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SLEEP HEALTH EDUCATION AND A PERSONALIZED SMARTPHONE APPLICATION IMPROVE SLEEP AND PRODUCTIVITY AND REDUCE HEALTHCARE UTILIZATION AMONG EMPLOYEES: RESULTS OF A RANDOMIZED CLINICAL TRIAL

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Introduction: Sleep deficiency and undiagnosed or untreated sleep disorders are pervasive among employed adults, yet are often ignored in the context of workplace health promotion. Smartphone applications (apps) are a promising, scalable approach to improving sleep among employees. We evaluated an online sleep education program followed by access to a mobile sleep training program, the dayzz app, that promotes healthy sleep, sleep disorders awareness and intervention.

Methods: In a sample of daytime employees affiliated with a large healthcare organization, we evaluated the intervention (sleep education at baseline plus access to the personalized app for up to 9 months) in a parallel group, randomized controlled trial. Participants were randomly assigned to either the experimental condition that received the intervention in months 1 through 9 or the control group that was assigned to receive the intervention in month 10. In a prespecified data analysis plan, the experimental and control groups were compared in months 1 through 9; no outcome data was collected thereafter. We collected data on employee sleep, workplace outcomes, and healthcare utilization, monthly throughout the study.

Results: The final cohort was comprised of 794 participants assigned to the experimental and 561 to the control condition. Those assigned to the experimental condition were more likely to maintain consistent sleep schedules (OR:1.40;95%CI:1.12-1.75) and less likely to experience fatigue and sleepiness (OR:1.30;95%CI:1.08-1.57). At the 9-month follow-up assessment, the experimental group reported significantly longer sleep duration than the control group on work (experimental: 7.20hrs; control: 6.99hrs, p=0.01) and free (experimental: 8.26hrs; control: 8.04hrs, p=0.03) nights. The odds of poor sleep quality at follow-up were lower in the experimental condition (OR:0.79,95%CI:0.63-0.98) as compared to control. Mean total dollars lost due to presenteeism was less among experimental compared to control participants (p=0.0001), corresponding to an average of $274 saved per person per month. Finally, participants in the experimental group were less likely to report mental health visits (p=0.01) and had a lower rate of overall healthcare utilization (p=0.03), compared to the control group.

Conclusion: Results from this randomized clinical trial demonstrate that a digital workplace sleep wellness program can be beneficial to both employees and employers, by improving employee sleep and fatigue, increasing work productivity, and reducing direct healthcare costs.

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SLEEP STAGING USING END-TO-END DEEP LEARNING MODEL BASED ON NOCTURNAL SOUND FOR SMARTPHONES

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Introduction: Convenient sleep tracking with mobile devices such as smartphones is desirable for people who want to easily objectify their sleep. The objective of this study was to introduce a deep learning model for sound-based sleep staging using audio data recorded with smartphones during sleep.

Methods: Two different audio datasets were used. One (N = 1,154) was extracted from polysomnography (PSG) data and the other (N = 327) was recorded using a smartphone during PSG from independent subjects. The performance of sound-based sleep staging would always depend on the quality of the audio. In practical conditions (non-contact and smartphone microphones), breathing and body movement sounds during night are so weak that the energy of such signals is sometimes smaller than that of ambient noise. The audio was converted into Mel spectrogram to detect latent temporal frequency patterns of breathing and body movement sound from ambient noise. The proposed neural network model consisted of two sub-models. The first sub-model extracted features from each 30-second epoch Mel spectrogram and the second one classified sleep stages through inter-epoch analysis of extracted features.

Results: Our model achieved 70 % epoch-by-epoch agreement for 4-class (wake, light, deep, rapid eye movement) stage classification and robust performance across various signal-to-noise conditions. More precisely, the model was correct in 77% of wake, 73% of light, 46% of deep, and 66% of REM. The model performance was not considerably affected by existence of sleep apnea but degradation observed with severe periodic limb movement. External validation with smartphone dataset also showed 68 % epoch-by-epoch agreement. Compared with some commercially available sleep trackers such as Fitbit Alta HR (0.6325 in mean per-class sensitivity) and SleepScore Max (0.565 in mean per-class sensitivity), our model showed superior performance in both PSG audio (0.655 in mean per-class sensitivity) and smartphone audio (0.6525 in mean per-class sensitivity).

Conclusion: To the best of our knowledge, this is the first end (Mel spectrogram-based feature extraction)-to-end (sleep staging) deep learning model that can work with audio data in practical conditions. Our proposed deep learning model of sound-based sleep staging has potential to be integrated in smartphone application for reliable at-home sleep tracking.

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