Homecare Interventions as a Service Model for Obstructive Sleep Apnea: Delivering personalised phone call using patient profiling and adherence predictions⋆

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ABSTRACT

Background and Objective: Obstructive Sleep Apnea (OSA) is a sleep disorder that leads to different pathologies like depression and cardiovascular problems. The first-line medical treatment for OSA is Continuous Positive Airway Pressure (CPAP) therapy. However, this therapy has the lowest adherence level when compared to other homecare therapies. Consequently, the main objective of this paper is to increase this adherence level with methods that can be replicated in a large number of patients.

Methods: The Homecare Intervention as a Service model can build, verify, and deliver personalised home care interventions. With the Homecare Intervention as a Service model, we build and provide on-demand personalised interventions according to the patient's needs. The 2 core components of this model are patient clustering and CPAP adherence predictions. To define the patient profiles and predict the adherence level, we apply the K-means and the Logistic Regression algorithm respectively. To support these algorithms, we use the CPAP monitoring data and qualitative data on the patients.

Results: We demonstrate that there are 3 patient profiles (non-adherent, attempter, and adherent). We draw a comparison with multiple machine learning algorithms to predict CPAP adherence at 30, 60 and 90 days. In this case, the Logistic Regression gives the best results with a f1-score of 0.84 for 30 days, 0.79 for 60 days and 0.76 for 90 days. These newly build profiles were to be used to deliver personalised phone call interventions. The phone call intervention shows an increase in adherence by 1.02h/night for non-adherent patients and 0.69h/night for attempter patients.

Conclusions: This is the first study in CPAP therapy that formalises the process of transforming raw data into effective home care interventions that can be delivered directly to the patients. In fact, it is the first time that both patient characterisation and predictions based on data are used to provide personalised patient management for CPAP therapy. Our model is flexible to be extended to new types of interventions and other homecare therapies.

1. Introduction

Obstructive Sleep Apnea (OSA) is an increasingly common sleep-related breathing disorder [22]. It is characterised by repetitive partial (hypopnea) or complete (apnea) upper airway closure during sleep. This causes intermittent hypox-aemia and frequent cortical arousals. If left untreated, OSA can harm the nervous system [17], cause hypertension [8], daytime sleepiness, and increase the risk of motor vehicle accidents [47].

Continuous Positive Airway Pressure (CPAP) is the first-line therapy for OSA. This therapy consists of a relatively small device connects to a mask via a flexible tube. There are three types of masks: full-face masks, nasal masks, and nasal pillow masks. The CPAP generates a constant airflow that prevents the collapse of the upper airway. Consequently, this airflow prevents hypopnea and apnea during the sleep of the patient.

The prime condition for the CPAP device to be useful is the patient's adherence level to the therapy. The patient must accept the CPAP device for at least 4h/night to expect any clinical improvement [32]. However, the CPAP has the lowest adherence level compared to 17 other therapies like HIV, cancer, etc. [11]. This adherence level remained stagnant over the last 20 years despite multiple-technological advances in CPAP therapy and interfaces [39].

With the advent of big data and highly accurate monitoring data in-home care, new opportunities open up to tackle these ongoing issues [36, 6]. One of these opportunities is a better understanding of the patient to deliver tailored interventions [49] to empower the patient in his CPAP therapy. This research project aims at developing, delivering, and monitoring tailored interventions for home care patients suf-fering from OSA. Furthermore, we also aim at validating the appropriateness of the delivered interventions. The expected outcome at the end of the process is to maximise adherence to CPAP therapy.

In this research, we develop a novel Homecare Interventions as a Service (HIaaS) model that delivers interventions through different mediums whenever needed to support the patient with CPAP therapy. This research paper focuses on these three pillars i.e., patient characterisation, personalised intervention buildup and delivery, and intervention consumption and evaluation. To maximise adherence to CPAP therapy, we develop a methodology as described in fig 1. Our approach relies on three main repositories:

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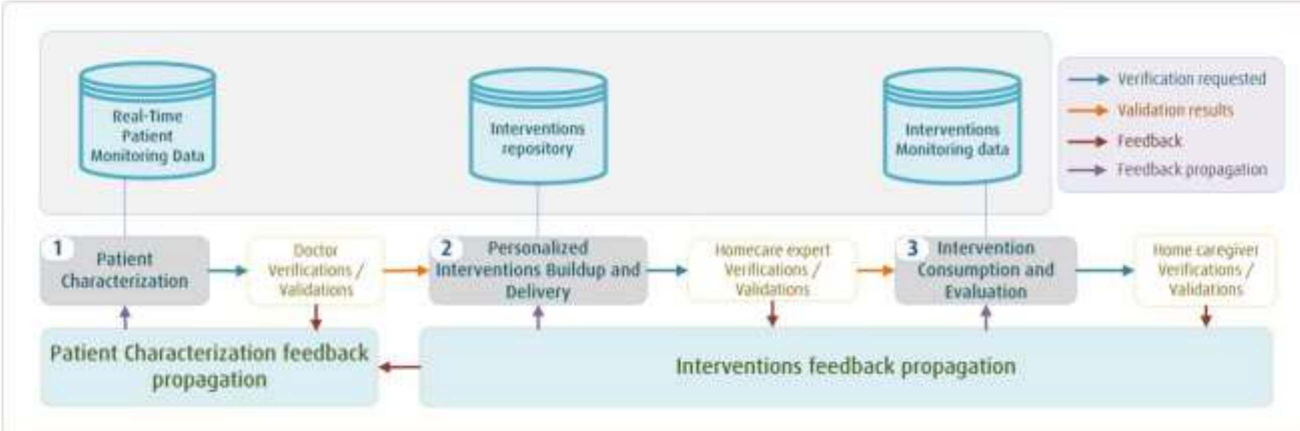

Figure 1: HIaaS Approach

1. *Real-time Patient Monitoring Data* containing data collected daily by the CPAP device
2. *Interventions Repository* containing a set of person-alised interventions
3. *Interventions Monitoring Data* containing the inter-vention consumption monitoring data required in the document.

Before developing and delivering personalised interventions, we must first characterise the patients to understand their needs to comply with the CPAP therapy (fig 1-1). Based on the CPAP monitoring data, we build multiple patient profiles at specific moments in the CPAP therapy. In a previous paper, we developed this patient profiling [25]. On the patient pathway, we define the exact schedule for intervention delivery. Hence, a patient can have an evolving profile over time and as a result, the combination of these different profiles gives the patient pathway. The patient pathway is a well-defined concept in the healthcare system [26, 13, 28]. The issue is that the patient pathway is a relatively new concept for home care treatments.

The patient pathway comes from different moments; the issue is how to align the different profiles to give an un-biased interpretation. Furthermore, this interpretation must be executed while combining analytics models with human verification and validations. The expected result of this interpretation is getting the impactful factors on adherence and the patient's vulnerabilities to comply with the CPAP therapy.

According to the patient's need, we select the most appropriate intervention from the intervention's repository. This raises two new issues, the first one what are the relevant interventions for OSA that can be delivered to the patient by a remote medium. The second issue is how to get the most accurate match between the vulnerabilities and the interventions present in the repository.

To go deeper into the patient-centric approach, we add a level of personalisation to each selected intervention. A homecare expert verifies the level of personalisation of the interventions before they are delivered. We then deliver the interventions to the patients via the Sleep.Py app, a personalised mHealth solution (fig 1-2).

Finally, the system tracks intervention consumption as well as the patient's perception of the interventions. However, in healthcare, the interventions' consumption is unique since it depends on the patient's intention to treat (ITT). When the patient completes the intervention consumption, the CPAP expert evaluates the intervention's effectiveness based on various criteria (fig 1-3).

The validation mechanism must gather feedback from various stakeholders and then propagate this feedback based on the various decision support models. As a result, our iterative approach incorporates expert feedback on a regular basis for the continual improvement of our models. The goal of this continual learning process is to maximise the ITT level of the patients for the CPAP therapy. However, to what extent the model must re-adapt itself without adverse effects?

Section 2 develops the proposed framework to trans-form raw data into personalised interventions. Section 3 details the implementation of this framework and the results obtained. In section 4, the paper provides an overview of the related works and the limits around different topics for building the HIaaS model for CPAP therapy. Section 5 discusses the limitations and perspectives of this work.

2. Methods

2.1. HIaaS main concepts

Before enlightening the framework, we will introduce the core concepts of the HIaaS model. The figure 2 shows the first three months of the beginning of the CPAP therapy. The figure shows a specific use case for the initial phase of therapy during which we can have the most impact on the patient's adherence [24].

2.1.1. Patient Profile

Before the intervention delivery, we cluster patients with the same characteristics and same needs. This clustering process is called patient profiles (PP). At specific intervals,

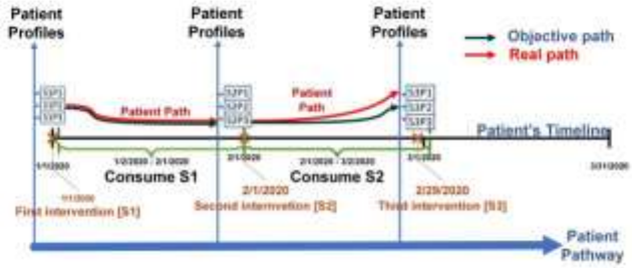

Figure 2: Pathway of a newly diagnosed patient suffering from OSA

we assign a profile to the patient. For example, in the figure 2.2.1, we assigned a profile every month. However, in a real-world situation, this interval may vary.

To assign the PP, we use the data collected from the last profile till the time of the new profile. For example, to assign the S3P1 profile to the patient, we use data from *02/01/2021* to *03/01/2021* only. This data selection allows us to get a microanalysis of the patient situation in his situations via the PP.

2.1.2. Patient Pathway

The collection of the different PPs that the patient pos-sesses throughout his therapy forms the patient pathway. Consequently, for new patients we rely only on the firstly assigned profile as the patient moves forward in his therapy, the patient pathway starts to build up. Contrary to the PPs, the patient pathway gives a macro view of the patient situa-tion.

In fact, the collection of PPs allows the analysis over a longer period. We can track the progression of the patient throughout the therapy and more important predict patients at risk. That is patients have a risk of low compliance. For example, in the figure 2.2.1, the patient is at risk as we expected the patient follows the "objective path". But the patient followed the red path.

2.2. HIaaS framework

This section presents the proposed framework to build the Homecare Intervention as a Service (HIaaS) model. Figure 3 shows the detailed processes present in the HIaaS framework. We will detail each process in the following sections. In this paper, we focus on patient characterisation, vulnerability detection and the personalised intervention buildup. In our previous paper [25], we give more details about the patient profile buildup.

2.2.1. Patient Pathway

In CPAP therapy, there are two main phases: the initial phase and the follow-up phase. Consequently, there are two different techniques to build the patient pathway. For the ini-tial phase, the French health authority defines a "one fits all" patient pathway[40]. This pathway consists of installing the CPAP at the patient's home. A home-/care expert performs this installation, and three days later, the same expert calls the patient to get the patient's first feedback. Afterwards, there are two other home interventions from a home-/care expert 15 days and 90 days after the installation. These 90 days visit marks the end of the initial phase. This predefined patient pathway is proven to be effective on the adherence level [31].

For the follow-up phase, there is no dictated patient pathway, and hence we need to build the optimal pathway for each patient. Using the data collected on the patient during the initial phase, we predict the adherence level for the next 90 days using supervised learning. Lower the adherence level, the higher the intervention frequency for better patient management. However, this assumption may not be valid for every patient. For this specific reason, we simulate the frequency of the calculated interventions on the patient's past data.

The prediction gives the optimal intervention frequency for the patient and gives the best timing for these inter-ventions. The simulation takes into consideration how the patient has consumed the previously delivered interventions. As a result, we get the patient pathway for the next 90 days for the patient: in other words, the exact timing for delivering the patient's interventions.

2.2.2. Vulnerabilities detection

Before choosing the appropriate interventions, we must first know the factors averse to comply with CPAP therapy. These vulnerabilities rely on analysing in-detail patient pro-files. Firstly, the model retrieves the current profile and the objective profile. This objective profile is the target profile for the patient found on his pathway. The model automat-ically sets the objective profile by analysing the patient's complete path (complete profile sequence) and deduces the converging profile for a better adherence level.

Secondly, the model compares the current and objective profiles to calculate the gap between these two profiles. This calculation gives the factors on which we should intervene for the patient to fit in the objective profile, and these factors are called the patient's vulnerabilities. Furthermore, the models select only the factors with a significant gap between the objective and current profiles so that there is enough room to improve adherence.

2.2.3. Personalised interventions

The model automatically gets the appropriate interven-tions from the intervention's repository based on the pre-viously detected vulnerabilities. While building the inter-ventions repository, we associate each intervention with the vulnerabilities it fills. We add a personalisation level to the interventions by tailoring the interventions' configuration according to the patient. The model calculates this configu-ration by analysing each vulnerability's severity, i.e., for each impacting factor, we apply a dynamic threshold to categorise these factors into low, mid, and high severity.

The interventions also contain an assessment method to measure their efficiency. The different metrics measured before and after the interventions' delivery and how to measure these metrics. The two most common assessment

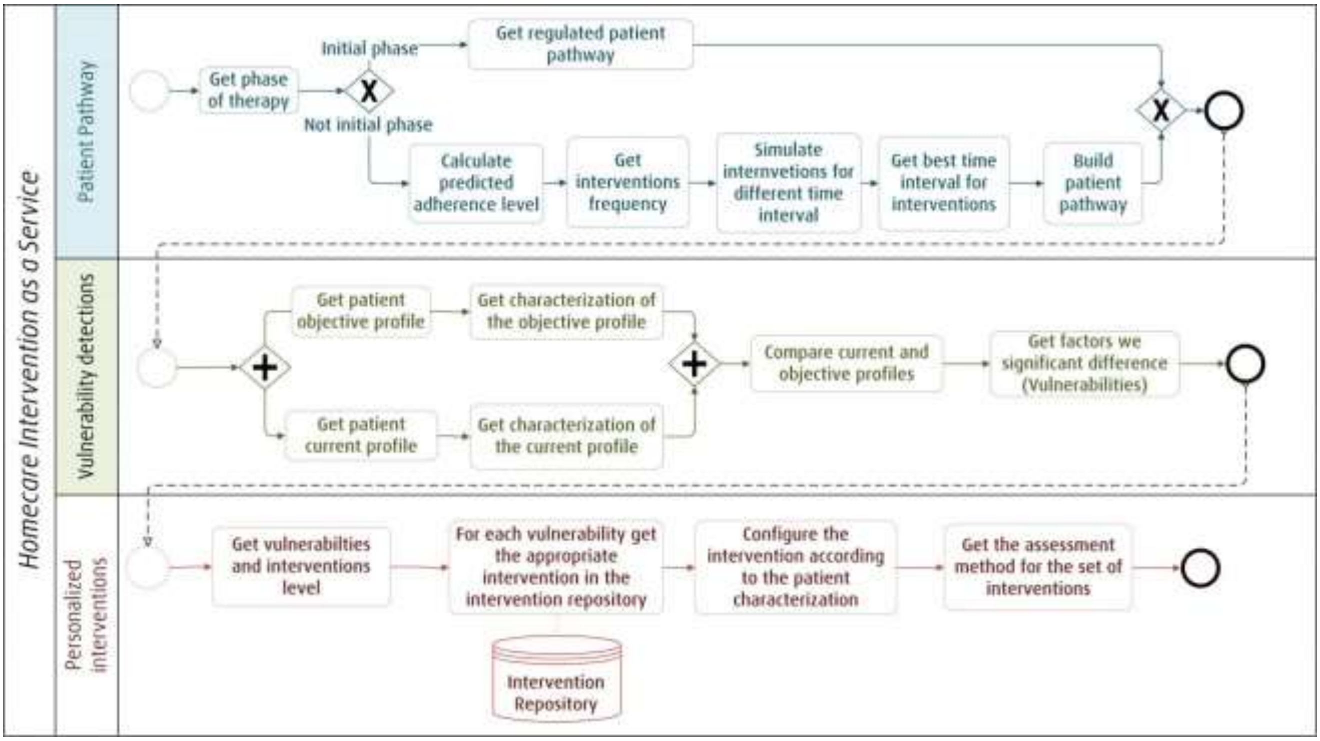

Figure 3: Detailed Framework

methods are patient monitoring via multiple sensors and questionnaires to get qualitative data on the patient. The assessment methods vary according to these metrics and consequently vary according to the interventions.

3. Results

In this section, we present the implementations of the core processes of the HIaaS model. Firstly, we present the buildup of the PPs for newly diagnosed OSA patients. Sec-ondly, we analyse the impact of personalised interventions on adherence levels in patients with low and mid-adherence levels. Lastly, we use the patient profile to build a model to predict the adherence of the patients to CPAP therapy. Based on machine learning, this model predicts the adherence level 30 days after the first night of CPAP therapy.

The quantitative data used in the different implementa-tions were collected by the CPAP devices. These quantitative monitoring data were retrieved from Philips Encoreany-where and ResMed Airview. Qualitative data on the patients were collected and validated by Linde's home care experts.

3.1. Patient Profile

The patient profiles rely solely on quantitative monitor-ing data. The monitoring data consists of adherence level (h/night), mask leakage (l/min), and Apnea-Hypopnea Index (AHI). In our previous study [25], we detailed the complete buildup process of the patient profile. For this work, we extend the PPs buildup to a larger database of 4030 patients.

Figure 4: Error Sum of Squares per Clusters

We perform the clustering using the Python library *scikit-learn* while applying the KMeans unsupervised learn-ing algorithm. To determine the most appropriate number of clusters, we plot the Error Sum of Squares (SSE). The lower the SSE, the better the clustering; the best clustering is equal to the number of patients in the database. To find the best compromise between the number of clusters and the quality of the clustering, use the Elbow method [44].

Figure 4 shows the SSE for the 10 clusters. The result of the Elbow method gives 3 as the optimal number of clusters. When analysing these profiles against the adherence level, we found three main clusters: non-adherent, attempters, and adherent patients. Non-adherent patients have adherence levels less than 2h/night, attempters between 2h/night and 4h/night, and adherent patients greater than 4h/night.

In the previous study, we identified 6 patient profiles whereas, in this study, we identified 3 clusters. In this study, the dataset contains 3048 more patients than in the previous study. The increase in the number of samples has a direct impact on the number of clusters and we obtained a smaller number of clusters. However, unlike the previous study, we were able to interpret each cluster (non-adherent, attempters, and adherent patients) and these 3 clusters reflect real-world situations. We used the same features of the previous study and this study and this increase in the sample causes faster convergence and better separated clusters. We reuse this result for the different implementations we present in this section.

3.2. Impact of personalised phone call interventions on CPAP adherence

Table 1
Adherence for personalised phone interventions

n	Non-adherent 717	Attempter 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

This implementation concerns only two profiles: non-adherent and attempters patients. Adherent patients were excluded because they already have an efficient adherence level [33]. The interventions consist of a homecare expert's phone call to the patient; the expert is specially trained to motivate the patient in using CPAP therapy. The expert carries out 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, we exclude the patient from this study. 291 patients (14.8%) were excluded for this study as the homecare experts were not able to deliver the motivational interventions.

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 attempter patients.

Table 1 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 adherence between and after the interventions. The default null hypothesis for a 2-sample paired t-test is that the two groups are equal, = 0.05, and if P-value is < then the null hypothesis is rejected. We applied the paired t-test as the same patients were in the same 2 samples.

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 for CPAP therapy.

3.3. Adherence predictions

In Section 2.2.1, we presented the patient pathway. One of the core components of this buildup is adherence predic-tion. In this implementation, we build a model to predict the adherence level 30, 60 and 90 days after the beginning of the CPAP therapy. We use machine learning algorithms to predict the patient's adherence level at the end of the initial phase.

To train the these algorithms we apply the pipeline detailed on the figure 5. The first step is the data ingestion to retrieve data from the different data sources. The learning process uses both quantitative (PAP monitoring) data and qualitative data. For the quantitative data, we use the first 10 days' adherence level, mask leakage and AHI. Linde's Homecare experts collect the qualitative data to evaluate the patient's on three points:

1. *Literacy* of the patient on the CPAP therapy; the knowledge level of the patient on multiple topics related to the CPAP therapy
2. *Motivation* of the patient to comply with the CPAP therapy
3. The *Epworth score* [23]; it is a questionnaire to mea-sure daytime sleepiness. In other words, the OSA severity and the effect of the CPAP therapy on the OSA.

We select patients that were diagnosed with OSA from 01/08/2017 to 30/10/2020. This is important to select these "new" patients as it is a key phase of CPAP therapy. Fur-thermore, we remove patients where there are missing data in either the qualitative or quantitative data for the first 30 days. At the end of the data selection process, we have 1236 patients in the dataset.

For better prediction capacity of the data, we transform the adherence data to binary data. When the adherence level is <4h/night = 0 and ≥4h/night = 1. Furthermore, we normalise the qualitative data in order to use different machine learning algorithms like Logistic regression. To standardise the data, we firstly scale the data between 0 and
1. We transform the data so that they have a mean of zero and a standard deviation of one. Then, we normalise the data in order for them to follow a normal distribution.

Figure 5: Models training pipeline

Table 2
Comparison of different Machine Learning Algorithms

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 neighbors	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

After the data transformation, we assign each of the 1236 patients to a PP. For this PP assignment, we use the K-Means model built in the section 3.1. From the initial dataset, we have 333 patients in the non-adherent profile, 629 patients in the adherent profile and 274 in the attempters' profile. Finally, to train the machine learning models, we divide the into 80:20 ratio to training and test datasets. In other 80% of the patients were in the training sample and 20% in the testing sample. There was a random selection of these following a normal distribution.

Section 4.1 showed that there is no best-supervised al-gorithm for all data. We tried multiple machine learning algorithms namely Logistic Regression, K-nearest neigh-bours, Naive Bayes, Support Vector Machine and Adaboost. Testing different algorithms allow us to select the most effective one for our dataset.

Table 2 shows the results obtained when comparing these machine learning algorithms on the test dataset. To analyse the results, we use the f1-score and ROC AUC. Especially the ROC AUC gives a metric on how the machine learning model is capable of distinguishing between the patients <4h/night and ≥4h/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 [30]. 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.

4. Related Works

This section describes the most relevant works according to the issues presented previously. To find the related works, we search for the following terms Web Of Science Core Collection, Scopus and PubMed: "obstructive sleep apnea,"

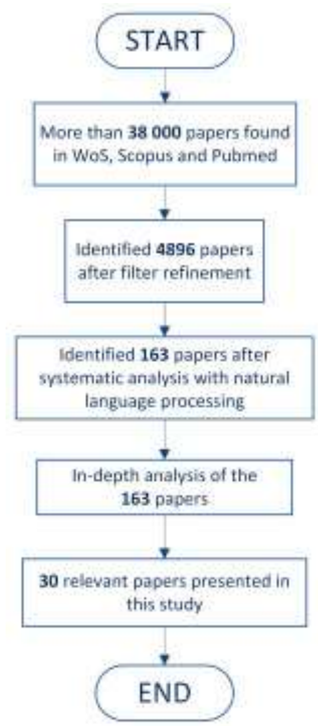

Figure 6: Flowchart for selecting relevant and related works

"home care" and "data analytic in healthcare". As a result, we found more than 38000 papers; we refine our search term by selecting only the recent work (from 2010 to 2020).

After this refine filter, we found 4896 papers in the Web of Science Core collection. There was a systematic analysis of these 4896 papers to get the recurrent keywords in all these works. We applied the natural learning processing on all of these papers to identify the relevant keywords and main concepts. In an iterative process we refine these keywords. Finally, we combine these keywords to get 163 studies that are closely related to our work. We perform an in-depth analysis of these works, and in this section, we present the 30 most relevant papers.

The four topics that we are presenting were extracted from the systematic analysis. The first topic is data analytics in healthcare, and the techniques, and tools to analyse healthcare. Secondly, the patient pathway; the definitions and buildup of the patient pathway. Thirdly, the personalised interventions for home care patients; the interventions for increasing OSA adherence level.

4.1. Data analytic in healthcare

In the healthcare research field, we explore four interesting types of data: clinical data, patient-related data, administration data, and pharmaceutical/R&D data [15]. Clinical and patient-related data, *Groves et al.* [18] pre-sented the capabilities of big data analytics in healthcare, namely monitoring, prediction, data mining, evaluation, and reporting. However, to exploit these new opportunities, it is compulsory to explore the raw data to extract the appropriate information [43].

The CPAP therapy is a "one size does not fit all" therapy; consequently, we need to build a subpopulation of patients based on their phenotypes [48]. The two most popular clustering algorithms to build the subpopulation are K-means[19] and hierarchical clustering [2]. *Wohlgemuth et al.* [50] used the latent profile analysis algorithm to build 3 sub/populations: attempters, adherers, and non-adherent patients to the CPAP therapy.

One of the aspects of the HIaaS model is predicting the adherence level of each patient. There are a wide variety of proven supervised learning algorithms used in healthcare for years to build predictive models. SVM [7], k-nearest neigh-bours [19], and neural networks [10], are some examples of supervised learning algorithms. There is no guarantee that an algorithm will have the best accuracy; thus, multiple studies compare multiple algorithms to get the best fitting one [10, 19].

In this paper, we are mainly dealing with patient-related data from multiple data collections. The collections con-tain very heterogeneous data; structured, semi-structured, and not structured data. We use the R software for data exploration and analysis as it is open-source and offers excellent flexibility for working with complex data structures. For the predictions and simulations, we will test multiple algorithms namely logistic regression[42], k-nearest neighbors[19], Naive Bayes classifier[52], SVM[7].

4.2. Patient characterisation and pathway

A patient pathway is a sequence of care transition (interventions) that a patient receives according to the pa-tient's disease [13]. The patient consists mainly of Electronic Health Record (EHR) [16], which contains the complete historic health-related data for a patient [3]. To build the EHR, there is a set of standards called HL7 (Health Level 7) that allows different EHR to interact with each other [19]. Each patient pathway must have a clear and well-defined objective [38].

To our knowledge, there is only one study that built a patient pathway for the CPAP therapy [27]. *Lai et al.* built a validated pathway from a hypothesised pathway for analysing the impact of the intimate relationship on CPAP adherence level. However, the pathway only records the different steps that explain the adherence to CPAP ther-apy but not the different interventions the patient received throughout his life.

Lismont et al. [28] proposed a methodology based on process mining to build the optimal patient pathway using the hospital event log. Different healthcare professionals validate each pathway manually, and this is an iterative process for continuous improvement of the pathways.

As exposed previously in this section, the patient pathway is mainly a concept applied to data in the hospital field, and it is a novel concept for home care. The main difference is in the intervention's consumption i.e., for the home care, the patient consumes the interventions over a time interval. Thus, each step in the patient pathway for home care is spaced over time. In contrast, in a hospital, the patient consumes the interventions as soon as the healthcare professionals deliver it.

4.3. Personalised interventions for OSA

Beforehand, all patients suffering from OSA received the same standard interventions to improve the adherence level [49]. However, as expressed previously, this approach is not as efficient as the adherence level remains stagnant. *Carberry et al.* [9] review the emerging interventions for personalised patient management for OSA. They recom-mend sleep positional therapy to improve sleep quality and personalised mask selection to improve adherence level for CPAP therapy. Furthermore, they show that a decrease in weight by 17% has significant beneficial effects on the OSA severity.

In the same vein, *Bradley et al.* [14] investigate the impact of diet and physical activity on body mass index (BMI) and OSA severity. There is a reduction in Apnea Hypopnea Index, AHI (-8.1 events/h) for diet interventions combined with physical activity interventions. Despite an improvement in OSA severity, there was no significant improvement in BMI. However, there is no significant difference in physical activity-only interventions.

One of the known factors to improve adherence is to include the partner in the CPAP therapy[51]. *Luyster et al.* [29] explore couples-oriented interventions; they provide education interventions and set personalised goals for different patients. There is a beneficial effect on the adherence level with the couples-oriented interventions when com-pared to usual interventions. However, there is no consistent adherence over a more extended period.

In addition to educational interventions, there are motivational interventions [4]. *Bakker et al.* performed a randomised controlled trial on 83 patients to test the feasibility of motivational interventions. These interventions consist of appointments and phone calls; the main objective is to maximise behaviour change over time. The study proves that patients who received motivational interventions use the

CPAP device for more than *1.5h/night* compared to usual interventions.

Multiple interventions are proven to be sufficient to increase adherence levels in various therapies [34]. However, this improvement is not consistent over time, mainly as each study tackle only one specific drawback to adherence. However, the patients' needs change with time, and hence the type of interventions must quickly change to respond to this need [48]. For this reason, HIaaS is pertinent as it offers excellent flexibility in the type of interventions to deliver to the patient and patient management over a long time.

5. Discussions

Multiple ongoing research are tackling the OSA screening using multiple sensing device and the results of the polysomnography. Advanced data analytic methods and techniques were applied successfully for better detecting OSA [21, 20]. In this study, we are focused on patients who were already diagnosed with OSA and were prescribed the CPAP therapy. There is a dearth of publications of applying these data analytics in the CPAP therapy and transform these results into concrete implementations for the patient like personalised interventions.

This project's early stage consists of knowledge extraction; we benchmark multiple data analytic techniques to find the best fitting one. To build the patient pathway, we must construct a new approach specifically to home care as there is no significant work that can be applied to our HIaaS model. The heart of the project is the personalised interventions for OSA, and as expressed in section 4.3, there is a plethora of interventions for OSA. For our approach, we build an intervention repository to support a wide range of patients' typologies as compared to the presented studies which targeted most two types of patients.

Bailly et al. and *Wang et al.* already use the K-Means clustering algorithms for defining multiple patient patterns [2, 46]. We got the same results as these two studies. That is we demonstrate that using the CPAP monitoring data, we can build 3 PPs namely non-adherent, attempters, and adherent PPs. However, our HIaaS model goes further in the consumption of these PPs. The PPs are used to build the patient pathway, select the most appropriate interventions and personalise the interventions. Furthermore, we plan to build these patient profiles at different moments during the CPAP therapy to refine the patient characterisations. This consumption of the PPs is a novel approach to CPAP therapy.

Different home care experts delivered these phone call interventions; the experts received the same training for motivating the patient. However, the experts did not receive any predefined process. Consequently, the methodology of intervention varies, and the results are not consistent among home care experts. There is a need to build a unified pro-cess for delivering the interventions but flexible enough for personalisation.

Linde's home care experts validated the different predictive models and the input dataset used to train and test the models. The qualitative data were collected by multi-ple CPAP technicians and there was no formal assessment method for the patient. For example, to assess the motivation of the patient, the technician collects feedback from the pa-tient and then the technician gives a motivation score. There was no systematic process for calculating the motivational score.

The models built for predicting the adherence level mainly used the CPAP monitoring data and only 3 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 col-lected via standardising questionnaires with a well-defined scale and interpretation.

The prediction model, used the patient profile in the dataset. Consequently, there performance of the adherence prediction is highly dependant on the patient profiling model. This combination of these 2 models, allows use to use both quantitative data (PP) and qualitative data (telemon-itoring data). The PP also induce the historical information of the patient (patient pathway) directly in the prediction models. Multiple clustering may also induce uncertainties in the model, however, this effect is contained as the volume of the CPAP monitoring data is high.

The machine learning models predict adherence only during the initial phase (first 90 days of the therapy). Nevertheless, to ultimately build the HIaaS model, we need to build multiple models to predict adherence over different phases of the therapy. This myriad of models requires a specific synchronisation model for continual learning in a continuous improvement process. There are multiple studies that tackle adherence prediction issues [1, 37, 5]. However, it is difficult to cross-check 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 very good results with well-characterised patients. The obtained results were compara-ble to our models (F1-score of 84%). However, they had a small cohort of patients (42 patients) and they include more variables in the learning process [5]. *Villanueva et al.* implement a machine learning model to predict CPAP compliance at 1-year. They use the basic examination, diagnostic cardiopulmonary polygraphy and home titration as input in their dataset and used the Support-Vector Machine (SVM) to get the most appropriate results. The AUC was 72.9 % and the F1-score 65.8% [45]. However, we cannot directly compare our 2 studies as the data topology was different from that used in this study and we predict compliance at 30,60 and 90 days. To have an unbiased comparison between the different adherence prediction mode there is a need to have a common and open dataset on OSA patients alongside CPAP monitoring data.

The personalised phone call interventions show an increase in adherence; however, none could change the patient profile. In other words, the attempters' patients remain in the attempters' profile, and it is the same for the non-adherent patients despite an increase in adherence level. This result can be explained by the fact that there is only one intervention, and there is a need to supply intervention at a regular time interval for better patient management. In other words, build a complete patient pathway to follow the patient through his therapy. Furthermore, phone call interventions are not feasible on a large scale. For this reason, mHealth is one solution for everyday patient management on a large scale.

To seize this new opportunity, we also implemented the Sleep.py mobile application that is currently being tested in a clinical trial. This mobile application uses the patient profiling to select the most appropriate interventions to be delivered. We uses the adherence prediction to have the cor-rect dosing and scheduling of these interventions. Through these interventions, we influence the patient profiling to improve the adherence level of the patient to the CPAP therapy. The different data analytic models present in this paper are the core element of the HIaaS framework and the mHealth solution.

Furthermore, we planned to collect qualitative data on patients through self-reporting questionnaires. It is proven that the patient Intention To Treat, motivations and health literacy have a direct impact on the adherence level [41, 4, 35, 12] We will be able to use these collected qualitative data in the patient profiling model to optimise the model and have a better representation of the patients.

The HIaaS framework is a data-driven approach. As a result, the overall framework's success relies on the 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 pro-vide 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.

6. Conclusions

In this paper, we proposed a novel framework to build, verify and deliver personalised home care interventions un-der the novel concept Homecare Intervention as a Service (HIaaS). We presented a complete scope from using raw data to deliver personalised interventions to provide complete patient management for the CPAP therapy.

Using the CPAP monitoring data, we confirm that there are 3 adherence profiles namely non-adherent patients, at-tempters patients, and adherent patients. We implement a machine learning model for predicting adherence 3 months ahead of time for the initial phase of the CPAP therapy. There is a comparison between 5 different machine learning algorithms. The most suitable algorithm for our case is the logistic regression. These different implements are only part of the HIaaS model. Moreover, these are preliminary results, and further studies on different datasets must be carried out to validate these results.

We used these profiles to consolidate the personalised phone interventions and the adherence predictions. We demonstrate that personalised interventions are efficient for increasing adherence to CPAP therapy via motivational phone call interventions. This is the first study in CPAP therapy that formalises the process of transforming raw data into effective home care interventions that can be delivered directly to the patients. In fact, it is the first time that both patient characterisation and predictions based on data are used to provide personalised patient management for CPAP therapy.

This whole research project also covers the interven-tions' consumption, validation, and feedback. The latter is crucial to build a continual learning model aiming for the automatic improvement of the analytic models. To conclude, we offer a flexible framework that can be used by researchers to deliver personalised home care interventions for reaching a given objective. This model uses the big data and mHealth opportunities to develop a patient-centric approach on a large scale.

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