Traumatic Brain Injury in Older adults: Fall Risk Assessment

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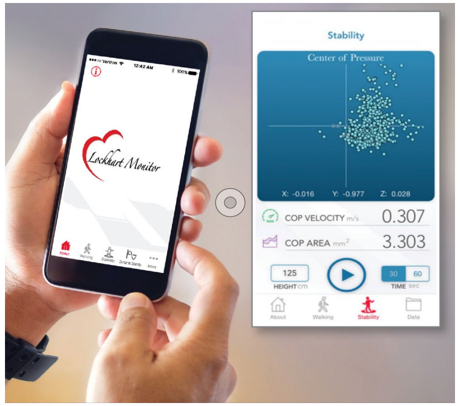

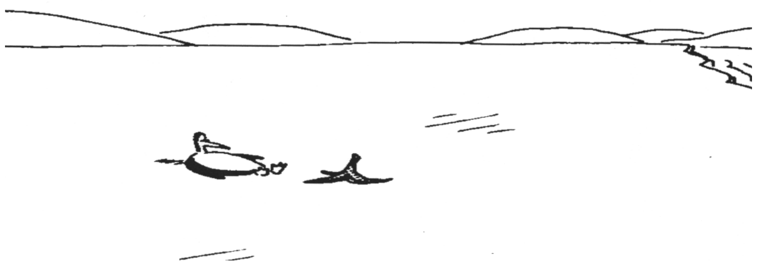

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LOCOMOTION LABORATORY

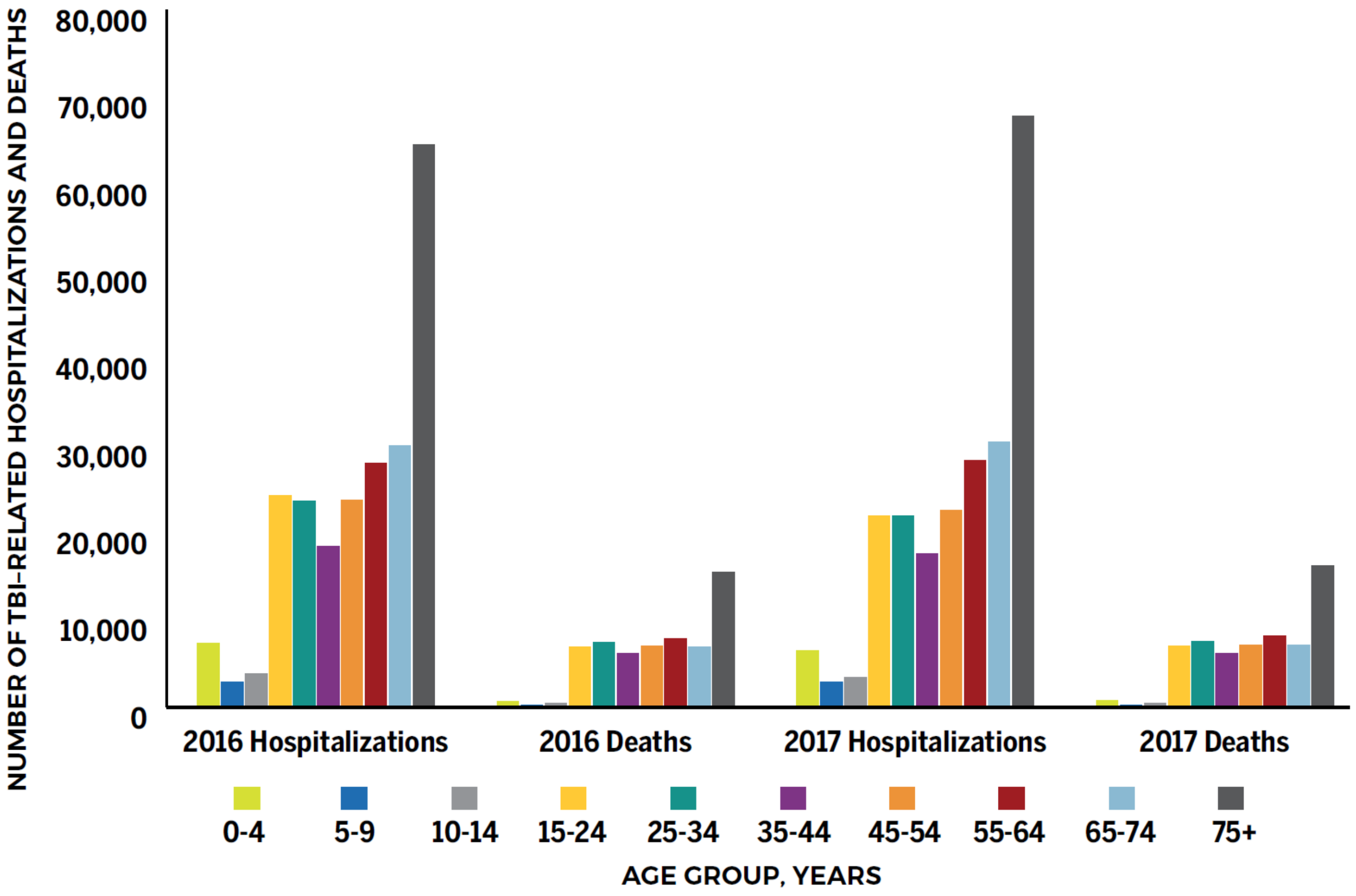
- Introduction
  - Problems Associated with Fall in the Elderly and TBI
  - Current Approaches to Reducing Fall Accidents
- Research
  - Mechanisms Related to Fall Accidents in the Elderly
  - Wearable Fall Risk Assessment Tool development using nonlinear dynamics and theory of Chaos
- Outreach
- Discussions
- Future Research

Traumatic Brain Injuries in the USA – Older Adults

TBI and Age Group

- **Traumatic brain injuries (TBIs) are a leading cause of morbidity and mortality in the US.**
- **in 2017, adults aged 65 years or older accounted for 38.4% of all TBI-related deaths and 43.9% of all TBI-related hospitalizations in the US**
- **Aged 75 years or older accounted for majority of all TBI-related deaths and hospitalizations in the US.**

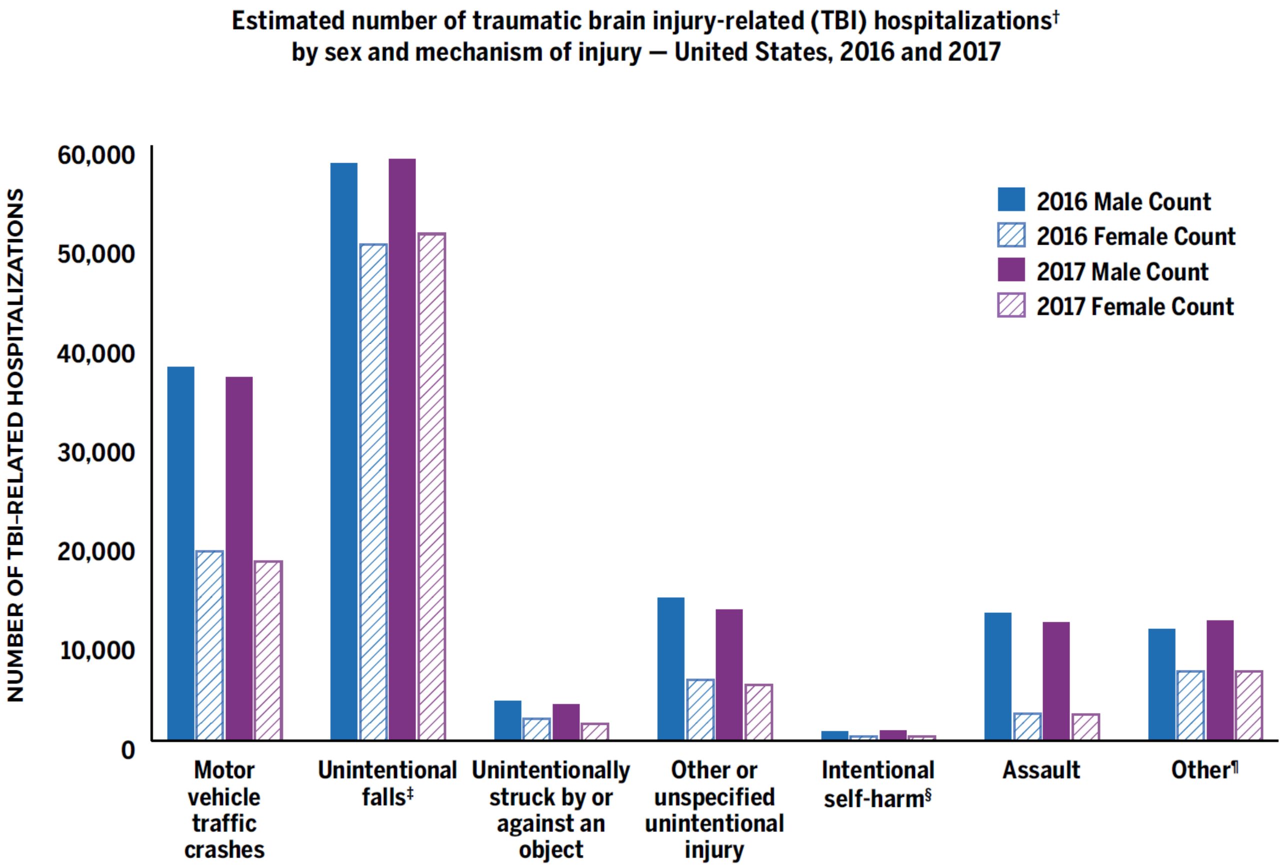
Estimated number of traumatic brain injury-related (TBI) hospitalizations† and deaths by age group — United States, 2016 and 2017



SOURCES: For hospitalizations, Healthcare Cost and Utilization Project's National Inpatient Sample; for deaths, CDC's National Vital Statistics System. TBI-surveillance-report-2016-2017, www.CDC.gov

Cause of TBI – *“Falls”*

- The majority (64.2%) of TBI were as a result of a fall on the same level from slipping, tripping or stumbling.



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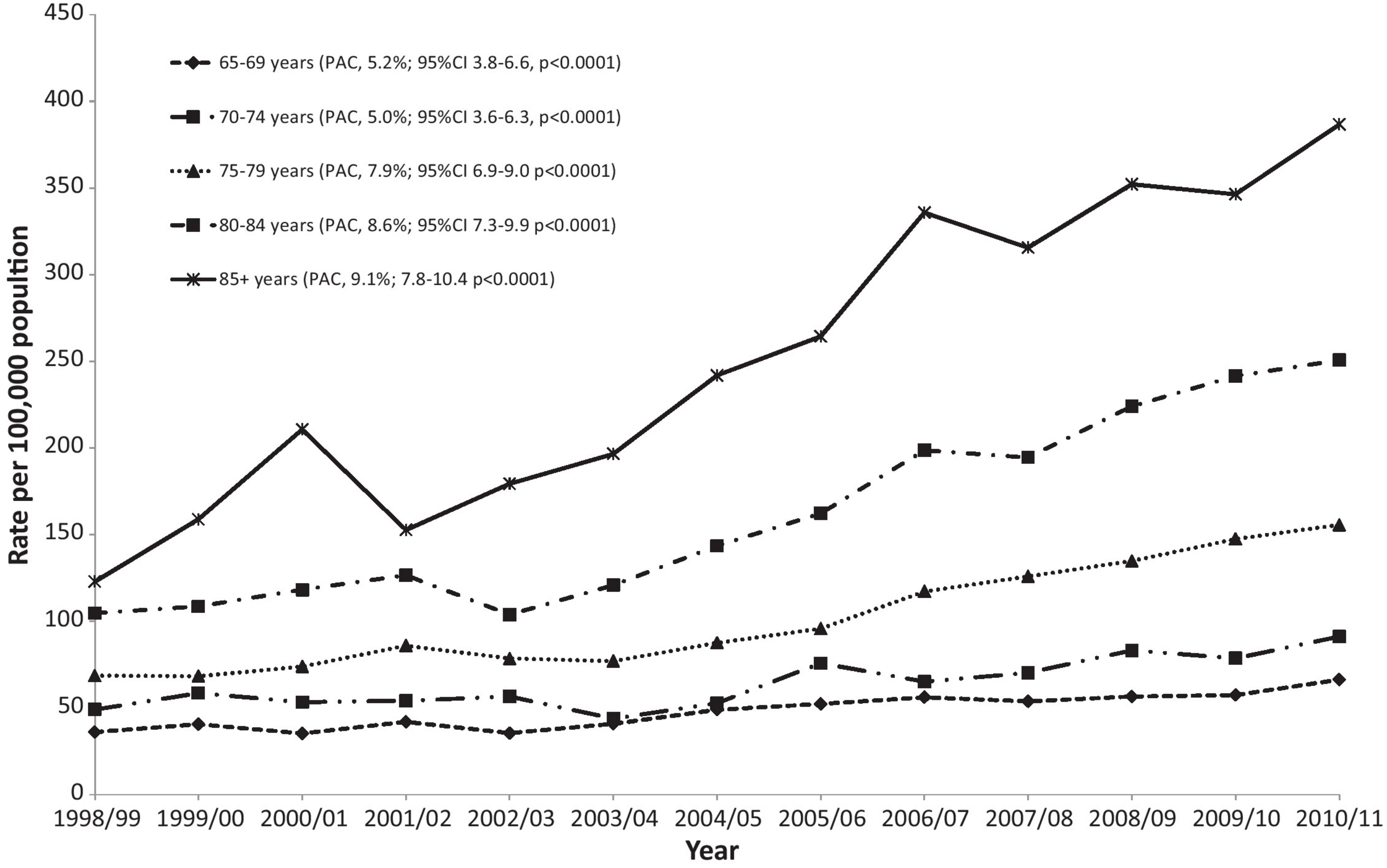
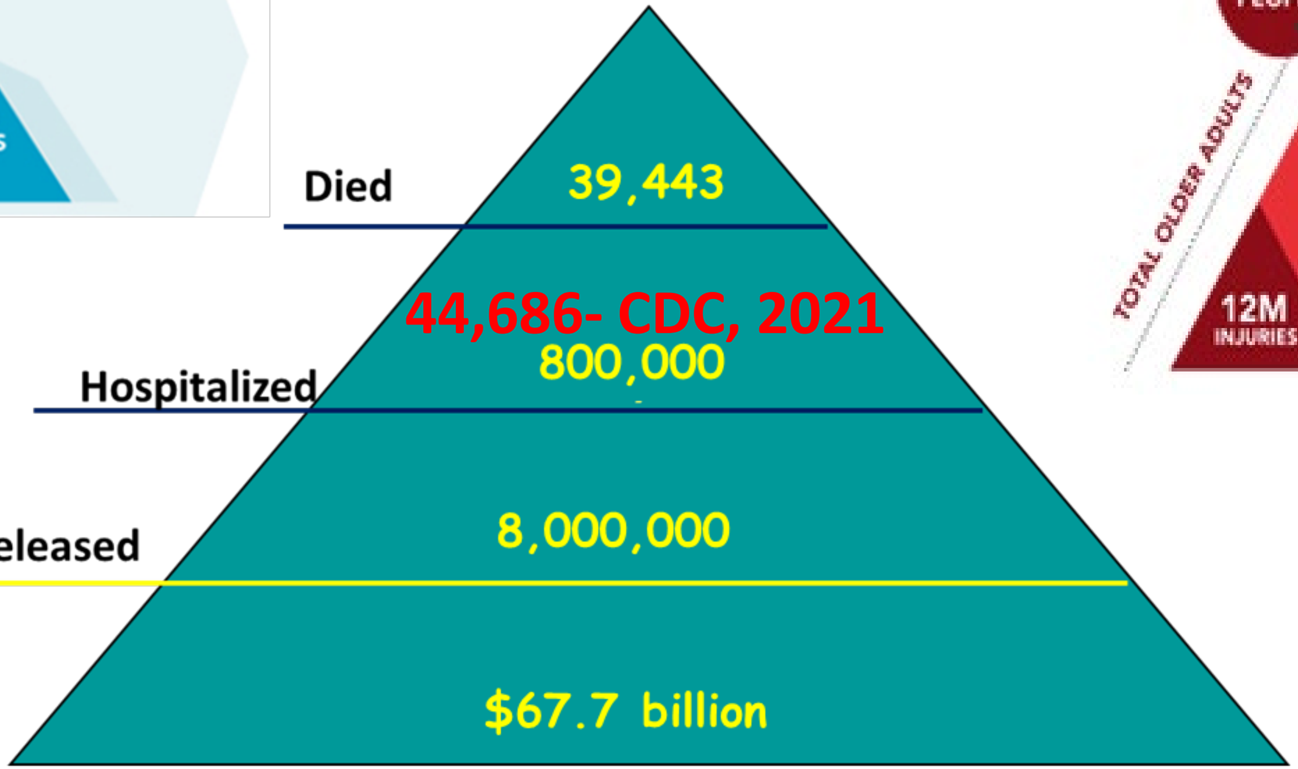
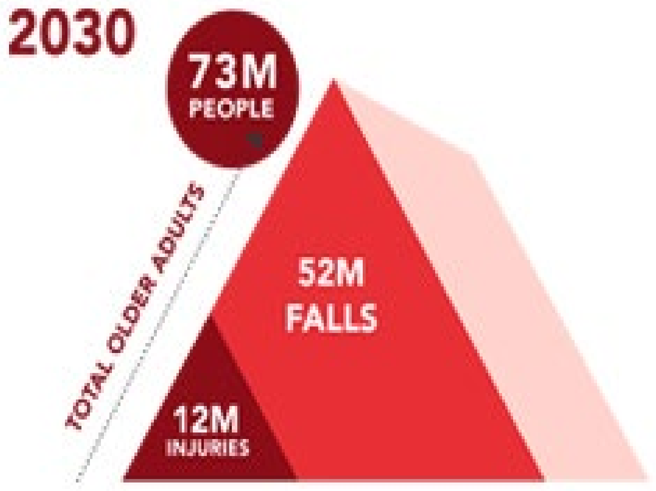
Increases in Traumatic Brain Injuries in the USA – Older Adults



Lara A. Harvey, Jacqueline C.T. Close, Traumatic brain injury in older adults: characteristics, causes and consequences, Injury, Volume 43, Issue 11, 2012, Pages 1821-1826, ISSN 0020-1383, https://doi.org/10.1016/j.injury.2012.07.188.

Falls the USA – Older Adults





Fatal and Nonfatal Fall Injuries in 2019 (CDC)

Quality of Life

20% - 36% fear falling[1]

20% die within a year after hip fracture[2]

25% in a nursing home one year later[3]

1. Vellas BJ, *Age & Aging*, 1997; Friedman SM, *JAGS*, 2002
2. Lu-Yao GL, *AJPH*, 1994
3. Magaziner, *J Gerontology: Medical Sciences*, 2000

Current Fall Interventions

Fall Protection

Fall Prevention

Personal Protective Equipment (e.g. hip pads, helmets, fall arresting harness)

BRAIN

Nutrition, cholinomimetic agent, neuro-technologies

Environmental control (e.g. COF)

Fall Risk Assessments, Training interventions (strength, endurance, balance)

How do we measure fall risk?

Fall Risk Assessment

Fall risk assessment tools have been used to provide an early detection of fall related risks to prevent falling episodes

Several assessment tools for fall risk evaluation can be divided into three categories:

- Comprehensive medical assessment
- Institutional assessment – Mores fall scale, STRATIFY, etc.
- Functional assessment – Berg balance test, timed get-up and go, etc.

- History of falling is also a good indicator of fall proneness, however, after incurring an injury.

Fall Risk Assessment

Fall risk assessment tools have been used to provide an <u>early detection</u> of fall related risks to prevent falling episodes

Morse Fall Scale

(Adapted with permission, SAGE Publications)

The Morse Fall Scale (MFS) is a rapid and simple method of assessing a patient's likelihood of falling. A large majority of nurses (82.9%) rate the scale as "quick and easy to use," and 54% estimated that it took less than 3 minutes to rate a patient. It consists of six variables that are quick and easy to score, and it has been shown to have predictive validity and interrater reliability. The MFS is used widely in acute care settings, both in the hospital and long term care inpatient settings.

Item	***Scale***	***Scoring***
1. History of falling; immediate or within 3 months	No 0 Yes 25	25
2. Secondary diagnosis	No 0 Yes 15	0
3. Ambulatory aid Bed rest/nurse assist Crutches/cane/walker Furniture	 0 15 30	15
4. IV/Heparin Lock	No 0 Yes 20	20
5. Gait/Transferring Normal/bedrest/immobile Weak Impaired	 0 10 20	10
6. Mental status Oriented to own ability Forgets limitations	 0 15	15

The items in the scale are scored as follows:

History of falling: This is scored as 25 if the patient has fallen during the present hospital admission or if there was an immediate history of physiological falls, such as from seizures or an impaired gait prior to admission. If the patient has not fallen, this is scored 0. Note: If a patient falls for the first time, then his or her score immediately increases by 25.

Secondary diagnosis: This is scored as 15 if more than one medical diagnosis is listed on the patient's chart; if not, score 0.

Ambulatory aids: This is scored as 0 if the patient walks without a walking aid (even if assisted by a nurse), uses a wheelchair, or is on a bed rest and does not get out of bed at all. If the patient uses crutches, a cane, or a walker, this item scores 15; if the patient ambulates clutching onto the furniture for support, score this item 30.

Intravenous therapy: This is scored as 20 if the patient has an intravenous apparatus or a heparin lock inserted; if not, score 0.

Risk level	**MFS score**	**Action**
No risk	0-24	Good basic nursing care
Low risk	25-50	Implement standard fall prevention interventions
High risk	≥51	Implement high-risk fall prevention interventions

MFS: Morse Fall Scale

Morse Fall Risk/Scale

Item	Scale	Scoring
1. History of falling, immediate or within 3 mo	No 0 Yes 25	
2. Secondary diagnosis	No 0 Yes 15	
3. Ambulatory aid Bed rest/nurse assist Crutches/cane/walker Furniture	 0 15 30	
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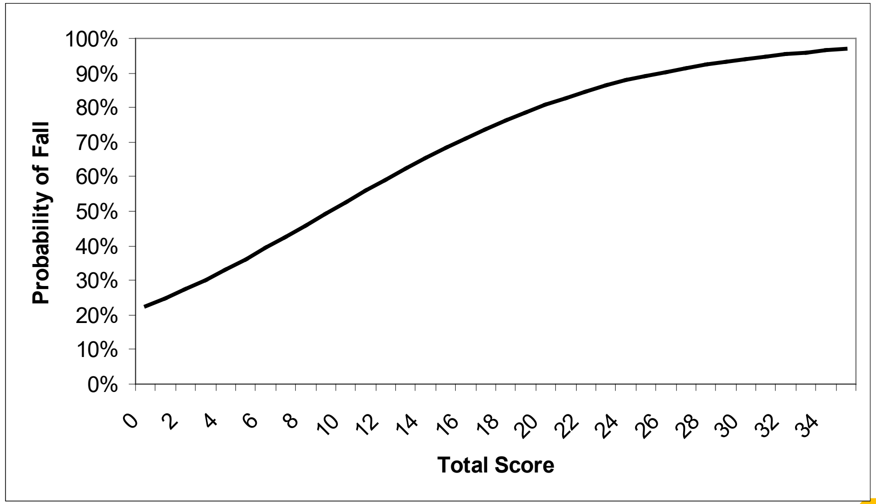
6. Mental status Oriented to own ability Forgets limitations	 0 15	

Current Fall Risk Assessment tool Problems and Needs

- Does not provide the cause(s) of one's fall risk (e.g., is it due to gait - balance?) - as the interventions can selectively target those weakness.
- Invasive, and Expensive
- Low prediction rates with 50% sensitivity and 43% specificity



Specific Aims

Study Objective:

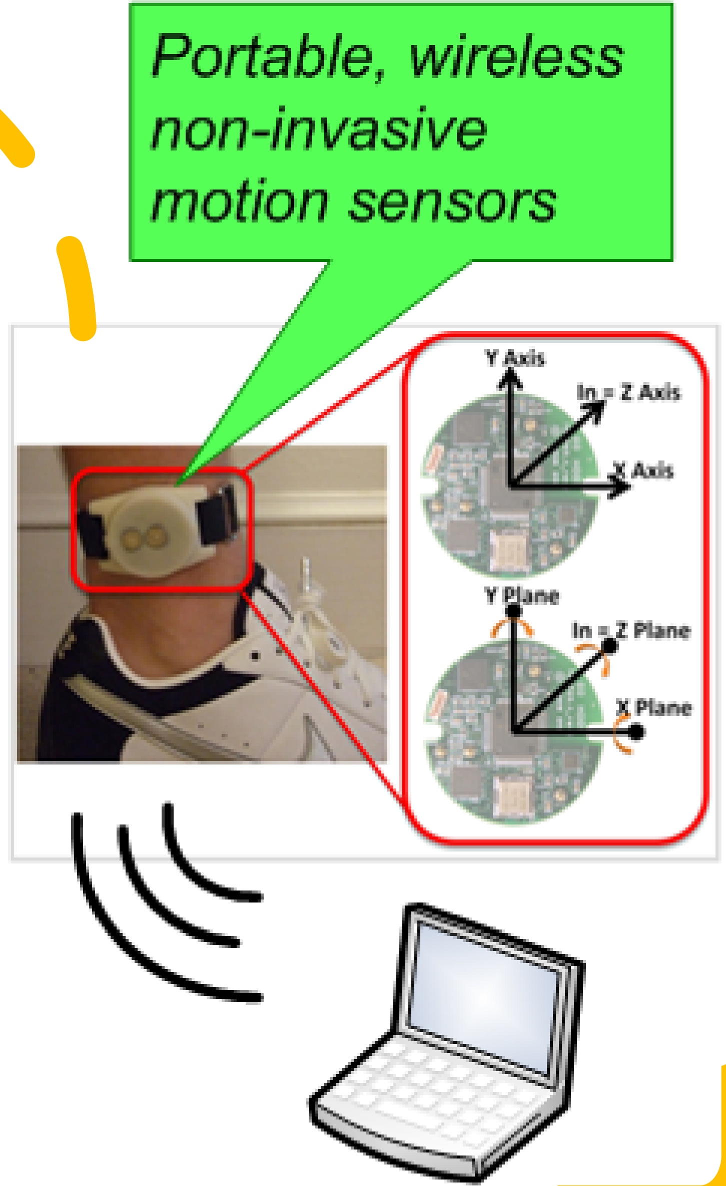
- To characterize fall risk of older adults
- Using the Portable Wireless System by monitoring functional and mobility characteristics

Central Tenet:

- Fall risk will be significantly higher for fall-prone elderly than their counterparts

Relevance:

- **Accurate fall risk assessment will allow us to help pinpoint and intervene early prior to falling episodes.**
- Portability and usability of fall risk assessment Technology



NSF (grant #CBET-0756058) and NSF-Information and Intelligent Systems (IIS) and Smart Connected Health-1065442 and 1065262.

Why do Older Adults Fall More than Younger Adults?

Factors Influencing Slips and Falls
(Intrinsic Changes Associated with Aging)

1. Sensory Degradation.
2. Cognitive Impairment.
3. Muscle Weakness.
4. Gait Adaptation.

More importantly, extrinsic environmental factors and how those factors interact with intrinsic conditions must be considered.

What is the relationship between these risk factors and fall accidents in the elderly?

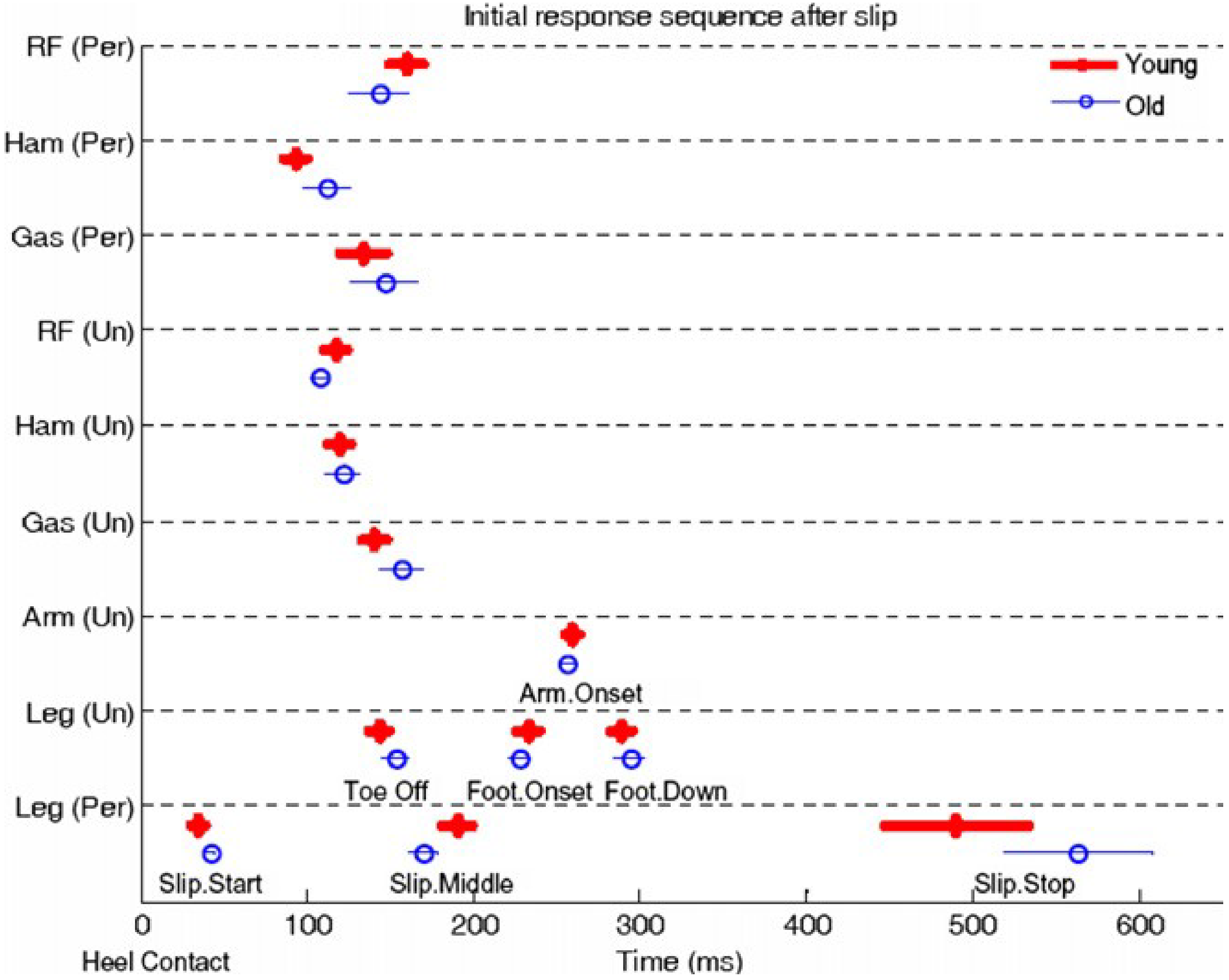
And, how can we use this info to assess Fall Risk.

Experiments: Slips trips and falls

Who fell and who recovered?

Experiments: Slips trips and falls

Bottom Line from the Balance Perturbation Studies



Summary of Gait Study Results

Spatial and temporal gait changes - fallers exhibited slower gait speed and shorter step length

Reactive Recovery Phase was very important for the elderly and related to sensory degradation.

Control systems exhibited a finite time delay between the moment a stimulus was provided (i.e., perturbation) and the moment the system returned a response (i.e., nothing happens instantaneously).

In many situations : the responses also depended nonlinearly on the input, such that the evolution of the system in the present depended sensitively on its state in the past (e.g., muscle fatigue).

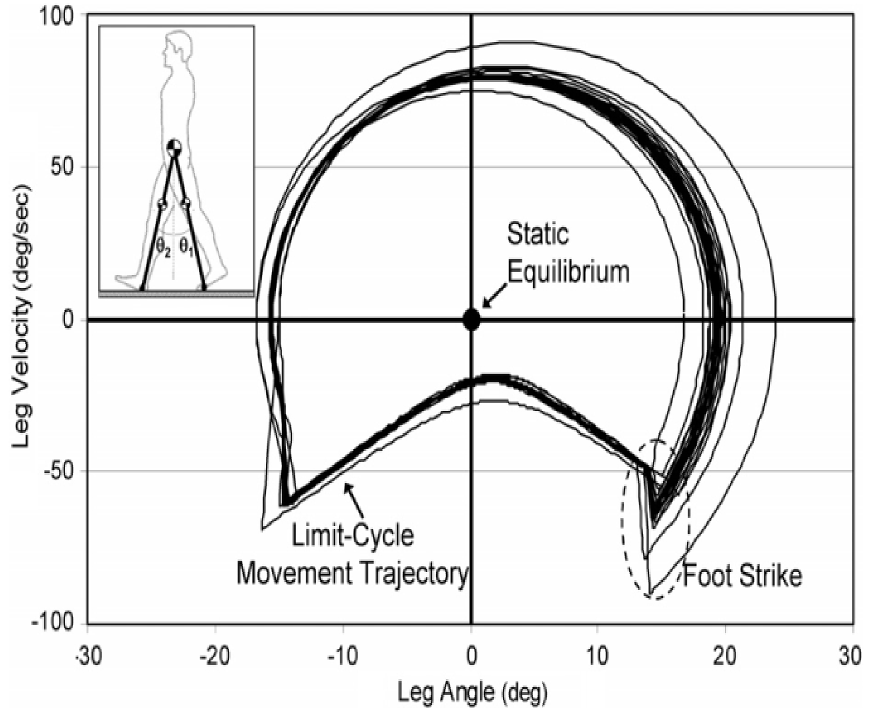
This nonlinear time-delay systems (autonomic motor control) can be quantified by nonlinear dynamics - stability assessments.

Stability Assessment and TEMPORAL VARIABILITIES

Regardless of how advance the device is, it is used to measure simple qualities – like – means- SD- variances etc.

However, due to the **TEMPORAL VARIABILITIES** (varied locations), the system dynamics may not be measured at the right time or can only describe an instant of time (e.g., at the Heel strike time point).

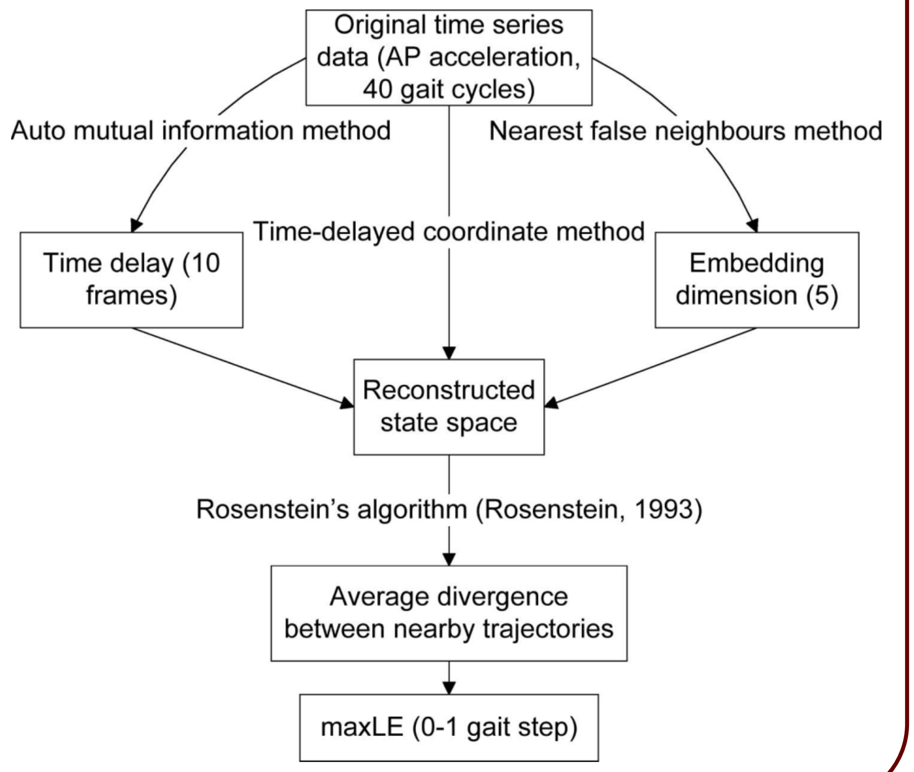
As such, temporal variation is not noticed in these measures which can be used to understand patterns and controls that exhibit these variations in time.

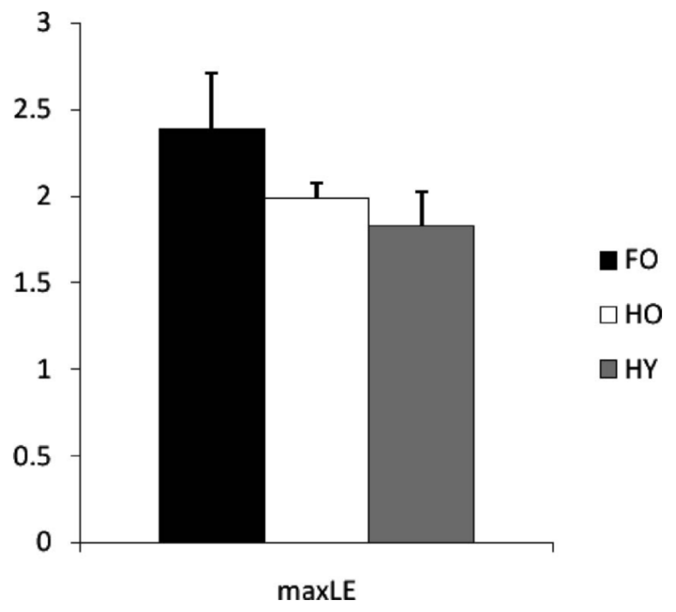


Nonlinear dynamical tools can be used

Dynamic Stability: Lyapunov Exponent (Chaos)

Stability Analysis: Overview





Maximum Lyapunov exponent (maxLE) by group. FO = fall-prone old; HO = healthy old; HY = healthy young (Lockhart and Liu, 2008)

Multi-Scale Entropy: BioComplexity (Nonlinear dynamics)

Age-related loss of complexity

Fig 3.—Age-related loss of fractal structure in the dendritic arbor of the giant pyramidal Betz cell of the mo-

Overly structured, stable, unchanging patterns suggest control processes are rigid and may not adapt to change or perturbation.

Age-related loss of fractal structure in the dendritic arbor of the giant pyramidal Betz cell of the motor cortex. Left, The complex, branching, fractal-like architecture of the dendritic arbor in a young adult man. Right, **suggestion of the loss of "complexity"** (fractal dimensionality) in the structure of the dendritic arbor in a 65-year-old man (reprinted with permission from WB Saunders Co28).

Approximate Entropy: Complexity

ApEn quantifies regularity and complexity of a system (Pincus, 1994)

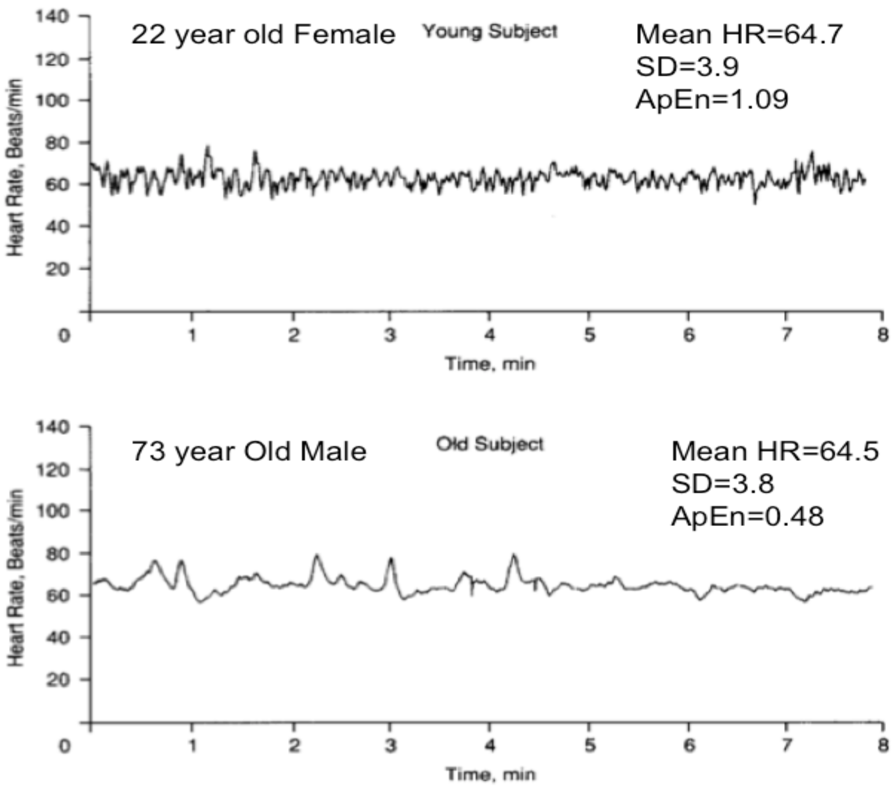
Approximate Entropy: It is the logarithmic likelihood that the patterns of the data are close to each other and will not remain close for the next comparison within a longer pattern.

- High ApEn values indicate unpredictability and random variation
- Low ApEn indicates high predictability and regularity of time series data

If S_N is a time series of length N

$$ApEn(N, m, d) = (N - m + 1)^{-1} \sum_{i=1}^{N-(m-1)} lnC_i^m(d) - (N - m)^{-1} \sum_{i=1}^{N-m} lnC_i^{m+1}(d)$$

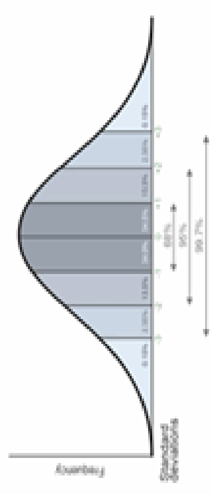
Where m is the pattern length (usually chosen as 2) and d is similarity coefficient (chosen as 0.2 % of SD of time series)

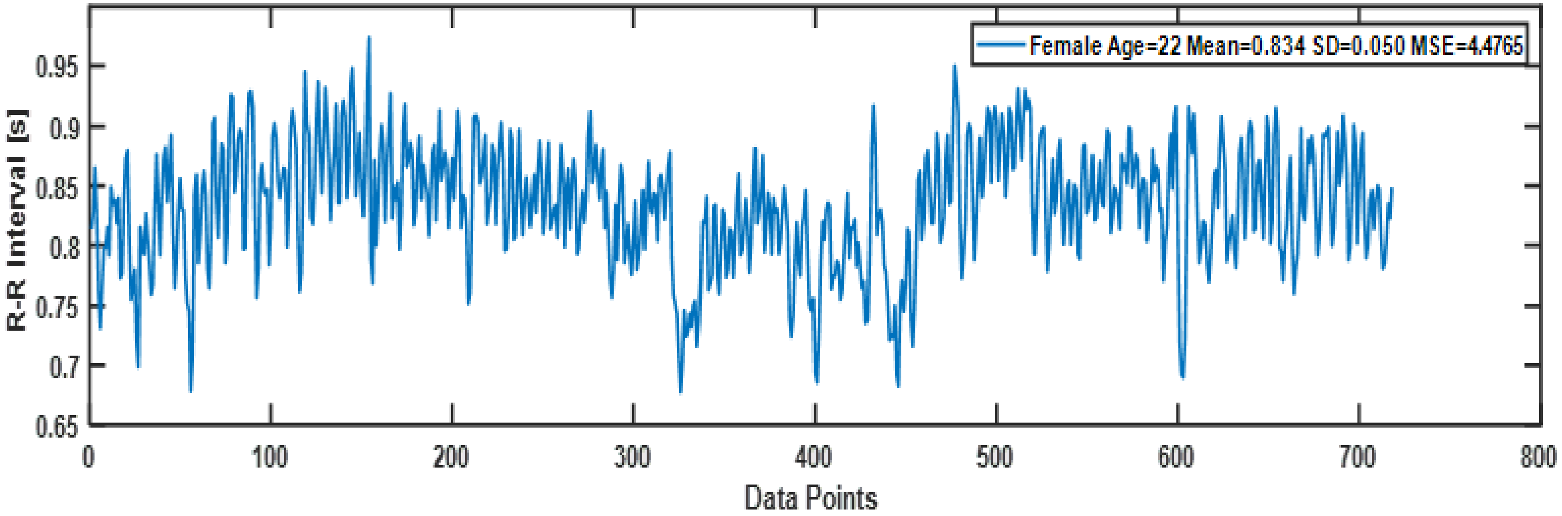


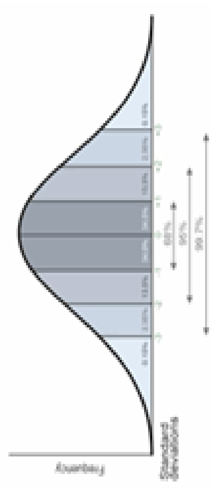
Heart rate signals of old and young participant.

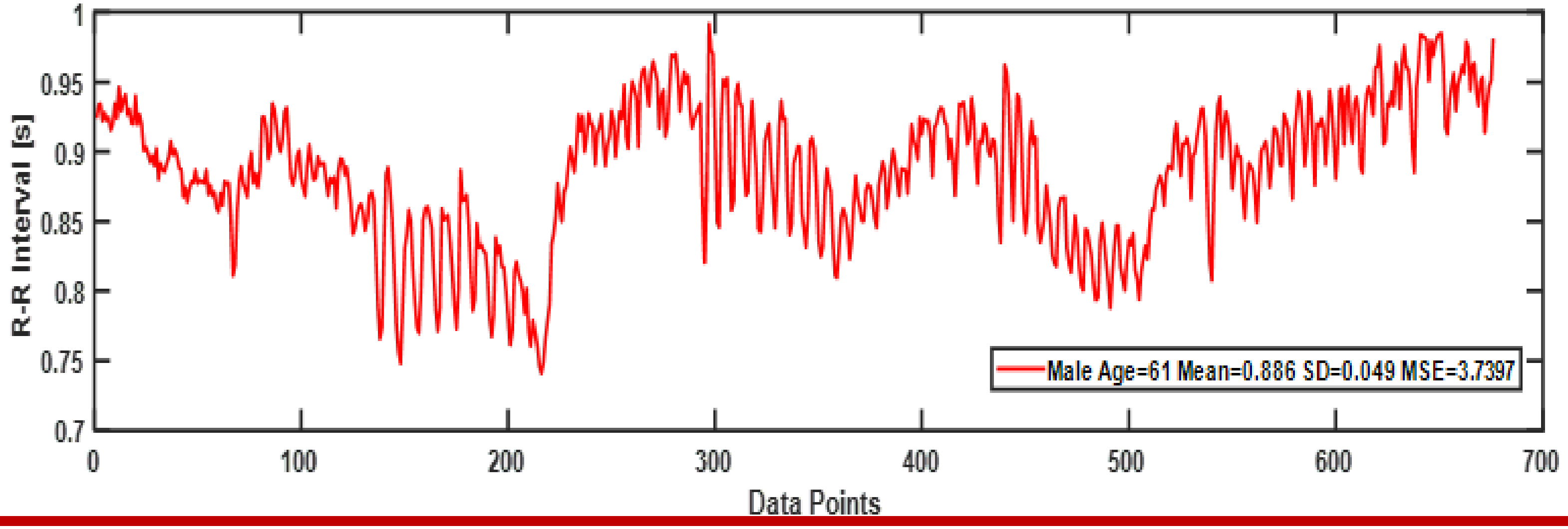
Adapted from Lipsitz and Goldberger, 1992

Multiscale Entropy shows aging effect









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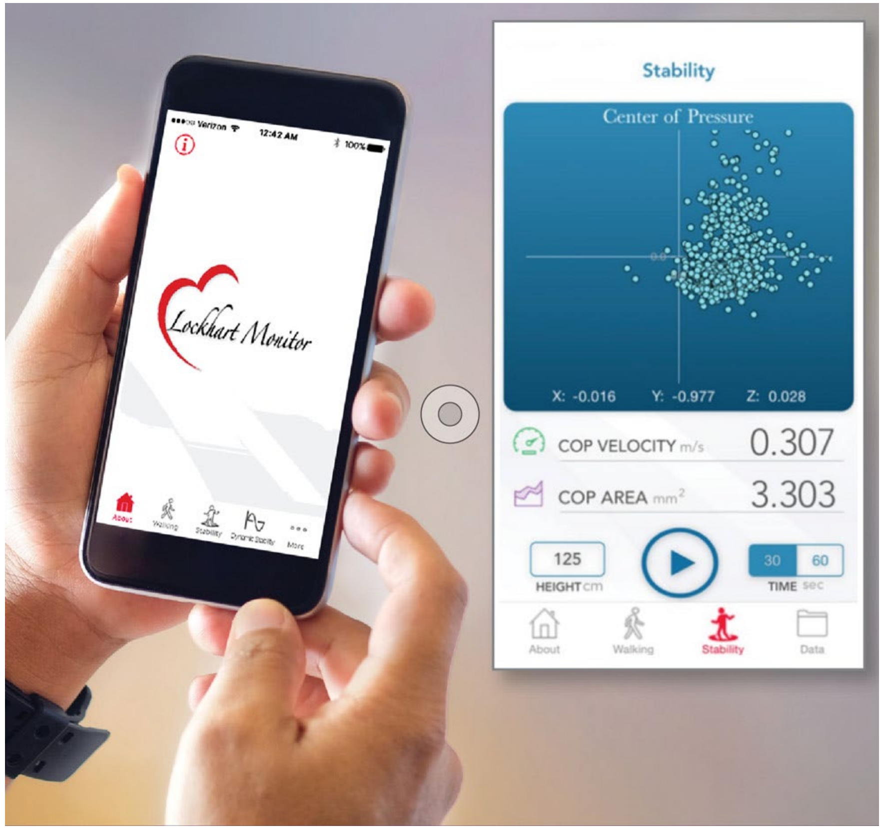
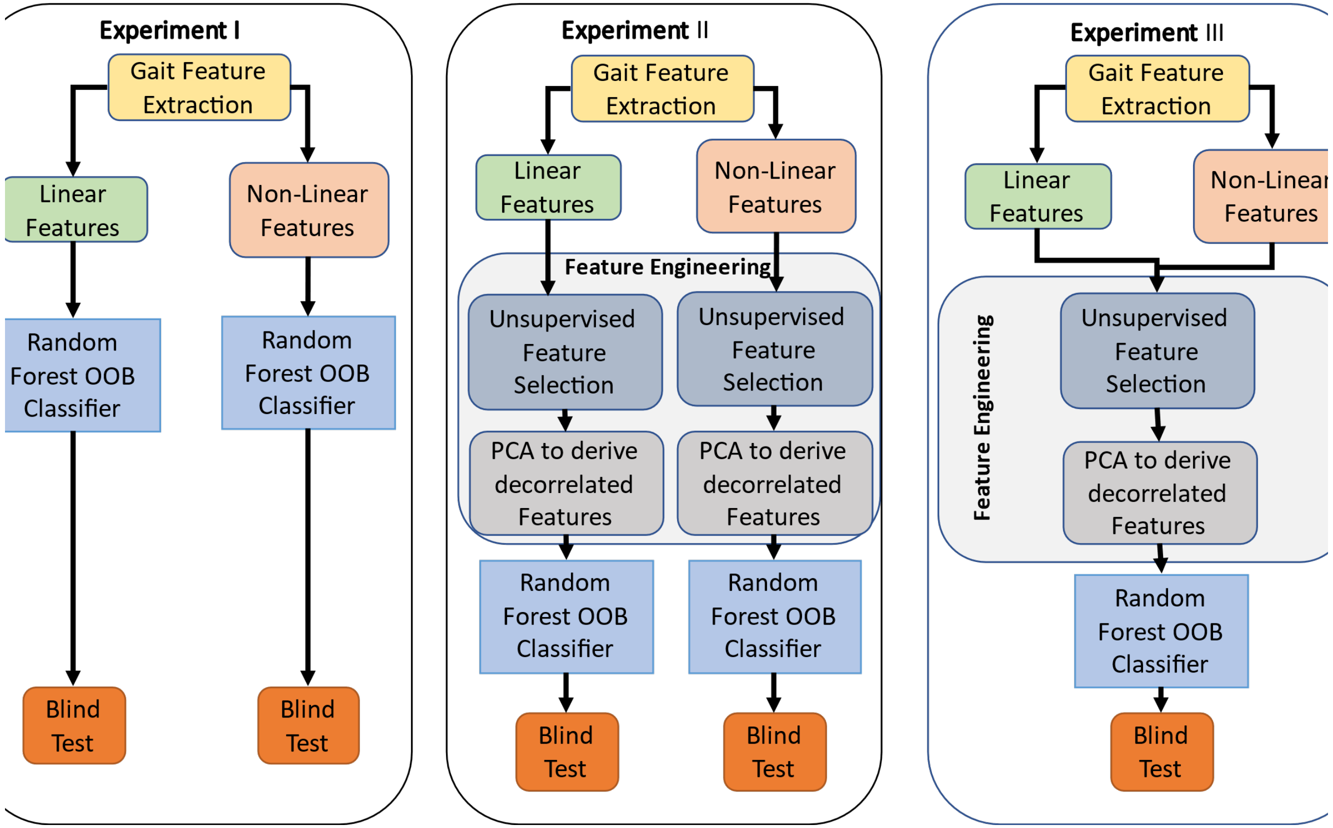
Fall Risk Prediction

- Lockhart, T., Soangra, R., Yoon, H., Wu, T., Frames, C., Weaver, R., and Roberto, K., (2021). Prediction of Fall Risk Among Community-Dwelling Older Adults Using a Wearable System. *Scientific Reports* 11, 20976.https://doi.org/10.1038/s41598-021-00458-5





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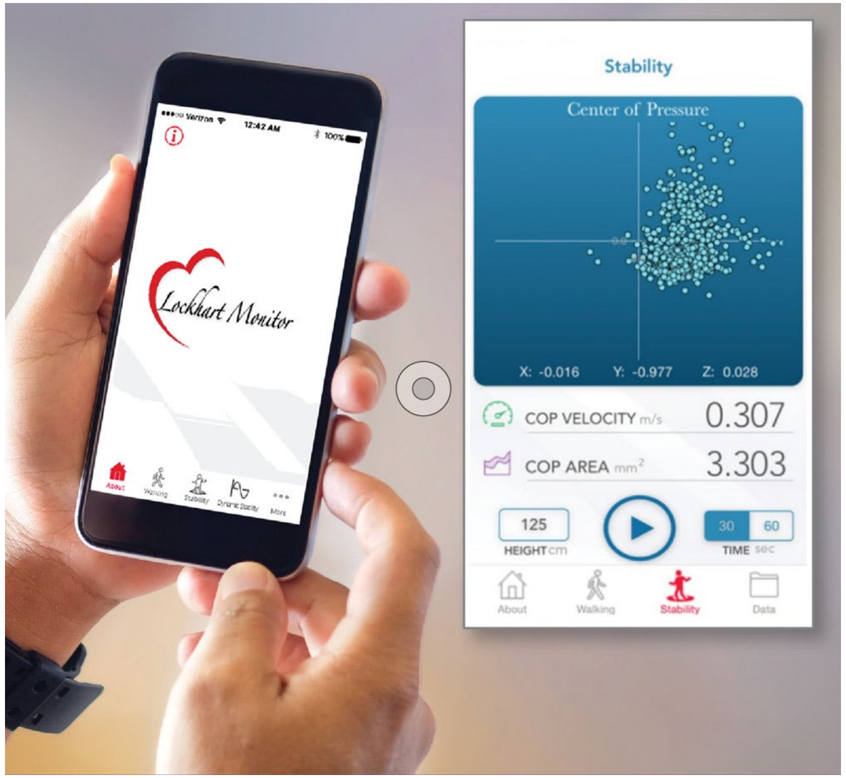
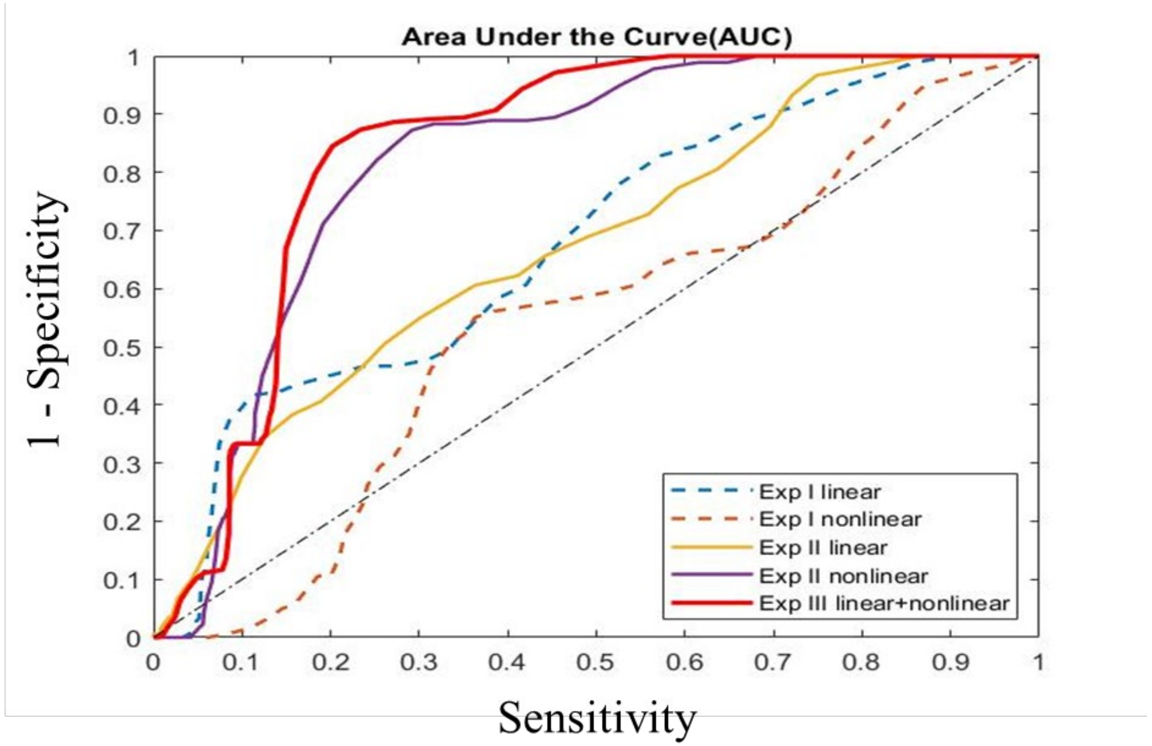
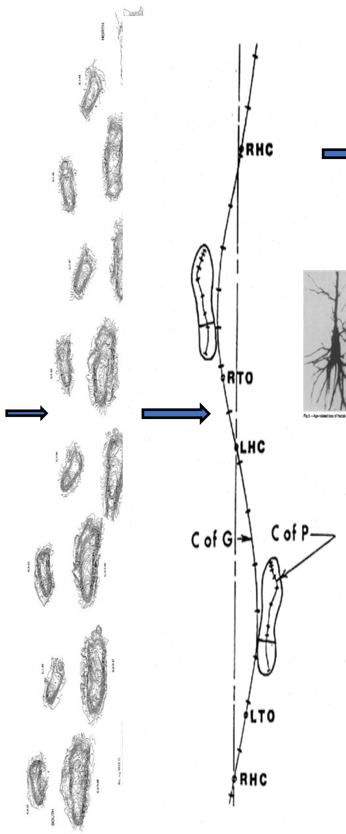
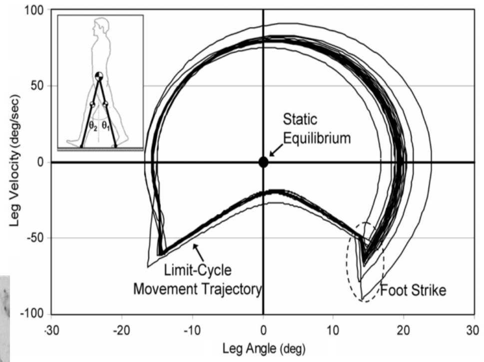
- Doshi, K.B., Moon, S.H., Whitaker, M.D. and, Lockhart T.E.. Assessment of gait and posture characteristics using a smartphone wearable system for persons with osteoporosis with and without falls. *Sci Rep* **13**, 538 (2023). https://doi.org/10.1038/s41598-023-27788-w

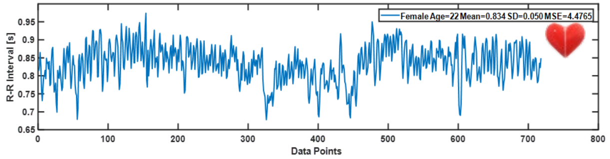


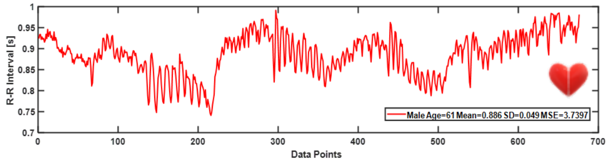


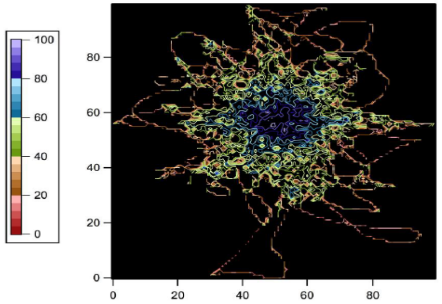
“Research to Practice”

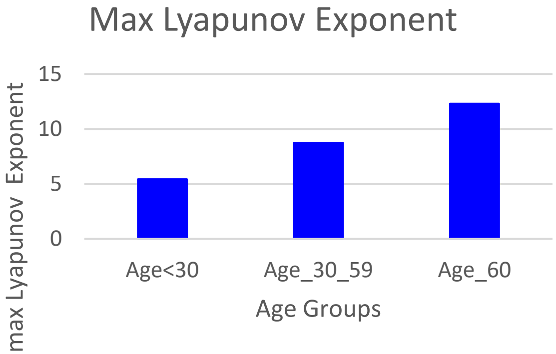


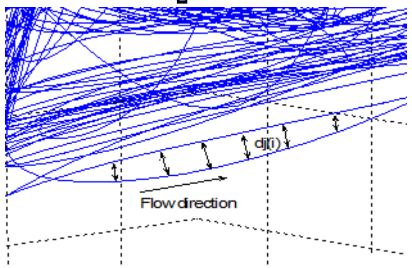


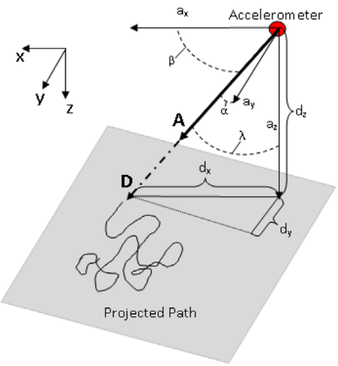


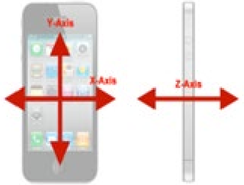












Following the arrows –
“research to reality”

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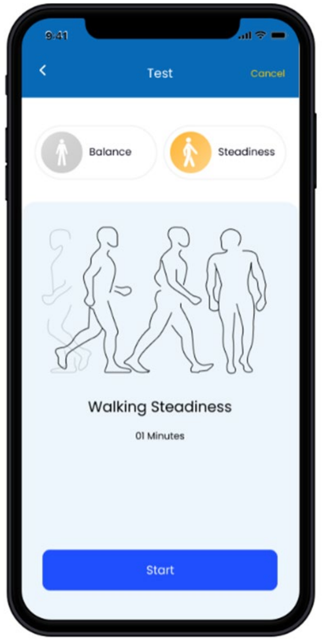

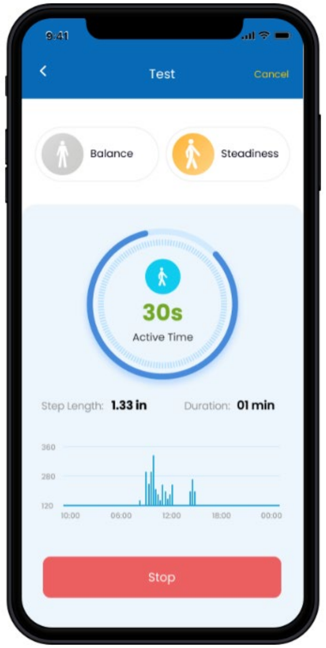

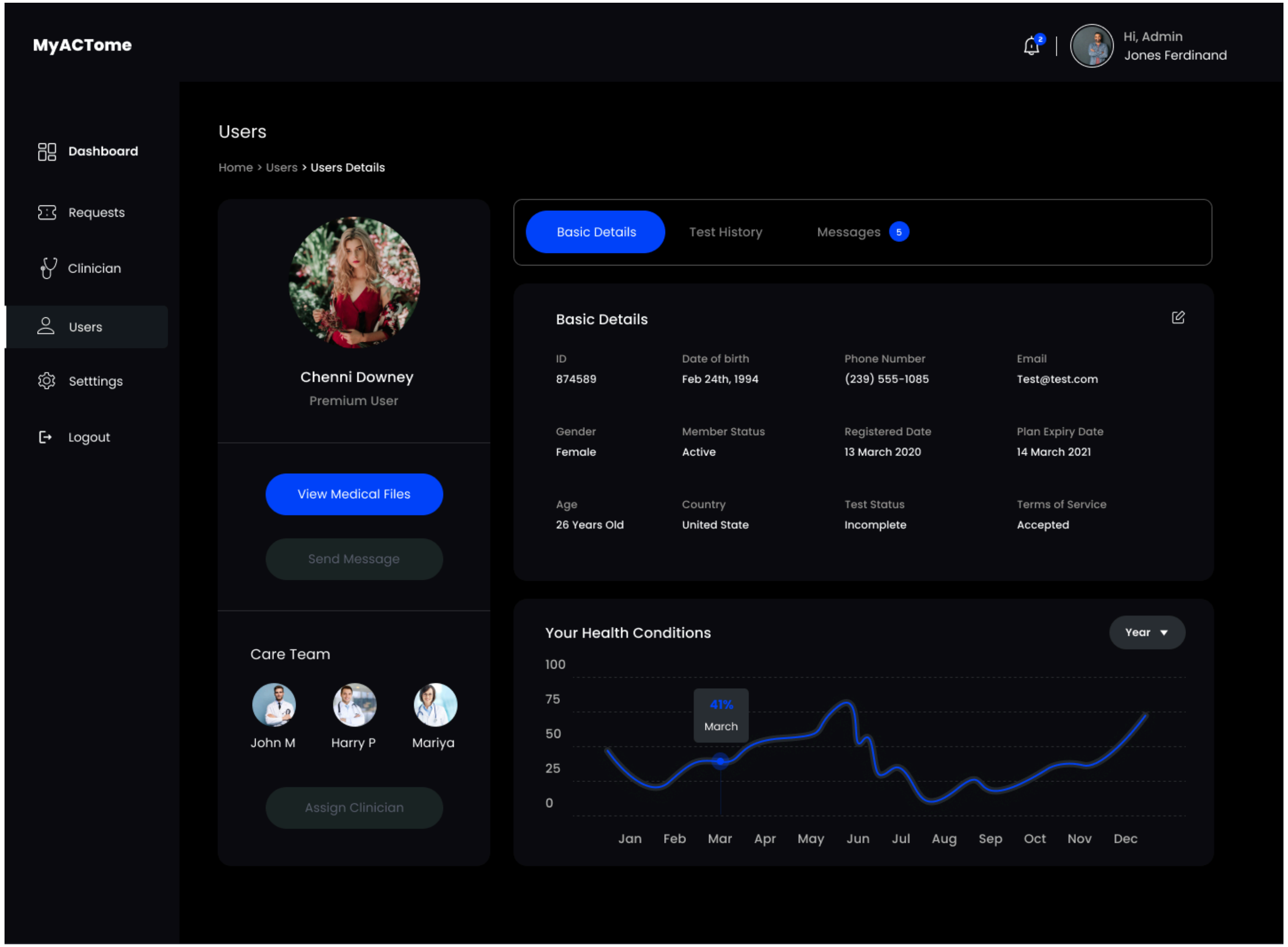

Parameter	Pre-Sx	6-Wk	P-Value
Dynamic Stability	0.547	0.514	**0.0475***
SwayArea_EO	2.73811	1.85674	0.0776
SwayArea_EC	3.87832	3.64742	0.4238
TUG Time	14.5909	12.5995	**0.0243***
SitToStand Time	2.25842	1.92	**0.0321***
Turn Velocity	2.12105	2.163	0.5983

https://www.myactome.com/

HOPCo Announces Acquisition of Digital Health Platform, MyACTome

The latest addition to HOPCo's integrated digital health portfolio will improve patient outcomes and greatly reduce healthcare costs through AI

Phoenix, AZ (December 6, 2023) – HOPCo (Healthcare Outcomes Performance Company), the leader in musculoskeletal (MSK) clinical outcomes management solutions and the country's largest orthopedic value-based care organization, continues its digital health platform expansion with its acquisition of MyACTome.

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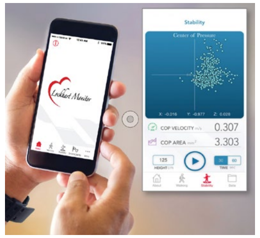
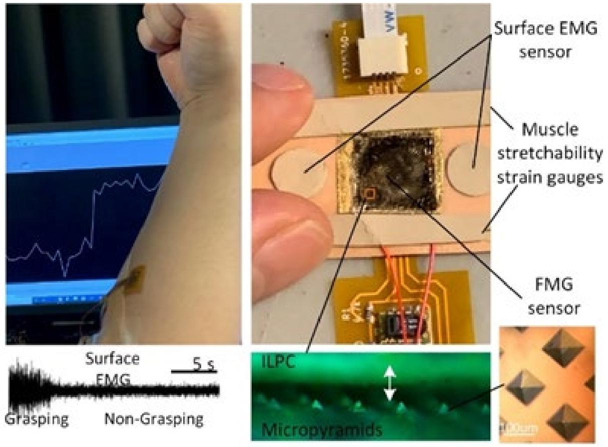
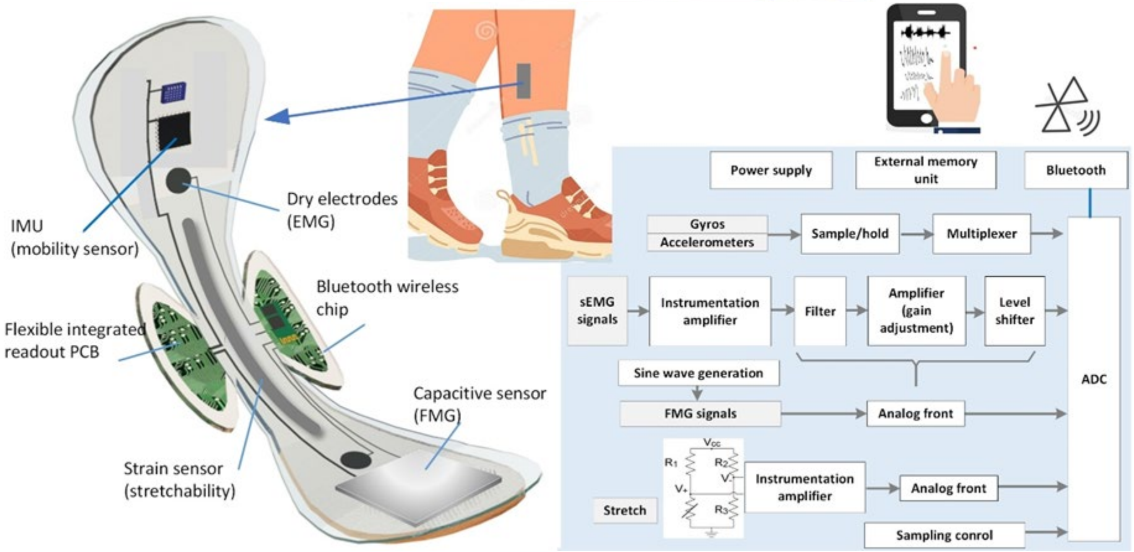
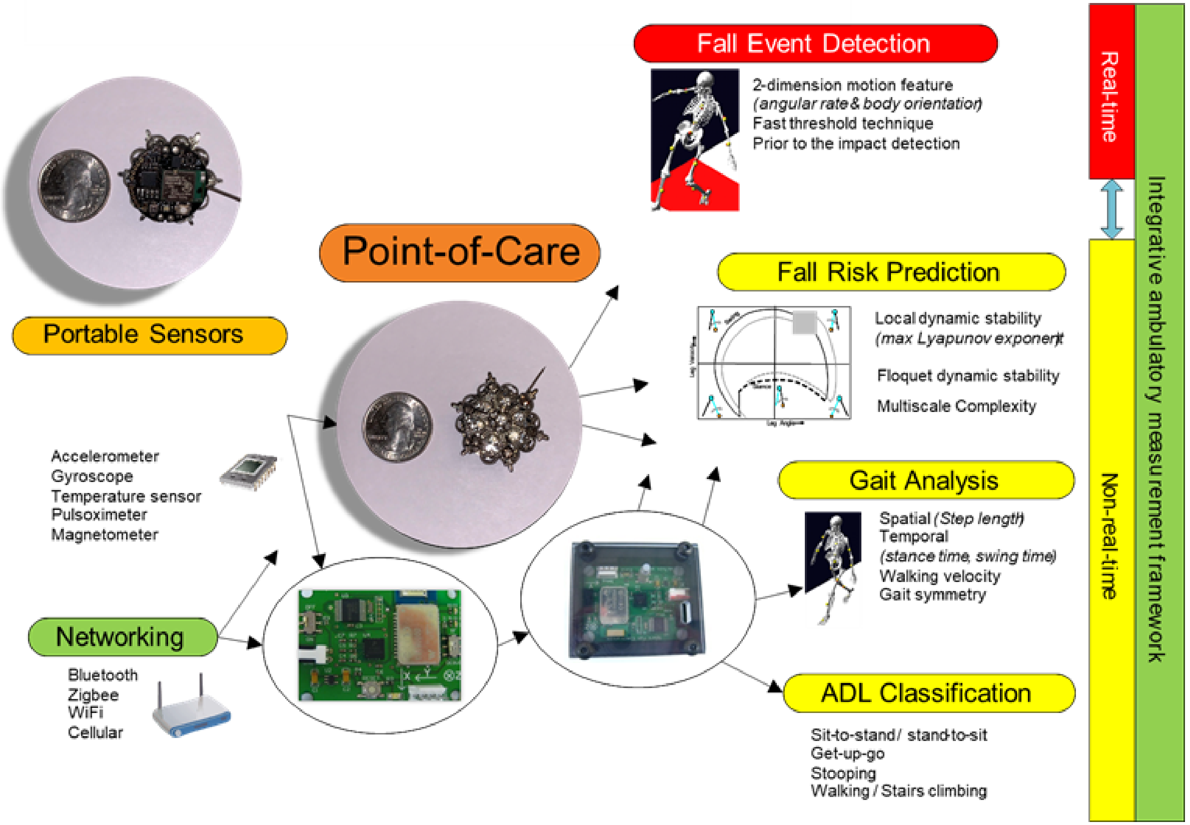
Wearable Fall Prevention System

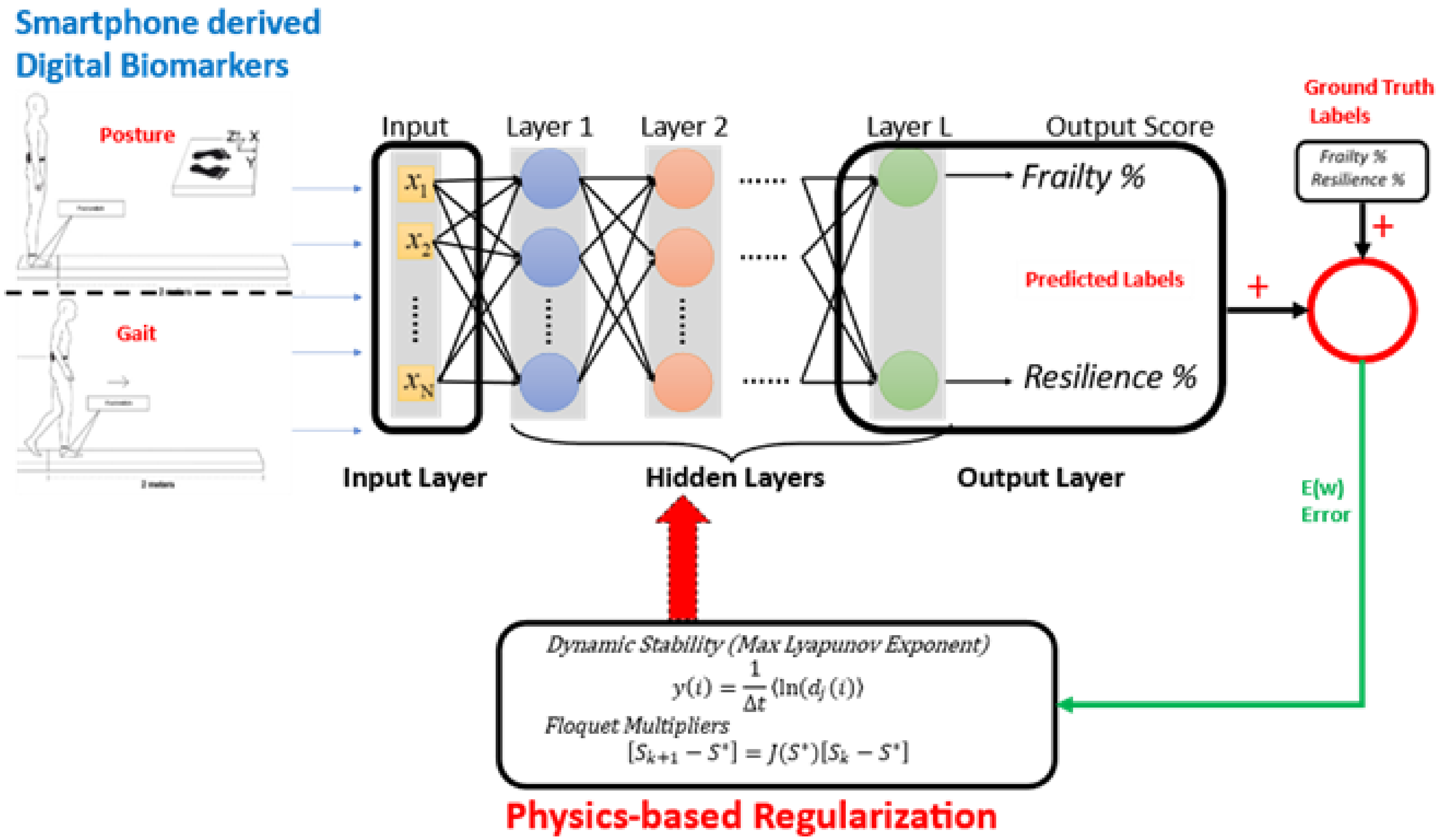


Liang Dong and Teresa Wu








Smartphone derived
Digital Biomarkers
Posture
Gait
Input
Layer 1
Layer 2
Layer L
Output Score
x_1
x_2
x_N
Frailty %
Predicted Labels
Resilience %
Ground Truth
Labels
Frailty %
Resilience %
+
+
Input Layer
Hidden Layers
Output Layer
E(w)
Error
Dynamic Stability (Max Lyapunov Exponent)
$y(i) = \frac{1}{\Delta t}\langle \ln(d_j(i)) \rangle$
Floquet Multipliers
$[S_{k+1} - S^*] = J(S^*)[S_k - S^*]$
Physics-based Regularization

Thank You !

This research was supported by the NSF (grant #CBET-0756058) and NSF-Information and Intelligent Systems (IIS) and Smart Health and Wellbeing - 1065442 and 1065262. NIOSH (grant #CDC/NIOSHR01-OH009222), and NIH (AG022963-04)