Associations Between In-Hospital Clinical Recovery Measures and Home Sleep-Activity Patterns in Early Stroke

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INTRODUCTION

•**Current limitation:** Most stroke research focuses on either the acute hospital phase or the chronic recovery phase separately.
•**Knowledge gap:** Limited understanding of how in-hospital status influences post-discharge recovery.
•**Wearable opportunity:** Continuous monitoring of activity and sleep enables longitudinal insights.
•**Previous limitation:** Prior studies used hand-crafted summary features, missing complex physiological dynamics.
•**Foundation model innovation:** Models like **WatchSleepNet** (for sleep staging) and **self-supervised activity recognition** extract rich, high-dimensional features from raw wearable signals.
•**Study goal:** Apply foundation model–derived features to post-stroke patients.
•**Overall aim:** Bridge acute clinical data with early recovery trajectories for a comprehensive view of stroke outcomes across care transitions.

METHODS

We recruited 42 post-stroke patients from Emory Healthcare who wore Moto 360 smartwatches for 14 days post-discharge. Wearable data were analyzed using foundation models:
•WatchSleepNet quantified sleep stages and efficiency.
•A self-supervised activity model (trained on 700K person-days) characterized sedentary, light, and moderate–vigorous activity patterns.
Clinical measures included stroke severity (NIHSS), functional independence (ADL), vitals (blood pressure, heart rate), and laboratory indices (renal, hematologic, metabolic).
Associations between wearable and clinical features were assessed using Spearman correlations (Figure 1).

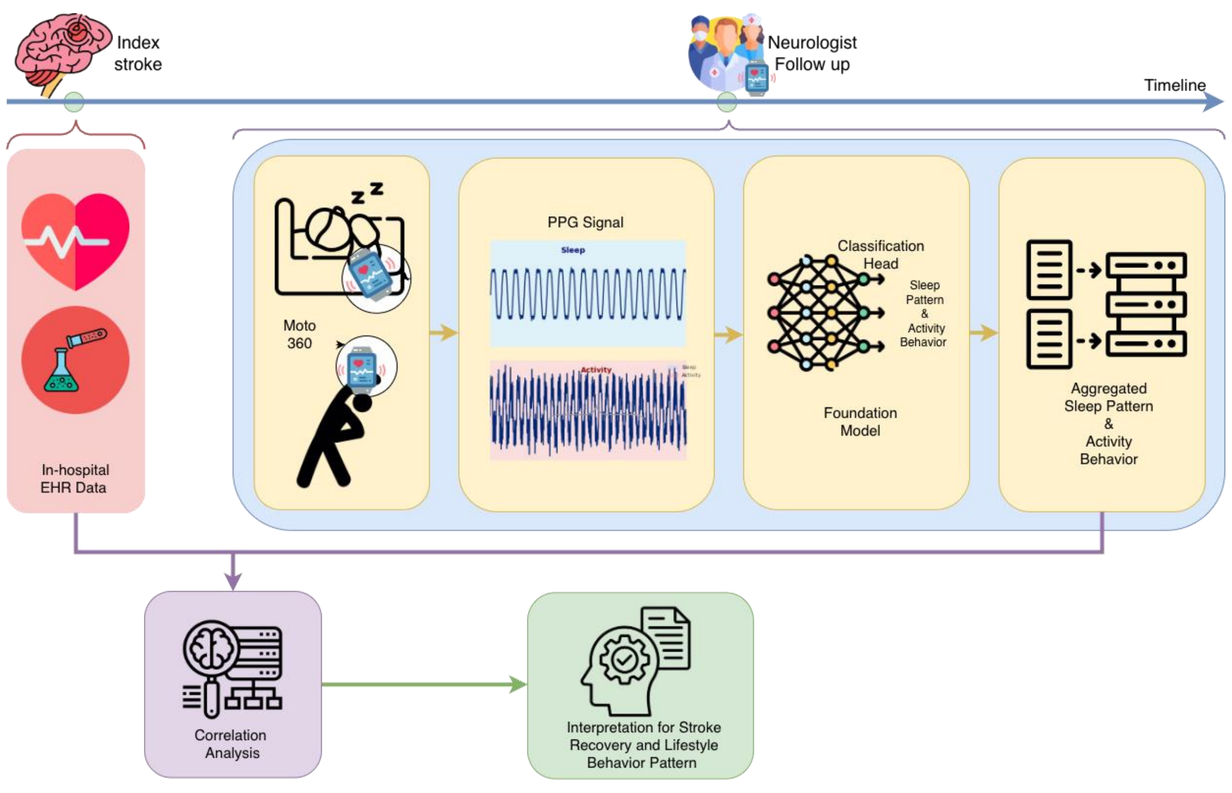

Figure 1:EHR-to-Wearable Data Analysis Pipeline

RESULTS

Clinical markers showed strong links with post-discharge behavioral patterns (Table 1).
•**Stroke severity:** Higher NIHSS scores were associated with irregular sleep–wake cycles and reduced daily activity.
•**Functional status:** Higher ADL scores correlated with better device wear compliance and more consistent sleep.
•**Cardiovascular measures:** Blood pressure and heart rate variability aligned with greater activity fragmentation and circadian rhythm disruption.
•**Laboratory markers:** Renal and hematologic indices were related to increased afternoon sleep and lower activity stability.

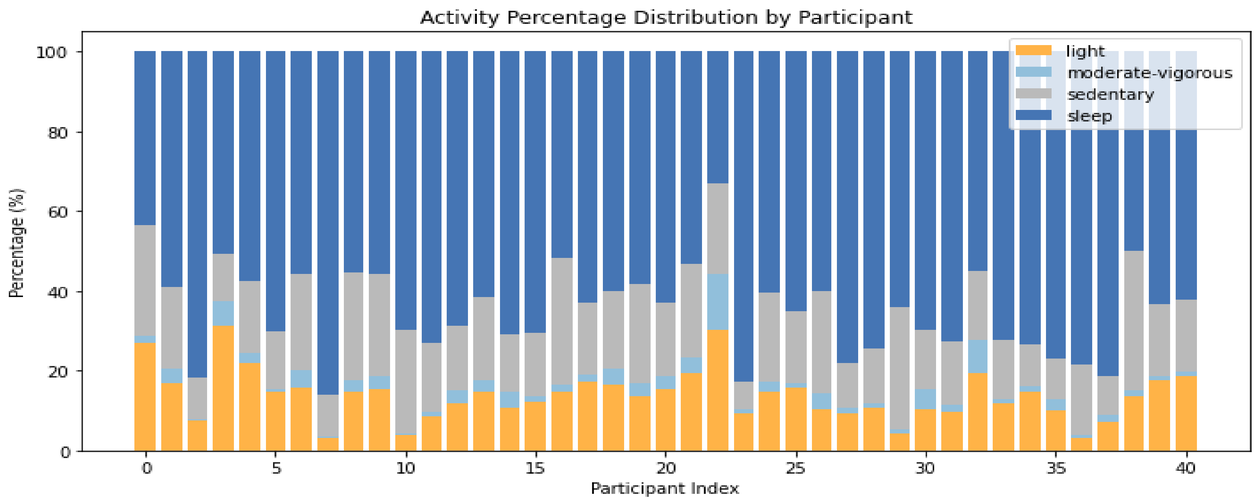

Figure 2:Daily composition of sleep and activity behaviors over time

Outcome	Wearable Feature (example)	ρ	p-value	n
NIHSS total	Sedentary bout duration (afternoon)	+0.43	0.012	33
ADL score	Wear time (afternoon)	+0.68	0.0003	24
SBP mean	Longest MVPA bout (evening)	–0.53	0.001	34
DBP mean	Afternoon MVPA bouts (max)	+0.58	0.0003	34
Creatinine	Afternoon sleep duration	+0.74	0.00002	26
Hemoglobin	MVPA bout duration variability	+0.64	0.0007	24

Table 1:Top correlations between wearable features and clinical outcomes

CONCLUSION

Wearable foundation models captured recovery patterns. Severe strokes showed irregular sleep and low activity, while stable sleep and consistent wear indicated better function. Correlations with vitals and labs support personalized post-stroke care.

REFERENCES

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