Journal Pre-proof

Remote monitoring of positive airway pressure data: Challenges, Pitfalls and Strategies to consider for optimal data science applications

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PII: S0012-3692(22)04204-0

DOI: https://doi.org/10.1016/j.chest.2022.11.034

Reference: CHEST 5397

To appear in: *CHEST*

Received Date: 19 July 2022

Revised Date: 6 November 2022

Accepted Date: 18 November 2022

Please cite this article as: Bottaz-Bosson G, Midelet A, Mendelson M, Borel JC, Martinot JB, Le Hy R, Schaeffer MC, Samson A, Hamon A, Tamisier R, Malhotra A, Pépin JL, Bailly S, Remote monitoring of positive airway pressure data: Challenges, Pitfalls and Strategies to consider for optimal data science applications, *CHEST* (2023), doi: https://doi.org/10.1016/j.chest.2022.11.034.

Word count:

Abstract: 199 words

Manuscript: 3959 words

Title: Remote monitoring of positive airway pressure data: Challenges, Pitfalls and Strategies to consider for optimal data science applications

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Funding

Funding GBB, JLP, SB, and RT are supported by the “e-health and integrated care and trajectories medicine and MIAI artificial intelligence” Chairs of excellence from the Grenoble Alpes University Foundation (ANR-19- P3IA-0003) and the French National Research Agency in the framework of the "Investissements d’avenir” program (ANR-15-IDEX-02). A. Midelet is supported by Probayes and MIAI (ANR-19- P3IA-0003) in the framework of a “Convention Industrielle de Formation par la Recherche” (CIFRE) PhD. Her PhD is also supported by the French National Research Agency (grant 2020/0007). A.Malhotra is funded by National Institutes of Health.

Conflict of interest: none of the authors have any competing interest in the manuscript

Author acknowledgements: GBB, AMidelet, MM, JLP and SB contributed substantially to the concept, literature search and the initial writing of the manuscript. JCB, JBM, AMalhotra and RT substantially improved the manuscript from an expert clinical perspective. RLH, MCS, AS, and AH further improved the manuscript by providing expertise from a data science point of view.

Acknowledgement

We thank Alison Foote PhD (an independent medical writer based in Grenoble, France) for critical reading, partial rewriting and editing of the manuscript.

Keywords: Data management, obstructive sleep apnea, Positive Airway Pressure, Remote monitoring, Time series.

Abbreviations list:

API: Application Programming Interfaces

COMISA: comorbid insomnia and sleep apnea

LOCF: last observation carried forward

NOCB: next observation carried backward

OSA: Obstructive sleep apnea

PAP: positive airway pressure

rAHI: residual apnea-hypopnea index

REM: Rapid Eye Movement

ABSTRACT

Over recent years positive airway pressure (PAP) remote monitoring has transformed the management of obstructive sleep apnea and produced a large amount of data. Accumulated PAP data provide valuable and objective information regarding patient treatment adherence and efficiency. However, the majority of studies analyzing longitudinal PAP remote monitoring summarize data trajectories in static and simplistic metrics for PAP adherence and the residual apnea-hypopnea index (AHI) by using mean or median values. The aims of this article are to suggest directions for improving data cleaning and processing and to address major concerns for data science applications including: 1) conditions for rAHI reliability, 2) lack of standardization of indicators provided by different PAP models, 3) missing values and 4) consideration of treatment interruptions.

To allow fair comparison between studies and to avoid biases in computation, PAP data processing and management should be conducted rigorously with these points in mind.

PAP remote monitoring data contain a wealth of information that is currently underused in the field of sleep research. Improving the quality and standardizing data handling could facilitate data sharing among specialists worldwide and enable artificial intelligence strategies to be applied in the field of sleep apnea.

Introduction

Obstructive sleep apnea (OSA) is a highly prevalent chronic disease with nearly one billion adults aged 30-69 years affected worldwide.[1] OSA is a systemic disease that presents multiple clinical phenotypes[2] and is independently associated with cardiovascular comorbidities, decreased quality of life, diminished neurocognitive function and depression.[3,4] Positive airway pressure (PAP), the first-line therapy for moderate to severe OSA, is used in millions of people worldwide[1] and improves symptoms and quality of life and may improve cardiovascular outcomes.[4-6] The effectiveness of PAP treatment relies on adherence[7] with some data suggesting that a minimum of four hours and probably 6 hours of PAP per/night is required in order to improve blood pressure control in minimally symptomatic patients.[6,8]

Over the past 10 years, the development of communicating PAP devices and the willingness of manufacturers and home care providers to reshape follow-up care have enabled the emergence of remote monitoring platforms for the visualization of nightly data generated by hundreds of millions of patients worldwide.[9] This technology has transformed the way patients are followed-up and monitored by providing an opportunity for early interventions in order to improve disease management,[10,11] PAP adherence [12,13] and augment telemedicine activities in sleep breathing disorders[14]. In some countries, such as France, remote monitoring of PAP adherence is a condition for healthcare insurance reimbursement of PAP devices, with rates of reimbursement proportionate to levels of adherence.

PAP data can be used to improve our understanding of OSA and to personalize treatment by using innovative statistical approaches alongside artificial intelligence for the identification and prediction of the trajectories of patients treated with PAP.[15,16] PAP monitoring data include daily aggregated measurements of adherence [17] and treatment efficacy (residual apnea-hypopnea index (rAHI) and leaks) (Figure 1).

The majority of studies based on longitudinal PAP remote monitoring summarize the data trajectories in static and simplistic metrics for PAP adherence and rAHI by using mean or median values.[10,18-20] However, much of the value of these data lies in the complexity of their evolution and variability over time which is very relevant for patients' care and management. As data are collected daily, they can be analyzed as time series, and modeled using multiple deterministic and stochastic components. Indeed, these data may reveal, for example, trends, cyclic components or disruptions in the observed behaviors.[21-23]

Yet currently, the reliability of summarized data remains questionable, owing in particular to the absence of standardization of PAP device generated indicators among the various PAP models and manufacturers, different approaches to the management of missing values[24] and the involvement of different intermediaries (i.e., home care providers or private digital health companies) that process original data with some approximations or reduction in dimensionality. Clinicians and data scientists accessing these data are often unaware of the entire processing pipeline that could impact interpretation of the data. Thus, there is a need to develop standardized methods, definitions and terminology for cleaning, processing, reporting and interpreting PAP data.

The aim of the present article is to suggest directions for improving the data cleaning and processing and to highlight major concerns for data science applications that rely on daily remote monitoring data from PAP devices (including fixed PAP, and automated PAP - APAP). The recommendations are intended not only for researchers analyzing PAP data, but also for home care providers and health services and those who develop PAP telemonitoring data visualization applications for the guidance and alerts to clinicians, caregivers and patients.

In the following sections, our objective is to provide an over view of the landscape of PAP remote monitoring data, including concerns regarding: 1) conditions for rAHI reliability, 2) lack of standardization of the summarized data provided by PAP manufacturers, 3) handling of missing

values and 4) consideration of treatment interruptions. These issues, their impact and potential solutions are summarized in Table 1.

Data source

Raw data, including airflow and pressure, are collected at a high frequency (i.e., 25 Hz for the airflow signal) by the PAP devices. Real-time respiratory event detection is performed during the night by the proprietary device's embedded software. At the end of the night, raw records and summary statistics of the data are sent to the equipment provider and stored in the SD card of the PAP device. Then, summarized data are made available to healthcare providers. This information usually includes the time and duration of PAP usage, the estimated rAHI and leaks (mean or median, 95th percentile and/or maximum), depending on the PAP device model/manufacturer.

Depending on the source of the data to be analyzed, its life-cycle and nature may be different (Figure 2) and can vary among different countries and health systems. Data are available from: 1) the manufacturers' databases, with mainly device generated data and some limited clinical data collected through patient engagement apps,[13] 2) the homecare providers' databases, with additional information on accessories, age, sex and sometimes body mass index and AHI at diagnosis 3) clinical databases, with primarily clinical data and limited device data from the manufacturers or home care providers. Raw data recorded by the PAP device can be transmitted via a: modem, external to the PAP device or a PAP device connected to the Wi-fi or Bluetooth, downloaded from the device during home visits by the homecare provider's technician or directly obtained during PAP device recalls.

Advances in technology have made the connected PAP device the most common remote monitoring system, sending data on a daily basis, and keeping data records over several weeks (to be sent later in case of transmission failure, e.g., due to an interrupted internet connection). Some limitations have to be considered due to transmission systems or due to specific device constraints.[25] Respiratory events detection and the computation of summary statistics are performed according to each individual manufacturer's specifications. Data can be displayed on the manufacturer's platform or sent to the various healthcare providers' platforms via Application Programming Interfaces (API) as raw or aggregated data, one value summarizing measurements made over 24 hours (from midnight to midnight or from noon to noon) for a given patient (Figure 2).

Reliability of the residual AHI

Independently of the data transmission procedure, device usage and leaks can influence the reliability of the reported rAHI.

First, we recommend analyzing the distribution of rAHI values throughout 24h, retaining in the final analysis only periods during which the device was used continuously for several hours and filtering out very short periods. We make this statement for several reasons. Firstly, the empirical mean of the events detected over a short period is a poor statistical estimator of the true rAHI for the whole night. Secondly, the occurrence of residual events is influenced by many factors including body position, sleep stage and time of night.[26] Sleep instability during the first hours of the night could impact the dynamics of the respiratory events. The risk of residual events despite PAP therapy increases during Rapid Eye Movement (REM) sleep whereas deep (N3) sleep is generally free of apneas and hypopneas.[27-29] Thus, the rAHI measured over one or two hours of the night might not be representative of the whole night and overall treatment efficacy.

Accordingly, in previous studies analyzing rAHI big data, the investigators discarded periods with device usage of < 1 hour.[27, 28]

Furthermore, above a maximum leak threshold the respiratory event detection is unreliable, and the rAHI can be distorted (as illustrated in Figure 3) and should probably not be retained.

Device change and absence of standardization of reported indicators

A change of PAP devices (e.g., change from one manufacturer to another or even to a different model from the same manufacturer), can generate some transmission bugs lasting a few days. This can cause missing values or periods with no recording, even though the patient has been using the device. Thus, all missing values cannot be interpreted as poor adherence to PAP therapy.

The algorithms used by each manufacturer are somewhat different, leading to important variations in the reported indicators as there is no standardization in the computation nor in reporting methods between PAP manufacturers or brands. Indeed, the parameters included in summary statistics for rAHI and leaks and how they are reported are different among PAP manufacturers (only non-intentional leaks or all leaks, median or mean and/or 95th percentile and/or maximum value over the night, etc.).[29]

Thus, one might observe an apparent sudden change in the rAHI, due to both the period of adaptation to the new device and/or a difference in the way of calculating the rAHI (Figure 4).[24]
As a consequence, for each patient, transition periods between two distinct devices require specific data pre-processing. To assess the impact of changes in PAP device at the individual level, we suggest that all device changes are systematically recorded, and the statistical

distribution of the indicators and rates of missing and null usage values over a period before and after the change are compared. In the analysis of large databases for data science purposes, one solution is to consider data from only one device for each patient and to censor the second device. Another solution is to consider only devices from a single manufacturer to ensure coherence in the method used to calculate the summary statistics. Supplementing the data downloads with clinical history can also be quite informative at an individual level.

Multiple records from the same patient

During database “cleaning” one should ensure that it does not include duplicate recordings or errors in device attribution. After checking for device changes, this problem may be due to one or more of three scenarios.

First, several recordings might be sent in the same day if multiple sleep periods are transmitted owing to the PAP device restarting several times during the night or when the patient takes several short daytime naps. We suggest aggregating them by summing the hours of use and computing the mean weighted rAHI values, bearing in mind that the rAHI is probably reliable only for longer periods of use.

Second, there might be mismatches between device identification numbers and patient identification, resulting in the records from two distinct devices being attributed to the same patient despite their using only one PAP device (Figure 5A). In practice, this situation can occur when a device develops faults and the patient returns it to the supplier. Mismatches can also occur when patients change their home care provider. The problem can be solved by asking the patient to always give the device ID number (Figure 5B and 5C) or by removing the period with duplicate devices from the database if it is impossible to identify them correctly (Figure 5D).

The third scenario is a dataflow issue, resulting in duplicate rows for a patient with the same device and collected values. This can be solved by removing duplicate rows where all the values are completely identical. This removal may be sufficient, keeping one row per patient per day.

Missing values

It is important to check the distribution of rates of missing values and null usage times, i.e., records with a zero-usage time, so as to reveal inconsistencies. One possible source of missing data is due to PAP devices that transmit data using an external modem, which may become disconnected or misconnected to the PAP device. These devices should be indicated in the database and preferentially excluded before analysis to avoid errors in interpretation of null or missing values. Moreover, depending on the country's data privacy regulations, patient consent and the personalization of follow up, additional annotations may be collected to explain the non-usage of the devices (hospitalizations, vacations, travel or discontinuation of PAP treatment) and thus reduce the rate of missing values.

Imputation of missing values

In the recent literature, different methods have been used to deal with missing values in remote monitoring of PAP adherence such as: 1) replacing missing values by zero [16,30-32], 2) using an imputation procedure when they are due to transmission failure,[21,23] 3) excluding patients with excessive missing data,[23] 4) not replacing data [33] or 5) not reporting what is done.[34]

The relevance of each method depends on the situation, if the missing values are observed between two transmissions or if missing values are observed at the end of the patient's time series.

a. Imputation of PAP adherence values in case of missing records between two transmissions

If we consider a patient with several consecutive missing records between two transmissions (Figure 6A and 6B). The storage capacity of their device is ***p*** days. Then the period with missing records can be imputed with zero values if the length of this period is inferior to ***p*** (Figure 6A) and if the patient was not using another device (for example during a hospitalization).

When information on periods such as vacations or travel is known, it is possible to consider these as specific cases for which missing values can be replaced by zero, whatever the storage period of the device providing the patient confirms that they did not use their device over this time period (Figure 6A). Different reasons can lead to change in data reporting such as a change of time-zone, mask changes, humidification, damage to the device, etc.

Otherwise, missing values cannot be imputed with zero values and have either to remain as missing values or a specific imputation method should be considered if the patient effectively used a PAP device; however, this approach requires an understanding of complex adherence behaviors (Figure 6B).

b. Imputation of PAP adherence values in case of missing records at the end of a patient's sequence

Some patients' data can show missing values during the interval between the last available record and the date when the data were exported for analysis (Figure 6C). This can be due to PAP termination (e.g., initiation of alternative therapies, change in PAP provider or death). If it is known that the patient stopped their therapy, then their missing sequence should be imputed with zero values. In the case of device restitutions due to a change in PAP provider, then the patient is considered to have continued their therapy so the sequences should not be filled with zero values.

A sequence that is interrupted because of death should be censored before being included in any analysis.

c. Example of impact of imputation of missing values on PAP adherence results

From a random sample of 407 patients with daily PAP adherence values collected from a home care provider over 3 months after PAP initiation, without any observed PAP termination, in our own data, 33 patients (8%) had missing values when PAP adherence was considered over the first month of use.

This proportion increased to 15% at month 2 and 19% at month 3. In the total sample, no change in the mean of the individual average adherence values was found whether individual averaging was done with or without imputation (Figure 7). The greatest difference was observed if patients with missing values were removed from the sample (Table 2). When we considered only patients with missing values, the imputation strategy leads to changes, due to the small sample size (N=33, 60, 78), especially if missing values were replaced by zeros (Table 2 and Figure 7). The proportion of missing values was related to both the sample size and the percentage of missing values within a given sample. Here we present a large sample with a low frequency of missing values, resulting in small differences whatever the methods used to handle missing values. This result contrasts to the proactive and efficient replacement of missing data in the case of a small sample or a significant percentage of missing values (e.g., >20%).

In summary, if missing values occur between two transmissions: it is suggested to replace them by zeros if the period is shorter than the PAP device's storage capacity and no other PAP device was used (e.g., at the hospital), and otherwise to leave the value(s) as missing or use an imputation strategy. If missing values are at the end of the exported sequence: it is suggested to censor the data in case of loss to follow up or death, to leave the missing values or use an

imputation strategy in case of change in provider, and to replace by zeros in case of PAP termination.

To impute missing data, one solution is to consider each indicator as an independent time series and compare the performance of several methods: mean/mode imputation, last observation carried forward (LOCF), next observation carried backward (NOCB), mean of the last and the next observation, interpolation (linear, spline), and time series modeling and forecasting.[35] Another solution consists in imputing the multiple incomplete variables with an imputation method suited to multivariate longitudinal data: either using joint modelling (multivariate normal imputation) or with fully conditional specification (sequential regression and multiple imputation by chained equations).[36]

Short treatment interruptions go undetected in aggregated data

When only the mean or median of aggregated 24h data are presented, there is no distinction between the patient using the PAP device for three 2-hour daytime naps or using it continuously for 6 hours at night. The following example shows that discontinuities in PAP use during the night, often due simply to removal of the mask, are frequent.

From an exploratory analysis of our ongoing research database, in a sample of 15.7 million night-time records from 2,607 patients using PAP devices from the same manufacturer between June 2017 and April 2021, the majority (81.3%) of the interruptions in records corresponded to one or two-mask removals. In 15.9% of the records the mask was removed between 3 and 5 times during the night. Moreover, 2.8% of the records were the aggregation of 5 to 10 separate short periods of use. If data about mask removals and the distinct periods of PAP use over 24 hours are] available, then nights that are broken up into many parts could be identified.

Indeed, the same aggregated 24h PAP adherence could hide completely different PAP usages, some potentially related to long-term PAP termination and poor prognosis. For example, in patients with comorbid insomnia and sleep apnea (COMISA),[37,38] one of the most frequent OSA phenotypes is that numerous distinct periods of PAP use occur during the night and during naps in the day, reflecting the severity of insomnia and sleep deprivation. Likewise, the 24h mean or median residual AHI does not reveal events that occur only during a particular phase of sleep, such as the increased AHI during REM sleep, which has been associated with hypertension and diabetes.[39,40] Thus, it is preferable to use raw data that provide the exact times of PAP exposure during the night and the day.

Furthermore, the timing of PAP use can provide information about the circadian rhythm, which can be valuable for some analyses.

Finally, when the analysis focuses on the indicators measured while the patients are using their PAP device (rAHI, leaks etc.), only relatively unfragmented nights with less than 5 mask removals and several hours of continuous use should be retained for the analysis.

SUMMARY AND PERSPECTIVES

The remote monitoring of PAP data provides the opportunity to access valuable and objective information regarding patient adherence, patterns of use and treatment efficiency. Continuous monitoring enables clinicians, healthcare providers and researchers to follow variations in several parameters over short and long periods of time. While numerous studies have been based on summary statistics (24h means or medians) of daily PAP usage and indicators, there is growing interest in considering the internal structure of the daily aggregated data, as well as longer term trajectories considered in the framework of time series analysis.

To increase the comparability among studies and to avoid biases in computation, the modalities of PAP data management and processing and should be carefully considered. Firstly, excessive leaks (for which thresholds defining what constitutes a leak vary among the device manufacturers) can result in inaccurate rAHI estimations. Secondly, when analyzing PAP reported rAHI, the inclusion of short periods of device usage should be avoided as they do not reflect the actual mean number of residual events. However, these short periods of usage should be kept when reporting detailed PAP adherence, disturbed sleep and sleep patterns across the 24 hour span.[37] Thirdly, if possible, the amount of missing values should be minimized and imputation strategies should be well described. However, future studies are needed to compare the effect of different imputation methods on PAP data in order to set guidelines. Fourth, ways of avoiding errors in PAP device/patient attribution or data transmission should be explored to prevent situations such as multiple devices being attributed to one patient (which can happen during a device change) or multiple sets of data for one patient in the same day.

In cross-sectional or short-term studies different levels of granularity of data aggregation could be provided, to reveal details such as mask removal during the night. Such data provide contextual annotations related to patient phenotypes influencing PAP device use, including nocturia, other sleep disorders such as insomnia or multiple sequential sleep periods, and daytime naps. To our knowledge, such detailed data are not currently considered in PAP data studies.

A change in device could impact long-term studies, particularly, if the new device comes from a different manufacturer. The non-standardization of indicator thresholds (leaks or rAHI) can lead to major biases in data analyses. To avoid such biases, it would be preferable to consider only records for patients with a single model of device. An alternative possibility is to use an external device which can ensure PAP data standardization regardless of the PAP manufacturer [41] but with current technology precautions must be taken to avoid the problems encountered with external modem transmissions. The creation and implementation of international guidelines for standardization might help to solve this concern.

Missing data is a concern in all types of study. Contacting individual patients to determine why the data are missing, duplicated or inconsistent might be considered, but only if it is essential for the analysis. Indeed, this can be a tedious task, only feasible in well-structured health services. This approach is probably unattainable in fragmented healthcare systems, as can occur in the USA, involving many private stakeholders.

The spread of PAP remote monitoring worldwide potentially increases the amount of data that could become available from a huge population of patients. Well managed national and international collaborative digital databanks will be essential for enhancing data science in this field and facilitating the move toward artificial intelligence approaches. There is a unique opportunity to develop and improve in-depth data analyses, considering not only computed features at the trajectory level, but whole time series of daily records, or even raw data sampled at a higher frequency, such as the raw airflow signal recorded by PAP devices. This approach could contribute to the development of personalized tools to improve PAP management, to ensure data quality control, for health insurance reimbursement purposes and ultimately the better health of patients.

By developing standardized processes for data management of PAP records and by working on a standardization of metrics produced by PAP devices, it could be possible to compare different management patterns and develop standardized tools for patient self-monitoring in order to improve PAP adherence and treatment efficiency.

The potential uses of PAP remote monitoring data are multiple and are currently underused in the field of sleep research. Improving the quality of data from PAP remote monitoring would encourage more widespread use. This approach would help promote personalized medicine through various applications, including the identification of patient trajectories of PAP use or the variability of treatment efficiency based on rAHI measures.[22,23,32,42] The different clusters of PAP trajectories are potentially linked to patient reported outcomes and long-term incident cardiovascular events and mortality.

However, only considering PAP data has some limitations. There are a number of other relevant parameters, such as the number of hours of sleep,[43] patient-reported outcomes measures,[44] technical alerts or patient demographics and socio-economic factors which can help to better characterize patient trajectories. Thus, the aggregation of clinical, technical and sociological data could help to improve personalized medicine in the field of sleep apnea by considering individual variability.[30]

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Table 1: summary of problems, impacts and solutions

Problem to address	Potential impact	Proposed solution
Reliability of the residual AHI		
The residual AHI measured over short periods of use is a poor statistical estimator and may not be representative of the whole night	The residual AHI measured over short periods of use may not be reliable or may be biased	Set a minimum device usage threshold (e.g., > 1 hour) for considering rAHI
Drift of the flow curve due to large number of leaks	Respiratory events cannot be detected and the reported residual AHI may be distorted	Do not interpret residual AHI in cases with excessive leaks
Device replacement and absence of standardization		
Transmission bugs resulting from change in device model and/or manufacturer	Data may not be transmitted even though the patients uses the device	Missing values should not be replaced by zero values
Parameters reported and summary statistics for leaks and residual AHI are different among PAP manufacturers	Impossible to directly compare data from different devices	Transition periods between two distinct devices require specific data pre-processing
Multiple records of the same device for a patient		
Several records can be sent on the same day	Multiple rows for a patient with different values	Aggregate multiple rows by summing the usage values and compute the mean weighted residual AHI
Mismatch between the machine ID and the patient ID	Assigns the records from two distinct devices to the same patient	Provide the device ID or remove the period with duplicate devices
Dataflow issue	Duplicate rows for a patient	Remove duplicates
Missing values		
Transmission with external modem	Missing values due to connecting issues	Remove data recorded by PAP device with external modem
Between two transmissions	Bias related to missing values	Missing values can be replaced by zero
At the end of a patient's sequence	Bias related to missing values	Imputation strategy should be defined
Treatment interruption		
With daily aggregated data there is no distinction whether the patient did three 2-hour naps or slept 6 hours consecutively at night, for example	The same aggregated value of CPAP adherence might reflect completely different CPAP usages potentially related to CPAP termination and prognosis (e.g., Insomnia)	Use raw data which provide the exact time of CPAP exposures during night and day

Table 2: Impact of different strategies for imputing adherence missing values on mean adherence value and rate of patients with mean PAP use ≥4h/night. Results are presented for two different populations: the entire sample (N=407) and the sub-sample of patients with missing values.

	Over 1 month	Over 2 months	Over 3 Months
Number of missing values (mean and SD)	0.5 (2.6)	1.6 (5.9)	3.5 (11.2)
Maximum number of missing values	29	58	86
All sample			
No strategy for missing values			
Individual Average PAP Adherence hour/night (mean and SD)	4.61 (2.4)	4.62 (2.4)	4.6 (2.4)
PAP adherent patients* (N %)	257 (63)	255 (63)	255 (63)
Replacing missing values by zeros			
Individual Average PAP Adherence hour/night (mean and SD)	4.56 (2.4)	4.55 (2.4)	4.5 (2.4)
PAP adherent patients (N %)	252 (62)	249 (61)	251 (62)
Removing patients with missing values			
Individual Average PAP Adherence hour/night (mean and SD)	4.69 (2.4)	4.85 (2.3)	4.89 (2.3)
PAP adherent patients (N %)	239 (64)	230 (66)	221 (67)
Patients with missing values (N %)	33 (8)	60 (15)	78 (19)
No strategy for missing values			
Individual Average PAP Adherence hour/night (mean and SD)	3.67 (2.4)	3.29 (2.4)	3.36 (2.4)
PAP adherent patients (N %)	18 (55)	25 (42)	34 (44)
Replacing missing values by zeros			
Individual Average PAP Adherence hour/night (mean and SD)	3.0 (2.1)	2.78 (2.2)	2.86 (2.3)
PAP adherent patients (N %)	13 (39)	19 (32)	30 (38)

PAP: positive airway pressure; SD: standard deviation

*PAP adherent patients: number and percentage of patients with mean PAP use ≥4h/night

Figure legends:

Figure 1:

Title: Daily computed indicators from positive airway pressure device records

Legend: CPAP adherence, residual apnea-hypopnea index (AHI) and leaks

Figure 2:

Title: From positive airway pressure (PAP) prescription to PAP data visualisation: PAP data processing

Legend: **1**: PAP prescription from clinician to the patient.
2: PAP device distribution either directly from the manufacturer **(2a)** or via a home care provider **(2b)**.
3: Real-time respiratory events detected by proprietary software embedded in PAP device.
4: Data transfer from the PAP device to the manufacturer.
5: PAP data are stored in a secured online platform either by the manufacturer (**5a**) or by the home care provider (by using an Application Programming Interface (API)) who can make data transformations (**5b**).
6: Clinician can visualize and download PAP data for their patient by using a web platform.
7: The patient can visualize data on the device's screen or by using a web platform or a mobile application.

Figure 3:

Illustration of the unreliability of the reported residual apnea-hypopnea index (AHI) in the presence of excessive leaks

Figure 4:

Title: Impact of device change in reported residual apnea-hypopnea index (AHI)

Legend: Dashed lines: mean residual AHI over time

Figure 5:

Title: Example of a situation where two positive airway pressure (PAP) devices are simultaneously assigned to a single patient

Legend: (A) Plot of the PAP usage of a patient who was assigned the records of two distinct devices. (B) Usage records to keep for analysis if the Device 2 was used by the patient after Device 1. (C) Usage records to keep for analysis if the Device 1 was used throughout the

period. (D) Usage records to keep for analysis if no information can be retrieved about which device was actually used by the patient after Device 1.

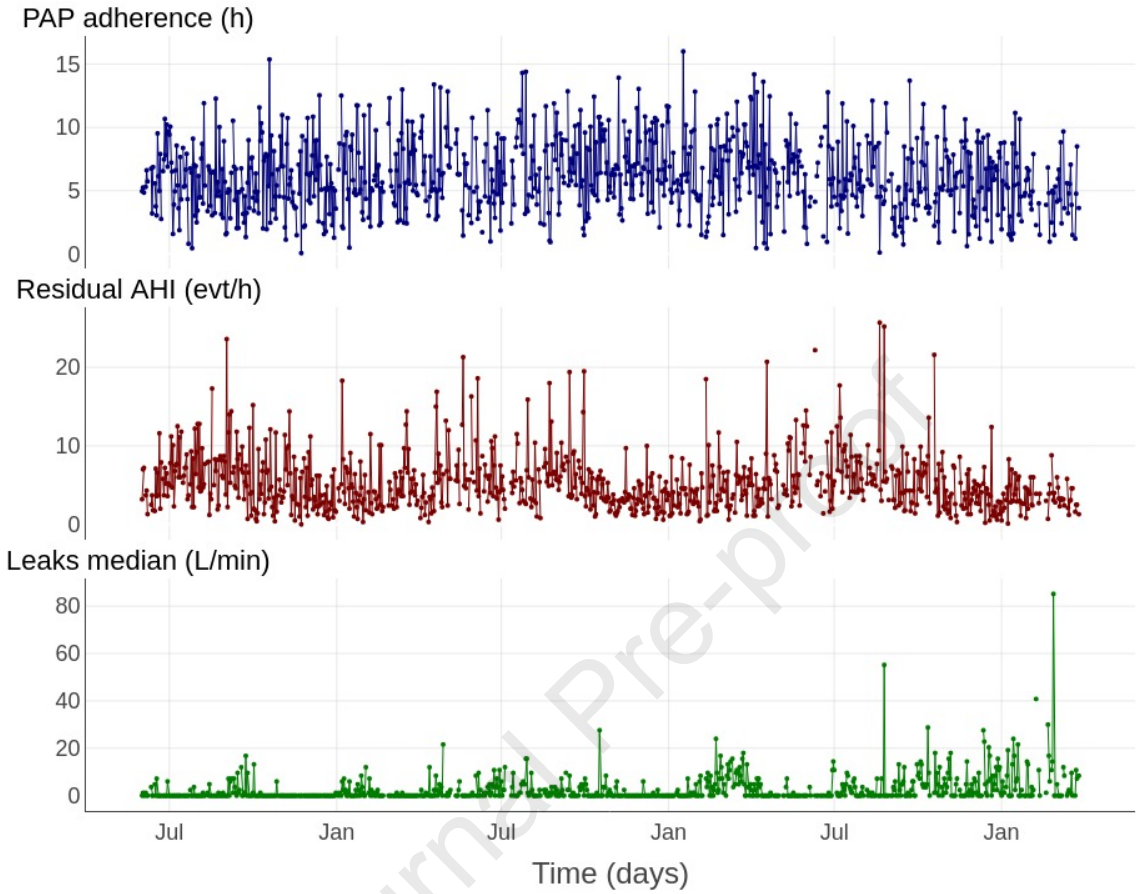
Figure 6:

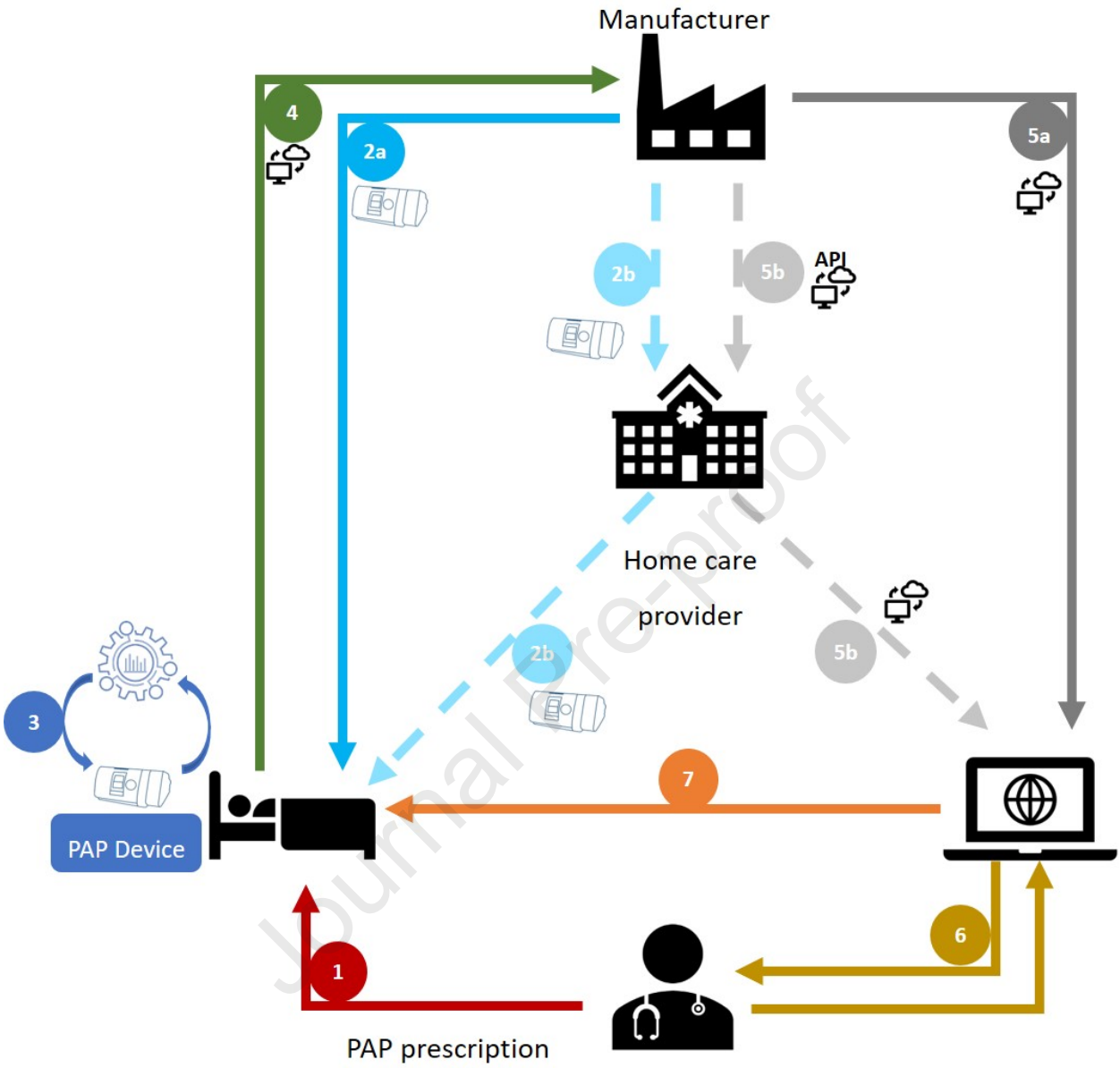
Title: Management of missing data

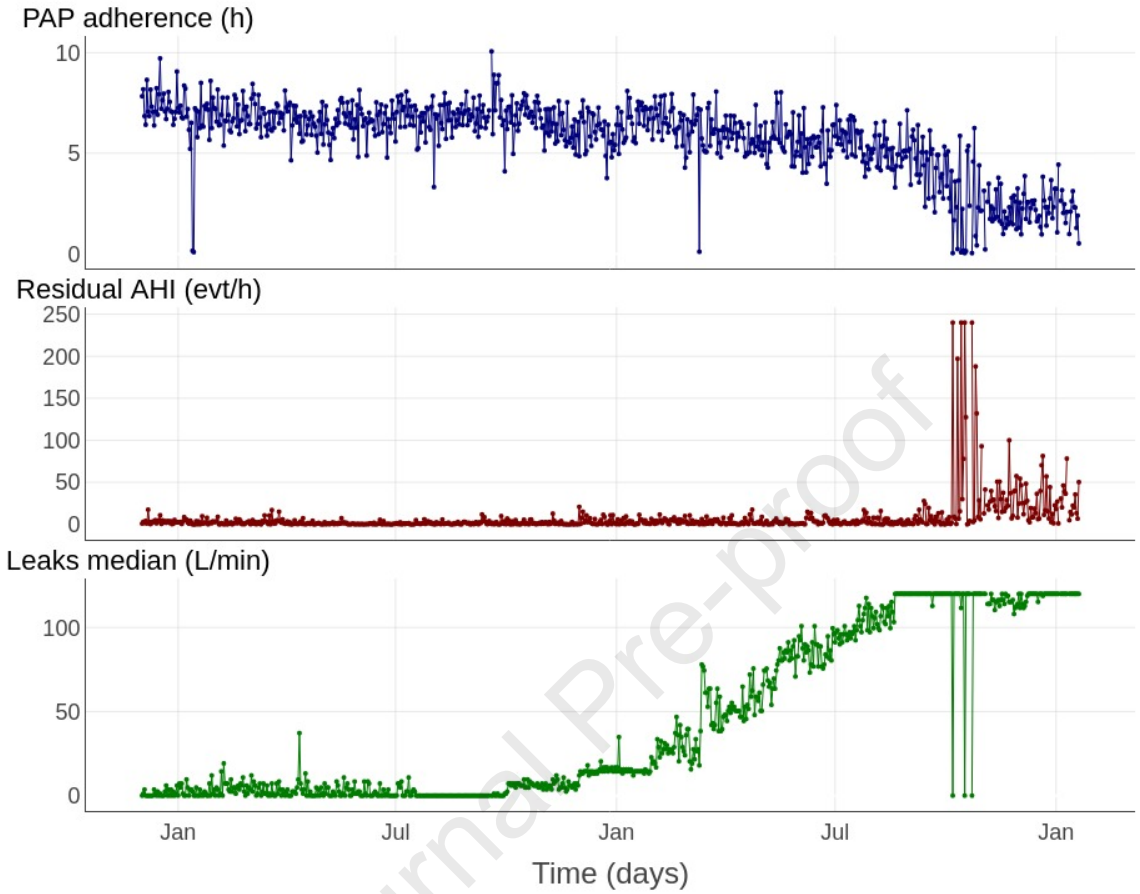
Legend: A: Missing values are observed within a patient sequence. Either the length of the missing value is lower than the data storage capacity of the positive airway pressure (PAP) device without usage of another device (for example, during a hospitalization) or the patient provides a reason for non-use of any PAP (for example, when on vacation or travelling). In these cases, missing values can be replaced by 0.
B: Missing values are observed within a patient sequence and the patient does not provide a reason for non-use of PAP or the length of missing values is higher than PAP storage capacity: missing values cannot be replaced by 0. An imputation method must be considered.
C: Missing values are observed at the end of a patient sequence and three possibilities can be considered according to the information about missing values.

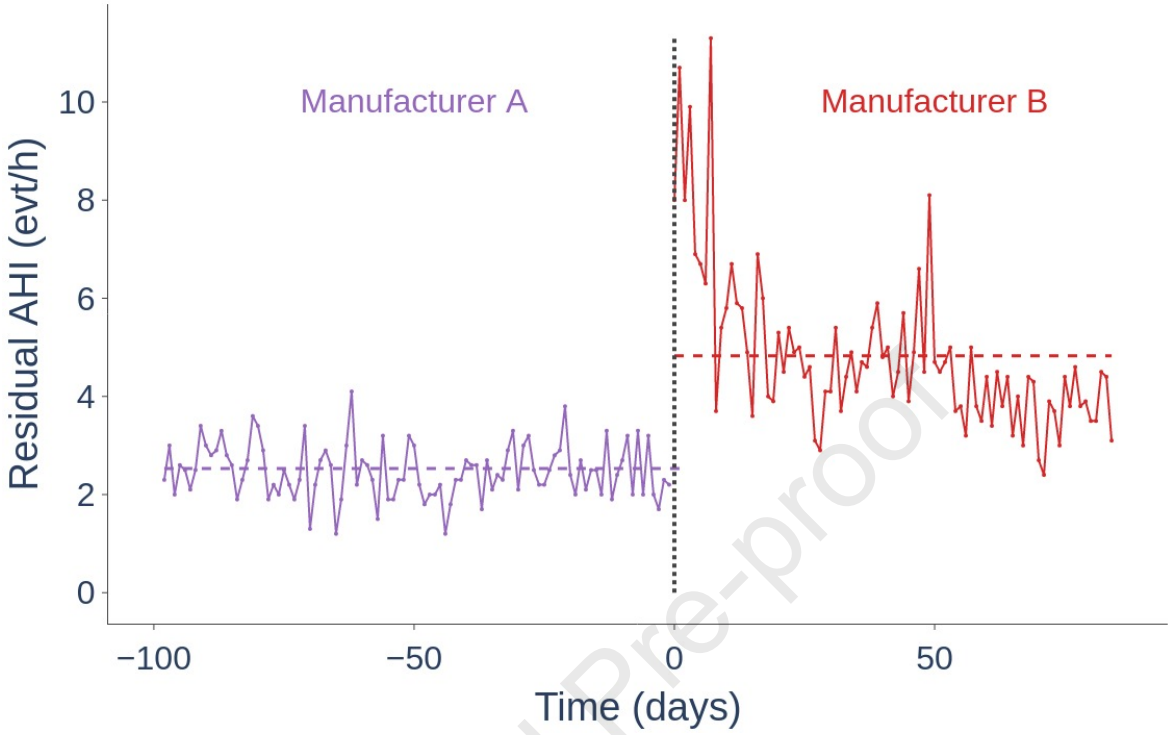
Figure 7:

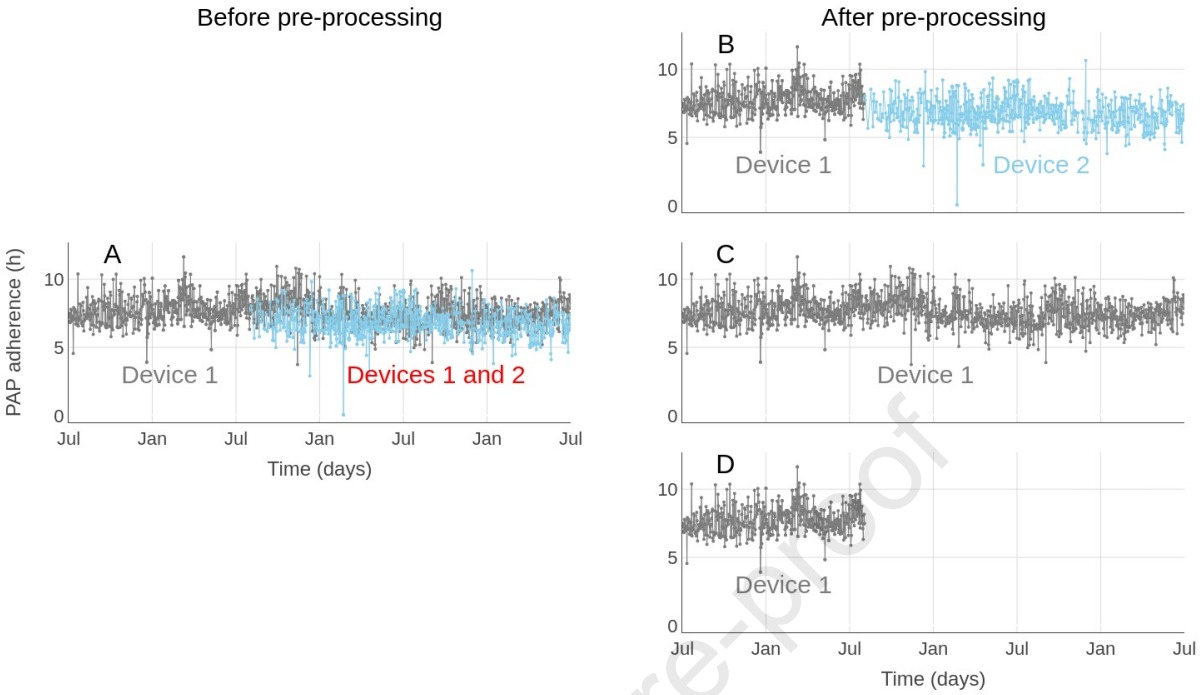
Title: Change in mean positive airway pressure (PAP) individual average adherence over different numbers of months of therapy according to sample and missing value imputation strategy

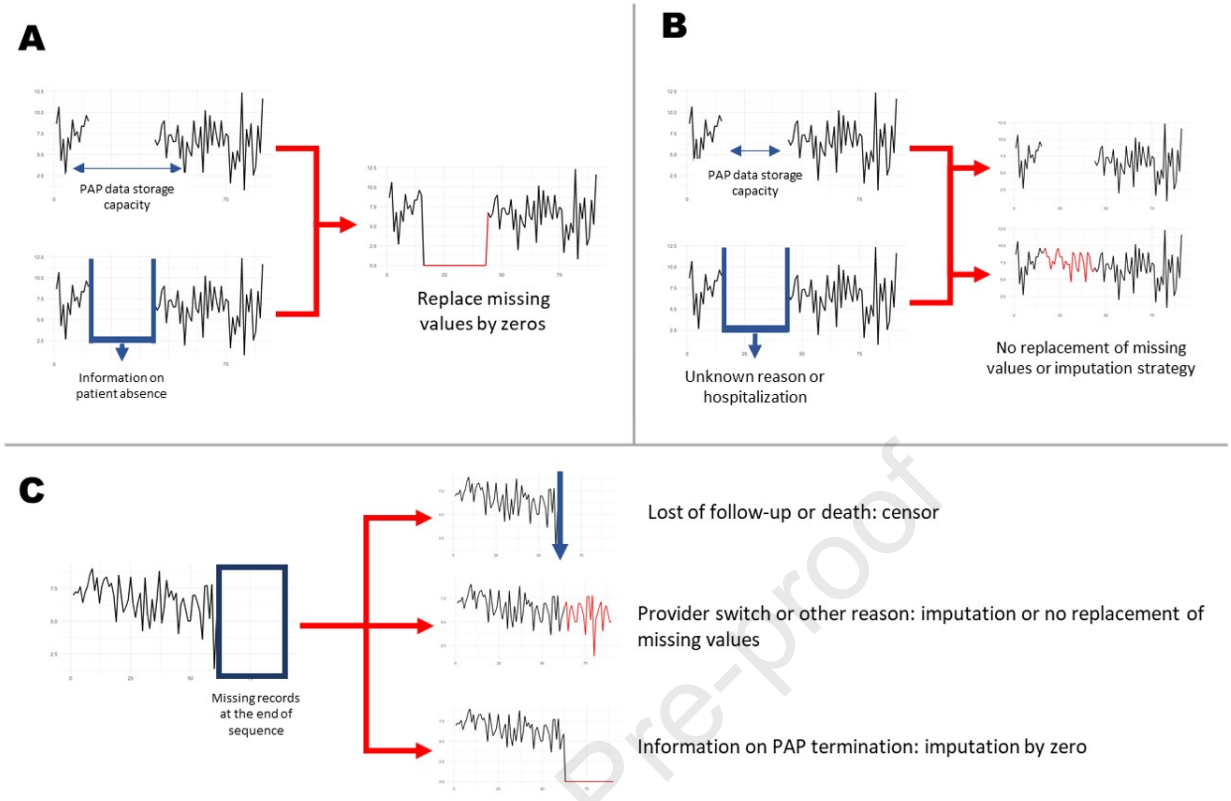


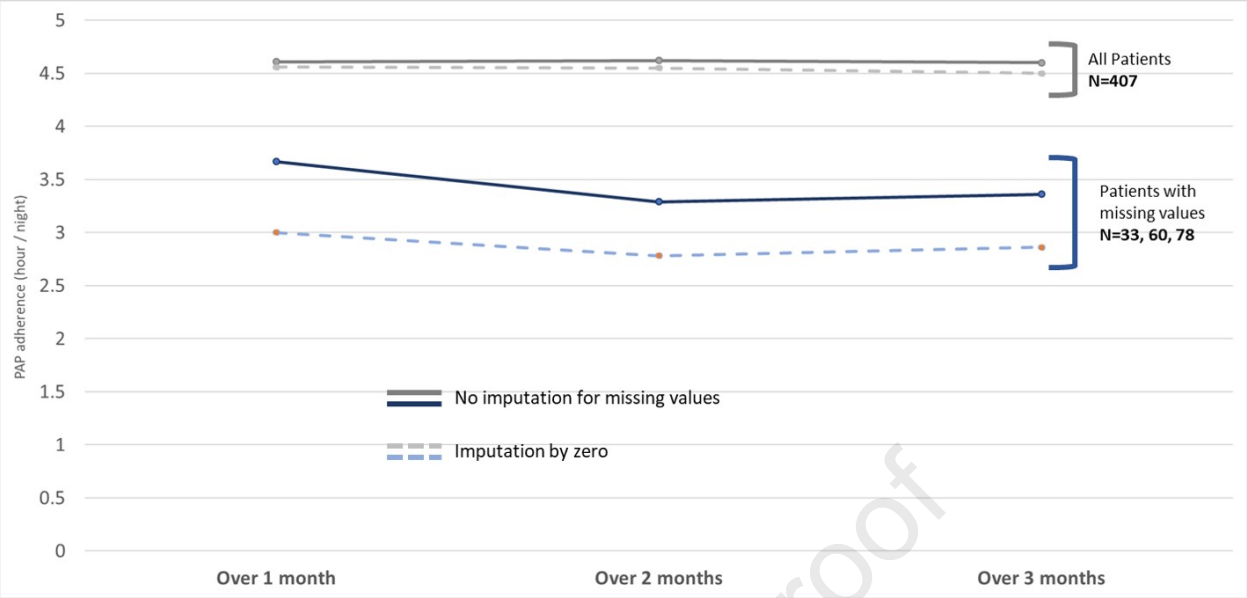












Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: