Computer-assisted analysis of polysomnographic recordings improves inter-scorer associated agreement and scoring times

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ABSTRACT

**Study Objectives:** To evaluate the current levels of human-expert performance and to assess the possible benefits of computer-assisted analysis for the scoring of polysomnographic sleep recordings (PSGs).

**Methods:** A group of 12 expert scorers independently reviewed 5 PSGs for each of the following tasks: (i) sleep staging, (ii) detection of EEG arousals, (iii) analysis of the respiratory activity, and (iv) identification of leg movements, thus amounting to a total of 20 recordings. For each one, rescoring was repeated separately, using the classical visually-based manual approach and a computer-assisted semi-automatic procedure. Resulting inter-scorer agreement and scoring times were examined and compared among the two methods.

**Results:** Computer-assisted sleep scoring showed a consistent and statistically relevant effect toward less time required for the completion of each of the PSG scoring tasks. Gain factors ranged from 1.26 (EEG arousals) to 2.41 (limb movements). Inter-scorer kappa agreement was also consistently increased with the use of supervised semi-automatic scoring. Specifically, from K=0.76 to K=0.80 (sleep stages), K=0.72 to K=0.91 (limb movements), K=0.55 to K=0.66 (respiratory activity), and K = 0.58 to K=0.65 (EEG arousals). Inter-scorer agreement on the examined set of diagnostic indices did also show a trend toward higher Interclass Correlation Coefficient scores when using the semi-automatic scoring approach.

**Conclusions:** Computer-assisted analysis can improve inter-scorer agreement and scoring times associated with the review of PSG studies resulting in higher efficiency and overall quality in the diagnosis sleep disorders.

**Keywords**

Polysomnographic recordings; Inter-scorer variability; Sleep staging; Limb movements; Respiratory activity; EEG arousals; Manual scoring; Automatic analysis;
STATEMENT OF SIGNIFICANCE

This study shows that, in comparison to manual scoring, the use of semi-automatic PSG analysis has benefits in the form of faster scoring and higher associated inter-scorer agreement. A number of firsts are included, as to our knowledge, this is the first work to systematically address the comparison between manual and semi-automatic scoring through the use of quantifiable metrics of scoring time and inter-scorer reliability. Existing literature regarding manual or semi-automatic scoring time analysis of limb movements or EEG arousals is scarce, and for sleep staging or apneic event detection, directly inexistent. Likewise, this is the first work to provide metrics of inter-scorer reliability for derived semi-automatic event markings as well as the resulting indices of diagnose.
1. INTRODUCTION

The analysis of polysomnographic sleep recordings (PSGs) constitutes one of the most time-consuming tasks in the daily work of a Sleep Center. A typical PSG examination contains somewhere between eight up to twenty-four hours of continuous neurophysiological activity recording. Common PSG data include, among others, different traces of electroencephalographic (EEG), electrooculographic (EOG), electrocardiographic (ECG), electromyographic (EMG), and respiratory activity [1]. Likewise, analysis of the PSG can be organized into different subtasks, for instance, analysis of the macro and micro structure of sleep, characterization of the respiratory function, or identification and scoring of limb movement activity.

Clinical findings over the last years have uncovered the negative consequences that Sleep Disorders exert over health, contributing to the general public awareness. The former has led to a steady increase in the demand for PSG investigations. This represents a challenge for the already congested sleep centers. Clinician's time is expensive and scant. In addition, the large amount and the complexity of the associated data, makes of PSG analysis a task prone to errors and to subjective interpretations [2]. Indeed, despite homogenization procedures promoted by development and usage of clinical standard guidelines [1] [3], different grades of intra- and inter-expert variability have been reported in the literature, affecting the resulting PSG outcomes, which vary among the specific references or tasks subject to evaluation [4] [5] [6] [7] [8]. In this context, the use of automatic scoring algorithms to support the clinician in the analysis of the PSG presents potential advantages. On one hand, in terms of great savings in scoring time, and thus in human resources, helping reducing the overall costs associated with the diagnosis. Literature, in fact, is rich on examples that focus on the development and validation of automatic analysis methods in different areas related to the scoring of sleep studies [5] [9] [10] [11] [12] [13] [14] [15] [16] [17]. However, despite the promising man-machine agreement results reported in some of these works, practical acceptance of these systems among the clinical community remains low. In fact, there are still open questions on whether “are we there yet”, in terms of acceptable performance and enough generalization capabilities of these algorithms as compared to well-trained human clinicians [2].
Automatic scoring, on the other hand, has another interesting property, which is the ability to provide deterministic (repeatable) diagnostic outcomes. Hence, it is conceivable that automatic scoring could play a role to help reduce the levels of inter-scorer variability, thus contributing to standardization and overall quality improvement in the diagnostic process. That we know of, however, no previous attempts have been made to formally address this hypothesis.

The main goal of this study is to evaluate the current levels of human-expert performance and to assess the possible benefits of using computer-assisted analysis in the scoring of PSGs. For this purpose, we are making use of objective (quantifiable) quality indicators regarding the scoring time (time needed to score a full PSG) and the repeatability of the scoring outcomes. More specifically, the following four (usually, the most important) PSG analysis subtasks are considered: sleep staging, analysis of EEG micro-arousals, evaluation of the respiratory function, and scoring of limb movement activity. For each of these tasks, the standard manual and computer-assisted scoring approaches are evaluated and compared. Under the manual approach the clinician performs analysis of PSG data using the commonly accepted ‘gold standard’ approach based on visual scoring. In the computer-assisted so-called “semi-automatic” approach, an automatic algorithm performs a preliminary analysis pass, and the clinician then reviews the results by adding, removing or editing miss-scorings from the automatic algorithm.

Our work is novel as no previous studies have attempted to examine the hypothesis on whether semi-automatic scoring can contribute to reduction of inter-scorer variability. To our knowledge this is also the first study to systematically address possible scoring time differences between the manual and semi-automatic approaches. Furthermore, there is a general lack of comprehensive studies that confront human and (semi)automatic scoring. In effect, the available literature usually targets the validation of the automatic algorithm by assessing its performance in comparison to one or more reference scorers. However, contextualization of the results with respect to the baseline levels of human performance in the corresponding task is often omitted. This is a problem as this is necessary to set a valid target reference for the automatic algorithm and to discard possible overfitting to specific scorers or bias effects. Extrapolation of human baseline levels from independent external studies, on the other hand, is in general not possible. As stated before, inter-scorer and database variability plays
a role, for which ideally the respective human and computer performances should be derived, and
compared, using a common patient dataset.

To have objective (measurable) references of the levels of human performance is as well of
fundamental importance to allow implementation of quality control mechanisms in the patient care. Our
work contributes to this aspect as well by adding to the existing literature. In this respect it should be
noted that evolution of the scoring methods and reference clinical guidelines motivates reassessment
of the existing references, for which some of them are outdated. Furthermore, for some of the
examined scoring tasks literature references of related quality factors have never been reported.

2. METHODS

2.1. Study database

PSG data for this study has been gathered by retrospective inspection of the Haaglanden Medisch
Centrum (HMC, The Hague, The Netherlands) Sleep Center clinical patient database. All data were
acquired in the course of the common clinical practice. No patient was therefore subjected to any
additional behavior in relation to this study, nor was prescribed any additional treatment outside of the
regular clinical workflow.

Recordings were de-identified and subrogate study numbers were assigned to each patient, avoiding
any possibility of individual patient identification. Under these conditions the study obtained approval
of the local Medical Ethics Committee (Medisch Ethische Toetsingscommissie Zuidwest Holland) under
code MTEC-19-065, who considered that the protocol did not fall under the scope of the Medical
Scientific Research Involving Human Subjects Act (WMO) and that no explicit informed consent was
required by participants. Study has as well obtained written permission from the database owner for
publication.

PSG data consisted of raw biomedical signals following standard acquisition procedures according to
the AASM guidelines [1]. SOMNOscreen™ plus devices (SOMNOmedics, Germany) were used as the
acquisition hardware. Event annotations resulting from the scorers’ reviews during regular clinical
workflow accompanied each recording. Clinical scorings were carried out by HMC sleep technicians
including the scoring of sleep stages, EEG arousals, and respiratory activity, following the AASM
standards [1], and the scoring of the limb movement activity following the WASM2016 guidelines [3].

Both the raw signal’s data and the resulting clinical scoring annotations were digitally stored using the EDF+ format [18].

2.2. Rescoring task

In the present study a group of sleep technicians were prompted to review 5 PSG recordings, independently for each of the following scoring subtasks: (i) sleep stating, (ii) detection of EEG arousals, (iii) analysis of the respiratory activity, and (iv) identification of leg movements. Thus, in total, 20 different PSG recordings were included in the study. All sleep scorers belonged to HMC staff and participated regularly on clinical workflow in an autonomous mode. Sleep technicians undergoing training or supervision were excluded. In total 12 scorers participated in this task.

Each of the participant scorers were tasked to review the exact same recordings. In all cases, scorers were blinded to both the patient identity (by using de-identified recordings) and possible results of previous scorings (e.g. that took place during regular clinical workflow, from other scorers, or during a previous self-rescoring subtask).

Rescoring was repeated, separately for each recording, using a purely manual and a semi-automatic approach. To avoid learning effects, at least 4 months of separation were scheduled between these two moments. For reference, the number of PSG recordings scored by each sleep technician due to the normal working routine in that time approximately averages to 70 patients. Scorers were also not informed of the fact that manual and semi-automatic scorings would involve the same recordings.

All scorings took place using the Polyman software [19]. For each task a timer was automatically set in the background by the program (not available to the human scorer). The tick counting was automatically paused if no mouse or keyboard interaction was detected during more than a minute, and the offline time was subtracted from the total scoring time. The resulting active scoring time was saved separately in a file for later analysis.

Scoring took place between time in bed periods only (between lights off – on markers, which were provided as pre-filled annotations). For scoring of EEG arousals, respiratory events and limb movements, the pre-filled clinical hypnogram was also provided as additional source for contextual interpretation. Regardless, scorers were instructed to stick to the scoring of the relevant events in the
context of the specific target task, not being allowed to change any pre-filled contextual information

During the semi-automatic scoring process, the annotations that resulted from the output of the corresponding automatic analysis algorithms were provided, in addition, at the start of the scoring. Scorers were instructed to review these scorings by adding, deleting, or editing the event’s onset and offset times, where corresponds, and according to their own expertise. Details regarding the development and validation of the automatic scoring algorithms that were used for this purpose have been reported in past works. The reader is referred to check the specific references regarding the automatic scoring of sleep stages [2] [20], leg movement activity [21] [22], respiratory events [23] [24], and EEG arousals [25] [26].

2.3. Selection of PSGs

For each of the scoring subtasks targeted in this study (i.e. sleep staging, EEG arousals, respiration, and limb movements) 5 PSG recordings were selected from an initial pre-sample dataset of 2801 recordings, corresponding to the most recent one-year data from the HMC database at the time (2019). Sampling size per task was determined by availability of resources with regard to expert scoring time. As result, 20 PSG recordings were selected that integrate the final scoring sample for the study.

The selection process was implemented with the objective to minimize the chance of selection bias and deal with the inherent inter-subject variability among the PSGs’ initial pre-sample distribution. No specific exclusion criteria were applied during the selection process to filter out recordings, for instance, due to specific patient conditions, or poor signal quality. A sufficient condition was that the recording had been accepted for manual scoring during the regular clinical workflow, a condition that, by definition, was already satisfied by all recordings included in the pre-sample dataset. The underlying motivation was that of reproducing, as close as possible, the same conditions as in real practice, by considering a representative sample of the general patient phenotype.

Hence, for each of the four scoring subtasks, the following selection procedure was scheduled:

(i) Taking as reference the complete pre-sample dataset (2801 PSGs) a full automatic analysis (no human intervention at all) of the recording was performed. This analysis led
to a list of automatically scored events $L_a(i)$, for each recording $i$, related to the corresponding target task on each case.

(ii) Using the list of automatically-generated events, $L_a(i)$, each PSG was compared with the corresponding list of events that resulted during routine clinical examination, $L_c(i)$. Confronting $L_a(i)$ with $L_c(i)$, a preliminary metric of performance agreement between the two scoring outputs, $K_{ac}(i)$, was obtained. Specifically, $K_{ac}$ was calculated using the Cohen’s Kappa statistic [27]. Details on the implementation of $K_{ac}$ for each of the four target subtasks are described in the “analysis methods” section.

(iii) By repeating this operation through all 2801 PSGs available in the initial pre-sample dataset, a distribution $DK_{ac}$ of $K_{ac}(i)$ values was obtained.

(iv) Using $DK_{ac}$ as reference, uniform sampling was performed to select the target number $N=5$ of recordings to be included in each subtasks’ final study dataset. Specifically, the 5 recordings whose associated $K_{ac}(i)$ performance metrics represent the middle of each inter-quartile range, plus the median, were selected as representatives of their respective whole populations. In other words, the recordings with performance scores representing the 12.5th, 37.5th, 50th, 62.5th and 87.5th percentiles of each $DK_{ac}$ distribution were selected for the final study dataset.

Effectively, the above described procedure is preferable over random resampling as it avoids potential selection of outliers by chance (i.e. extreme favorable or unfavorable cases for the automatic algorithm) that might bias the resulting sample. Instead, the procedure seeks an even distribution of the relative recording scoring difficulty throughout the final study dataset. In this respect, it is hypothesized that automatic scoring difficulty is correlated with the manual scoring difficulty: the lower (higher) the agreement between the automatic and the clinical reference would be, the lower (higher) the resulting inter-rater agreement is expected to be. Similar selection procedures were scheduled during the validation of different automatic scoring algorithms that were reported in the past [26] [20]. Correlation analyses are scheduled to analyze validity of this hypothesis whose results are provided in
Supplementary Table D1 and discussed in the corresponding Section D of the Supplementary Materials.

Table 1 summarizes the general demographics and PSG descriptors in the resulting patient study sample. Data are presented stratified among the corresponding task-specific subgroups.

2.4. Analysis methods

Analysis of inter-scorer agreement is carried out in the first place by discretizing the recording time into non-overlapping analysis mini-epochs. Each analysis mini-epoch is assigned the corresponding scorer's output in the context of the specific target subtask. Duration of the mini-epochs are task-related as well. In the case of the sleep scoring, analysis epochs have the standard duration of 30s and take possible values according to the AASM clinical guidelines, that is, either W, N1, N2, N3, or R [1]. In the context of the EEG arousals, respiratory events, and limb movement's scoring subtasks, each mini-epoch takes a binary value noting the presence or absence of event, respectively, if overlapping or not with the events marked by the scorer. Analysis mini-epoch duration is set to 0.5s for all the three subtasks.

Time discretization in the above terms leads to the construction of $k$-dimensional contingency tables ($k=5$ for sleep staging, $k=2$ otherwise) from which standard metrics of agreement for categorical data can be derived. Within each task, agreement between each score's pair combination is calculated. More specifically, the Cohen's kappa statistic is used for this purpose. The use of the Cohen's kappa is motivated given its widespread use in the field, as well as its robustness in the case of imbalanced class distributions as it corrects for agreement due to chance [27].

Inter-scorer agreement is also evaluated among the diagnostic indices resulting from the respective scorings. Following the list of recommended parameters to be reported in PSG studies [1] [3], a representative subset for each of the subtasks targeted in this study is selected. In particular, sleep quality-related parameters of Sleep Efficiency (SE), Sleep Onset Latency (SOL), and Wake After Sleep Onset (WASO) [28], in relation to the sleep scoring task; Apnea-Hypopnea Index (AHI), Apnea Index (AI), Hypopnea Index (HI) and Oxygen Desaturation Index (ODI), in relation to the scoring of
respiratory events; Arousal Index (ArI), in relation to the scoring of EEG arousal events; and Leg Movement Index (LMI) and the Periodic Leg Movement Index (PLMI), in relation to the limb movement scoring task. LMI and PLMI indices are calculated according to the WASM2016 scoring guidelines, the former as the number of limb movements ≥ 0.5s after bilateral combinations per hour of sleep, and the latter including respiratory-related LMs as well [3]. Inter-scorer agreement among the resulting indices within each method is evaluated using the Intraclass Correlation Coefficient (ICC) [29]. Specifically, a two-way absolute single-measures variant of the statistic, ICC(A,1), is used [30]. A Matlab implementation for calculation of this coefficient has been used whose source code is available at [31].

Hypothesis testing is carried out to check for significant differences between the manual and semi-automatic scoring approaches. For this purpose, the reference level for statistical significance is set to α = 0.05. Kappa agreement differences between the two approaches are examined using the paired version of the Wilcoxon signed rank test among all the matched scorer pair combinations. Analogous analysis is performed for checking out differences in the respective scoring times among the matched individual scorers. For each test the corresponding effect size is reported using the Cohen's D statistic. Statistical significance on inter-scorer ICC agreement differences among diagnostic indices is also evaluated. For this purpose, the a priori expected agreement (r0) for the semi-automatic approach is set to the effective ICC levels achieved with manual scoring.

Results of the above-mentioned analyses are presented in the subsequent section by aggregating the respective scorings among the five recordings involved within each scoring task. In order to keep the main text extension attainable, individualized per-recording results are provided as Supplementary Material. Manual vs. semi-automatic differences in diagnostic indices in this case are examined using paired analyses, and comparison of the respective variance distributions is examined using the Brown-Forsythe (unpaired) test. For the latter, i.e. comparison of distribution’s variance, the corresponding manual and semi-automatic indices are first mean normalized within their respective distributions to avoid possible bias due to differences in the respective population means. Supplementary materials do also provide correlation analyses aiming to test the PSG selection hypothesis, namely that automatic scoring difficulty is correlated with manual scoring variability.
3. RESULTS

3.1. Analysis of scoring time

Figure 1 shows the median scoring time associated with the completion of the different analysis tasks according to the followed approach, i.e. manual or semi-automatic. Values on the bar plot are shown in minutes and aggregate the results among the five recordings involved on each case.

Table 2 expands the results of Figure 1 and shows the results of the associated statistical analyses involving the two scoring approaches. Data in Table 2 unveil a consistent and statistically relevant effect toward less time required for the completion of each task when using the semi-automatic scoring approach. Gain factors vary per task, with the largest time savings relating to the scoring of limb movements, followed by the analysis of the respiratory activity, and a less pronounced effect associated with the sleep staging task and the scoring of EEG arousals. The associated effect sizes on each case support these interpretations. In this regard, notice that a positive sign on the corresponding index indicates that the overall effect (in this case scoring time) is bigger in the manual scoring scenario, with the associated absolute value being an indicative of how much bigger the effect is.

When comparing absolute time values among the different tasks, our results show that identification of limb movements is the most time consuming task when using manual analysis. Scoring of respiratory events is relatively the quickest. The trend changes a bit when using the semi-automatic approach, resulting in sleep staging being the slowest, with analysis of respiratory activity remains as the fastest task.

Individualized per-recording and per-scorer analyses for each task can be found, respectively, in Supplementary Tables A1-A4 and Supplementary Figures A1-A4.

3.2. Analysis of kappa agreement

Figure 2 shows the global kappa agreement results per scoring task when comparing manual and semi-automatic scoring approaches. Values on the bar plot represent the median expert paired agreements among the five recordings within the corresponding task.
Table 3 shows results of the statistical analyses between the corresponding manual and semi-automatic scoring differences. Moreover, results are subcategorized for some of the tasks into different contexts of clinical interest. In particular, differences between wake and sleep periods are reported for limb movements, as well as results involving different types of events within the respiratory analysis task. For the analysis of the limb movement activity, the individual kappa scores for each leg channel (left / right) were averaged together before statistical analysis was executed.

Results from Table 3 show that statistically significant differences between manual and semi-automatic scoring are reached regardless of the specific task or the event subtype. A consistent trend toward higher inter-scorer agreement associated with the use of semi-automatic scoring is shown. Notice the associated effect sizes overall show a negative sign, being indicative of the general smaller agreement achieved in the manual scoring scenario. The highest absolute effect in this context is associated with the analysis of the limb movement activity task.

When comparing among the different tasks, the highest (either manual or semi-automatic) agreements are achieved in the case of the sleep staging and limb movements’ analysis tasks. For the latter, higher agreement is obtained during sleep periods than during wakefulness. With regard to the analysis of respiratory activity, and attending to the different event subtypes, higher agreement is achieved for the scoring of apneas than of hypopneas. Rather low agreement is achieved associated with manual scoring of oxygen desaturation events (median K = 0.40), which is much improved when using the semi-automatic approach (median K = 0.82). Finally, reliability associated with the scoring of EEG arousal events reaches agreement levels similar to those obtained for the identification of respiratory events in general (i.e. apneas, hypopneas and RERAs altogether).

Individualized per-recording analyses for each of the tasks are supplied in Supplementary Tables B1-B9.

### 3.3. Analysis of derived diagnostic indices

Table 4 examines inter-scorer agreement among the selected list of diagnostic parameters for the manual and semi-automatic scoring approaches. Agreement is evaluated using the Interclass Correlation Coefficient (ICC).
When comparing absolute ICC values among the different tasks, a trend can be seen toward higher inter-scorer agreement when using the semi-automatic scoring approach, with the only exception of SOL. Regardless of the scoring approach, the highest general agreement is achieved in the case of SE, AI, and WASO (ICC > 0.99 in all cases). Agreement associated with the scoring of apneas probably contributes to the relative high scores achieved for the AHI too. Detection of hypopneas as reflected by HI, on the other hand, shows relative lower levels of ICC agreement. HI is, in fact, the index where the lowest overall agreement is achieved, followed by ArI. All the obtained ICC values, also regardless of the scoring approach, achieve statistical significance when the null hypothesis assumes no a priori agreement ($r_0 = 0$).

For examining statistical significance of the observed differences between the manual and semi-automatic approaches, the null hypothesis is set, in addition, to assume baseline ICC levels corresponding to manual scoring. In this case, significant differences are obtained for the indices of WASO, LMI, PLMI, AI and ODI. In the case of SE, AHI, HI and ArI, the trend remains consistent toward higher ICC values when using the semi-automatic scoring approach, albeit analyses do not reach statistical relevance. And finally, only for SOL, higher ICC values are obtained using manual scoring, but again differences do not reach the level of statistical significance.

Individualized per-recording analyses are supplied in Supplementary Tables C1-C10. In this case manual vs. semi-automatic differences are examined both using paired Wilcoxon sign-rank and unpaired Brown-Forsythe tests, as described in the methods section.

**4. DISCUSSION**

The main goal of this study was to evaluate the current levels of human-expert performance in the scoring of PSGs, and to assess the possible benefits of using automatic analysis in supporting this task. For this purpose, we have considered four of the most common subtasks involved in the analysis of PSGs: sleep staging, identification of EEG arousals, evaluation of the respiratory function, and scoring of limb movement activity. On each case, quantifiable metrics of performance regarding the scoring time, and inter-scorer agreement, have been examined and compared among the manual and semi-automatic scoring procedures. To our knowledge, this is the first study to systematically address the differences between these two approaches.
Our experimentation has shown that the use of semi-automatic analysis has benefits in the form of faster scoring and higher inter-scorer agreement. Faster scoring means reduced associated costs, and the possibility to reduce the waiting lists by the consequent increase in the scoring production. Higher inter-scorer agreement means better consistency and reliability of the PSG outcomes, and therefore improved quality of the diagnosis. The trend is consistent though all of the four examined tasks.

Differences between the two approaches have achieved statistical significance both for the scoring time and the expert agreement measured in terms of Cohen's $\kappa$. The impact of these differences on a subset of derived diagnostic indices, analyzed in terms of ICC agreement, has shown a more heterogeneous pattern. While statistical significant differences have been observed for indices of WASO, LMI, LMI, AI and ODI, this was not the case for indices of SE, SOL, AHI, HI and ArI.

Regardless, for all the examined indices with the exception of SOL, the trend was consistent toward higher ICC values when using the semi-automatic scoring approach.

Our study provides a number of firsts. To the authors knowledge, for example, this is the first study reporting and comparing the time associated with the scoring of sleep stages and respiratory events (both for the manual and semi-automatic approaches). Our data shows an average gain factor in scoring time of 1.33 and 1.63, respectively, when using semi-automatic scoring. With regard to the detection of limb movements, at least one earlier work has also examined the hypothesis of scoring time differences between manual and semi-automatic scoring. Specifically, in Roessen et al. [32], the manual review of 30 PSGs took a total of 28 man-hours, whereas the semi-automatic procedure required 10 man-hours, hence resulting in a 2.8 gain factor favoring the latter. This result is consistent with our experiments in which we obtained a 2.41 gain factor for the limb movement detection task.

More specifically, in our case the associated median scoring time per recording was of 44.53 minutes for the manual approach, and 18.50 minutes when using the semi-automatic procedure. With regard to the scoring of EEG arousals, in a past work we have already reported an estimated 20-25% speed improvement associated with the use of semi-automatic scoring [26]. In both studies the same automatic EEG arousal scoring algorithm was used, with the estimation reported back then not differing much from the 26% improvement obtained in the present study. In [26] only the mean manual scoring time per individual was reported, averaging to 25 minutes (18 – 50 minute range), which is also not far from the median 27.50 minutes, but with higher variability (12.91 – 92.15 range), obtained
in the present work. In addition, the respective values when using semi-automatic scoring are also reported in this study, decreasing to a median of 21.78 minutes per recording for the same task.

Our study is also the first to investigate inter-scorer reliability in the context of semi-automatic scoring. In the case of manual scoring, the availability of past references for contextualization of our results depends on the specific task. For example, several studies have previously addressed inter-scorer reliability associated with manual scoring of sleep stages. Detailed discussion can be found in another recent publication by the authors [20], resulting in kappa coefficients ranging widely between 0.46 and 0.89 depending on the consulted reference. This range is compatible with the median agreement achieved in this study (K = 0.76 for manual, K = 0.80 for semi-auto). On the other hand, only one past reference was found examining inter-scorer kappa agreement in the detection of limb movements. In the study of Pittman et al. [5] K = 0.77 was obtained between two scoring experts on a dataset of 31 PSGs. Notice, however, that agreement reported in Pittman et al. refers only to the scoring of PLMS, not LMs, and that the scoring reference was based on older standards (ASDA1993 [33]). Moreover, analysis was constrained to sleep periods only, and its associated resolution was 30s. Our results using the recent WASM2016 scoring standards resulted in a global K = 0.72 for manual, and K = 0.91 for semi-automatic scoring, when examining LMs during TIB using a 0.5s analysis step. Agreement falls respectively to K = 0.67 and K = 0.89 during wake periods, and improves to K = 0.75 and K = 0.92 during TST.

Pitman et al. have reported as well a K = 0.82 for the manual scoring of apneas and hypopneas using the 2001 AASM Medicare scoring definitions on a 30s analysis epoch [5]. With our settings, we have achieved rather lower agreement resulting in median K = 0.55 (improving to K = 0.66 with semi-automatic scoring). We have obtained higher agreement for the scoring of apneas (median K = 0.74 for manual, K = 0.88 for semi-automatic) than for the case of hypopneas (respectively K = 0.46 and K = 0.61). This is an expected result, however no study that we know of had attempted to quantify this difference in terms of kappa agreement so far. Perhaps more surprising, rather low agreement has been obtained for the manual scoring of desaturation events (median K = 0.40), which however improved significantly with the use of semi-automatic scoring (K = 0.82). The underlying reason that explains this difference has yet to be determined.
As for the EEG arousal task, some studies can be found reporting kappa values for manual scoring in the 0.47 – 0.59 range [26] [34] [35]. Once again, some of these studies use older scoring guidelines (ASDA1992) besides other sources of variability, and therefore direct comparison has to be carefully considered. Regardless, the reported range is consistent with our experimental results in the case of manual scoring ($\kappa = 0.58$). Our study shows, in addition, that better inter-scorer agreement can be achieved if using semi-automatic scoring (up to $\kappa = 0.65$ in our dataset).

In this study we have also examined possible differences among the resulting derived indices for clinical diagnosis. This is, to our knowledge, the first study to address inter-scorer agreement of diagnostic indices obtained during semi-automatic scoring. In the context of manual analysis, on the other hand, one can find several other past studies reporting on related ICC agreement scores [5] [36] [37] [38] [39] [6] [40] [41]. In this regard, the specific agreement references vary per study. Danker-Hopfe et al. [6] and Kuna et al. [41], for example, have reported ICC values for SE of 0.91 and 0.77 respectively, which is below the agreement obtained in this study (ICC = 0.99). Reliability on PLMS has been reported by Pittman et al. [5] (ICC = 0.93) and Bliwise et al. [36] (ICC = 0.91 – 0.99), however, using older definitions of the index [42] [43]. This is relevant as recent studies [44] [45] [46] have pointed out to significant differences in the resulting PLM index calculations when using as reference the latest clinical scoring guidelines. The agreement results are nevertheless comparable to the levels obtained in our work (ICC = 0.94), which use the recent WASM2016 standards [3]. Under this reference, our study is in fact the first one to set a reference for the agreement associated with manual derivation of the LM and PLM indices (ICC = 0.92 and 0.94, respectively). With regard to respiratory-derived indices, possibly the most widely reported is the AHI, with reliability scores for manual scoring nevertheless ranging widely between ICC 0.54-0.99 depending on the consulted study [5] [7] [41] [47]. Most likely, these differences are to a great extent driven by the specific rule used for the scoring of hypopneas. As stated before, it is widely accepted that agreement regarding scoring of hypopneas is lower as compared to that of apneas. This can also be observed by comparing ICC agreement values associated with AI and HI indices reported the literature. This is also the case in our study, with ICC agreement for the manual derivation of respiratory related indices showing a relatively high score for AHI (ICC = 0.98), following the expected trend of higher agreement for AI (ICC = 0.99) in comparison to HI (ICC = 0.60). In the case of the associated oxygen desaturation index, and ICC of
0.84 was obtained. Finally, and with regard to reliability of ArI indices resulting from manual scoring, literature shows high variability as well (ICC = 0.52-0.96 [39] [37] [7] [38] [5]). Our results for manual scoring approximately fit in the middle of that range (ICC = 0.68).

A general warning when comparing results from different works in the literature, is that one has always to bear in mind that relevant differences might exist between the respective population samples, the analysis methods, or the clinical scoring references valid at the time of the study.

That said, some limitations of our study have to be mentioned as well. First, it is important to remark that absolute values of the investigated quality scores are associated with performance of expert scorers from one specific sleep lab. This study does not involve analysis of inter-scorer variability across multiple centers, and thus results might not generalize to other centers. In such scenario, the respective values of scoring agreement are expected to be lower in comparison due to the greater amount of variability involved [2]. This study neither has attempted to quantify the corresponding levels of intra-scorer variability. It cannot completely be ruled-out that some of the differences between manual and semi-automatic approaches could be influenced by a component of intra-scorer variability effects, at the individual scorer case at least. Nevertheless, the relative high number of involved experts (12 in our study) should contribute to limit its the impact on the global results.

It should also be remarked that quality indicators derived from the semi-automatic scoring procedure are likely modulated by the reliability and performance of the specific automatic analysis algorithms used in the first instance. One might speculate with the idea that the better the algorithm, the higher the improvement on expert agreement with respect to the manual approach. However, there is no actual evidence allowing the support of this hypothesis. The usage of alternative automatic scoring methods might lead to different results. Regardless, our results support the hypothesis that semi-automatic algorithm can improve scoring quality in terms of both speed and resulting inter-scorer agreement. Also interesting, inter-scorer reliability studies available through literature, and this is no exception, implicitly assume that the outcome of all human scorers is equally valid. This might be a risky assumption, although there is no clear formula to discern who (out of a set of human experts) represents the best reference, and who does not. This propounds an interesting line of future research linked to another non-less interesting debate: can automatic scoring perform better than human experts? Of course, in terms of its capacity to correctly identify the relevant events associated with the
physiological activity’s ground truth, as automatic analysis can obviously outperform manual counterpart in terms of scoring speed. If, like in this case, the standard reference is subject to variability associated with human decision, it does not seem very plausible that any automatic algorithm could perform beyond the limit set by the average human agreement. After all, as stated before, deviations from such a reference do not necessarily correlate with the quality of the associated scorings. This is a subject that deserves more study.

Last but not least, another possible limitation of this study relates to the number of PSGs involved in the evaluation of each analysis subtask. The relative high number of sleep experts involved partially counteracts this fact, and indeed, the number has proven enough to reach statistical significance among many of the reported hypothesis tests. However, a higher number of PSGs per task would in general be desirable. More specifically, for those cases in which the reported trends did not achieve significant effects, the question remains open on whether this could be attributed to the relative small PSG sample size. Notice, on the other hand, that post-hoc power analyses were consciously omitted because no useful conclusions are expected from them [48]. A higher sample size would also contribute to spread the bias risk due to demographic and physiological subject variability.

Unfortunately, the chosen sample size was imposed by the available resources; thus this was not a design parameter we were able to tune. As noticed, scoring of PSG data is complex and time-consuming, and expert’s time is expensive and scant.

In conclusion, our results provide an updated reference for inter-scorer agreement levels and scoring times associated with both manual and semi-automatic scoring of PSG studies. We have systematically analyzed and compared the resulting differences, showing that the use of semi-automatic scoring can improve both speed and consistency of the PSG analysis outcomes. Benefits include reduction of the associated diagnostic costs, shortening of patient’s waiting lists, and overall improved productivity. In addition, enhancement of inter-scorer agreement leads to higher repeatability and quality of the diagnosis. More work has to be done to investigate generalization of these results by increasing the subject sample and its heterogeneity. Future work should also assess the effects of inter-center and intra-expert scoring variability, and goodness of fully automatic scoring in comparison to manual and semi-automatic approaches.
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**FIGURE CAPTIONS**

**Figure 1.** Differences in scoring time between manual and semi-automatic scoring approaches. Median scoring time per task is shown in minutes.

**Figure 2.** Agreement comparison between manual and semi-automatic scoring approaches. Median Kappa agreement for each task is shown by aggregating all the expert pair combinations throughout the five corresponding recordings.
# TABLES

**Table 1.** Summary of general demographics and PSG descriptors in the study dataset. PSG descriptors correspond to values resulting from retrospective examination in the clinical database, i.e. prior to the multi-expert rescoring procedures carried out in this study. Distributions are characterized using the median and the corresponding interquartile ranges.

| Parameter                        | Subset A    | Subset B    | Subset C    | Subset D    | Total       |
|----------------------------------|-------------|-------------|-------------|-------------|-------------|
| **n**                            | 5           | 5           | 5           | 5           | 20          |
| **Age (years)**                  | 52.0 [47.0, 57.0] | 57.0 [51.0, 68.0] | 59.0 [57.0, 61.0] | 55.0 [52.0, 63.0] | 57.0 [51.8, 61.5] |
| Male (n, %)                      | 5 (100%)    | 1 (20%)     | 3 (60%)     | 3 (60%)     | 12 (60%)    |
| **Time In Bed (TIB, hours)**     | 7.5 [7.4, 8.0] | 7.3 [7.0, 7.3] | 6.5 [6.4, 7.4] | 8.1 [7.2, 8.2] | 7.3 [7.0, 8.0] |
| **Total Sleep Time (TST, hours)** | 5.9 [5.9, 7.1] | 6.7 [5.9, 6.7] | 6.0 [5.8, 6.1] | 7.3 [5.5, 7.4] | 6.0 [5.7, 7.0] |
| **Sleep Latency (SL, min)**      | 4.6 [3.0, 5.4] | 1.8 [1.5, 3.3] | 9.7 [2.6, 14.5] | 1.9 [1.0, 21.5] | 3.1 [1.6, 16.2] |
| **Stage R latency (min)**        | 69.5 [40.0, 174.0] | 104 [64.5, 124.0] | 59.0 [52.0, 138.0] | 83.5 [80.0, 85.0] | 81.8 [58.0, 127.0] |
| **Wake After Sleep Onset (WASO, min)** | 72.8 [24.7, 124.0] | 53.0 [39.9, 68.2] | 38.9 [28.1, 52.2] | 89.6 [46.7, 100.4] | 52.6 [27.3, 106.3] |
| **Sleep Efficiency (SE, %)**     | 91.1 [74.2, 94.5] | 88.6 [83.8, 90.9] | 89.9 [84.7, 92.8] | 83.0 [76.6, 90.5] | 89.2 [76.0, 93.2] |
| **Arousal Index (ArI, n/TST)**   | 4.7 [1.8, 17.6] | 14.3 [13.4, 16.0] | 19.8 [9.6, 23.4] | 9.6 [7.9, 13.7] | 13.5 [7.5, 20.7] |
| **Apnea-Hypopnea Index (AHI, n/TST)** | 9.1 [6.0, 9.4] | 5.1 [0.6, 20.7] | 6.2 [5.8, 13.1] | 7.2 [3.0, 20.6] | 6.7 [5.0, 20.6] |
| **Oxygen Desaturation Index (ODI, n/TST)** | 10.7 [10.5, 10.8] | 1.4 [0.6, 24.8] | 9.9 [5.5, 15.4] | 9.9 [2.8, 15.7] | 10.2 [4.4, 18.0] |
| **Leg Movement Index (n/TST)**   | 52.3 [9.0, 56.5] | 32.0 [21.0, 57.7] | 14.2 [8.6, 39.8] | 30.0 [19.3, 43.2] | 31.0 [12.9, 53.4] |
| **Periodic Leg Movement Index (PLMI, n/TST)** | 13.0 [0.3, 45.7] | 13.8 [13.4, 49.0] | 0.8 [0.4, 26.7] | 22.4 [4.1, 28.4] | 13.6 [0.7, 32.8] |

Subset-scoring task correspondences: A - sleep stages; B - Limb Movements; C - Respiratory Events; D - EEG arousals.
Table 2. Analysis of scoring time differences per task between manual and semi-automatic approaches. Distributions are characterized using the corresponding median and interquartile ranges in minutes. Gain factors are calculated on each case as the ratio between the corresponding median scoring times.

| Scoring task     | Manual       | Semi-Auto    | Gain factor | p-value   | Effect size |
|------------------|--------------|--------------|-------------|-----------|-------------|
| Sleep staging    | 32.62 [21.74, 48.64] | 24.54 [16.25, 39.81] | 1.33        | 0.0005*   | 0.4297      |
| Limb movements   | 44.53 [31.00, 65.30] | 18.50 [12.63, 26.73] | 2.41        | < 0.0001* | 1.3475      |
| Respiration      | 23.81 [17.62, 46.72] | 14.58 [10.46, 20.68] | 1.63        | < 0.0001* | 0.9474      |
| EEG arousals     | 27.50 [21.22, 37.65] | 21.78 [15.96, 28.59] | 1.26        | 0.0011*   | 0.4233      |
| Altogether       | 134.92 [113.08, 187.65] | 80.59 [66.75, 107.89] | 1.67        | < 0.0001* | 1.7527      |

n = 60 resulting from all scoring experts (n = 12) and analyzed recordings (n = 5) for each of the corresponding tasks;

*Statistically significant result
Table 3. Overall kappa inter-scorer agreement per scoring task and comparison between manual and semi-automatic approaches. Distributions are characterized using the corresponding median and interquartile ranges.

TIB = Time in Bed

| Scoring task       | Context              | Manual      | Semi-auto  | p-value | Effect size |
|--------------------|----------------------|-------------|------------|---------|-------------|
| Sleep staging      | TIB                  | 0.76 [0.69, 0.80] | 0.80 [0.76, 0.83] | < 0.0001* | -0.7146     |
| Limb Movements     | TIB                  | 0.72 [0.64, 0.79] | 0.91 [0.86, 0.95] | < 0.0001* | -2.0223     |
| Wake               |                      | 0.67 [0.57, 0.77] | 0.89 [0.82, 0.94] | < 0.0001* | -1.7121     |
| Sleep              |                      | 0.75 [0.65, 0.81] | 0.92 [0.86, 0.95] | < 0.0001* | -1.6704     |
| Respiratory activity | Apnea, Hypopnea, RERA (TIB) | 0.55 [0.43, 0.78] | 0.66 [0.53, 0.89] | < 0.0001* | -0.8315     |
|                    | Apneas (TIB)         | 0.74 [0.35, 0.88] | 0.88 [0.57, 0.98] | < 0.0001* | -0.3783     |
|                    | Hypopneas (TIB)      | 0.46 [0.36, 0.53] | 0.61 [0.51, 0.68] | < 0.0001* | -0.9569     |
|                    | Desaturations (TIB)  | 0.40 [0.24, 0.55] | 0.82 [0.71, 0.92] | < 0.0001* | -1.8525     |
| EEG Arousals       | TIB                  | 0.58 [0.48, 0.65] | 0.65 [0.56, 0.71] | < 0.0001* | -0.6166     |

n = 330 resulting from all distinct combinations of expert scorer pairs (n = 66) on each of the five recordings related to the corresponding scoring task; *Statistically significant result.
Table 4. Comparison of inter-scoring agreement among diagnostic indices between manual and semi-automatic approaches. Agreement is characterized in terms of Interclass Correlation Coefficient (ICC), and corresponding index distributions using the respective median and interquartile ranges. \( r_0 \) = null hypothesis on ICC score; SE = Sleep Efficiency; SOL = Sleep Onset Latency; WASO = Wake After Sleep Onset; (P)LMI = (Periodic) Leg Movement Index; AHI = Apnea-Hypopnea Index; AI = Apnea Index; HI = Hypopnea Index; ODI = Oxygen Desaturation Index; ArI = Arousal Index.

| Index (TST) | Summary of index distributions | ICC | r0 | ICC p-value |
|-------------|---------------------------------|-----|----|-------------|
|             | Manual                          | Semi-auto | Manual | Semi-auto | Manual | Semi-auto |
| SE (%)      | 89.11 [68.05, 94.87]            | 90.31 [70.59, 94.86] | 0.9938 | 0.9974 | 0 < 0.0001* | < 0.0001* |
|             |                                 |             |       |           | 0.9938 | --- | 0.0665 |
| SOL (min)   | 5.27 [2.50, 107.41]             | 4.11 [2.31, 104.81] | 0.8720 | 0.8367 | 0 < 0.0001* | < 0.0001* |
|             |                                 |             |       |           | 0.8720 | --- | 0.5589 |
| WASO (min)  | 86.20 [22.27, 151.77]           | 79.18 [23.02, 139.51] | 0.9924 | 0.9970 | 0 < 0.0001* | < 0.0001* |
|             |                                 |             |       |           | 0.9924 | --- | 0.0481* |
| LMI         | 25.27 [19.78, 70.19]            | 31.73 [20.89, 61.82] | 0.9227 | 0.9757 | 0 < 0.0001* | < 0.0001* |
|             |                                 |             |       |           | 0.9227 | --- | 0.0166* |
| PLMI        | 13.91 [9.20, 61.70]             | 14.14 [12.79, 53.70] | 0.9351 | 0.9771 | 0 < 0.0001* | < 0.0001* |
|             |                                 |             |       |           | 0.9351 | --- | 0.0282* |
| AHI         | 5.86 [3.71, 12.47]              | 6.54 [4.70, 14.61] | 0.9878 | 0.9924 | 0 < 0.0001* | < 0.0001* |
|             |                                 |             |       |           | 0.9878 | --- | 0.1901 |
| AI          | 1.26 [0.31, 3.46]               | 1.57 [0.00, 3.54] | 0.9962 | 0.9986 | 0 < 0.0001* | < 0.0001* |
|             |                                 |             |       |           | 0.9962 | --- | 0.0441* |
| HI          | 3.10 [2.38, 4.87]               | 4.55 [3.13, 6.68] | 0.6010 | 0.7540 | 0 < 0.0001* | < 0.0001* |
|             |                                 |             |       |           | 0.6010 | --- | 0.1160 |
| ODI         | 6.48 [4.24, 14.38]              | 12.04 [6.01, 15.89] | 0.8370 | 0.9843 | 0 < 0.0001* | < 0.0001* |
|             |                                 |             |       |           | 0.8370 | --- | < 0.0001* |
| ArI         | 17.57 [12.98, 25.64]            | 18.38 [13.82, 25.41] | 0.6824 | 0.7673 | 0 < 0.0001* | < 0.0001* |
|             |                                 |             |       |           | 0.6824 | --- | 0.2290 |
n = 60 resulting from all scoring experts (n = 12) and analyzed recordings (n = 5) for each of the corresponding tasks;

*Statistically significant result
