# Multi-Task Learning for Automated Cardiac Event Detection in Sleep Polysomnography

Foivos N. Papathanasiou*[1], Jing Han[1,2], Cecilia Mascolo[1]

[1] *University of Cambridge, Cambridge, UK*

[2] *Hunan University, Changsha, China*

**Introduction:** Sleep-related cardiac events, such as bradycardia, tachycardia, prolonged RR intervals, and pulse transit time drops, are associated with cardiovascular morbidity and are routinely scored during clinical polysomnography (PSG). Although automated detection of respiratory events has been extensively investigated, to the best of our knowledge, no prior work has addressed automated epoch-level detection of clinically scored cardiac events from multi-channel PSG. Consequently, cardiac event scoring remains a manual, labor-intensive process. Given the known physiological coupling between cardiac and respiratory events during sleep, we hypothesise that respiratory event labels can provide auxiliary supervision to improve cardiac event detection.

**Methodology:** Event coincidence analysis was performed on 193 expert-scored overnight PSG recordings, which revealed significant cardiorespiratory coupling extending to ±90 seconds (FDR-corrected, Figure 1, left), thus motivating our multi-task approach. Six channels (ECG, nasal thermistor, nasal pressure, SpO2, thoracic and abdominal effort) were resampled to 128 Hz and segmented into 312,467 ten-second epochs. A 1D-ResNet with squeeze-and-excitation blocks encoded each epoch, and a BiLSTM captured temporal context across 25 consecutive epochs (250s), encompassing the observed coupling window. We compared single-task (cardiac only, respiratory only) vs. multi-task (cardiac + respiratory) training using 5-fold participant-independent cross-validation, stratified by apnea-hypopnea index severity and cardiac event burden.

**Results:** Multi-task learning improved cardiac event detection in terms of AUROC from 0.600 ± 0.091 to 0.634 ± 0.044 and halved the cross-fold standard deviation (Figure 1, right). The modest mean gain belies a substantial improvement in stability, suggesting that respiratory co-supervision primarily enhances robustness across patient folds.

**Conclusion:** This work establishes a first baseline for automated cardiac event detection in PSG. Our results show that respiratory co-supervision via multi-task learning improves model robustness, reducing cross-fold variability despite a modest gain in mean AUROC. Leveraging physiological cardiorespiratory coupling paves the way for future work in sleep research.

| Direction | Event pair | Lag (s) | RR |
|---|---|---|---|
| Resp → Card | MixedApnea → Brady | 60 | 1.25 |
| | ObstrApnea → PttDrop | 45 | 1.17 |
| | RelDesat → PttDrop | 45 | 1.19 |
| | RelDesat → Tachy | 10 | 1.48 |
| Card → Resp | PttDrop → Hypopnea | 20 | 1.33 |
| | PttDrop → MixedApnea | 90 | 1.18 |
| | PttDrop → CentralApnea | 60 | 1.17 |

| Model | Card AUC | Card PRC | Resp AUC |
|---|---|---|---|
| **Multi-task** | **.634±.044** | **.264±.051** | **.945±.010** |
| Single card | .600±.091 | .258±.077 | — |
| Single resp | — | — | .954±.006 |

*Figure 1: Left: FDR-significant cardiorespiratory event pairs from trigger rate event coincidence analysis on 193 PSG recordings, showing bidirectional coupling at lags up to 90 s. RR = rate ratio. Right: Five-fold patient-level cross-validation results (mean ± std). Cardiac positive rate: 15.4%.*