

Application of Generalized Linear Mixed-Effects Model Regression Trees with Multi-Modal Data

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1. INTRODUCTION

MULTI-MODAL DATA

Such data often straddle multiple fields, limiting analysts' ability to inform models with theory

Parameterization often difficult

- Limited statistical power
- Unknown interactions
- Complex functional forms

Generalized linear mixed effects model regression (GLMM) trees are promising in exploration of multi-modal data

GLMM TREES

Analyst specifies GLMM and model finds subgroups with unique GLMM parameters with recursive partitioning.

Subgroups formed with respect to user-specified "splitting" variables, which are analogous to moderators.

Parameter instability tests determine if subgroups are significantly different.

DATA SOURCE

Secondary data analysis Electrodermal activity (EDA) from 71 engineering students taking 15-item practice exam (DOI: 10.1037/a0019506)

- Item-average EDA (microSiemens)
- EDA peaks per item
- Nervousness (1-9 scale)
- Self-efficacy (1-9 scale)

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4. TABLES & FIGURES

4a. ITEM-AVERAGE EDA (MICROSIEMENS)

Presenting results as GLMM

Random Effects		
Standard Deviation		
Participant (Intercept)		0.32
Item (Intercept)		0.03
Residual		0.37
Fixed Effects		
	Estimate (SE)	t p
Intercept	0.21 (0.05)	4.20 <0.001
Dummy-Coded High Self-efficacy	-0.08 (0.04)	-2.23 0.026

Presenting results as discontinuous linear models

Self-efficacy ≤ 4		
	t	p
Estimate (SE)	4.68	<0.001
0.21 (0.05)		
Self-efficacy > 4		
	t	p
Estimate (SE)	13.64	<0.001
0.13 (0.01)		

NOTE: Linear models were fit with offsets for random intercepts

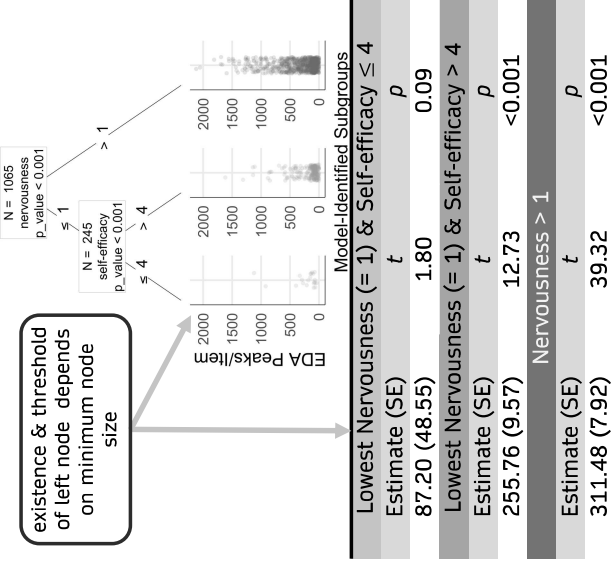
5. THEORETICAL CONTRIBUTIONS

We provide exploratory work that can be confirmed *a priori* by future researchers, specifically that each psychological measure has differential associations to EDA measures.

Low self-efficacy associated with higher item-average EDA, compared to higher self-efficacy. Any amount of nervousness leads to more EDA peaks per item than when not nervous

The influence of self-efficacy on number of EDA peaks per item may be more evident when not nervous. Level of participant nervousness, thus, should be controlled for in experiments to prevent systematic influence of this factor.

4b. NUMBER OF EDA PEAKS PER ITEM



6. METHODOLOGICAL CONSIDERATIONS

Hyperparameters influence model results & interpretation. Sensitivity checks should be conducted with varied hyperparameters (e.g., minimum node size, alpha, etc.)

Though not explored for simplicity of presenting the method, estimating instability across slopes—analogueous to growth mixture modeling—can be extremely informative

Cluster covariances are currently implemented for 1 level in parameter stability tests, even if GLMMs use > 1 level. In such cases, consideration should be taken as to which level to use. Simulation studies are recommended.

2. METHOD

Fit separate intercept-only GLMM trees for each EDA measure, accounting for participant and item variance (a cross-classified model) with {glmtree} in R

EDA ~ 1 +

(1 | participant) + (1 | item)

Potential Splitting Variables:

- Self-efficacy, nervousness, gender, age, major, item performance (correct/incorrect) and intervention status* (utility value/control)

*Prior research showed no effect of condition on EDA measures, but included for completeness

3. RESULTS

Item-average EDA demonstrated 1 split:

- Higher when self-efficacy ≤ 4, compared to 5-9
- *Instability Statistic* (S) = 8.29, Bonferroni-adjusted $p < 0.001$.

When participants endorsed nervousness = 1, they had significantly fewer EDA peaks than other levels of nervousness (S = 5.02, $p < 0.001$).

At nervousness = 1, a difference in EDA peaks per item was observed:

- Those with greater levels of self-efficacy had more peaks than those endorsing lower levels (S = 27.96, $p < 0.001$)
- The threshold of effect varied from self-efficacy ≥ 4 to self-efficacy ≥ 7, depending on minimum node size, with the effect disappearing entirely when node size < 8% sample

7. REFERENCES & SUPPLEMENTAL

www.christopherloan.com/blog/apa-2021