Modeling Age-Related Changes in Emotion Regulation within a Hierarchical Latent Stochastic Differential Equation Framework

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Feelings change.

How can the dynamics of emotion be represented in a modeling framework?

One model of emotion dynamics, the DynAffect model (Kuppens, Oravecz, & Tuerlinckx, 2010), uses an Ornstein-Uhlenbeck process model to describe affective dynamics with home base, intraindividual variability, and attractor strength parameters.

DynAffect models affective dynamics:

- In continuous time
- With continuous measurement dimensions
- As a person-specific process

The current study is an application of the DynAffect model to examine the relations of age, sex, and emotion regulation strategies to DynAffect's affective dynamic parameters.

Empirical Example

Participants: N=150 individuals from the Intraindividual Study of Affect Health and Interpersonal Behavior (iSAHIB) provided ratings on feelings and behaviors after social interactions lasting >5 minutes for 21 consecutive days via study-provided smartphone. Participants made 35-265 (M=145.46, SD=39.59) reports each.

Demographics: 51% women, aged 18-89 years (M_{Age}=47.10, SD_{Age}=18.76). Participants were mostly well-educated (M_{Educ}=16.36, SD_{Educ}=3.90), mostly white (91% Caucasian), and mostly heterosexual (93%).

Measures:

Core affect: *Valence* ("Unpleasant"-"Pleasant"), *Arousal* ("Sleepy"-"Activated/aroused"); continuous, scaled 0-10

Emotion regulation: *Cognitive reappraisal* ("I changed how I thought about the interaction"),
Expressive suppression ("I kept my emotions to myself"); continuous, scaled 0-10.
Summarized in terms of individual means (*iMean*) and standard deviations (*iSD*).

Data Analysis: 2-dimensional HOU model with uncorrelated affect dimensions was run in the Bayesian Hierarchical Ornstein-Uhlenbeck Modeling (BHOUM) Matlab toolbox (available from zitaoravecz.net). Age, sex (1=female, 0=male), and *iMeans* and *iSDs* of reappraisal and suppression engagement were included as person-specific covariates.

Table 1. Group level DynAffect Estimates and Credibly Nonzero Time-Invariant Regression Coefficient Estimates

	Valence		Arousal	
	Posterior Mean	95% Credible Interval	Posterior Mean	95% Credible Interval
Intercept Home Base (μ)	7.842	(7.676, 8.009)	6.007	(5.798, 2.215)
Age	--	--	0.289	(0.065, 0.503)
iMean Reappraisal	-0.351	(-0.673, -0.026)	--	--
Intercept Intraind. Variability (γ)	2.000	(1.674, 2.415)	2.566	(2.128, 3.143)
*Age**	--	--	-0.192	(-0.360, -0.027)
*iSD Reappraisal**	--	--	0.433	(0.040, 0.823)
*iSD Suppression**	0.730	(0.400, 1.061)	--	--
Intercept Attractor Strength (β)	25.554	(13.231, 49.364)	9.845	(6.043, 16.101)
*iSD Suppression**	--	--	1.205	(0.522, 1.865)
SD Home Base (σ_μ)	1.012	(0.898, 1.141)	1.277	(1.132, 1.437)
SD Intraind. Var. (σ_γ)	2.328	(1.655, 3.242)	3.196	(2.236, 4.506)
SD Attractor Strength (σ_β)	311.326	(68.842, 721.558)	48.960	(18.913, 99.740)
Measurement error (σ_ϵ)	0.560	(0.539, 0.592)	0.636	(0.600, 0.671)

Note. Parameters with an asterisk (covariate effects for γ's and β's) are on a log-scale. Covariate effects not printed if 95% CI included 0.

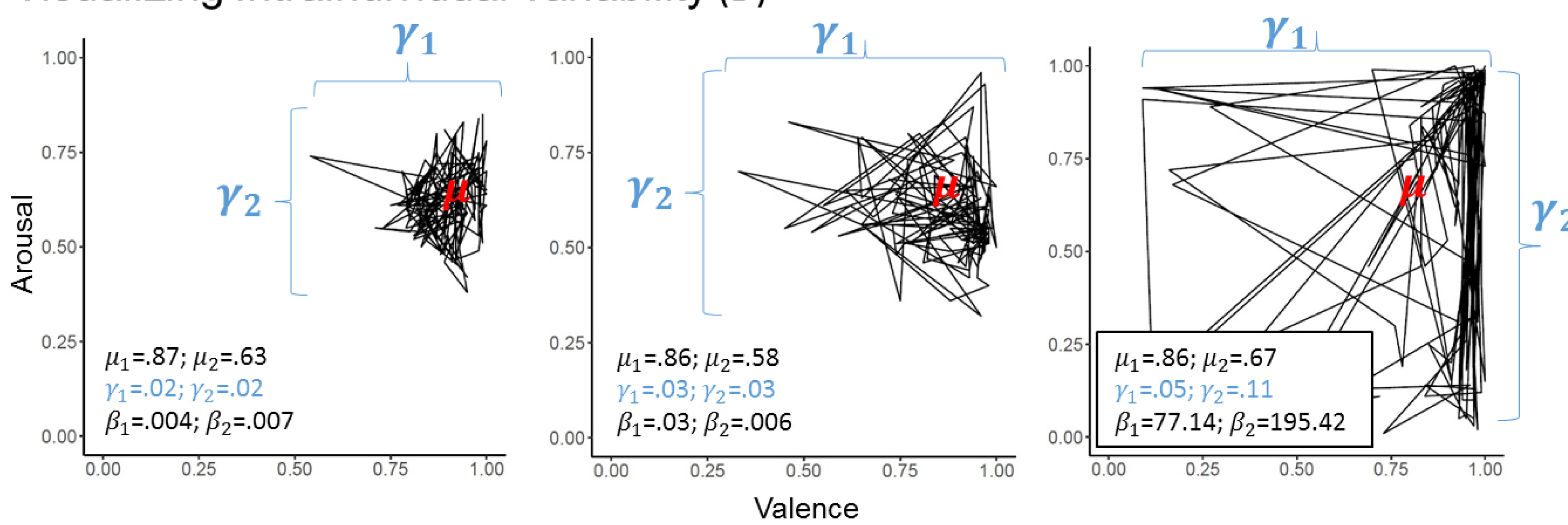
Hierarchical Ornstein-Uhlenbeck Model

The DynAffect model parameterizes affective dynamics with an Ornstein-Uhlenbeck process model (Uhlenbeck & Ornstein, 1930), an attractor model with stochastic inputs.

The 2D model, in a measurement framework, is:

$$\begin{cases} d\boldsymbol{\Theta}_p(t) = \boldsymbol{B}_p\left(\boldsymbol{\mu}_p - \boldsymbol{\Theta}_p(t)\right)dt + \boldsymbol{\Sigma}_p d\boldsymbol{W}(t) & \text{(change equation)} \\ \boldsymbol{Y}_{ps} = \boldsymbol{\Theta}_{ps} + \boldsymbol{\varepsilon}_{ps} & \text{(measurement equation)} \end{cases}$$

Visualizing Intraindividual Variability ($\boldsymbol{\Gamma}$)



Visualizing Attractor Strength ($\boldsymbol{B}$)

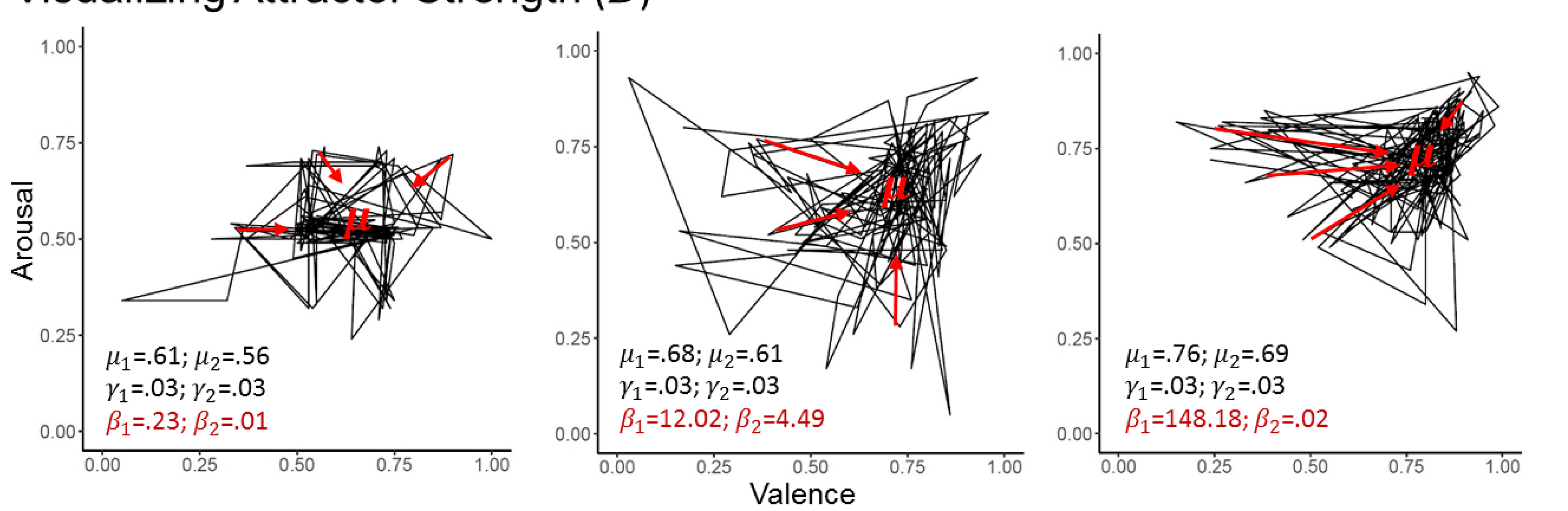


Table 2. DynAffect Parameter Guide

Parameter	Interpretation
$\boldsymbol{\Theta}_{ps}$	True valence and arousal
$\boldsymbol{Y}_{ps}$	Measured valence and arousal
$d\boldsymbol{W}(t)$	Stochastic noise
$\boldsymbol{\mu}$	"Home base", attractor
$\boldsymbol{B}$	Attractor strength
$\boldsymbol{\Gamma}$	Intraindividual variability
$\boldsymbol{\Sigma}$	Diffusion scale
$\boldsymbol{\varepsilon}_{ps}$	Measurement error

Note. s = measurement occasions, p = person index; $\boldsymbol{\Gamma}$ defined $\boldsymbol{\Sigma}\boldsymbol{\Sigma}^T = \boldsymbol{B}\boldsymbol{\Gamma} + \boldsymbol{\Gamma}\boldsymbol{B}^T$

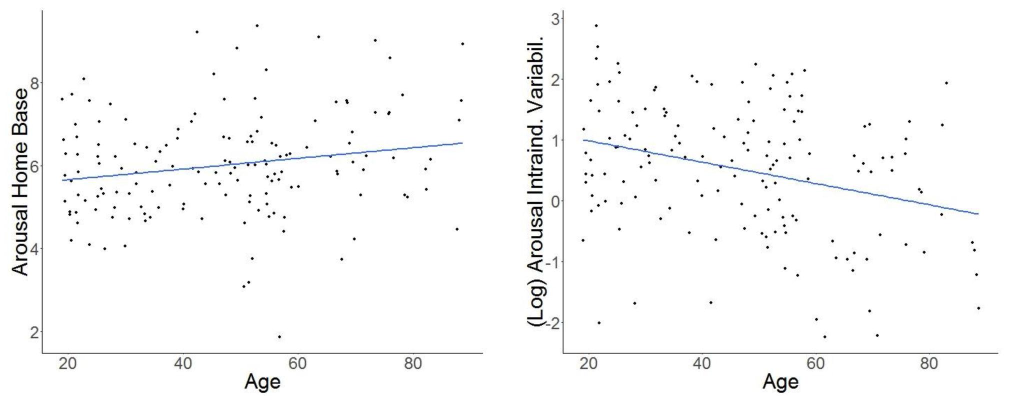
The HOU model is estimated in a Bayesian framework. For more information on the mathematical estimation of the HOU model, see Oravecz & Tuerlinckx (2008) and Oravecz, Tuerlinckx, &Vandekerckhove (2011).

Key advantages:

1. State-space model formulation to decompose manifest variation in observed data into intraindividual variation in latent change process and measurement error.
2. Captures intraindividual variation and regulation (or autocorrelation) as parameters of person-specific process model.
3. Simultaneously estimates person-specific process model parameters and regresses them on time-invariant covariates (realistic standard errors).

Conclusions

I. Higher **age** was associated with:
- Higher average levels of arousal
- Less intraindividual variability in arousal



Increased average arousal with age may concur with socioemotional selectivity theory. Decreased arousal variability matches SAVI theory

II. Higher **individual means of emotion reappraisal** were associated with:
- Lower valence home base

III. Higher **individual standard deviations of emotion reappraisal** were associated with:
- More intraindividual variability in arousal

IV. Higher **individual standard deviations of emotion suppression** were associated with
- Larger intraindividual variability in valence
- Greater attractor strength of arousal.

Emotion regulation findings may be related to social context (e.g. individuals utilizing emotion regulation strategies in contexts that call for regulation)

Limitations

- Model does not allow multiple attractors
- Computationally intensive
- Measurement invariance, demographically homogenous

Take-home message:

The study of affective and emotion dynamics is increasingly relevant to the emotion (regulation) field. The use of differential equations-based models allows researchers to articulate theories about dynamics and implicit regulation.

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