Editorial

Stimulating new and innovative perspectives on old and persistent problems: a commentary on "Attempters adherers and non-adherers: latent profile analysis of CPAP use with correlates" by Wohlgemuth et al.

The clinical guidelines for the evaluation, management, and long-term care of obstructive sleep apnea (OSA) in adults emphasize a multidisciplinary, chronic care approach to the treatment and management of OSA [1]. The guidelines, consistent with earlier practice parameters [2], include consensus standards to monitor early continuous positive airway pressure (CPAP) compliance (ie, adherence) for utilization patterns/rates. The guidelines also recommend early support for treatment and for those with poor or low utilization of CPAP, "prompt and intensive efforts to remediate low use" or alternative treatments should be pursued [1]. While evidence abounds for the diagnosis and initiation of CPAP treatment for OSA, there is far less evidence that directly addresses the everyday practice implementation of the standards and recommendations of these guidelines. Beyond a timely review of objective CPAP use records in the clinical setting and trouble-shooting for common complaints about the treatment, there is a paucity of evidence-based recommendations for using objective CPAP use data to guide clinical decision-making in concert with patients. Evidence suggests that simplistic overt monitoring of CPAP use as an "awareness" intervention does not improve CPAP adherence [3]. When CPAP use data is shared with patients, there is emerging evidence that early CPAP adherence is improved [4]. So how can the field move beyond simplistic monitoring of CPAP use to truly harness the power of such data for shared clinical decision-making?

In this issue of *Sleep Medicine,* Wohlgemuth and colleagues [5] report the results of a retrospective cohort study wherein patterns of CPAP use were systematically analyzed using latent profile analysis. The objective of the research was to deduce CPAP user profiles from an existing cohort of CPAP-treated OSA veteran patients with at least seven days of CPAP usage data available and identify predictors of CPAP use profile membership. Using latent profile analysis and standard evaluative criteria, a three-cluster solution (ie, three profiles) was identified as significant and efficient. Predictive factors for profile membership in one of the three profiles, named by the investigators as adherers, non-adherers, and attempters, included self-efficacy, insomnia, apnea-hypopnea index, CPAP pressure, and duration of treatment; unique and modifiable factors were identified for each profile [5]. Though not without limitations that include a retrospective design and limited generalizability, this study [5] addresses two opportunities for advancing the research agenda to support everyday clinical decision-making for the management of CPAP-treated OSA: (1) risk stratification, or profiling, for treatment

non-adherence; and (2) moving beyond traditional statistical modeling approaches of readily-available clinical data, specifically objective CPAP use, to effectively use this complex and comprehensive data to potentially support clinical decision-making.

The identification of CPAP-treated OSA patients who are likely to be non-adherent, or those likely to struggle with CPAP is important for responsible allocation of resources in the clinical management of OSA. Several previously published studies have reported CPAP non-adherence risk stratification methods [6–8] and have similarly advocated such an approach be empirically advanced and translated. Risk stratification approaches are indeed important so that CPAP-treated OSA patients that require adherence promotion interventions or early referral to alternative treatment options are readily identified. As early CPAP use predicts long-term patterns of use [9–11], permitting non-adherent patterns of CPAP use to go unaddressed for any length of time risks unremitting CPAP non-adherence and treatment failure. Developing evidence that addresses early risk stratification for non-adherence, or user profiles, is likely to translate in the future to the allocation of timely and intensive resources to those most likely to benefit from the investment (ie, non-adherers and attempters).

To further extend the potential usefulness of Wohlgemuth and colleagues' findings [5] as a risk stratification method, future research will need to examine the necessary minimum data set required for CPAP user profiles to emerge and examine the dynamic patterns of usage states. The approach to the discovery of usage profiles by Wohlegemuth et al. [5] limits profile definitions to a single-point in time, as is consistent with a cross-sectional perspective of profiles. This perspective does not account for the dynamic, or time-varying, nature of CPAP use as a behavior. Complementing latent profile analysis with latent profile transition analysis may reveal if membership in any one CPAP profile changes with time and/or intervention. To fully capitalize on available CPAP use data with dynamic characteristics (ie, time varying) and clinically respond to such dynamical data, or behaviors, employing data mining analytic approaches such as probabilistic suffix trees has the potential to provide "early warning signals" to accurately identify non-adherence and transitions between CPAP use states (eg, intermediate to low; attempter to non-adherer) [12]. This approach can provide important insights into the timing of interventions by individual patients in order to "shift" profiles/states.

A second opportunity that is highlighted by the analytic approach employed by Wohlgemuth and colleagues [5] is the use of comprehensive and complex CPAP use data to discern behavioral insights to the problem of CPAP non-adherence. Our current disciplinary approach to CPAP non-adherence is notably neglectful of these data being available in real-time. To date, CPAP use data is commonly reduced to a dichotomized outcome variable that is consistent with CPAP reimbursement policy [13]; the outcome is statistically modeled with consideration of characteristic co-variables of importance. Reducing the readily-available, complex data of CPAP use in this way significantly curtails an in-depth understanding of this behavioral outcome. CPAP use data is now available in real-time permitting real-time decision-making to support clinical management of CPAP-treated OSA. Such real-time data analytics can be regarded as sequential data of CPAP use over time, permitting researchers to extract meaningful CPAP use patterns over any treatment period. To support such an approach, innovative and validated analytical models, or predictive healthcare analytics (HPA) are needed [14,15] such that information systems or cloud-based servers that currently <u>only</u> collect and store CPAP use data might also guide everyday clinical decision-making with evidence-based analytics. To pursue such a path of innovative research that addresses the complex and dynamic problem of CPAP non-adherence, transdisciplinary teams of investigators with varied perspectives and expertise are essential to evolving a new level of intellectual depth for translational solutions [16].

Since the first empiric reports of CPAP non-adherence in the mid-1990s [17–19], the field has been continuously challenged to improve CPAP use among adults with OSA. Though two decades of research have enhanced our overall understanding of CPAP non-adherence [20,21], there remains a preponderance of under-treated or untreated OSA due to non-adherence and CPAP attrition. The novel approach and interesting findings reported by Wohlgemuth and colleagues [5] serve as a stimulus to the field to entertain innovative and new approaches to an "old and persistent" problem.

Conflict of interest

The ICMJE Uniform Disclosure Form for Potential Conflicts of Interest associated with this article can be viewed by clicking on the following link: http://dx.doi.org/10.1016/j.sleep.2014.01.011.

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Amy M. Sawyer *
College of Nursing, The Pennsylvania State University, 201 HHD East, University Park, Pennsylvania 16802, USA
* Tel.: +1 814 863 1020; fax: +1 814 863 1027.
E-mail address: ams24@psu.edu

Yuncheol Kang
College of Engineering, Department of Industrial Engineering, The Pennsylvania State University, University Park, Pennsylvania, USA

Vasant Honavar
College of Information Sciences and Technology, The Pennsylvania State University, University Park, Pennsylvania, USA

Paul Griffin
College of Engineering, Department of Industrial Engineering, The Pennsylvania State University, University Park, Pennsylvania, USA

Vittal Prabhu
College of Engineering, Department of Industrial Engineering, The Pennsylvania State University, University Park, Pennsylvania, USA
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