
- [179] K. H. Prang, R. Maritz, H. Sabanovic, et al. "Mechanisms and impact of public reporting on physicians and hospitals' performance: A systematic review (2000-2020)". In: *PLoS One* 16.2 (2021), e0247297. ISSN: 1932-6203 (Electronic) 1932-6203 (Linking). DOI: 10.1371/journal.pone.0247297. URL: <https://www.ncbi.nlm.nih.gov/pubmed/33626055>.
- [180] K. A. Roecklein, J. A. Schumacher, J. M. Gabriele, et al. "Personalized feedback to improve CPAP adherence in obstructive sleep apnea". In: *Behav Sleep Med* 8.2 (2010), pp. 105–12. ISSN: 1540-2010 (Electronic) 1540-2002 (Linking). DOI: 10.1080/15402001003622859. URL: <https://www.ncbi.nlm.nih.gov/pubmed/20352546>.
- [181] M. R. Crawford, C. A. Espie, D. J. Bartlett, et al. "Integrating psychology and medicine in CPAP adherence—new concepts?" In: *Sleep Med Rev* 18.2 (2014), pp. 123–39. ISSN: 1532-2955 (Electronic) 1087-0792 (Linking). DOI: 10.1016/j.smrv.2013.03.002. URL: <https://www.ncbi.nlm.nih.gov/pubmed/23725820>.
- [182] S. T. Hu, C. C. Yu, P. S. Lee, et al. "Life experiences among obstructive sleep apnoea patients receiving continuous positive airway pressure therapy". In: *J Clin Nurs* 23.1-2 (2014), pp. 268–78. ISSN: 1365-2702 (Electronic) 0962-1067 (Linking). DOI: 10.1111/jocn.12414. URL: <https://www.ncbi.nlm.nih.gov/pubmed/24313940>.
- [183] J. L. Pepin. "[Obstructive sleep apnea: Time to design new clinical pathways and develop personalized medicine]". In: *Presse Med* 46.5 (2017), pp. 465–467.

- ISSN: 2213-0276 (Electronic) 0755-4982 (Linking). DOI: [10.1016/j.lpm.2017.05.012](https://doi.org/10.1016/j.lpm.2017.05.012). URL: <https://www.ncbi.nlm.nih.gov/pubmed/28550932>.
- [184] J. Swieca, G. S. Hamilton, and H. Meaklim. "The management, privacy and medico-legal issues of electronic CPAP data in Australia and New Zealand: Electronic CPAP data management in Australia and New Zealand". In: *Sleep Med* 36 Suppl 1 (2017), S48–S55. ISSN: 1878-5506 (Electronic) 1389-9457 (Linking). DOI: [10.1016/j.sleep.2017.03.018](https://doi.org/10.1016/j.sleep.2017.03.018). URL: <https://www.ncbi.nlm.nih.gov/pubmed/28648227>.
- [185] D. C. Lim, K. Sutherland, P. A. Cistulli, et al. "P4 medicine approach to obstructive sleep apnoea". In: *Respirology* 22.5 (2017), pp. 849–860. ISSN: 1440-1843 (Electronic) 1323-7799 (Linking). DOI: [10.1111/resp.13063](https://doi.org/10.1111/resp.13063). URL: <https://www.ncbi.nlm.nih.gov/pubmed/28477347>.
- [186] K. Sutherland, K. Kairaitis, B. J. Yee, et al. "From CPAP to tailored therapy for obstructive sleep Apnoea". In: *Multidiscip Respir Med* 13.1 (2018), p. 44. ISSN: 1828-695X (Print) 1828-695X (Linking). DOI: [10.1186/s40248-018-0157-0](https://doi.org/10.1186/s40248-018-0157-0). URL: <https://www.ncbi.nlm.nih.gov/pubmed/30524729>.
- [187] J. Hilbert and H. K. Yaggi. "Patient-centered care in obstructive sleep apnea: A vision for the future". In: *Sleep Med Rev* 37 (2018), pp. 138–147. ISSN: 1532-2955 (Electronic) 1087-0792 (Linking). DOI: [10.1016/j.smrv.2017.02.004](https://doi.org/10.1016/j.smrv.2017.02.004). URL: <https://www.ncbi.nlm.nih.gov/pubmed/28633915>.
- [188] A. Brostrom, A. H. Pakpour, P. Nilsen, et al. "Promoting CPAP adherence in clinical practice: A survey of Swedish and Norwegian CPAP practitioners' beliefs and practices". In: *J Sleep Res* 27.6 (2018), e12675. ISSN: 1365-2869 (Electronic) 0962-1105 (Linking). DOI: [10.1111/jsr.12675](https://doi.org/10.1111/jsr.12675). URL: <https://www.ncbi.nlm.nih.gov/pubmed/29493035>.
- [189] A. A. Tabriz, S. A. Flocke, D. Shires, et al. "Logic model framework for considering the inputs, processes and outcomes of a healthcare organisation-research partnership". In: *BMJ Qual Saf* 29.9 (2020), pp. 746–755. ISSN: 2044-5423 (Electronic) 2044-5415 (Linking). DOI: [10.1136/bmjqs-2019-010059](https://doi.org/10.1136/bmjqs-2019-010059). URL: <https://www.ncbi.nlm.nih.gov/pubmed/31826921>.
- [190] *Roundtable on Value & Science-Driven Health Care*. URL: <https://www.ncbi.nlm.nih.gov/books/NBK61957/>.
- [191] S. McLachlan, H. W. W. Potts, K. Dube, et al. "The Heimdall Framework for Supporting Characterisation of Learning Health Systems". In: *J Innov Health Inform* 25.2 (2018), pp. 77–87. ISSN: 2058-4563 (Electronic) 2058-4555 (Linking). DOI: [10.14236/jhi.v25i2.996](https://doi.org/10.14236/jhi.v25i2.996). URL: <https://www.ncbi.nlm.nih.gov/pubmed/30398449>.
- [192] M. Smith, R. Saunders, L. Stuckhardt, et al. "Best Care at Lower Cost: The Path to Continuously Learning Health Care in America". In: *Best Care at Lower Cost: The Path to Continuously Learning Health Care in America*. Ed. by M. Smith, R. Saunders, L. Stuckhardt, et al. Washington (DC): National Academies Press (US) Copyright 2013 by the National Academy of Sciences. All rights reserved., 2013. ISBN: 9780309260732. DOI: [10.17226/13444](https://doi.org/10.17226/13444). URL: <https://www.ncbi.nlm.nih.gov/pubmed/24901184>.
- [193] R. W. Smith, E. Orlando, and W. Berta. "Enabling continuous learning and quality improvement in health care". In: *Int J Health Care Qual Assur* 31.6 (2018), pp. 587–599. ISSN: 0952-6862 (Print) 0952-6862 (Linking). DOI: [10.1185/09526862.2018.1511111](https://doi.org/10.1185/09526862.2018.1511111).

- 1108 / IJHCQA - 10 - 2017 - 0198. URL: <https://www.ncbi.nlm.nih.gov/pubmed/29954273>.
- [194] J. C. Enticott, A. Melder, A. Johnson, et al. "A Learning Health System Framework to Operationalize Health Data to Improve Quality Care: An Australian Perspective". In: *Front Med (Lausanne)* 8 (2021), p. 730021. ISSN: 2296-858X (Print) 2296-858X (Linking). DOI: 10.3389/fmed.2021.730021. URL: <https://www.ncbi.nlm.nih.gov/pubmed/34778291>.
- [195] A. P. Abernethy, J. L. Wheeler, and S. Y. Zafar. "Management of gastrointestinal symptoms in advanced cancer patients: the rapid learning cancer clinic model". In: *Curr Opin Support Palliat Care* 4.1 (2010), pp. 36–45. ISSN: 1751-4266 (Electronic) 1751-4258 (Linking). DOI: 10.1097/SPC.0b013e32833575fd. URL: <https://www.ncbi.nlm.nih.gov/pubmed/19952928>.
- [196] A. P. Abernethy, A. Ahmad, S. Y. Zafar, et al. "Electronic patient-reported data capture as a foundation of rapid learning cancer care". In: *Med Care* 48.6 Suppl (2010), S32–8. ISSN: 1537-1948 (Electronic) 0025-7079 (Linking). DOI: 10.1097/MLR.0b013e3181db53a4. URL: <https://www.ncbi.nlm.nih.gov/pubmed/20473201>.
- [197] A. Flynn. "Informatics and technology enable us to learn from every patient: Pharmacists' many roles in learning health systems". In: *Am J Health Syst Pharm* 76.15 (2019), pp. 1095–1096. ISSN: 1535-2900 (Electronic) 1079-2082 (Linking). DOI: 10.1093/ajhp/zxz118. URL: <https://www.ncbi.nlm.nih.gov/pubmed/31361872>.
- [198] K. Patel, C. Mistry, D. Mehta, et al. "A survey on artificial intelligence techniques for chronic diseases: open issues and challenges". In: *Artificial Intelligence Review* (2021). ISSN: 0269-2821. DOI: 10.1007/s10462-021-10084-2. URL: <https://www.wos.org/wos/doi/10.1007/s10462-021-10084-2>.
- [199] Wolfgang Fruehwirt and Paul Duckworth. "Towards better healthcare: What could and should be automated?" In: *Technological Forecasting and Social Change* 172 (2021), p. 120967. ISSN: 00401625. DOI: 10.1016/j.techfore.2021.120967.
- [200] M. Weiss, S. Muegge, A. Nazari, et al. "Incremental Analysis in Machine Learning". In: *24th European Conference on Pattern Languages of Programs (Euro-PLoP)*. ML + Feedback: Assoc Computing Machinery, 2019, pp. 1–3. ISBN: 978-1-4503-6206-1. DOI: 10.1145/3361149.3361150. URL: <https://www.wos.org/wos/doi/10.1145/3361149.3361150>.
- [201] E. D. Gennatas, J. H. Friedman, L. H. Ungar, et al. "Expert-augmented machine learning". In: *Proc Natl Acad Sci U S A* 117.9 (2020), pp. 4571–4577. ISSN: 1091-6490 (Electronic) 0027-8424 (Linking). DOI: 10.1073/pnas.1906831117. URL: <https://www.ncbi.nlm.nih.gov/pubmed/32071251>.
- [202] J. S. Joy Mangul, A. Sekhari, N. Moalla, et al. "Data-oriented approach to improve adherence to CPAP therapy during the initiation phase". In: *2019 13th International Conference on Software, Knowledge, Information Management and Applications (SKIMA)* (2019). ISSN: 2373-082x. URL: <https://www.wos.org/wos/doi/10.1109/SKIMA48920.2019.9005455>.
- [203] T. E. Weaver and R. R. Grunstein. "Adherence to continuous positive airway pressure therapy: the challenge to effective treatment". In: *Proc Am Thorac Soc* 5.2 (2008), pp. 173–8. ISSN: 1546-3222 (Print) 1546-3222 (Linking). DOI:

- 10.1513/pats.200708-119MG. URL: <https://www.ncbi.nlm.nih.gov/pubmed/18250209>.
- [204] M. Lebret, N. Arnol, J. B. Martinot, et al. "Determinants of Unintentional Leaks During CPAP Treatment in OSA". In: *Chest* 153.4 (2018), pp. 834–842. ISSN: 1931-3543 (Electronic) 0012-3692 (Linking). DOI: 10.1016/j.chest.2017.08.017. URL: <https://www.ncbi.nlm.nih.gov/pubmed/28847549>.
- [205] Haute autorisé de santé. *Évaluation clinique et économique des dispositifs médicaux et prestations associées pour la prise en charge du syndrome d'apnées hypopnées obstructives du sommeil (SAHOS)*. Report. Haute autorisé de santé, July 2014.
- [206] J. C. Meurice, P. Ingrand, F. Portier, et al. "A multicentre trial of education strategies at CPAP induction in the treatment of severe sleep apnoea-hypopnoea syndrome". In: *Sleep Med* 8.1 (2007), pp. 37–42. ISSN: 1389-9457 (Print) 1389-9457. DOI: 10.1016/j.sleep.2006.05.010.
- [207] D. C. Mohr, K. Cheung, S. M. Schueller, et al. "Continuous evaluation of evolving behavioral intervention technologies". In: *Am J Prev Med* 45.4 (2013), pp. 517–23. ISSN: 1873-2607 (Electronic) 0749-3797 (Linking). DOI: 10.1016/j.amepre.2013.06.006. URL: <https://www.ncbi.nlm.nih.gov/pubmed/24050429>.
- [208] "IEEE Standard Glossary of Software Engineering Terminology". In: *IEEE Std 610.12-1990* (1990), pp. 1–84. DOI: 10.1109/ieeestd.1990.101064.
- [209] Jonas Mellin and Mikael Berndtsson. "Event Specification". In: *Encyclopedia of Database Systems*. Ed. by Ling Liu and M. Tamer Özsu. Boston, MA: Springer US, 2009. Chap. Chapter 505, pp. 1059–1063. ISBN: 978-0-387-35544-3 978-0-387-39940-9. DOI: 10.1007/978-0-387-39940-9_505. URL: https://doi.org/10.1007/978-0-387-39940-9_505.
- [210] S. Rautmare and D. M. Bhalerao. "MySQL and NoSQL database comparison for IoT application". In: *IEEE International Conference on Advances in Computer Applications (ICACA)*. NEW YORK: Ieee, 2016, pp. 235–238.
- [211] C. Győrödi, R. Győrödi, G. Pecherle, et al. "A comparative study: MongoDB vs. MySQL". In: *2015 13th International Conference on Engineering of Modern Electric Systems (EMES)*, pp. 1–6. DOI: 10.1109/EMES.2015.7158433.
- [212] db-engines. *Historical trend of document stores popularity*. URL: https://db-engines.com/en/ranking_trend/document+store.
- [213] The R Foundation. *What is R?* URL: <https://www.r-project.org/about.html>.
- [214] Flask. *Flask*. URL: <https://palletsprojects.com/p/flask/>.
- [215] Apache. *Apache Airflow*. URL: <https://airflow.apache.org/>.
- [216] Google. *Flutter*. URL: <https://flutter.dev/>.
- [217] Edy Umargono, Jatmiko Endro Suseno, and S.K Vincensius Gunawan. "K-Means Clustering Optimization Using the Elbow Method and Early Centroid Determination Based on Mean and Median Formula". In: *Proceedings of the 2nd International Seminar on Science and Technology (ISSTEC 2019)*. Atlantis Press. DOI: 10.2991/assehr.k.201010.019.
- [218] C. Goutte and E. Gaussier. *A probabilistic interpretation of precision, recall and F-score, with implication for evaluation*. Vol. 3408. Lecture Notes in Computer Science. Berlin: Springer-Verlag Berlin, 2005, pp. 345–359. ISBN: 3-540-25295-9.

- [219] Huang Jin and C. X. Ling. "Using AUC and accuracy in evaluating learning algorithms". In: *IEEE Transactions on Knowledge and Data Engineering* 17.3 (2005), pp. 299–310. ISSN: 1041-4347. DOI: [10.1109/tkde.2005.50](https://doi.org/10.1109/tkde.2005.50).
- [220] E. Ferry, J. O. Raw, and K. Curran. "Security evaluation of the OAuth 2.0 framework". In: *Information and Computer Security* 23.1 (2015), pp. 73–101. ISSN: 2056-4961. DOI: [10.1108/Ics-12-2013-0089](https://doi.org/10.1108/Ics-12-2013-0089). URL: <https://www.proquest.com/information-computer-security/security-evaluation-of-the-oauth-2-0-framework/docview/200218507500005>.
- [221] S. Bailly, M. Destors, Y. Grillet, et al. "Obstructive Sleep Apnea: A Cluster Analysis at Time of Diagnosis". In: *PLoS One* 11.6 (2016), e0157318. ISSN: 1932-6203 (Electronic) 1932-6203 (Linking). DOI: [10.1371/journal.pone.0157318](https://doi.org/10.1371/journal.pone.0157318). URL: <https://www.ncbi.nlm.nih.gov/pubmed/27314230>.
- [222] Y. Y. Wang, A. F. Geater, Y. L. Chai, et al. "Pre- and in-therapy predictive score models of adult OSAS patients with poor adherence pattern on nC-PAP therapy". In: *Patient Preference and Adherence* 9 (2015), pp. 715–723. ISSN: 1177-889x. DOI: [10.2147/Ppa.S83105](https://doi.org/10.2147/Ppa.S83105). URL: <https://www.dovepress.com/getfile.php?fileID=25262>.
- [223] L. Liu, E. Stroulia, I. Nikolaidis, et al. "Smart homes and home health monitoring technologies for older adults: A systematic review". In: *Int J Med Inform* 91 (2016), pp. 44–59. ISSN: 1872-8243 (Electronic) 1386-5056 (Linking). DOI: [10.1016/j.ijmedinf.2016.04.007](https://doi.org/10.1016/j.ijmedinf.2016.04.007). URL: <https://www.ncbi.nlm.nih.gov/pubmed/27185508>.
- [224] M. Araujo, R. Bhojwani, J. Srivastava, et al. "ML Approach for Early Detection of Sleep Apnea Treatment Abandonment: A Case Study". In: *Dh '18: Proceedings of the 2018 International Conference on Digital Health* (2018), pp. 75–79. DOI: [10.1145/3194658.3194681](https://doi.org/10.1145/3194658.3194681). URL: <https://www.proquest.com/digital-health/ml-approach-for-early-detection-of-sleep-apnea-treatment-abandonment-a-case-study/docview/200460466600012>.
- [225] X. Rafael-Palou, C. Turino, A. Steblin, et al. "Comparative analysis of predictive methods for early assessment of compliance with continuous positive airway pressure therapy". In: *BMC Med Inform Decis Mak* 18.1 (2018), p. 81. ISSN: 1472-6947 (Electronic) 1472-6947 (Linking). DOI: [10.1186/s12911-018-0657-z](https://doi.org/10.1186/s12911-018-0657-z). URL: <https://www.ncbi.nlm.nih.gov/pubmed/30227856>.
- [226] Centers for Medicare & Medicaid Services (CMS). *Oasis data sets* | CMS. en. Accessed: 2022-3-14. URL: <https://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/HomeHealthQualityInits/OASIS-Data-Sets>.