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#GHC15

Wearable Sensor Data and Medical Records for Clinical Outcome Prediction

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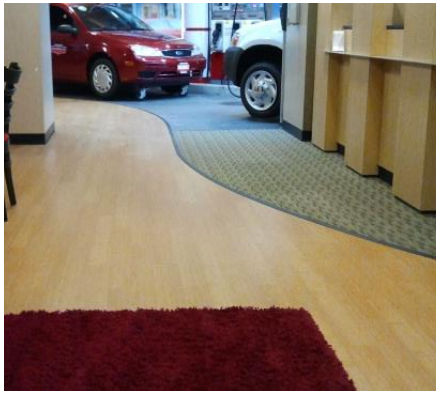
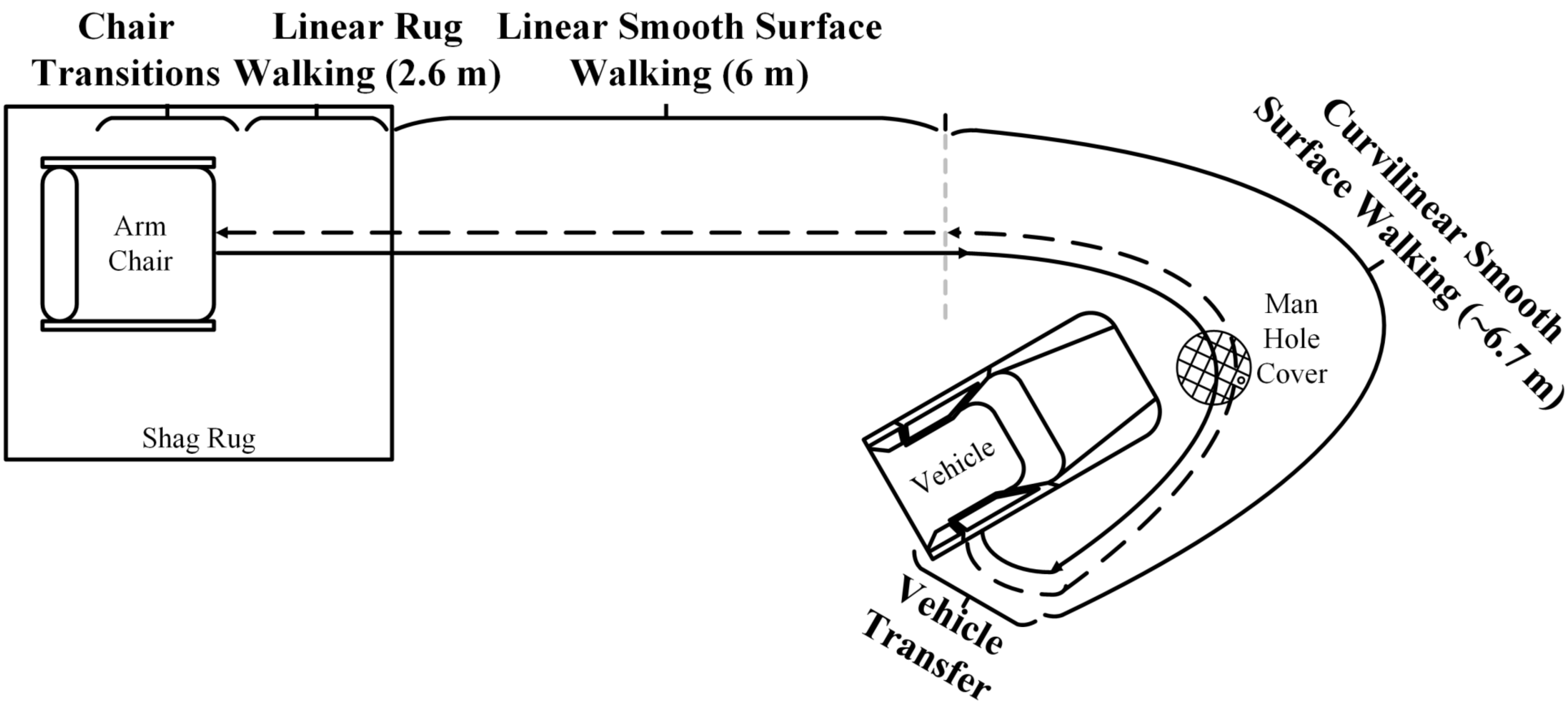
Wearables for Rehabilitation

- Why technology for rehabilitation?
  - Fine-grained, objective data
- Why wearable sensors?
  - Portable, inexpensive, unobtrusive
- Why ecological environments?
  - More representative of abilities
  - Resembles discharge environment

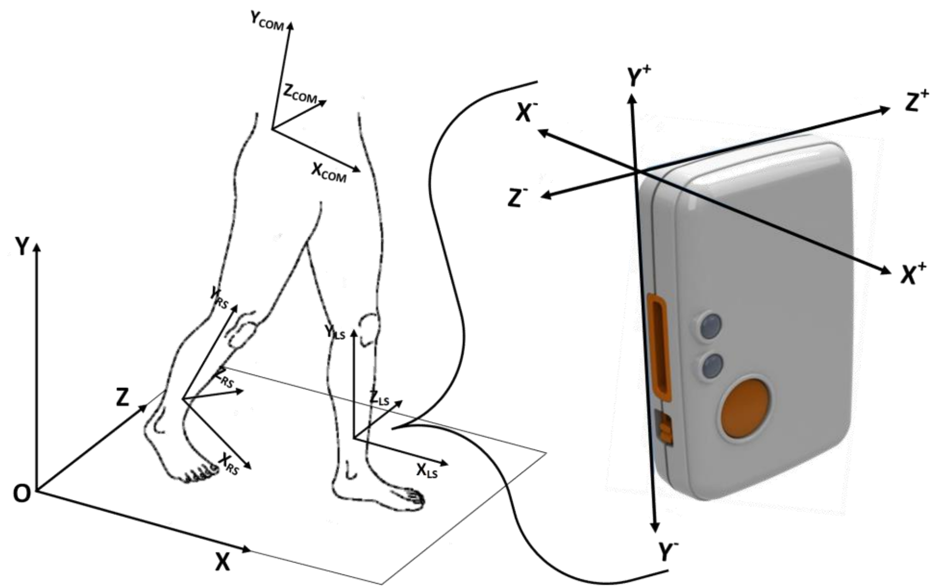


Ambulation Circuit (AC)

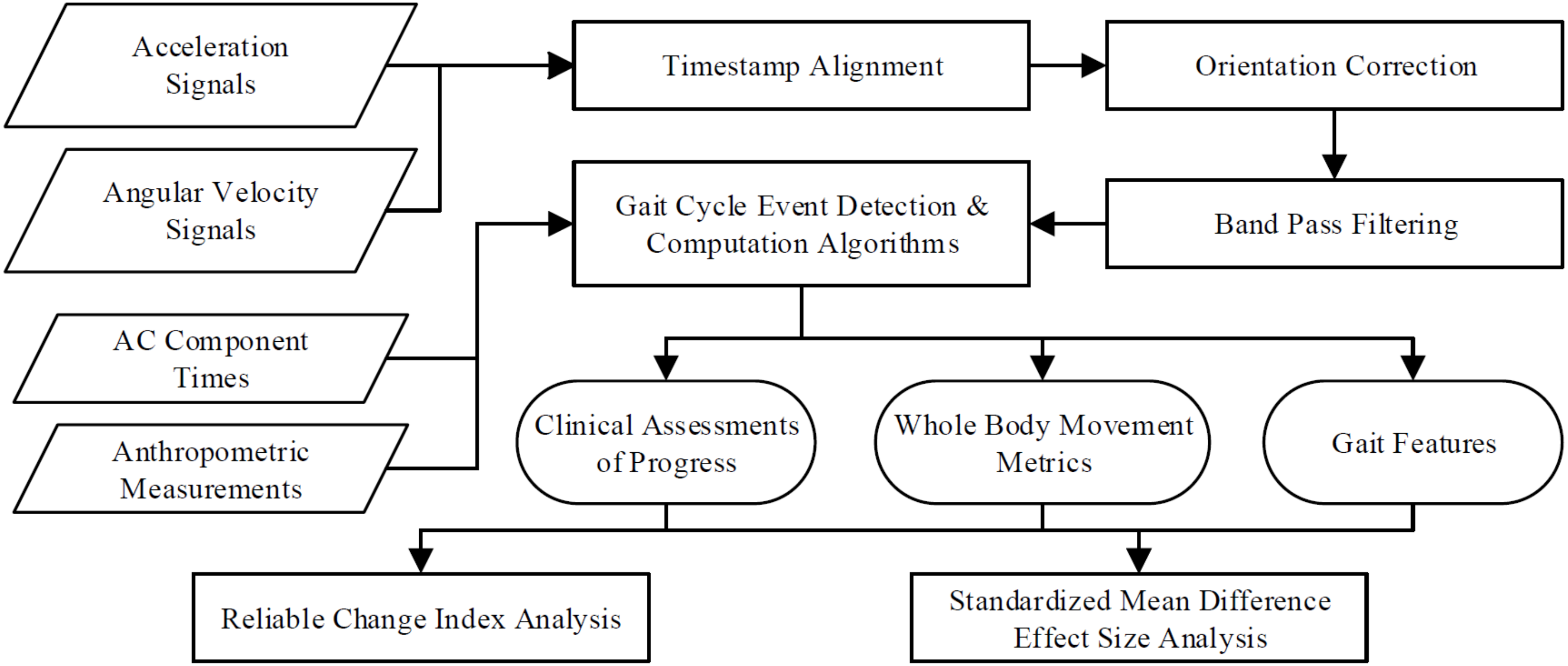


AC Study Participants

- N=20 (M=14, F=6)
- 71.55 ± 10.62 years of age
- Stroke, brain injury, debility, cardiac, etc.
- 2 Testing sessions
  - 1 Week apart



Data Processing



Clinical Outcome Prediction

- Functional Independence Measure (FIM)
  - Measured at admission and discharge
  - 13 Motor tasks
    - Transfers
    - Locomotion
  - 5 Cognitive tasks
- Utilize additional patient medical records (N=4936) for training (NAC dataset)

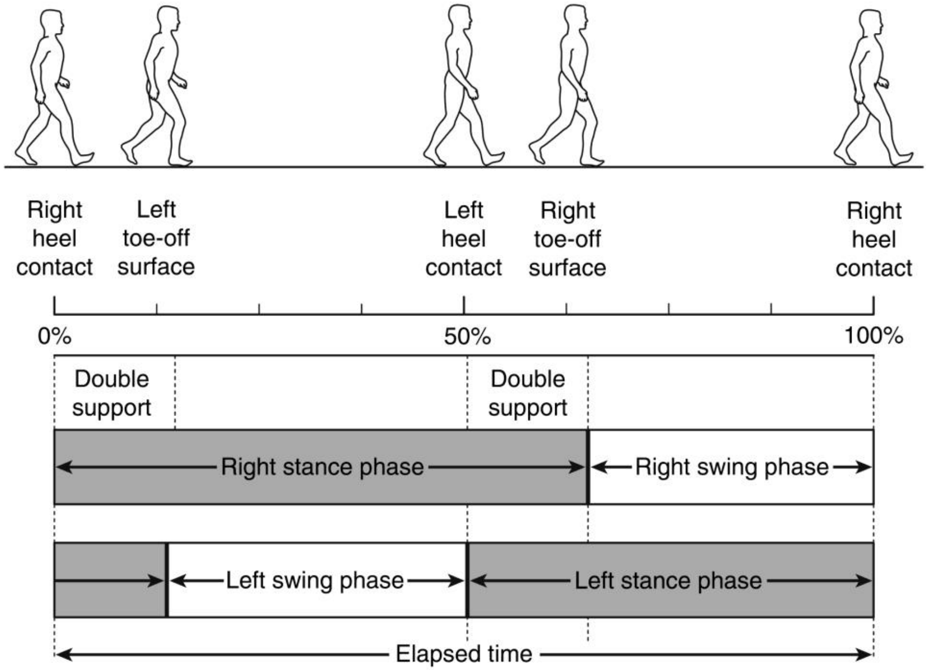
Task Type	#	Task
Motor	1	Eating
	2	Grooming
	3	Bathing
	4	Upper body dressing
	5	Lower body dressing
	6	Toileting
	7	Bladder management
	8	Bowel management
	9	Bed to chair transfer
	10	Toilet transfer
	11	Shower transfer
	12	Locomotion (ambulatory or wheelchair level)
	13	Stairs
Cognitive	14	Cognitive comprehension
	15	Expression
	16	Social interaction
	17	Problem solving
	18	Memory

Medical Record Features

- Patient characteristics
  - Age
  - Gender
  - Rehabilitation impairment category (RIC)
  - Comorbidity tier
  - Case mix group (accounts for medical complications)
- Admission Functional Independence Measure (FIM)
  - Individual tasks
  - Motor aggregate score
  - Cognitive aggregate score

AC Features

- Gait
  - Velocity, cadence, timing, symmetry, smoothness, double support percent, etc.
  - Variability
- Chair transfer
  - Root mean square (RMS) duration, range of motion, etc.
- Vehicle transfer
  - RMS, duration, peak angular velocity, etc.



[Faruqui, 2010]

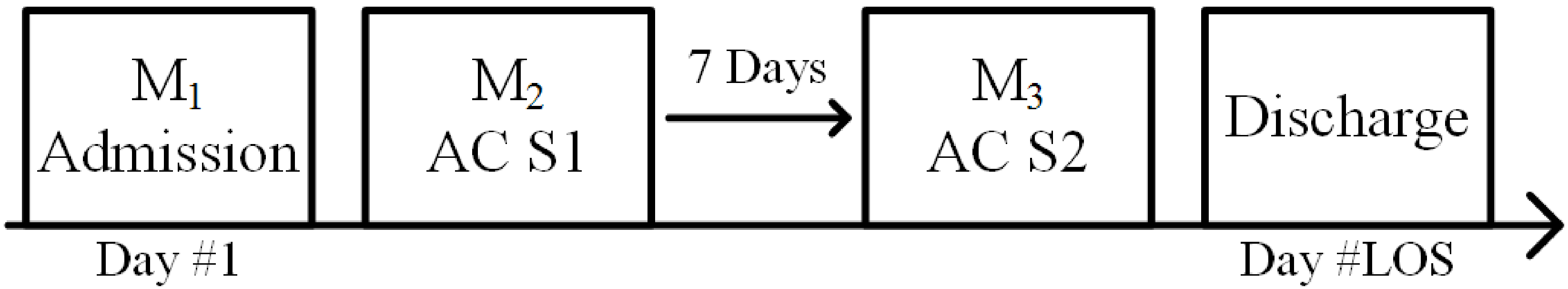
AC Change Features

- Percent change
  - $x_{\Delta\%} = \frac{x_{S2} - x_{S1}}{x_{S1}}$
- Standardized mean difference effect size for repeated measures
  - $d_{RM} = \frac{\bar{X}_{post} - \bar{X}_{pre}}{S_D}$ [Viechtbauer, 2007]
  - $d_{RM} \pm CS * \hat{\sigma}_d^{2\;(L1)}, \hat{\sigma}_d^{2\;(L1)} = \sqrt{\frac{2(1-\hat{\rho})}{n} + \frac{{d_{RM}}^2}{2(n-1)}}$

    [Wolff Smith and Beretvas, 2009]

Supervised Models

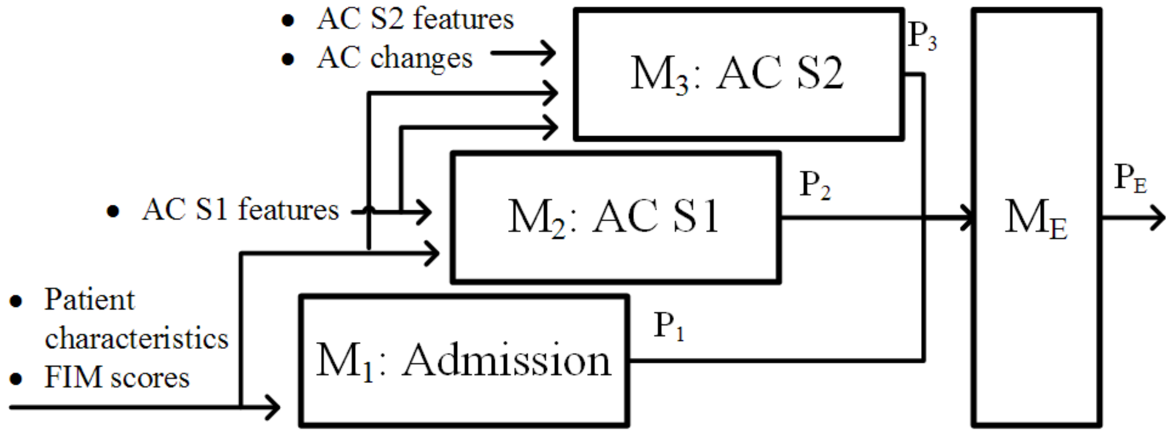
- Train prediction models M_1 (admission), M_2 (AC S1), and M_3 (AC S2)



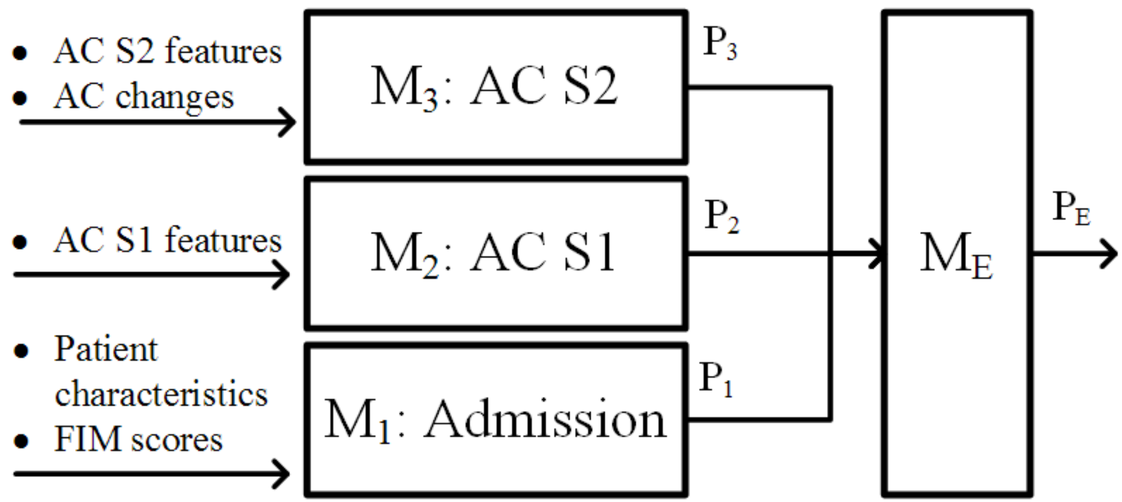
- Linear SVM, linear regression, random forest w/100 trees
- Evaluation
  - Mean absolute error (MAE), root mean squared error (RMSE), normalized RMSE, and correlations

Model Approaches

- Cumulative model construction



- Separate model construction



Discharge FIM Motor Prediction

	Model	Linear SVM RMSE	Linear SVM NRMSE	Linear SVM r	Linear Regression RMSE	Linear Regression NRMSE	Linear Regression r	Random Forest RMSE	Random Forest NRMSE	Random Forest r
M_1	M_1 (w/o NAC)	4.66	11.65%	0.89**	6.07	15.19%	0.87**	8.14	20.36%	0.61**
	M_1	7.36	18.41%	0.82**	7.95	19.87%	0.80**	10.86	27.14%	0.73**
Separate	M_2	8.55	21.38%	0.60*	9.82	24.55%	0.55*	10.18	25.45%	0.25
	M_3	5.54	13.86%	0.85**	5.43	13.57%	0.86**	10.70	26.76%	0.07
	M_{avg}	5.54	13.86%	0.87**	5.27	13.18%	0.89**	8.04	20.09%	0.69**
	M_E	5.50	13.74%	0.84**	5.69	14.22%	0.84**	9.38	23.46%	0.44
Cumulative	M_2	5.49	13.71%	0.85**	5.88	14.69%	0.85**	8.51	21.27%	0.59*
	M_3	2.32	5.80%	0.97**†	2.60	6.50%	0.97**†	9.78	24.46%	0.31
	M_{avg}	4.00	10.01%	0.94**†	4.05	10.12%	0.94**†	7.38	18.46%	0.77**†
	M_E	3.41	8.53%	0.95**†	2.90	7.26%	0.96**†	9.30	23.24%	0.45*

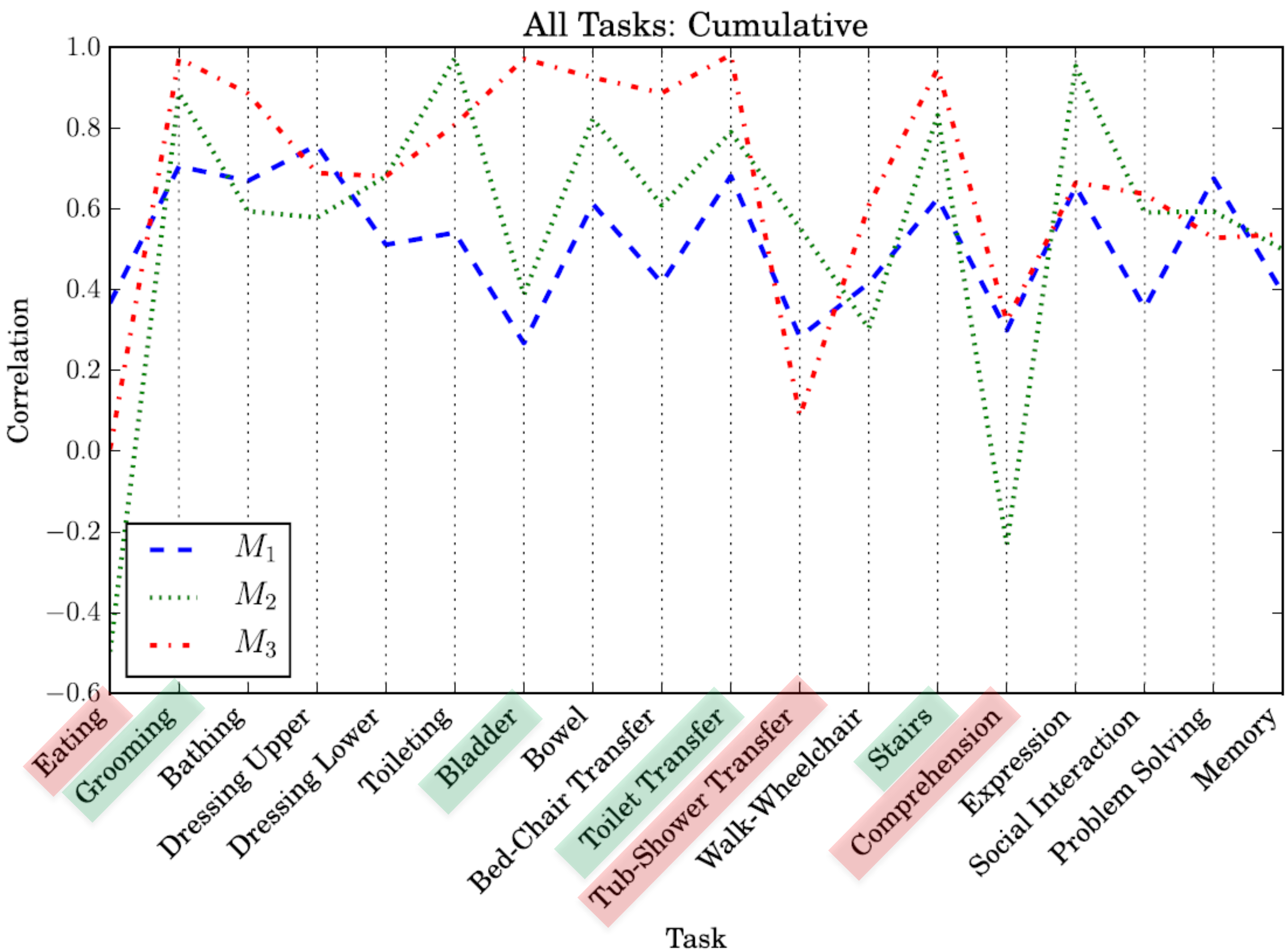
avg = average, E = ensemble, M = model, NAC = non-ambulatory circuit, NRMSE = normalized root mean square error, r = Pearson correlation coefficient, RMSE = root mean square error, SVM = support vector machine, * = $p < 0.05$, ** = $p < 0.01$, † = significantly ($p < 0.05$) improved results from M_1.

Discharge FIM Cognitive Prediction

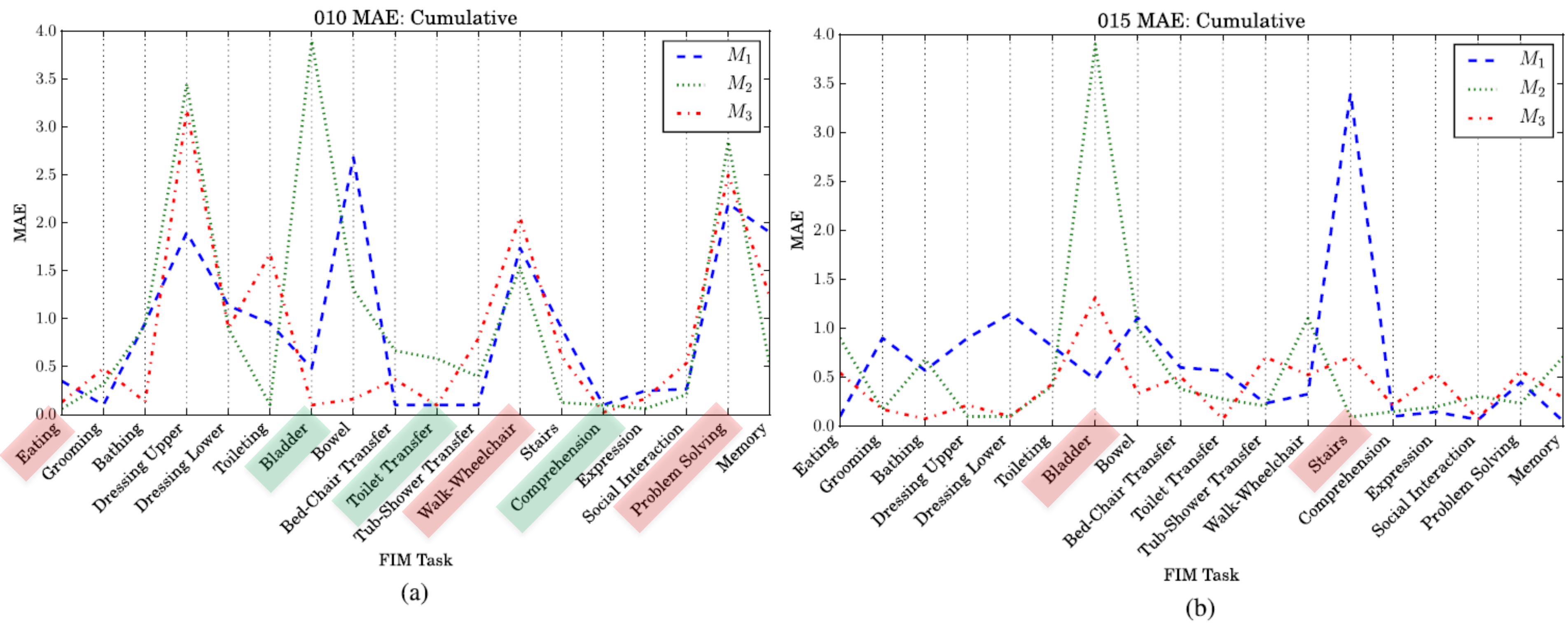
	Model	Linear SVM RMSE	Linear SVM NRMSE	Linear SVM r	Linear Regression RMSE	Linear Regression NRMSE	Linear Regression r	Random Forest RMSE	Random Forest NRMSE	Random Forest r
M_1	M_1 (w/o NAC)	2.42	20.19%	0.70**	2.50	20.86%	0.67**	2.61	21.72%	0.64**
	M_1	2.34	19.49%	0.73**	2.56	21.30%	0.73**	2.36	19.69%	0.73**
Separate	M_2	3.10	25.82%	0.51*	5.50	45.81%	0.17	3.80	31.7%	-0.09
	M_3	3.74	31.17%	-0.34	3.61	30.11%	-0.23	4.15	34.57%	-0.12
	M_{avg}	2.56	21.36%	0.68**	3.06	25.52%	0.45*	2.93	24.40%	0.52*
	M_E	2.66	22.14%	0.64**	3.09	25.77%	0.56*	2.87	23.92%	0.53*
Cumulative	M_2	3.44	28.69%	0.19	3.13	26.08%	0.37*	3.77	31.45%	0.15
	M_3	2.42	20.19%	0.70**	2.50	20.86%	0.67**	2.61	21.72%	0.64**
	M_{avg}	2.40	20.01%	0.73**	2.32	19.34%	0.74**	2.47	20.56%	0.68**
	M_E	2.71	22.59%	0.59*	1.48	12.36%	0.90**†	2.46	20.52%	0.68**

avg = average, E = ensemble, M = model, NAC = non-ambulatory circuit, NRMSE = normalized root mean square error, r = Pearson correlation coefficient, RMSE = root mean square error, SVM = support vector machine, * = $p < 0.05$, ** = $p < 0.01$, † = significantly ($p < 0.05$) improved results from M_1.

Individual FIM Tasks



Individual Patient Prediction



Clinical Utility of FIM Predictions

- 7 Physical therapists interviewed
- 7/7 are interested in using wearable technologies for their patients
- 6/7 said they would make use of FIM predictions for patients mid-stay
  - *"It would be very useful, it could help with discharge planning if we needed to steer one way or another."*

What's Next?

- Increase sample size
  - Enough participants → condition-specific models
  - Investigate the effects of comorbidities
- Mobile app!
  - Online collection, processing, and prediction
- Advanced machine learning techniques
- Adding sensor-based cognitive features

Thank You!

- Questions?
- Connect with me
  - Gina Sprint
  - Computer Science PhD Student
  - Washington State University
  - gsprint@eecs.wsu.edu
  - www.eecs.wsu.edu/~gsprint
- Related publications
  - G. Sprint, D. Cook, D. Weeks, and V. Borisov. *Predicting Functional Independence Measure Scores During Rehabilitation with Wearable Inertial Sensors*. IEEE Access, 2015.
  - G. Sprint, D. Cook, and D. Weeks. *Towards Automating Clinical Assessments: A Survey of the Timed Up and Go (TUG)*. IEEE Reviews in Biomedical Engineering, 2015.
  - G. Sprint, V. Borisov, D. Cook, and D. Weeks. *Wearable Sensors in Ecological Rehabilitation Environments*. ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication, 2014.

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