Latent Profile Analysis as a Data-Driven Approach to Characterize Infant Baseline Electroencephalography (EEG)

P2-G-360

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Electroencephalography (EEG)

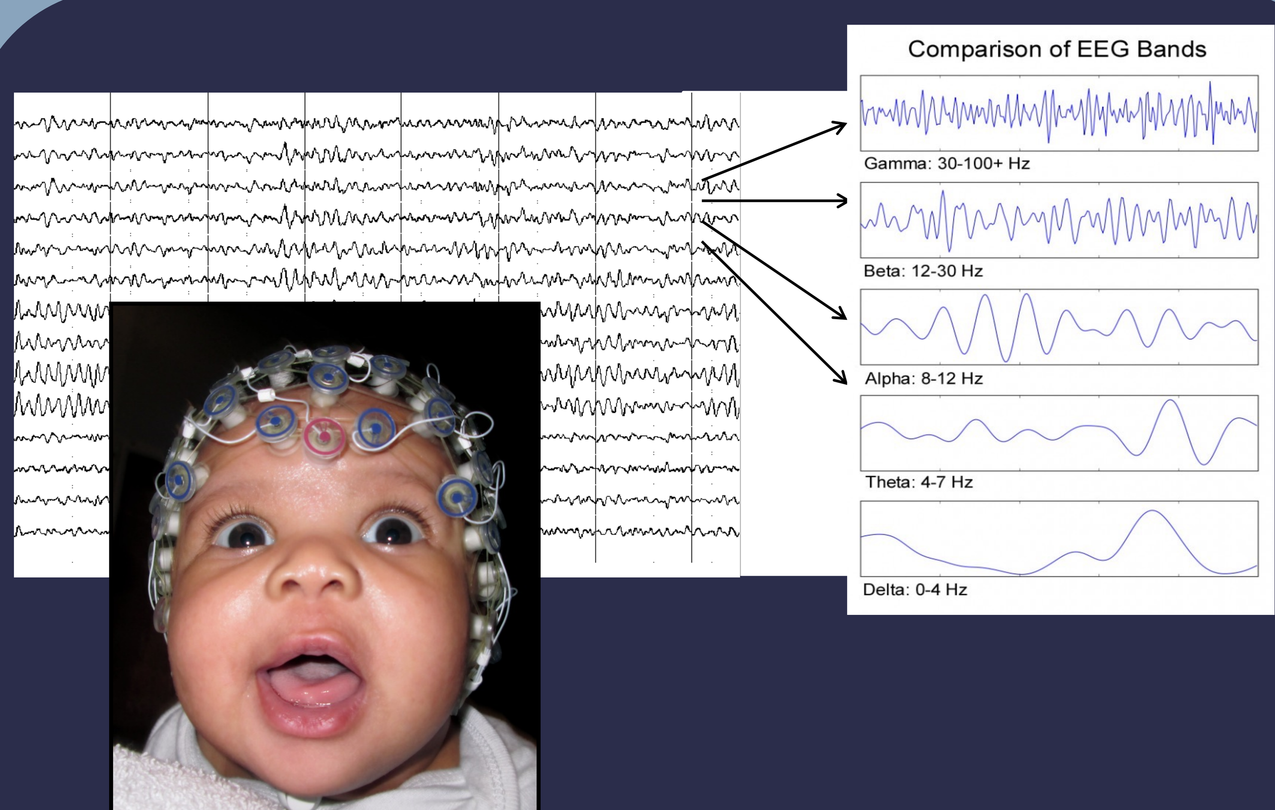
EEG, recorded from scalp electrodes, reflects electrical activity generated by the brain

Easily measured in lab; well-tolerated even from infancy

Powerful tool to probe neurodevelopment

HOW IS IT ANALYZED?

EEG data can be analyzed in many ways. One is to decompose the oscillatory EEG signal into component frequency bands. This approach can reveal properties of cortical maturation and functional organization from the earliest stages of life (e.g., Saby & Marshall, 2012; Anderson & Perone, 2018)



HOW IS IT INTERPRETED?

Patterns of EEG power are functionally significant (e.g., gamma → language outcomes)

Some children vary from a "typical" developmental pattern

- e.g., children exposed to early psychosocial adversity, poverty, high levels of stress show higher power in low frequency bands and lower power in high frequency bands

BUT, determining what contributes to individual variation in the EEG power spectrum is constrained by statistical power requirements

- Associations between multiple environmental variables and power in multiple frequency bands

At the same time, considering patterns ACROSS frequency bands (versus individual bands in isolation) might reveal important new insights into neurodevelopmental processes.

Latent Profile Analysis (LPA)

Latent Profile Analysis (LPA) pulls apart clusters of participants who show similar responses across several different continuous indicators (e.g., Nylund-Gibson & Choi, 2018).

Patterns of EEG power *across frequency bands*, as opposed to each band individually

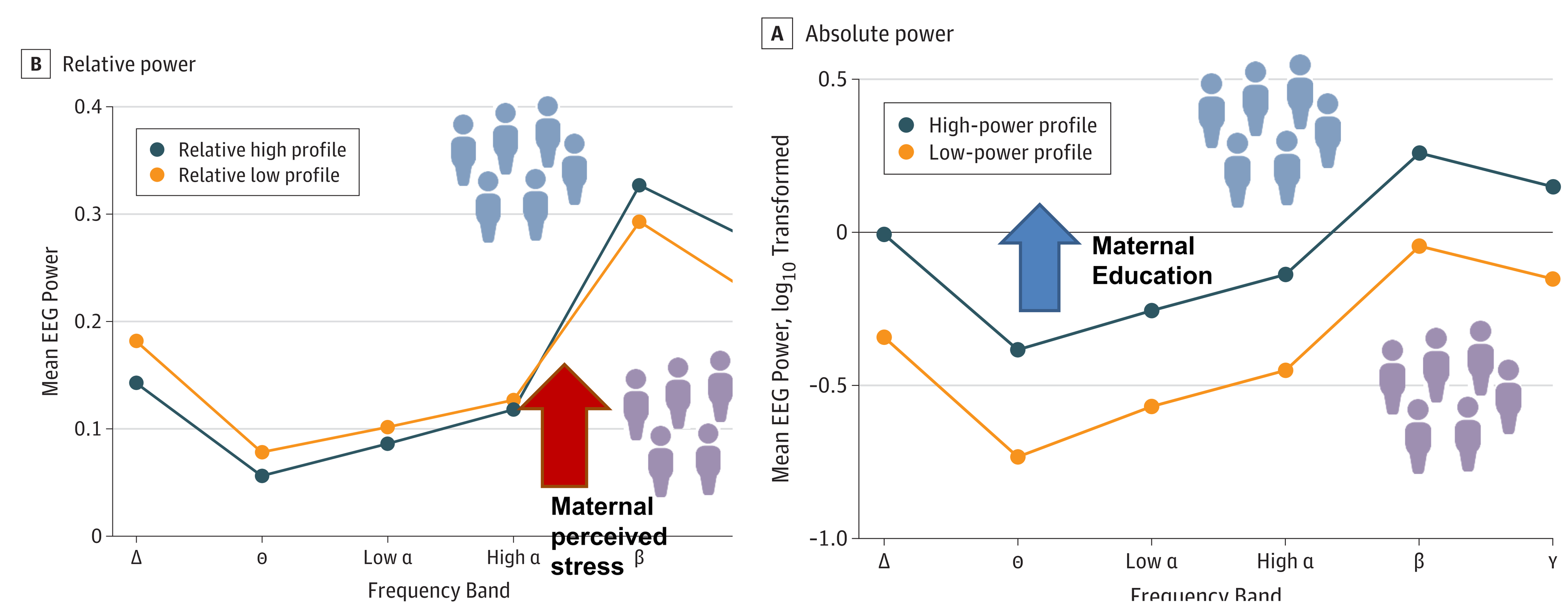
Environmental variables as predictors of latent profiles AND latent profiles as predictors of distal outcomes

Useful in many contexts, for example LPA has been used to identify neural predictors of symptom expression in ADHD (Loo et al., 2018). Latent profiles of behavioural adversity measures have also been used to predict physiological outcomes (e.g. inflammatory response; Lacey et al., 2020).

Sample size considerations: typically, N = 300+ though as few as 30 is possible if profiles are well separated. One risk of smaller samples is missing true classes.

An Example…

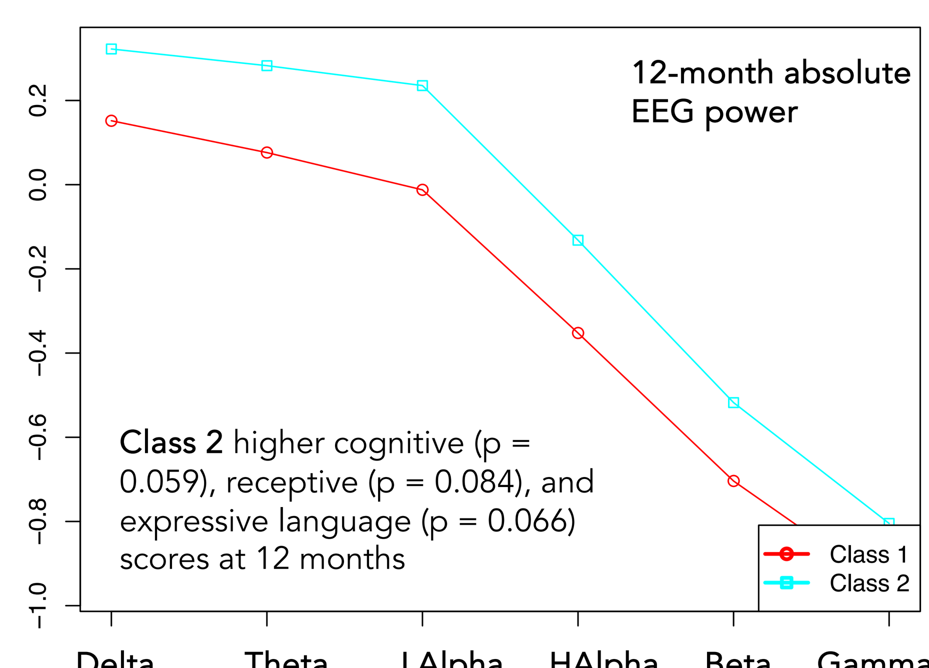
- 116 mother-infant dyads from socioeconomically diverse backgrounds
- Maternal-report demographic variables and exposure to stress
- Baseline EEG (5 min) collected from infants at 2, 6, 9, 12, 24, and 36 months
- Developmental assessment: 6, 12 and 24 months (Mullen Scales of Early Learning).
- Latent class models fit to whole brain EEG power across 6 frequency bands (Delta, Theta, Low Alpha, High Alpha, Beta, Gamma) using Mplus software. Model fit assessed using goodness-of-fit statistics (BIC, AIC, ENT, LMR p-value).
- 3-step approach was taken (Asparouhov & Muthen, 2014) to a) regress profile membership on predictor variables, or b) compare distal outcomes across profile membership, each accounting for potential error in classification.

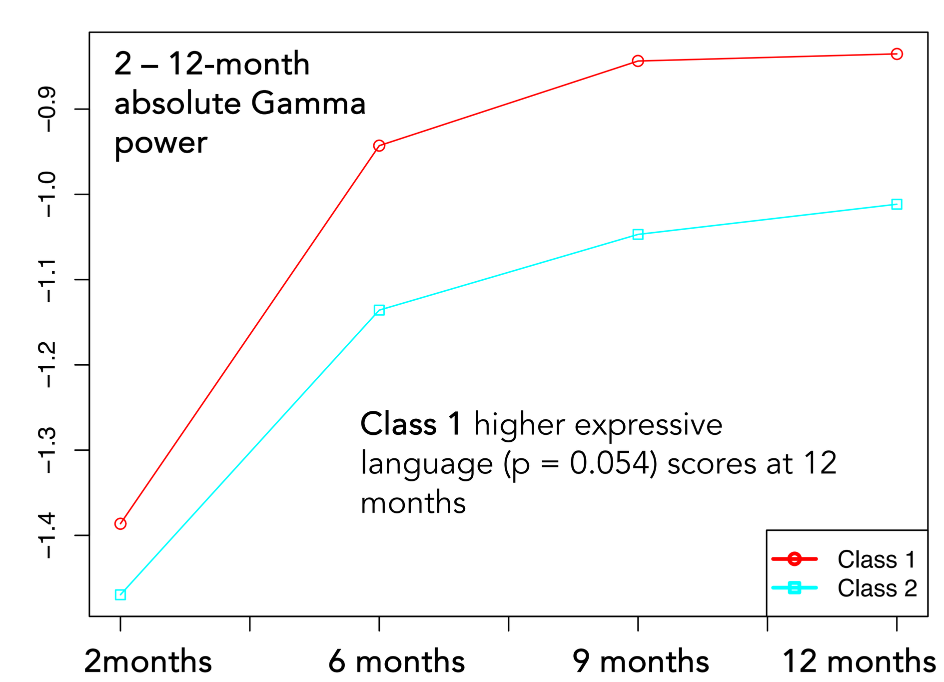


Pierce, Thompson, Gharib, Schlueter, Reilly, Valdes, Roberts, Conroy, Levitt, & Nelson (2019) JAMA Pediatrics

At 2 MONTHS two-profile solutions best fit both absolute and relative EEG power

Maternal stress and education each associated with unique EEG profiles at 2 months, adjusting for other demographic variables





At 12 MONTHS a two-profile solutions best fit absolute EEG power. A two-profile solution also emerged for Gamma power across the first year (2 – 12 months)

Trend level associations were observed between profiles and developmental outcomes. Profiles with higher power were associated with higher scores on Mullen subscales

Questions

CAN DATA-DRIVEN METHODS BE USED TO ISOLATE SUBGROUPS OF INDIVIDUALS WITH DIFFERENT EARLY EEG PATTERNS?

Are subgroups **functionally** meaningful?

Can subgroups be **predicted** by observed variables in the environment?

Are subgroups **predictive** of meaningful outcomes?

Can subgroups help to **identify early risk**?

Conclusions

Latent profile analysis (LPA) may be used to extract functionally meaningful subgroups of participants

Can identify predictors of profiles as well as whether profile membership predicts later outcomes – potentially a powerful tool for identifying risk

Applications for both cross-sectional and longitudinal data, as well as clinical and non-clinical populations

Potential to include other variables (e.g., other physiological markers and/or behavioural indicators) as part of profile identification

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