

Idiographic, Cross-task Architectural Parameter Variation as Compu-Cognomic Data

Edward Cranford¹

Katherine Judy²

Connor Manion²

Weiss O'Connor²

Katherine Mortimore¹

Kevin Gluck¹

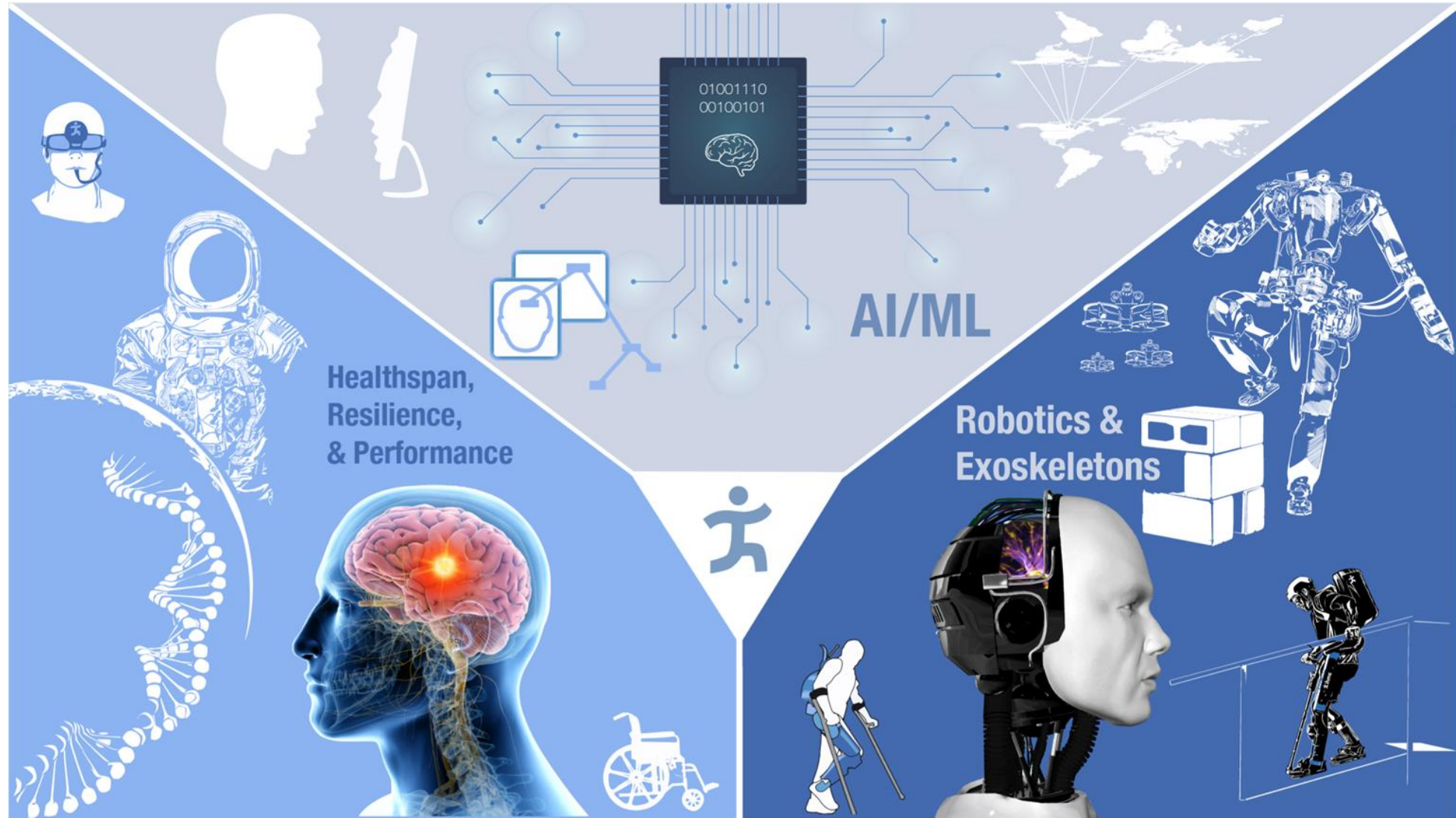
¹ Institute for Human & Machine Cognition

² United States Air Force Academy

Contact: ecranford@ihmc.org



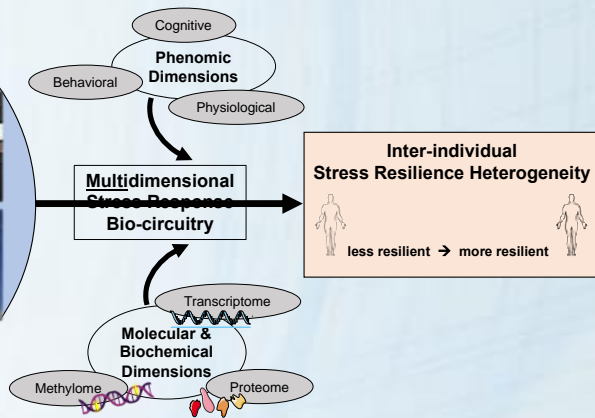
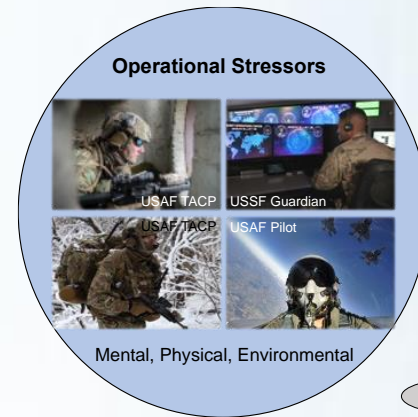
Human-Centered Science and Technology



Healthspan, Resilience & Performance



SENSE



AUGMENT

ASSESS

Biospecimen and Performance Data Sources

Project	Study Identifier (Acronym)	Cohort	Stressors	Stress Duration
ROPER (Retrospective Studies)	NCT02057094 (SERE)	N = 71 all males	MARSOC SERE school: mental, physical, environmental	18 days
	NCT02731066 (HIGH)	N = 23 all males	Simulated SUSOPS with energy deficit at sustained high altitude: mental, physical, environmental	21 days
	NCT02734238 (OPS)	N = 50 all males	Sea level training with energy deficit: mental, physical	28 days
	NCT04120363 (OPS II)	N = 32 all males	Simulated multi-stressor SUSOPS: mental, physical	21 days
	PEERLESS (TACP TOPT)	N = 74 all males	TACP TOPT selection course: mental, physical, environmental	5 days
A2PEX (Studies in Progress)	Sleep Deprivation (Sleep Dep)	N* = 30	Sleep deprivation: mental, physical	27 hours
	Cognitive Fatigue (Cog Fatigue)	N* = 30	Cognitive fatigue: mental	14 hours
	Physical Fatigue (Phys Fatigue)	N* = 30 DoD-affiliated personnel	Physical fatigue: mental, physical	5 days

N* - expected number of participants

Suite of Cognitive Tasks in ROPER & A2PEX

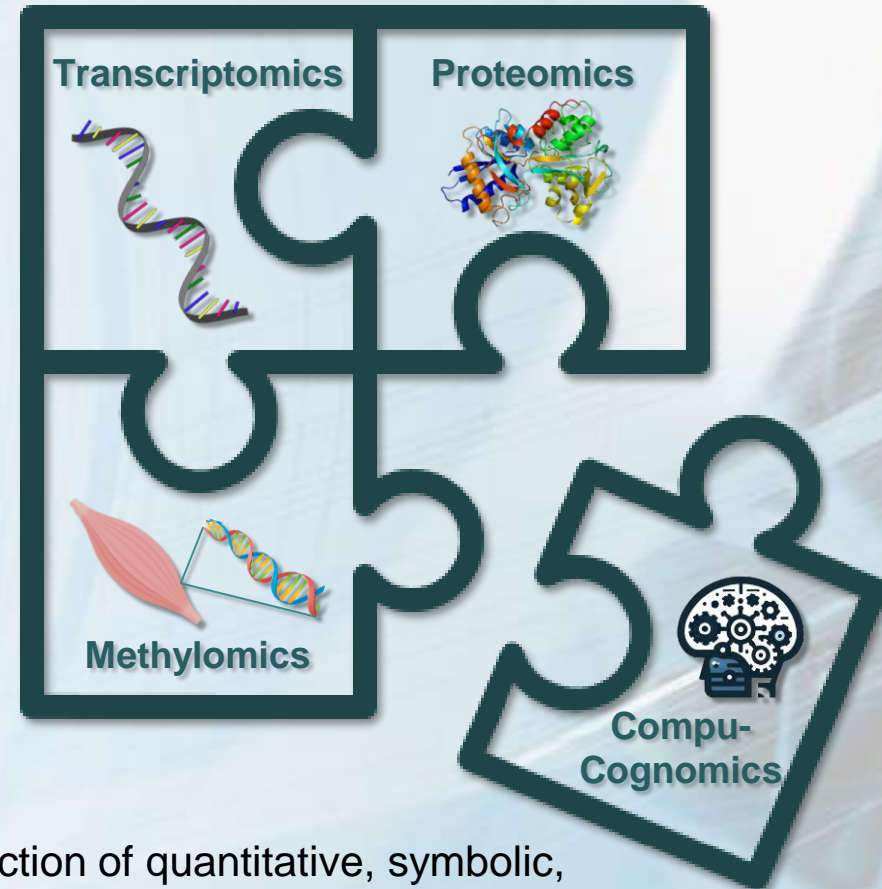
	Study	Procedural			Working Memory			Visual/Spatial		Reasoning/Decision Making				Multimodal/Multitasking			
		PVT/SRT	PRO RT	Go/No-Go	N-Back	Code-Digit Sub	Match to Sample	Scanning Visual Vigilance	Neuro-tracker/VisTrack	Grammatical Reasoning	Math Processing	Balloon Analog Risk Task	Ultimatum Game	AF-MATB	CA2PES	VirTra	SP-VISTa
ROPER	SERE	X								X							
	HIGH	X			X		X	X		X		X	X				
	OPS	X			X		X	X		X		X	X				
	OPS II	X			X		X	X				X	X				
	TOPT	X	X	X		X	X		X		X					X	
A2PEX	Sleep Deprivation	X		X	X				X		X			X	X		X
	Cognitive Fatigue	X		X	X				X		X			X	X		X
	Physical Fatigue	X		X	X												X

Unique Modeling Opportunities

- Idiographic, Cross-task Parameterization Variation
 - Many participants performing multiple tasks across multiple days while stressed
- Parameter Optimization methodology
 - Must develop efficient methods for exploration of very large parameter space
- ACT-R models as a source for the Compu-Cognome
 - Architectural parameterization provides a way to identify cognitive markers of resilience (or any phenotype of interest)

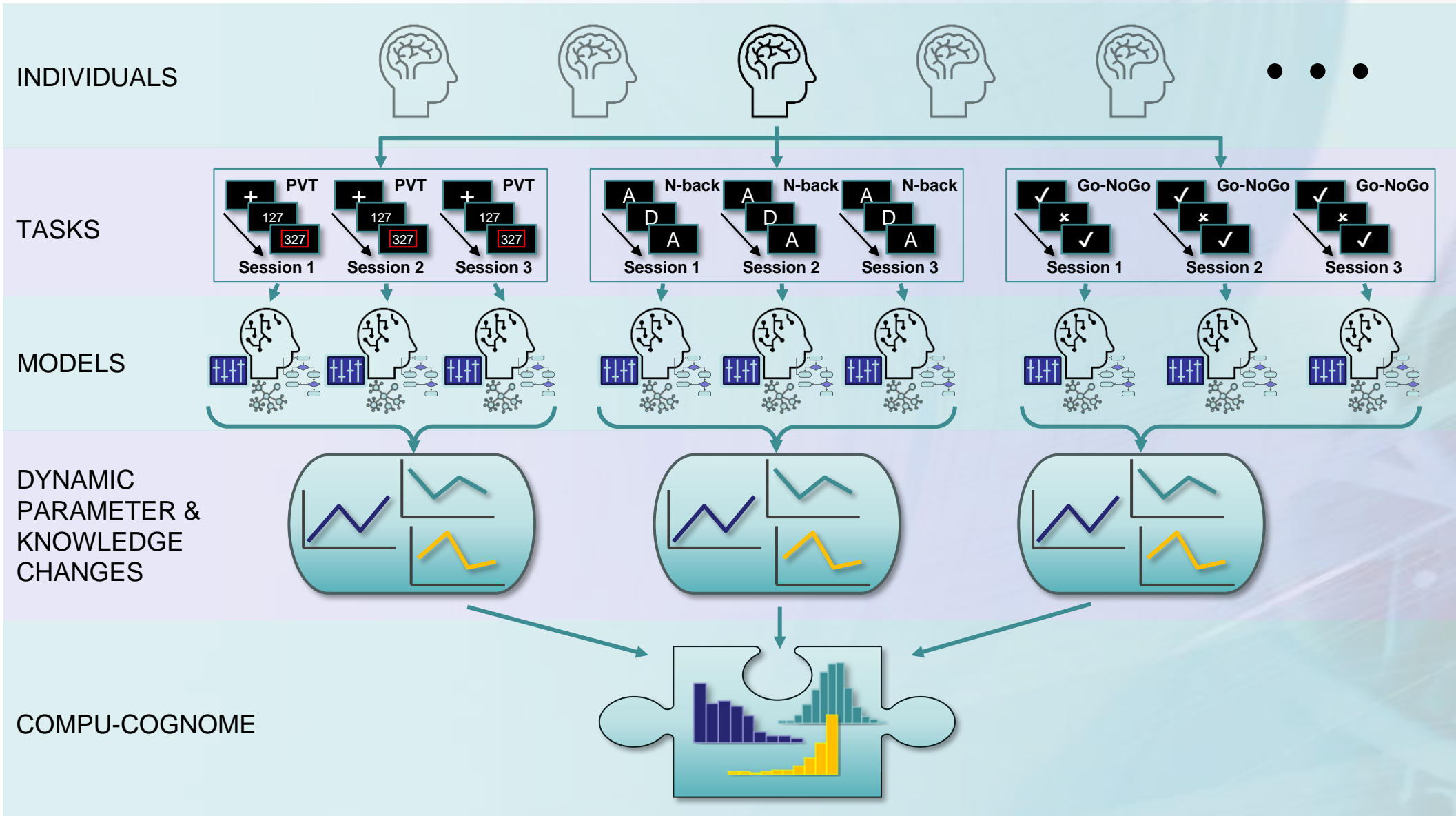
Compu-Cognomics as a Piece of the Multi-Omics Methodology

- The suffix *-ome* refers to a *totality* or *collective*
- Compu-Cognome serves as additional data sources for multi-omic analyses
- Unique scientific opportunity to build an analytical bridge from “molecules to minds”
 - From traditional multi-omic data to observable behavior (the phenome)
 - Through the explanatory mechanisms available in the Compu-Cognome of cognitive architectural theory



Compu-Cognome (*n*) – collection of quantitative, symbolic, and neurofunctional mechanisms that explain and predict variation in cognitive performance.

Constructing a Compu-Cognome

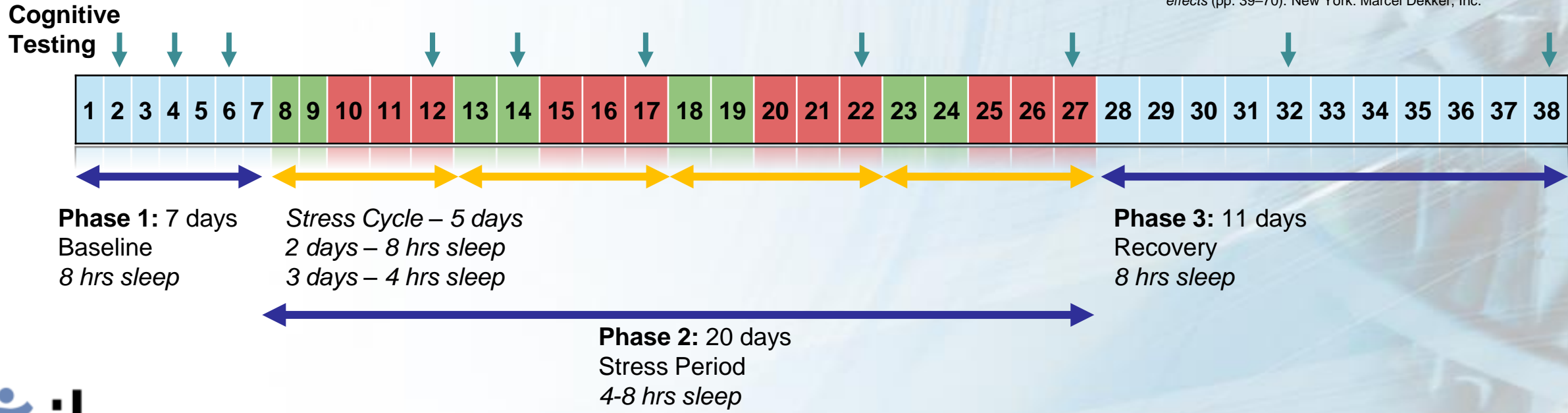
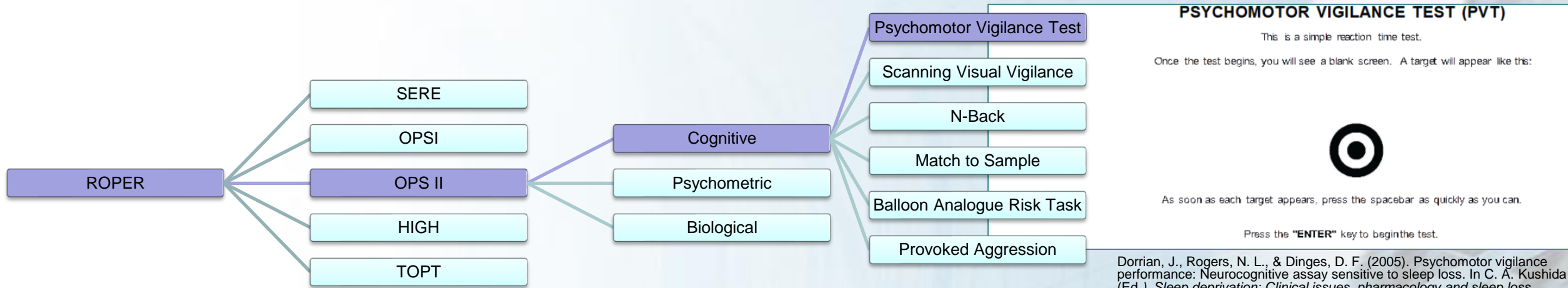


Architectural Parameters Across Tasks (partial example)

- Unique opportunity in ROPER/A2PEX to gain a better understanding of the space of architectural parameters and their relationship to performance across a range of tasks

Mechanism	Parameter	Meaning	TASKS (example subset)		
			PVT	N-Back	Go/No-Go
Declarative Memory	:ans	activation noise (s)		X	
	:bll	activation decay (d)		X	
	:mp	mismatch penalty (similarity weighting; P)		X	
	:lf	latency factor (retrieval time; F)		X	
Procedural Memory	:dat	default action time (cognitive cycle time)	X	X	X
	:egs	expected gain noise added to utility	X	X	X
	:ut	utility threshold	X	X	X
	:iu	initial utility value	X	X	X
	:p	production value (cost)			X
	:ppm	production partial matching	X		
Goal/Intention	:g	goal value (cost)			X
	:ga	spreading activation value from goal buffer		X	
	:imaginal-activation	spreading activation value from imaginal buffer		X	
Fatigue	:utmc	utility threshold minute constant	X	X	X
	:utbmc	utility threshold biomath model constant	X	X	X
	:fpdec	fatigue procedural decrement	X	X	X
	:fpmc	fatigue procedural minute constant	X	X	X
	:fpbmc	fatigue procedural biomath model constant	X	X	X

OPS-II PVT – Preliminary Analyses



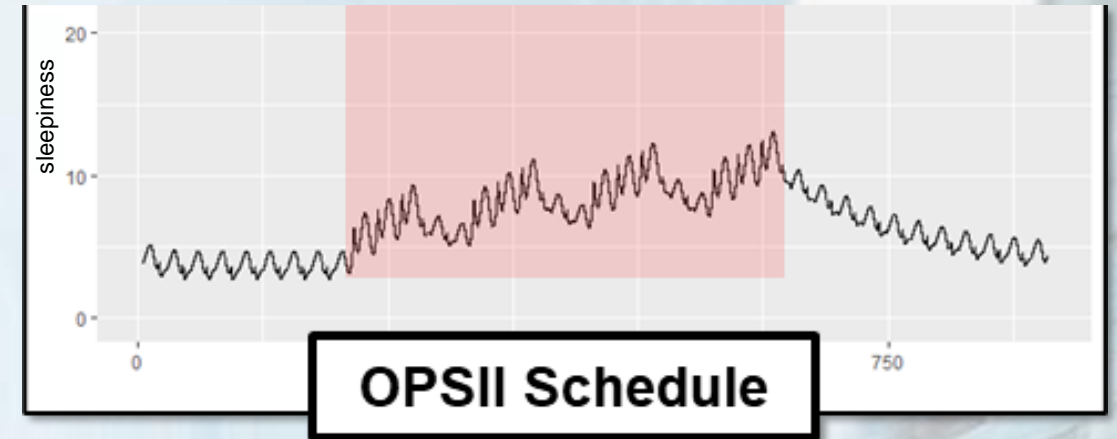
PVT Model & Fatigue Module

- PVT Model
 - 3 Production Rules
 - **Wait** – explicitly waits during the delay
 - **Attend** – shifts attention to the stimulus
 - **Respond** – executes a key press once the stimulus has been attended
- Fatigue Module
 - Introduces *microlapses* – requires rescheduling of conflict resolution
 - Utility and Utility Threshold attenuated by biomathematical model of alertness¹ based on given sleep schedule

$$FP = :fp\text{-percent} * (1 - :fpbmc * biomath\text{-prediction}) * (1 + time\text{-on-task})^{:fpmc}$$

$$Utility = alertUtility * FP$$

$$UT = :ut * (1 - :utbmc * biomath\text{-prediction}) * (1 + time\text{-on-task})^{:utmc}$$



Gunzelmann et al. (2009) model accounted very well for sleep deprivation effects on PVT performance.²

PVT and Fatigue Module Acknowledgements:

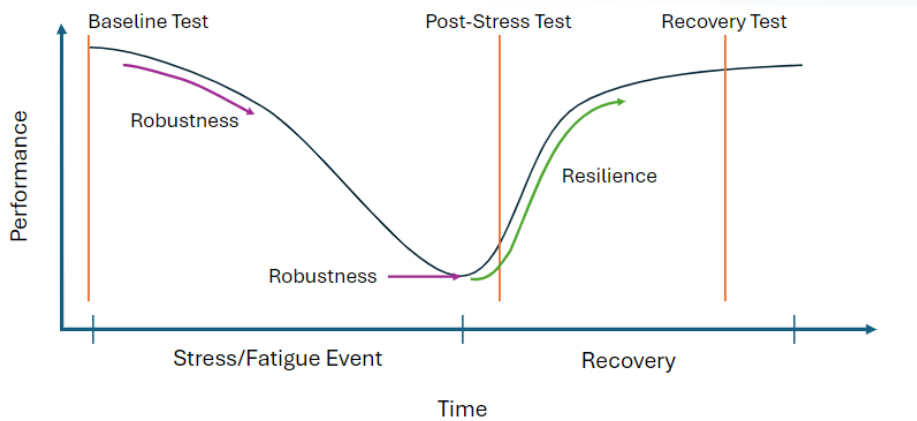
Glenn Gunzelmann, Rick Moore, Tim Halverson, Bella Veksler, Kevin Gluck, Michael Krusmark, Taylor Curley, and Dan Bothell

¹McCauley, P., Kalachev, L. V., Mollicone, D. J., Banks, S., Dinges, D. F., & Van Dongen, H. P. a. (2013). Dynamic circadian modulation in a biomathematical model for the effects of sleep and sleep loss on waking neurobehavioral performance. *Sleep*, 36(12), 1987–97.

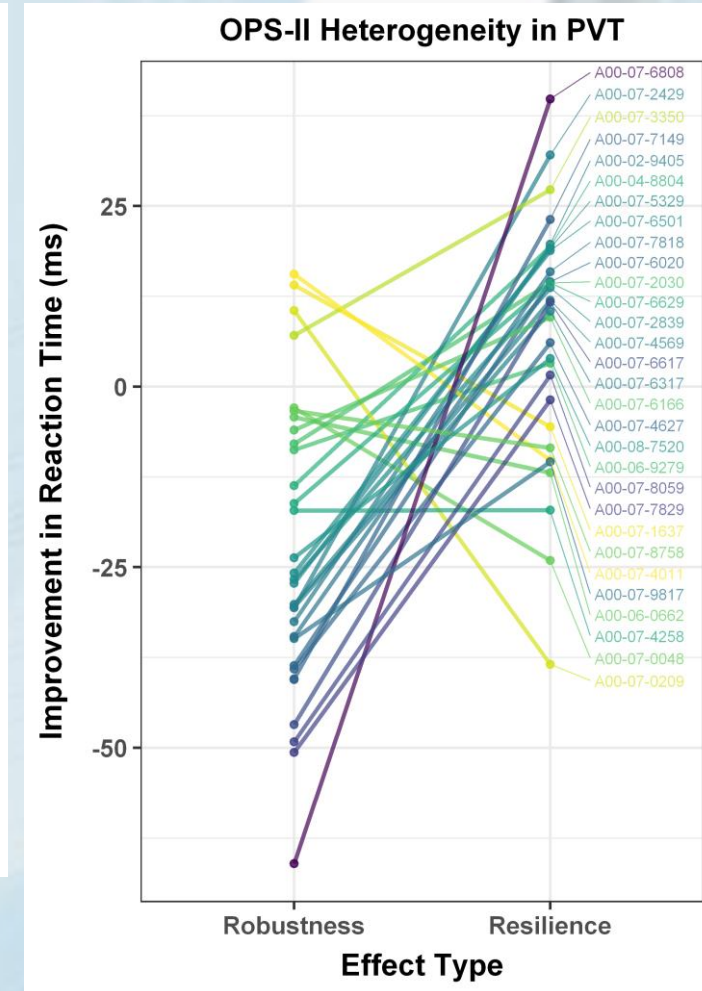
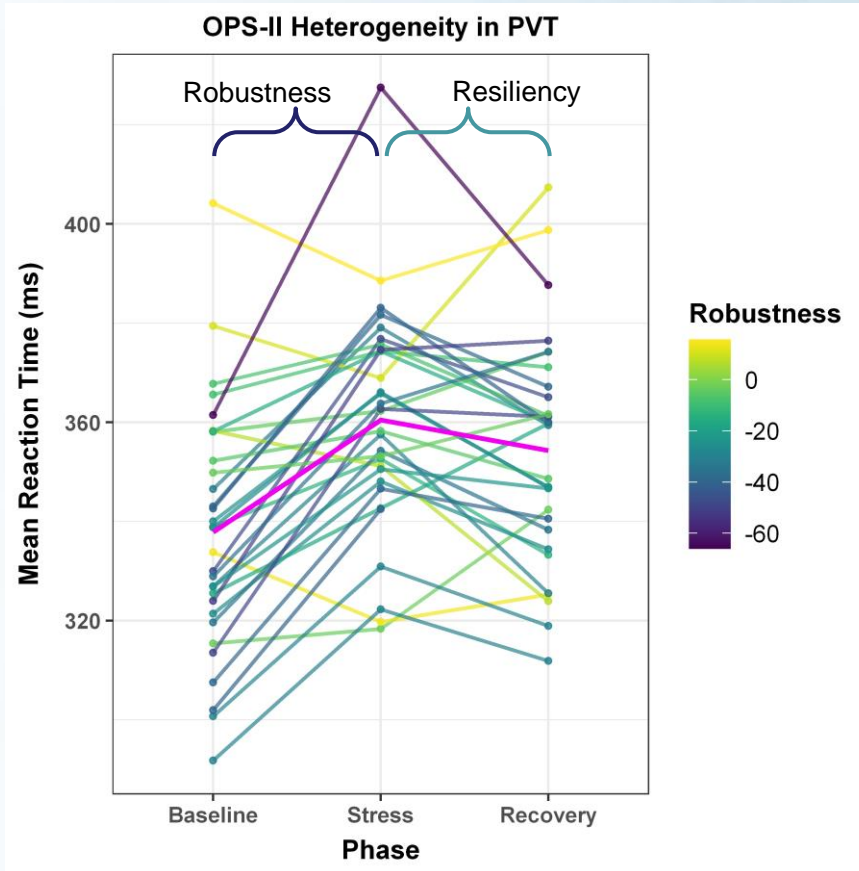
²Gunzelmann, G., Gross, J. B., Gluck, K. A., & Dinges, D. F. (2009). Sleep deprivation and sustained attention performance: Integrating mathematical and cognitive modeling. *Cognitive Science*, 33(5), 880-910.

Heterogeneity in robustness and resilience to stress

- Avg performance degrades from Baseline to Stress and rebounds during Recovery
- Extreme heterogeneity at the individual level



- Robustness: ability to maintain performance level
- Resilience: ability to recover to baseline



Parameter Optimization for Modeling Individual Performance Over Time

- Simulated Annealing

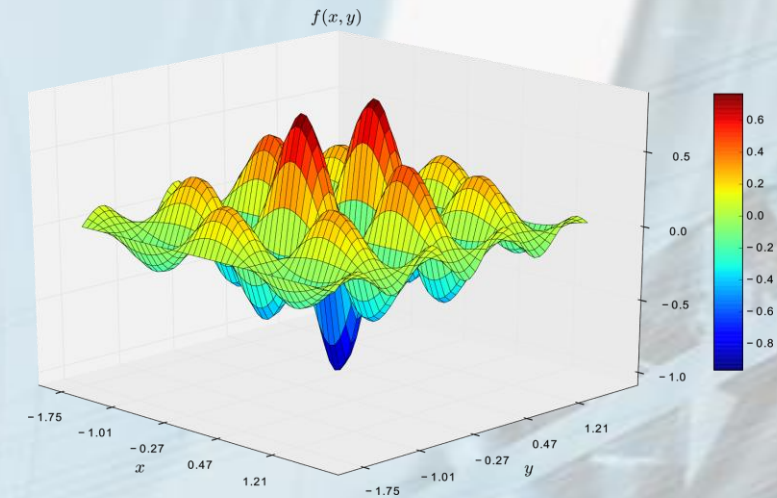
- random search optimization method with systematic component for searching for the global optimum
 - Speed vs Completeness in search space
 - Escapes local minima (with enough iterations)
 - Handles complex parameter spaces well
 - optimSA package in R can only specify one objective function

- Objective Function

- RMSE between distributions of RTs for Humans vs Model
- Also explored squared Pearson Correlation Coefficient (r^2)

- Initial Param Opt with 4 Edge-case Participants

- Very low temp and few iterations
 - only ~150 samples per participant (7hr to solution)



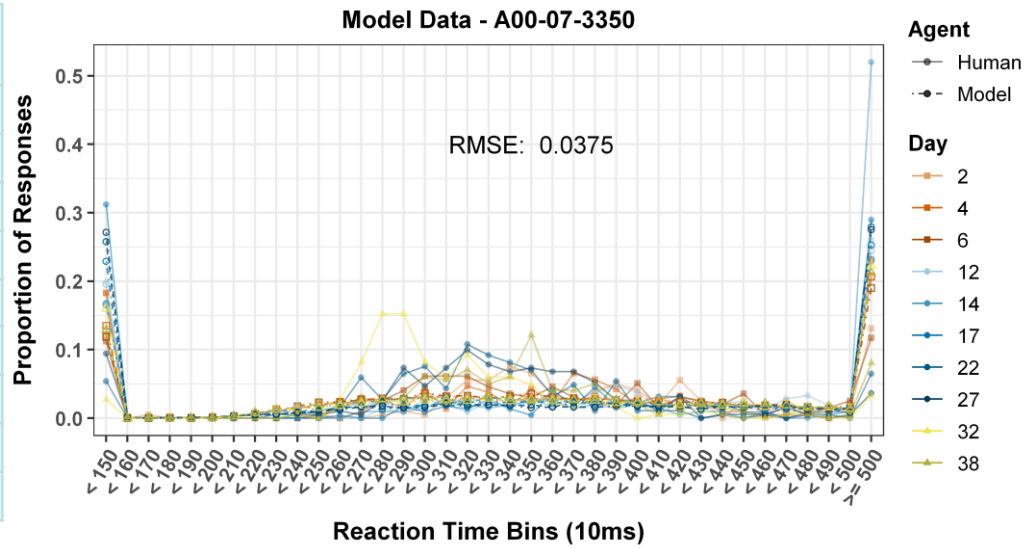
		Resilience	
		Best	Worst
Robustness	Best	<u>A00-07-3350</u>	<u>A00-07-0209</u>
	Worst	<u>A00-07-2429</u>	<u>A00-07-7829</u>

Identifying Parameters to Characterize Individuals

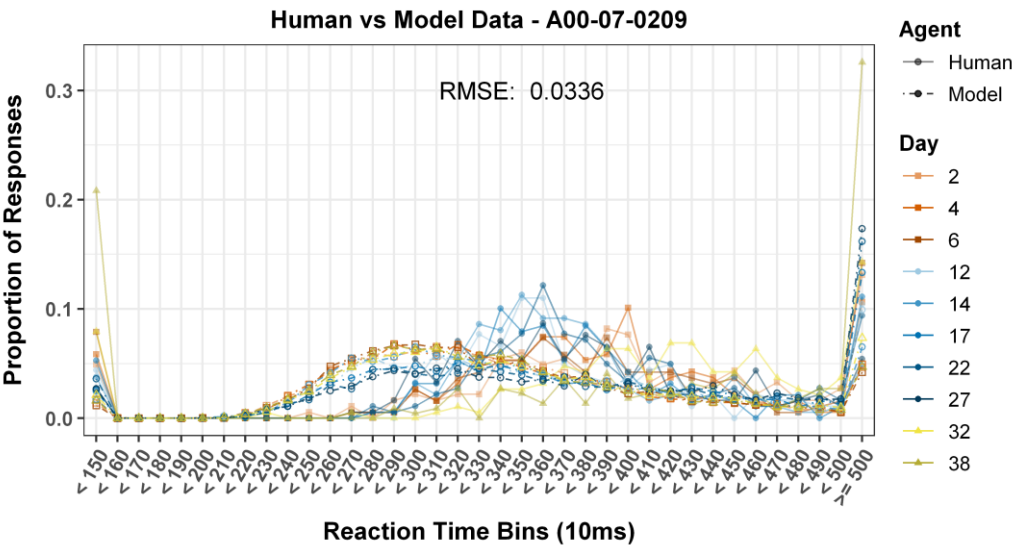
Best ← Resilience → Worst

Best ↑ Robustness ↓ Worst

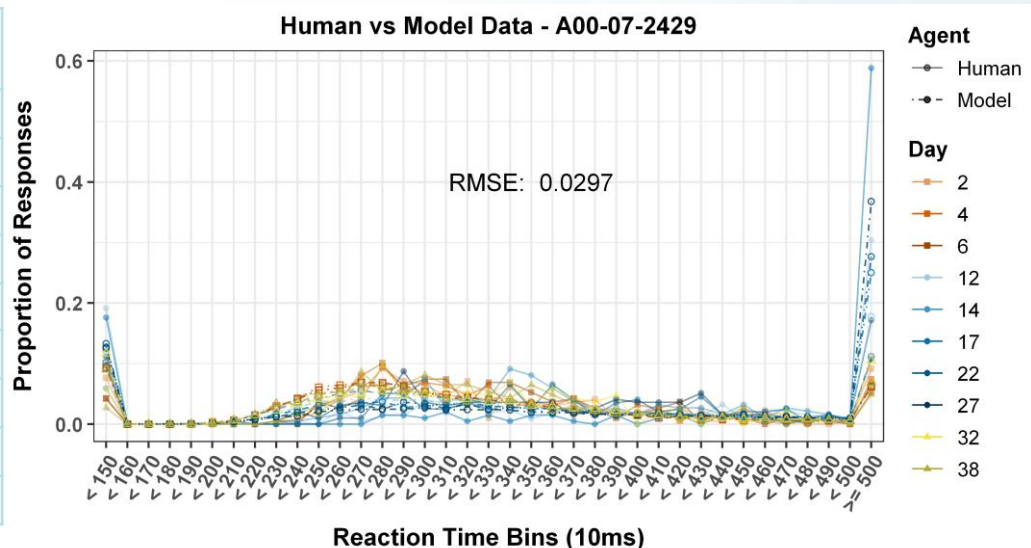
Param	Best Val
:dat	0.05
:egs	0.36
:ut	2.26
:iu	2.2
:utmc	0.0
:utbmc	0.02
:fpdec	1.0
:fpmc	-0.03
:fpbmc	0.03



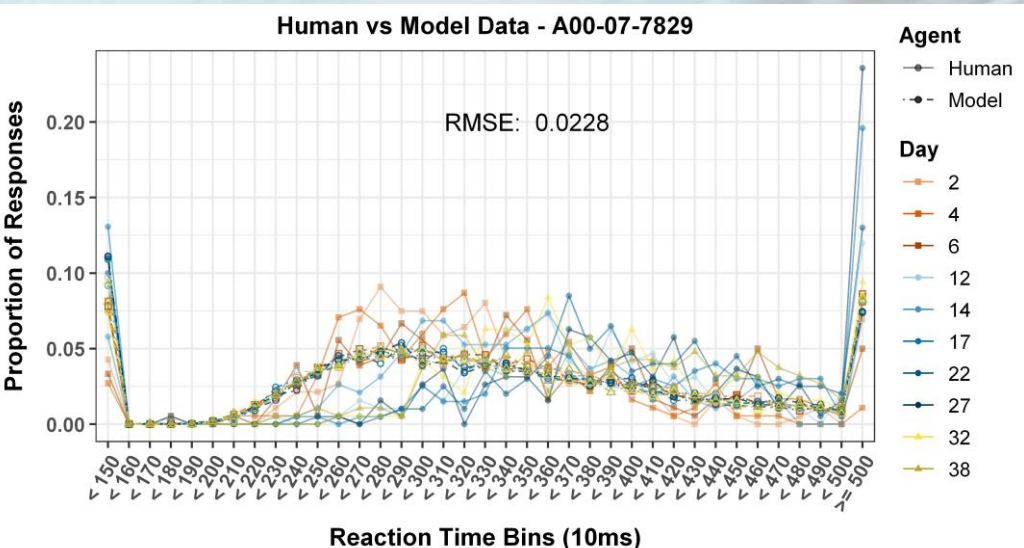
Param	Best Val
:dat	0.06
:egs	0.27
:ut	2.15
:iu	2.73
:utmc	-0.01
:utbmc	0.01
:fpdec	1.0
:fpmc	-0.07
:fpbmc	0.02



Param	Best Val
:dat	0.05
:egs	0.33
:ut	2.23
:iu	2.73
:utmc	-0.1
:utbmc	0.0
:fpdec	0.96
:fpmc	-0.1
:fpbmc	0.02



Param	Best Val
:dat	0.05
:egs	0.38
:ut	2.46
:iu	2.46
:utmc	0.0
:utbmc	0.01
:fpdec	1.0
:fpmc	-0.01
:fpbmc	0.01

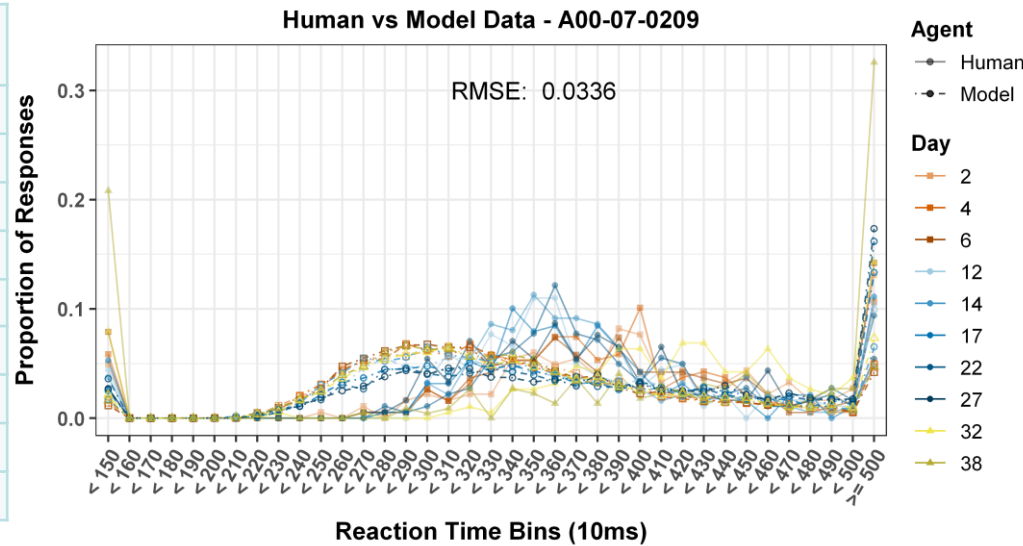


r^2 better at fitting longitudinal patterns

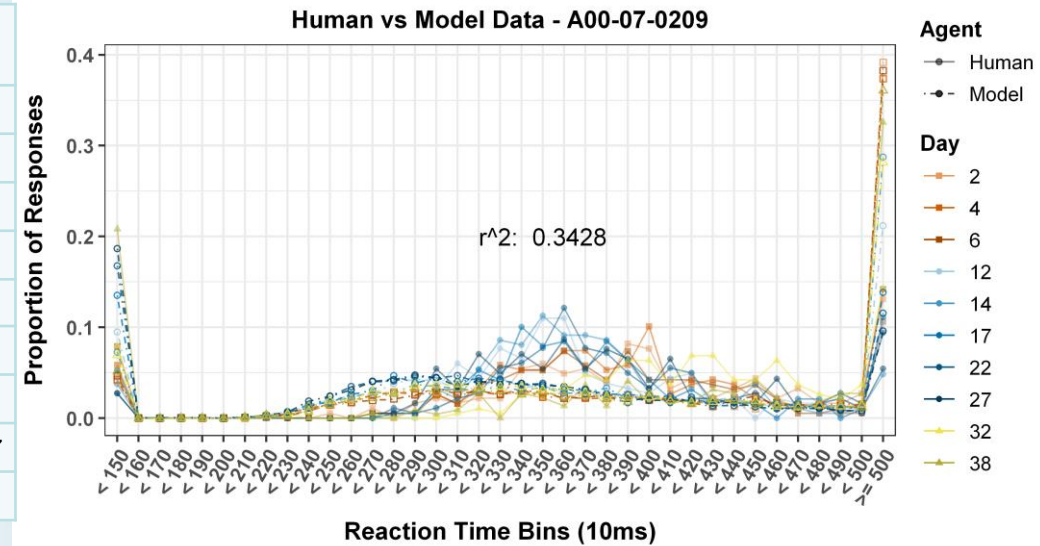
RMSE

r^2

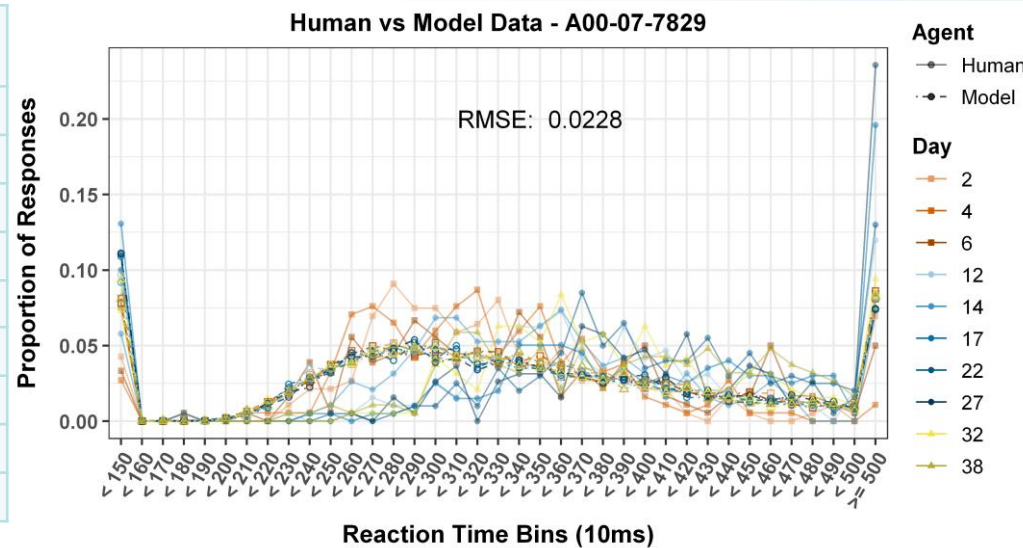
Param	Best Val
:dat	0.06
:egs	0.27
:ut	2.15
:iu	2.73
:utmc	-0.01
:utbmc	0.01
:fpdec	1.0
:fpmc	-0.07
:fpbmc	0.02



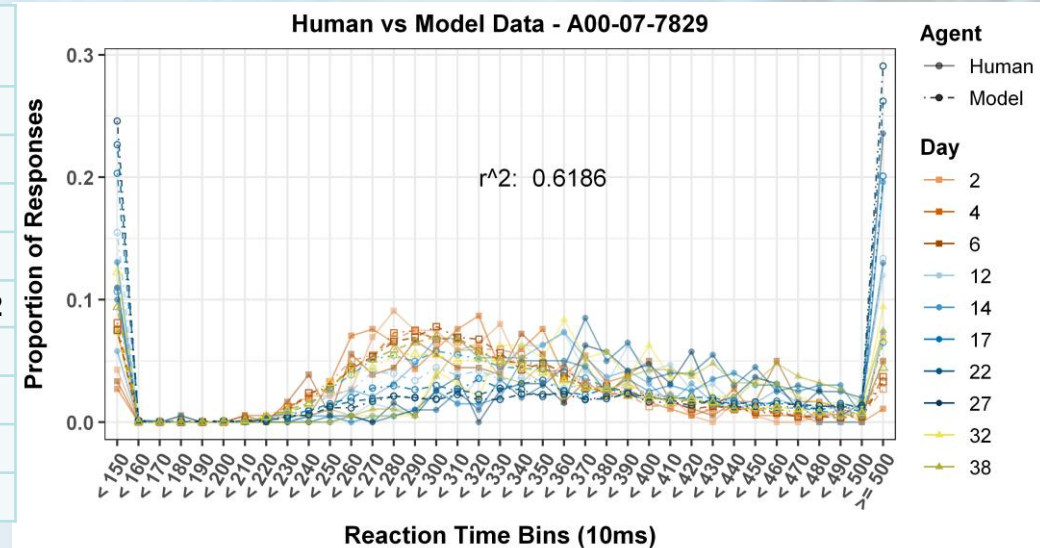
Param	Best Val
:dat	0.06
:egs	0.26
:ut	2.03
:iu	2.02
:utmc	-0.01
:utbmc	0.03
:fpdec	0.97
:fpmc	-0.07
:fpbmc	0.02



Param	Best Val
:dat	0.05
:egs	0.38
:ut	2.46
:iu	2.46
:utmc	0.0
:utbmc	0.01
:fpdec	1.0
:fpmc	-0.01
:fpbmc	0.01

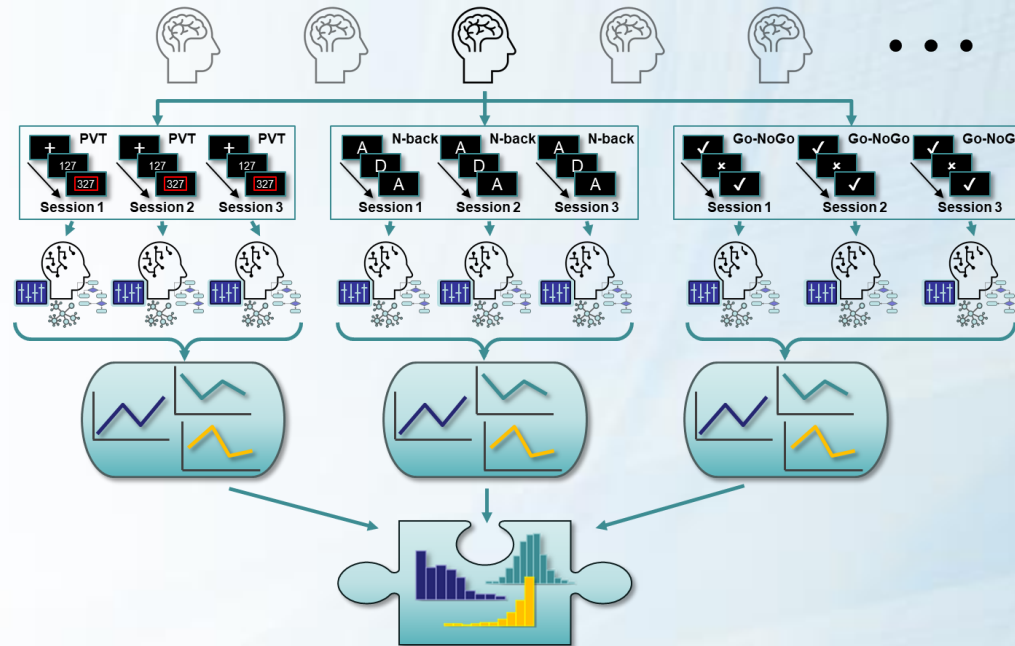


Param	Best Val
:dat	0.06
:egs	0.36
:ut	2.27
:iu	2.94
:utmc	-0.02
:utbmc	0.02
:fpdec	0.97
:fpmc	0.0
:fpbmc	0.04



What's Next?

- Expand set of models
 - Acquired models of N-back and Go/No-Go. Can we find any more?
 - Will create our own models of other tasks.
- Scale up parameter optimization methods to model individual heterogeneity in stress response
 - Multiple studies X many participants X multiple tasks X multiple days



Modeling Approach Considerations

- Modeling individual tasks separately does not inherently account for intra-individual architectural constraints
 - Theoretically, same architectural parameters for explaining performance in one task should also explain performance in another task
- Modeling multiple tasks performed by the same model is desirable
 - Cognitive Supermodels¹ (Salvucci, [ACT-R Workshop 2010](#))
 - Primitive Operations² (Taatgen, [ACT-R Workshop 2017](#))

¹Salvucci D. D. (2013). Integration and reuse in cognitive skill acquisition. *Cognitive science*, 37(5), 829–860.
<https://doi.org/10.1111/cogs.12032>

²Taatgen, N. A. (2013). The nature and transfer of cognitive skills. *Psychological Review*, 120(3), 439–471.

Decisions for Scaling up Parameter Optimization

- Programming language:
 - R – fits within current data pipeline, many parameter optimization packages available
 - Python – newer and more advanced parameter optimization packages available
 - LISP – fits current modeling language; potentially computationally faster; need to code our own algorithm = more overhead
- Optimization Method:
 - Multitude of possibilities to choose from! (brute-force; random; SA; Genetic; Bayesian; etc.)
 - Important needs:
 - Computational efficiency
 - Parallelization (may need high performance computing center/cluster)
 - Systematic search
 - Multiple Objective Functions?
- Objective Functions:
 - RMSE/D – Root Mean Squared Error/Deviation
 - r^2 – squared Pearson correlation coefficient
 - R^2 – Coefficient of Determination
 - Maximum Likelihood Estimation (Stocco et al., *in prep*; Fisher, Houpt, & Gunzelmann, 2022)
 - Multiple Objective Functions?
- Data interpolation could help reduce model run time (Moore & Gunzelmann, 2014)

Stocco, A., Mitsopoulos, K., Yang, Y. C., Hake, H. S., Haile, T., Leonard, B., & Gluck, K. (*in prep*). Fitting, Evaluating, and Comparing Cognitive Architecture Models Using Likelihood Measures: A Tutorial With Examples in ACT-R.

Fisher, C. R., Houpt, J. W., & Gunzelmann, G. (2022). Fundamental tools for developing likelihood functions within ACT-R. *Journal of mathematical Psychology*, 107, 1-17.

Moore, R. L. & Gunzelmann, G. (2014). An interpolation approach for fitting computationally intensive models. *Cognitive Systems Research*, 29-30, 53-65.

Unique Modeling Opportunities

- Idiographic, Cross-task Parameterization Variation
 - Many participants performing multiple tasks across multiple days
- Parameter Optimization methodology
 - Must develop efficient methods for exploration of very large parameter space
- ACT-R models as a source for the Compu-Cognome
 - Architectural parameterization provides a way to identify cognitive markers of resilience (or any phenotype of interest)

Acknowledgments



Thank You!

Questions?

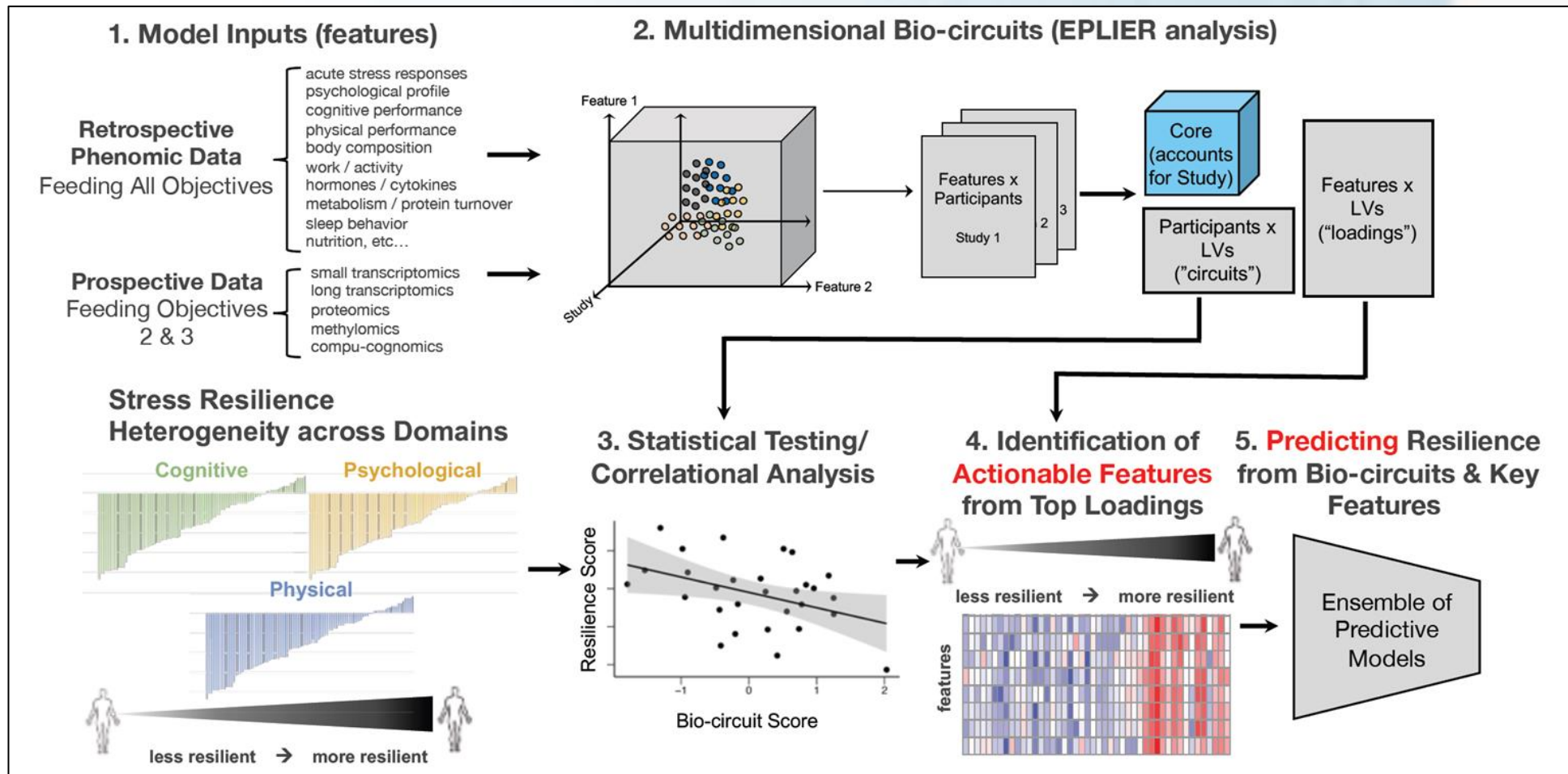


FLORIDA INSTITUTE FOR HUMAN & MACHINE COGNITION

BACKUP

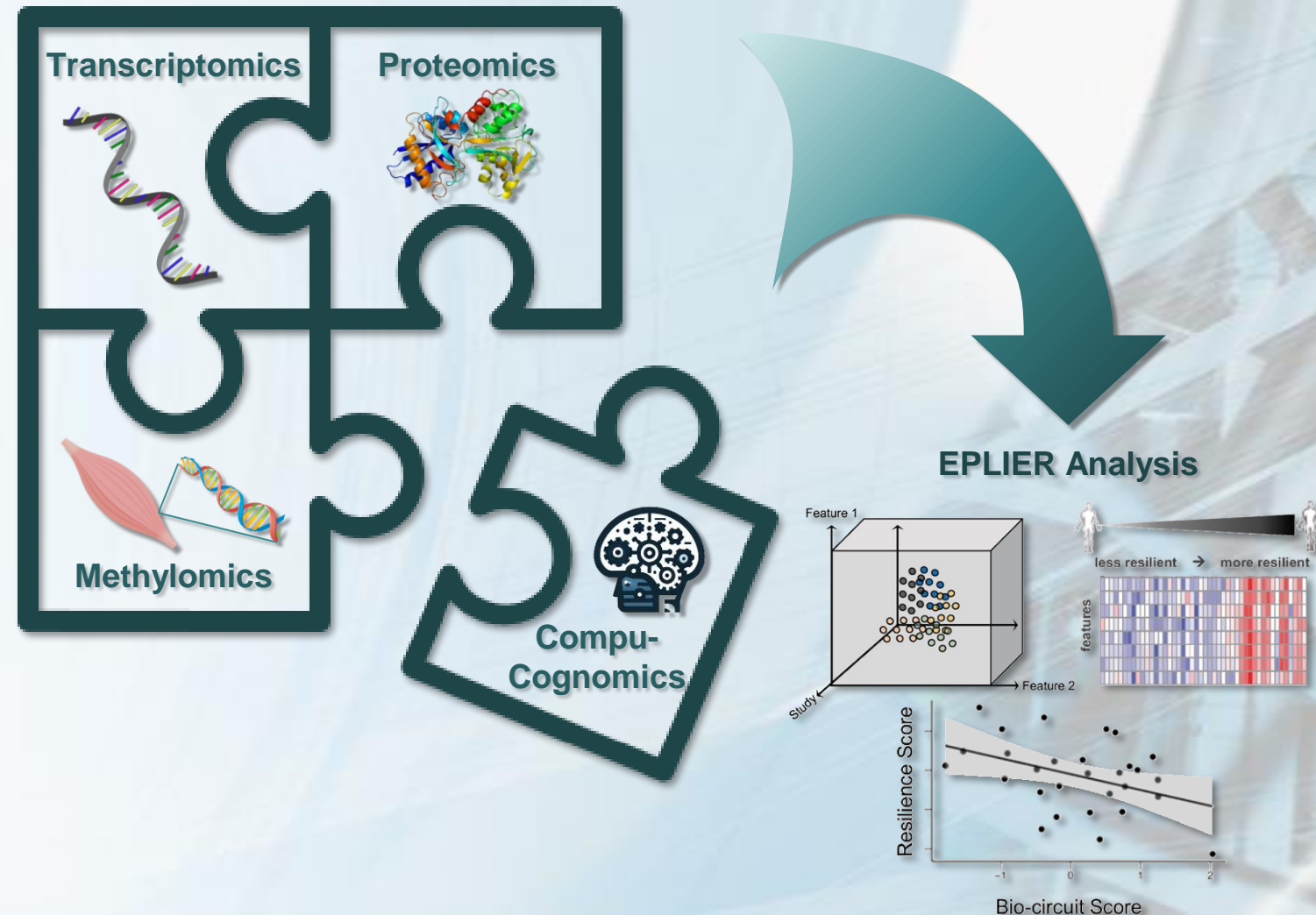
Resilience to Optimize PERFORMANCE (ROPER)

What are the fundamental bases of stress response heterogeneity?



Compu-Cognomics as a Piece of the Multi-Omics Methodology

- Compu-Cognome serves as additional data sources for multi-omic analyses
- Unique scientific opportunity to build an analytical bridge from “molecules to minds”
 - Phenomic and multiomic data to observable behavior
 - Through the explanatory mechanisms available in the Compu-Cognome of cognitive architectural theory





**Research that makes a
difference...
*that makes a difference***

