

Adventures in Digital.....

Augmenting the Physiotherapist

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Insight
Centre for Data Analytics





Combines 5 Centres of Excellence

8 Institutions

40+ Principal & Funded Investigators

400+ Researchers (PD, PhD)

50+ Collaboration Partners

30% of primary funding base from industry

Data Science

Biomedical Engineering

Chemistry

Data Science

Physiotherapy

Material Science

Medicine

Sports Science

Nursing

Systems

Biology

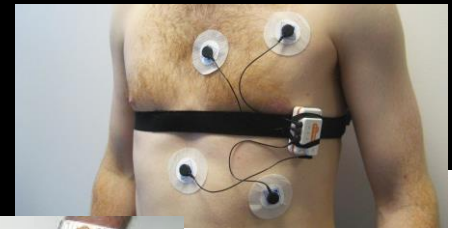


**Rehabilitation &
Exercise Science**

Sensing & Processing

Knowledge Extraction

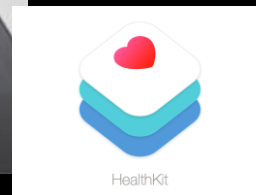
**Visualisation,
Recommendation & Actuation**

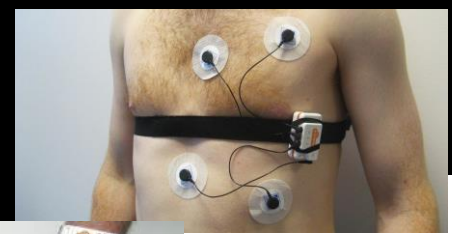


7.12 Mph 32:34
8:25 min/mile 10.2 miles



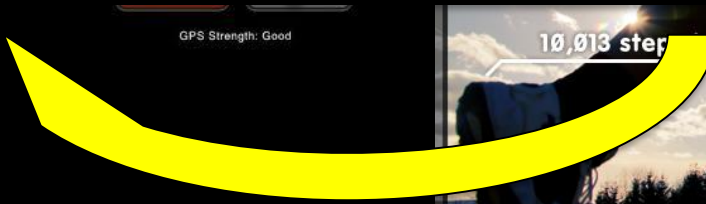
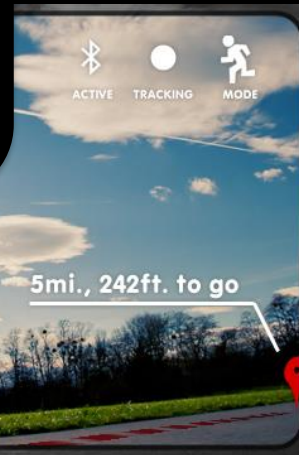
GPS Strength: Good





Measuring & Understanding Human Performance

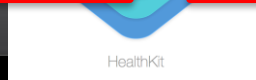
Enhancing Human Performance



Wellness

Sport

Healthcare



Augmenting Human Effectiveness in a Digital World



.....where we create an enormous digital footprint and are overwhelmed with data....

.....but get limited intelligence from it....

.....and have little control over its journey....



Augmented Privacy

Augmented Cognition

Intelligence
Decisions

Augmented Performance

The Augmented Human



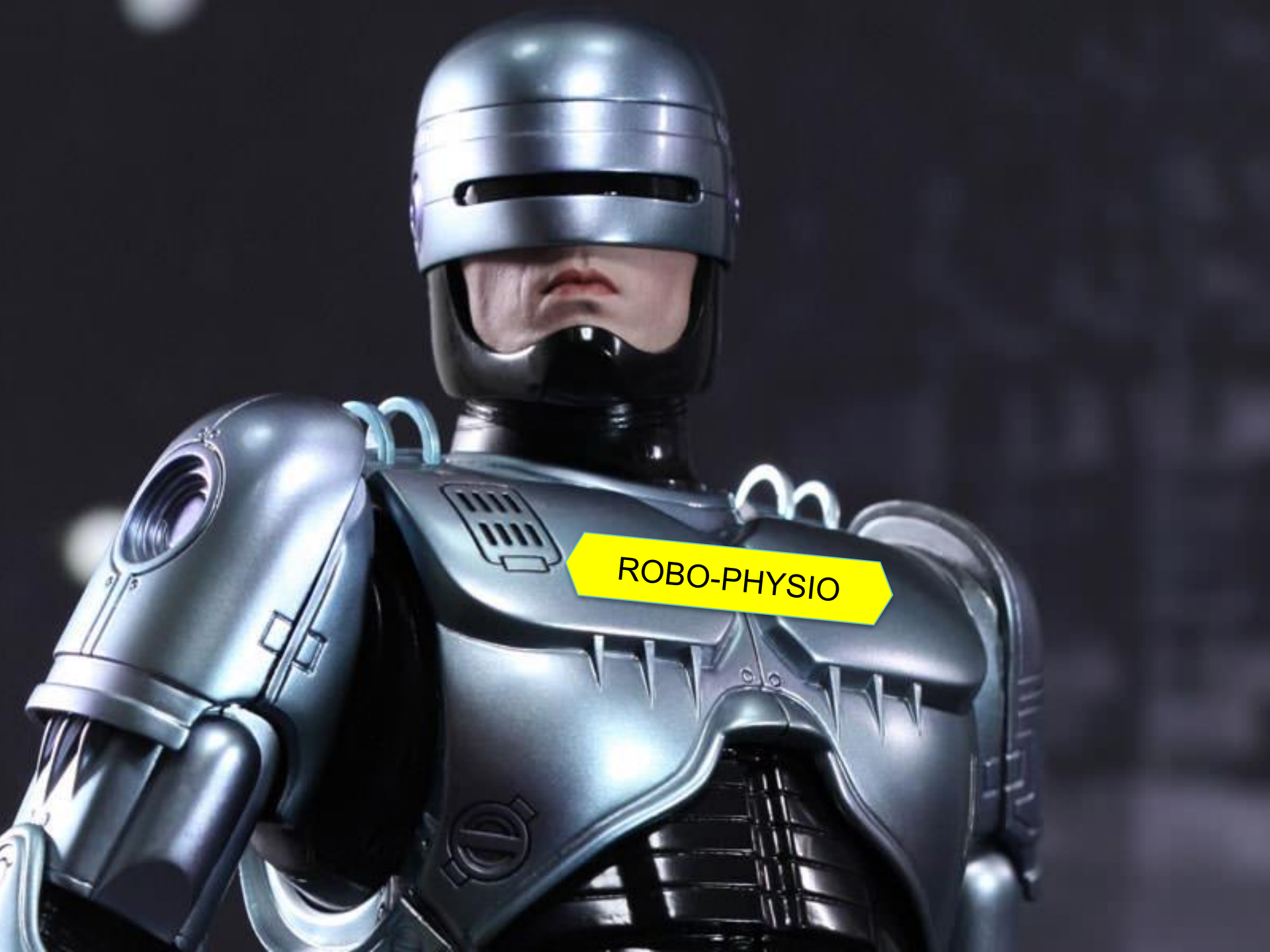
Augmented Privacy

Augmented Cognition

Intelligence
Decisions

Augmented Performance

The Augmented PHYSIO??



ROBO-PHYSIO



TRATAMIENTOS ROBOTIZADOS

Automated PT?

Robotic PT?

Automated PT?

Robotic PT?



augment

verb

/ɔːɡ'ment/ 

1. make (something) greater by adding to it; increase.

synonyms: increase, make larger, make bigger, make greater, add to, supplement, top up, build up, enlarge, expand, extend, raise, multiply, elevate, swell, inflate; [More](#)

Effective Exercise Implementation





Existing technologies to assist with implementation of Rehabilitation Exercise.....



**provision of interactive feedback to
motivate patient**



guidance through exercise performance

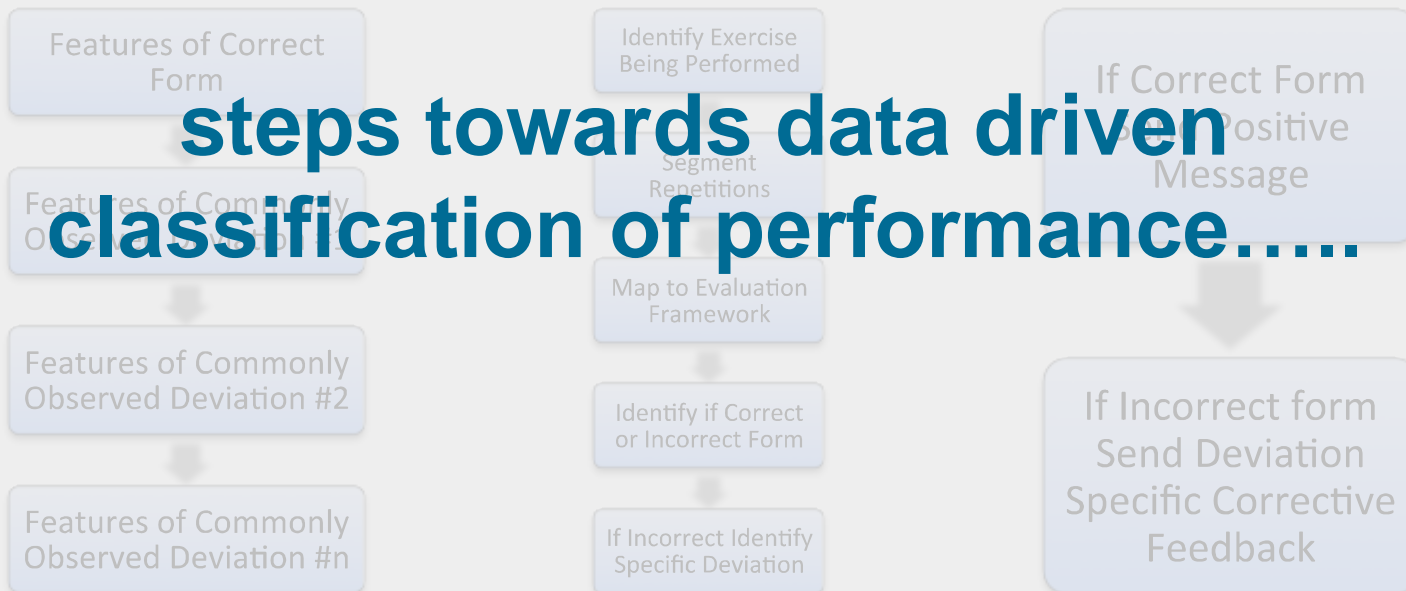
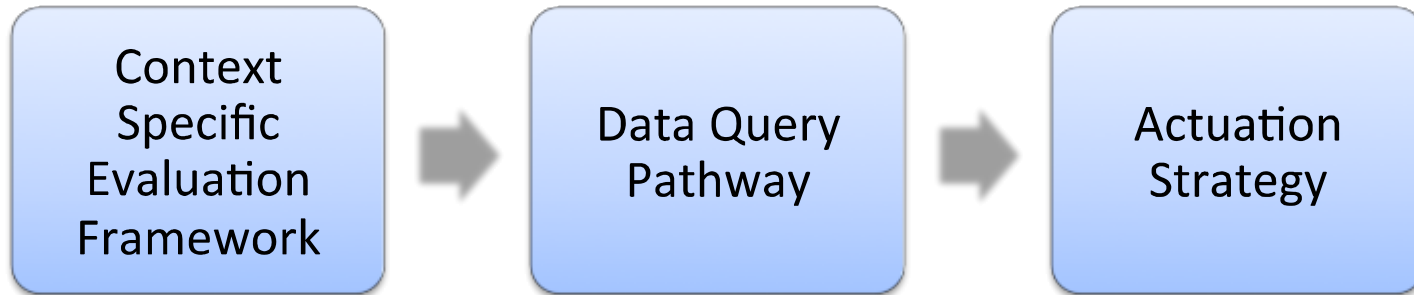


measurement of compliance



**accurate measurement of technique
with clinically relevant feedback**





steps towards data driven classification of performance.....

Context Specific Evaluation Framework

Features of Correct
Form

Features of Commonly
Observed Deviation #1

Features of Commonly
Observed Deviation #2

Features of Commonly
Observed Deviation #n

Data Query Pathway

Identify Exercise
Being Performed

Segment
Repetitions

Map to Evaluation
Framework

Identify if Correct
or Incorrect Form

If Incorrect Identify
Specific Deviation

Actuation Strategy

If Correct Form
Send Positive
Message

If Incorrect form
Send Deviation
Specific Corrective
Feedback

Context Specific Evaluation Framework

Features of Correct
Form

Features of Commonly
Observed Deviation #1

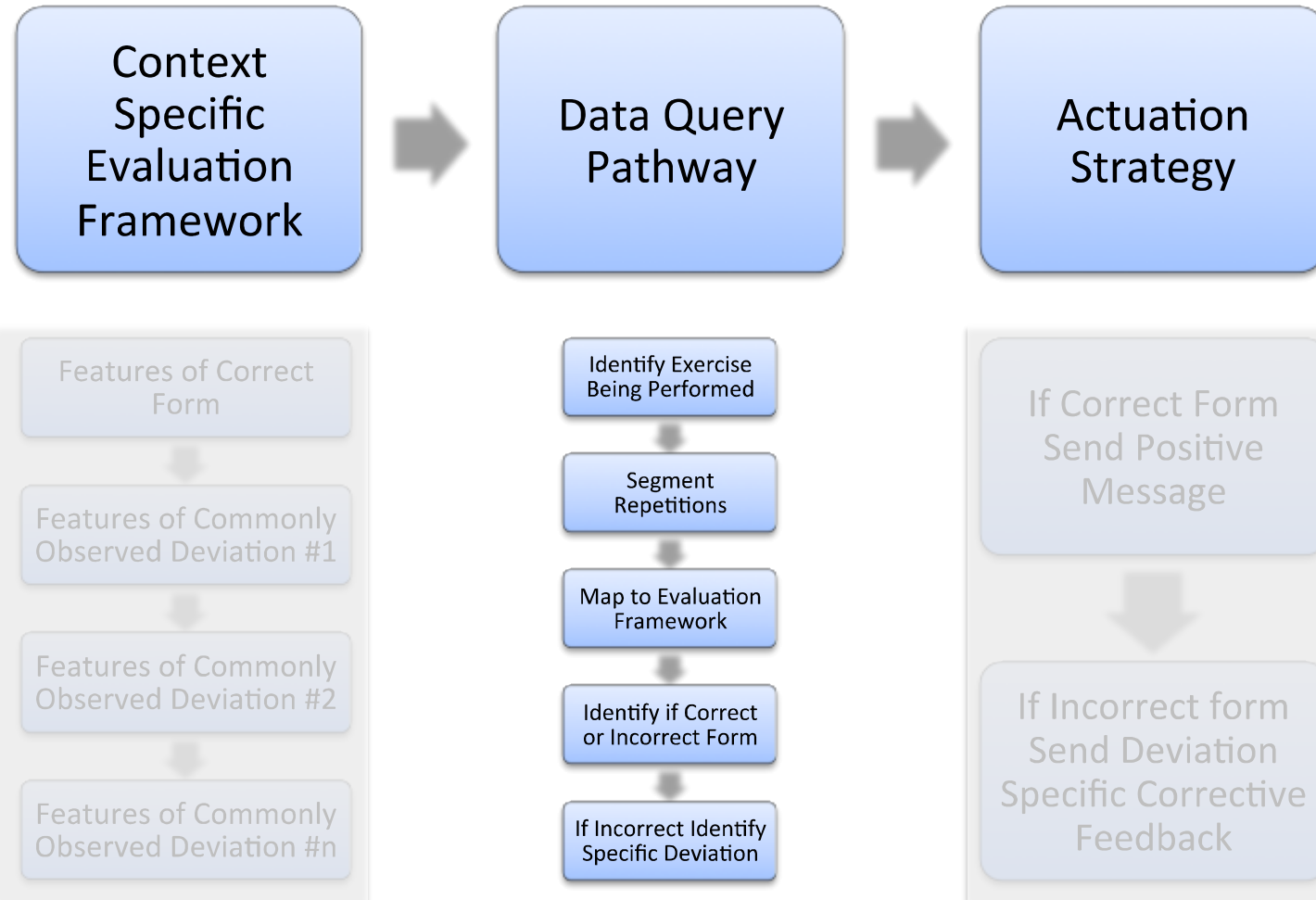
Features of Commonly
Observed Deviation #2

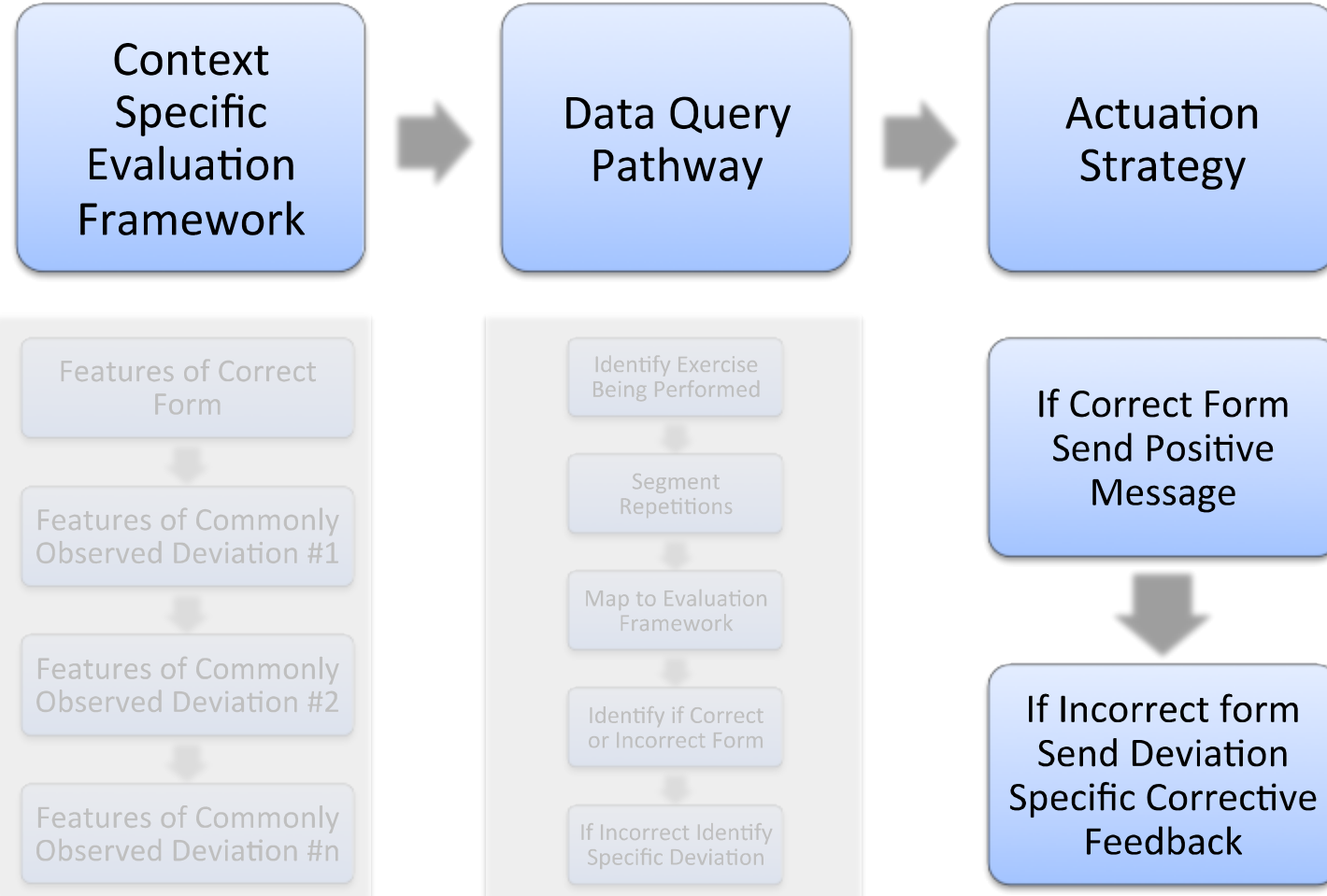
Features of Commonly
Observed Deviation #n

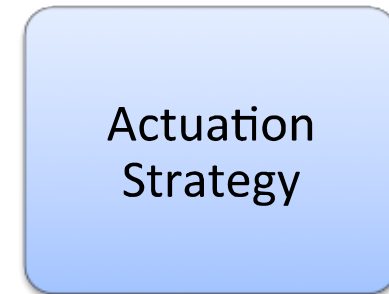
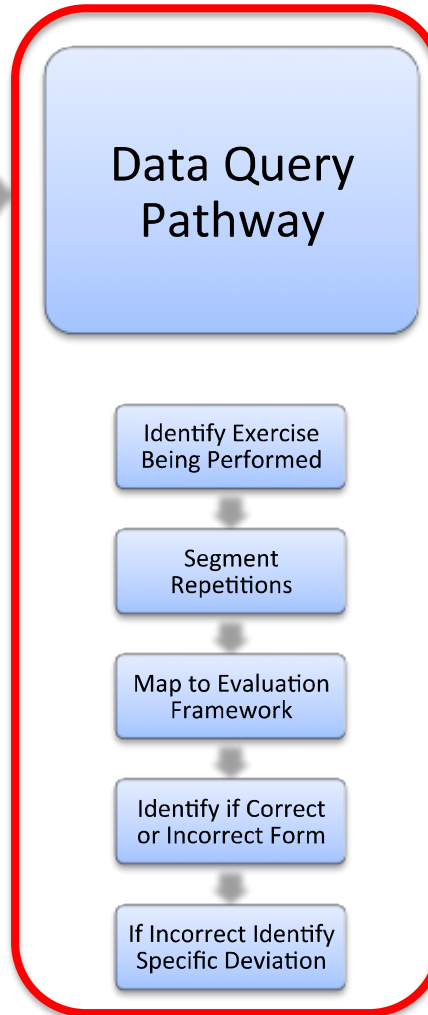
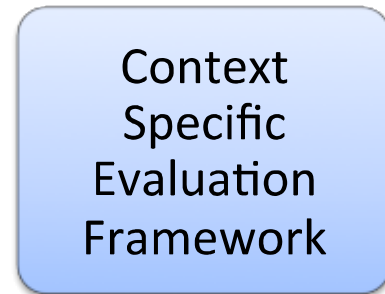


Specific Deviation

KVL	Left knee coming towards mid-line during downwards phase
KVR	Left knee moving away from mid-line during downward phase
KTF	Left knee ahead of toes during downward phase
HSR	Excessive lean to left hand side during entire lunge exercise
HSL	Excessive lean to right hand side during entire lunge exercise
BO	Excessive flexion of hip and torso during entire lunge exercise
BFO	Right foot externally rotated
SS	Loss of balance during upward phase resulting stuttered steps
PB	Pushing backwards during upwards phase
STS	Starting stance too short
STL	Starting stance too long







IMUs

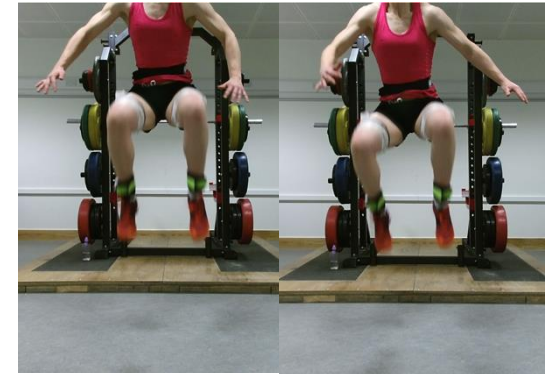
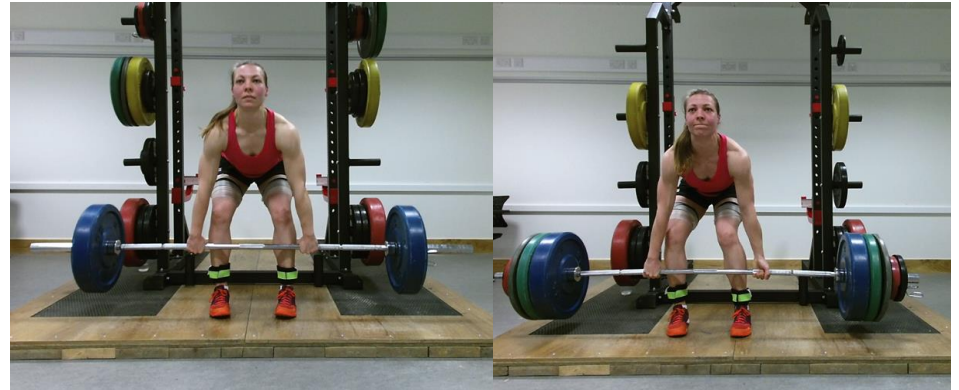
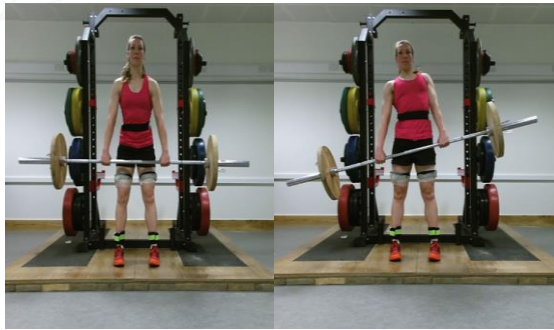
- Advantages
 - Objective measurement
 - Quick to apply
 - Inexpensive
 - Allow natural movement
 - Lead to possibility of using mobile phone as sensor





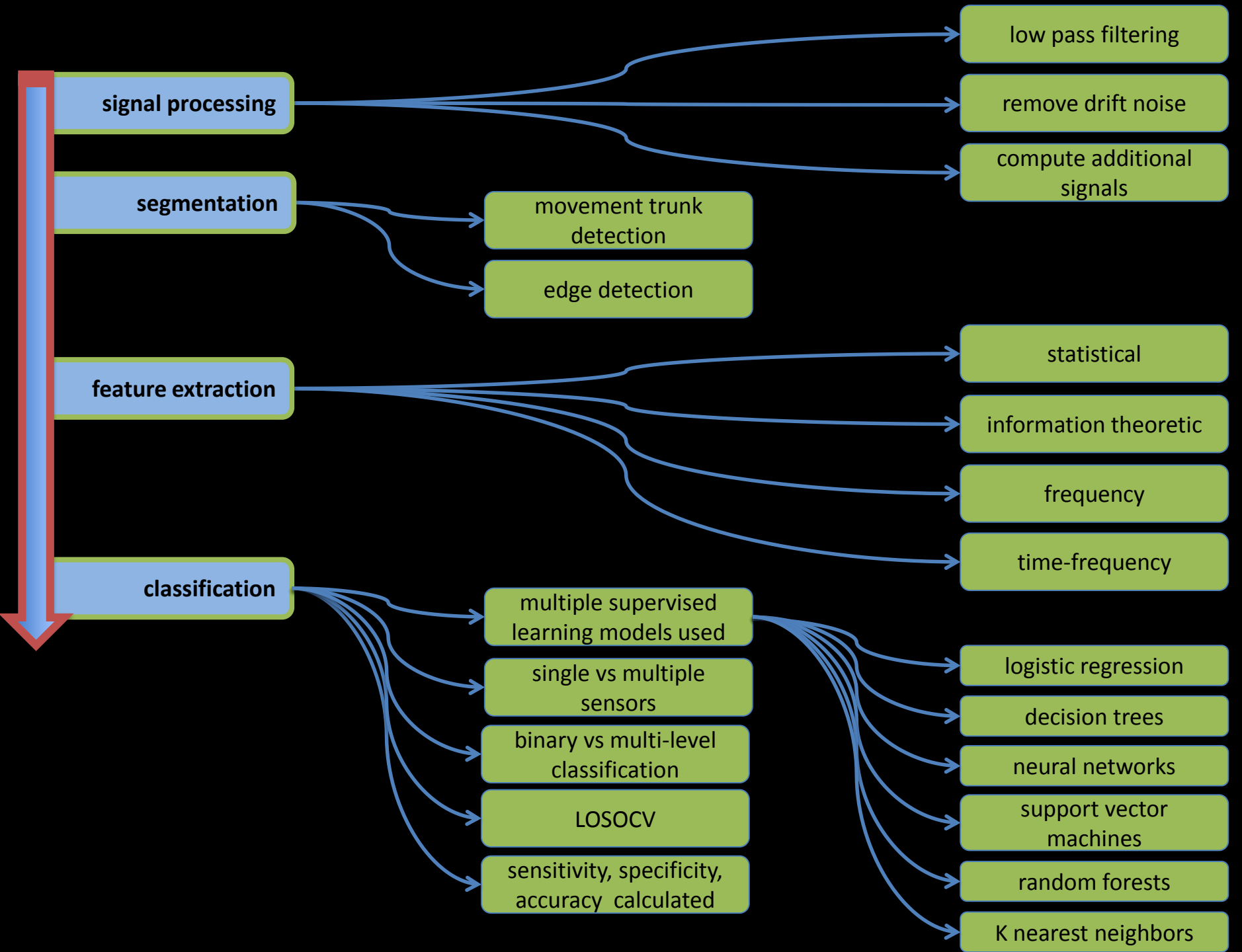


Insight



creating a data-driven **society**

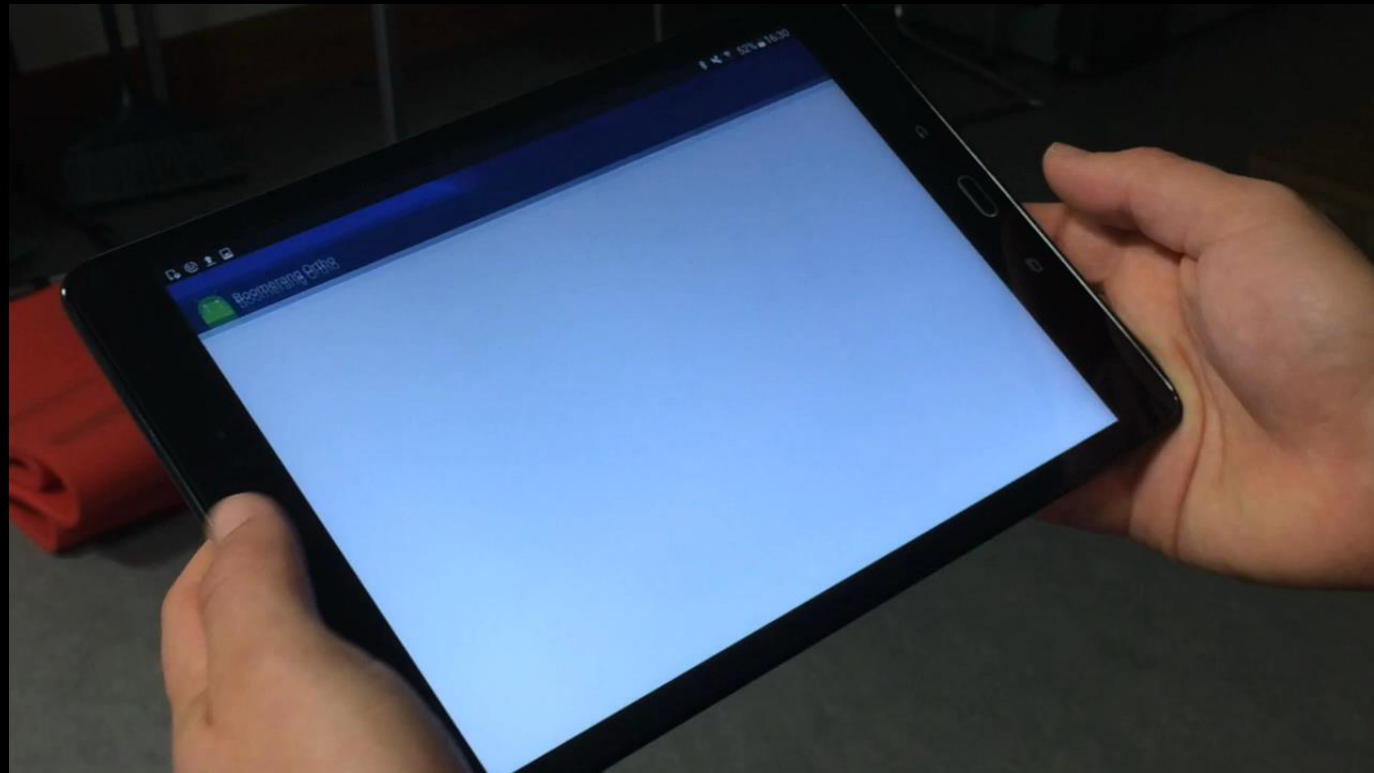
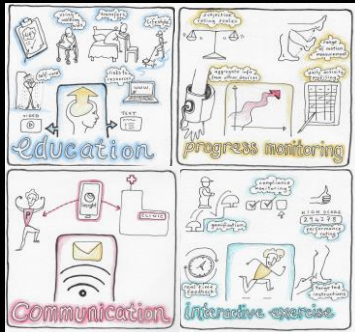




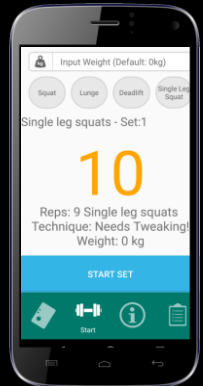
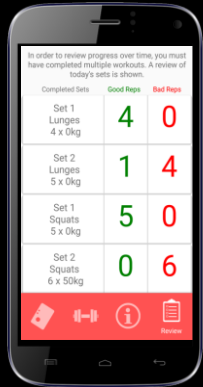
Model Evaluation

		% ACCURACY (Single Sensor)	% ACCURACY (Multiple Sensors)
Single Limb Exercises (Ortho Rehab)	<i>Detection & Segmentation</i>	95-99	95-99
	<i>Binary Classification</i>	80-85	85-95
	<i>Multi-label Classification</i>	80-85	85-95
Complex Multijoint Exercises (S&C Exercises)	<i>Detection & Segmentation</i>	95-99	95-99
	<i>Binary Classification</i>	80-85	85-95
	<i>Multi-label Classification</i>	40-50	70-75

currently evaluating personalised classifier model.....



FormuLift



Mobile Balance Evaluation Toolkit



Y Balance Test



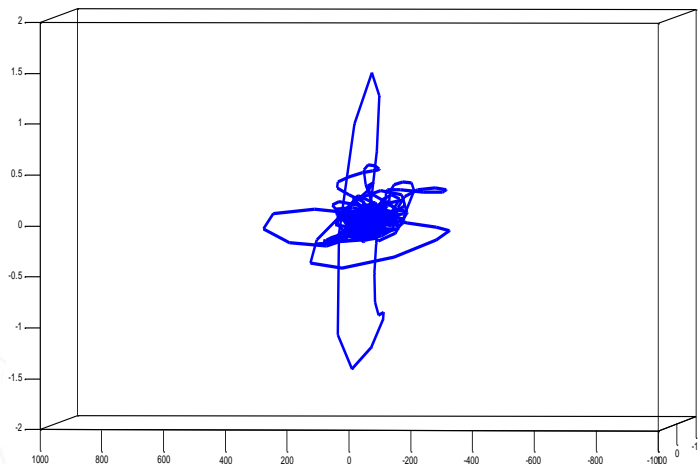
Y Balance Test

Can we move it from analog to digital?

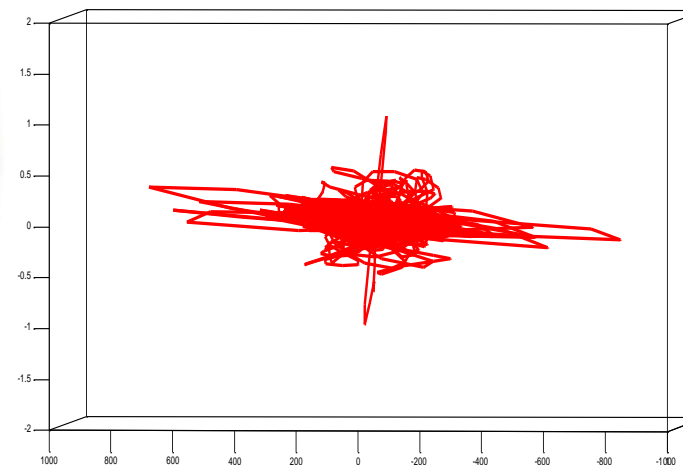
If so, what more can we learn from it?

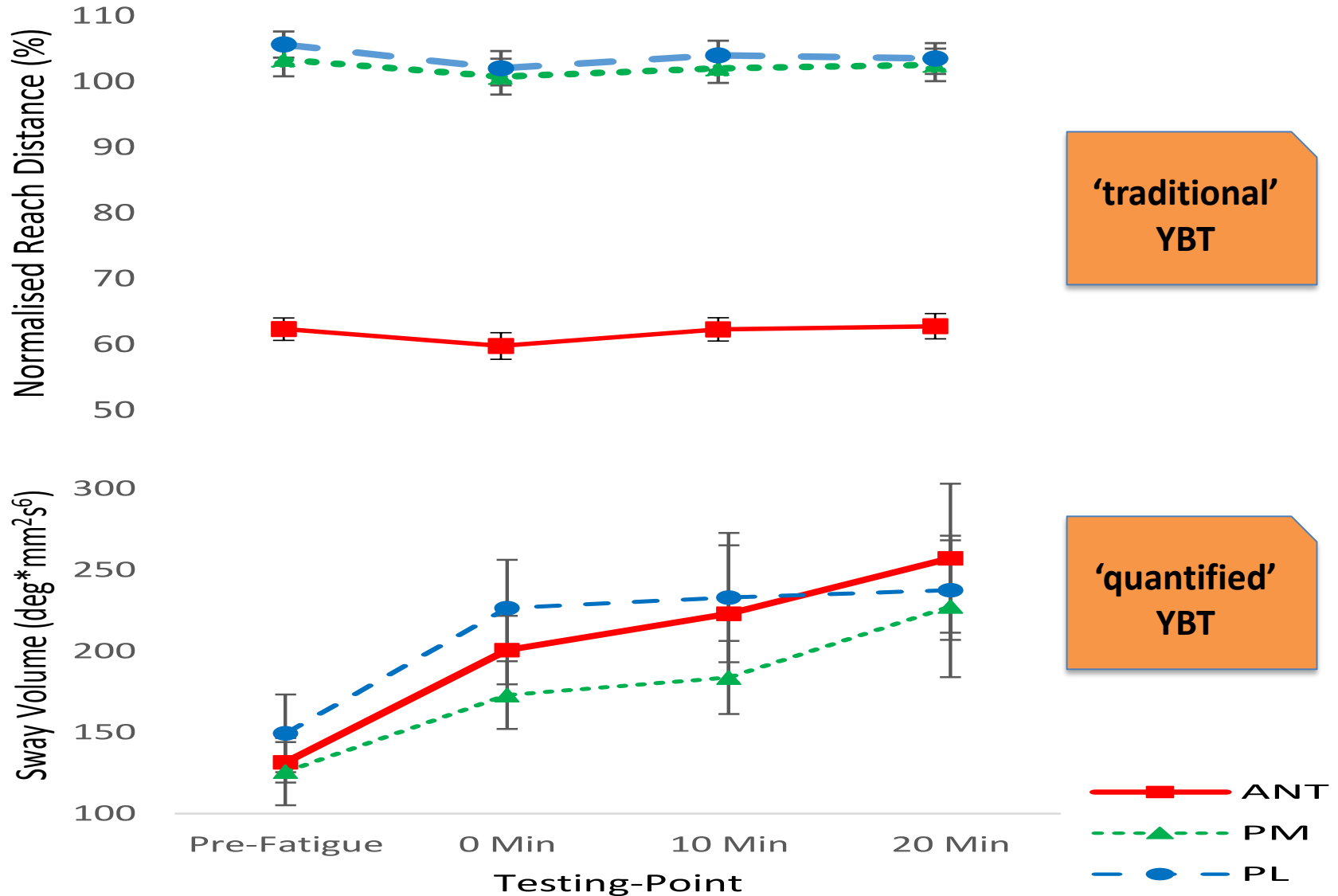


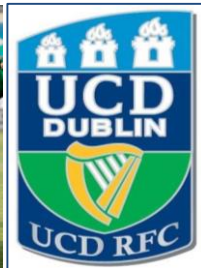
Normal Balance



Abnormal Balance







YBT Testing Points

Pre-Season

Mid-Season

Concussion

HIA2

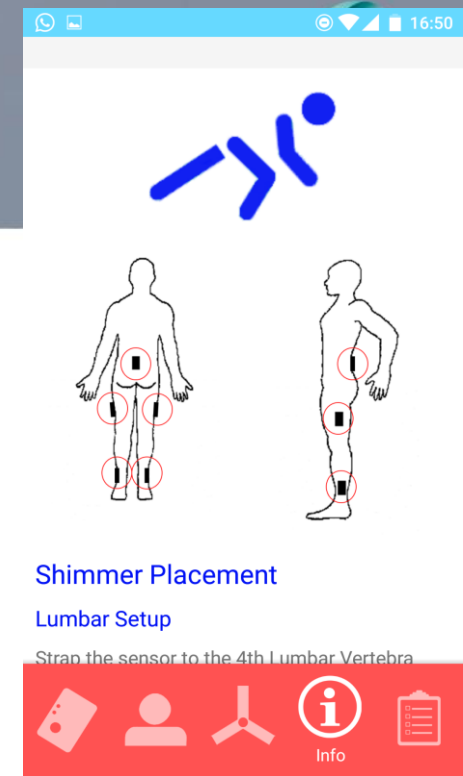
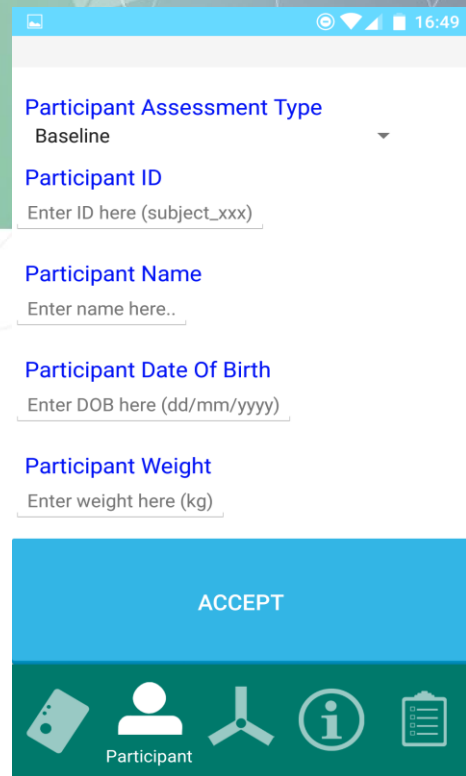
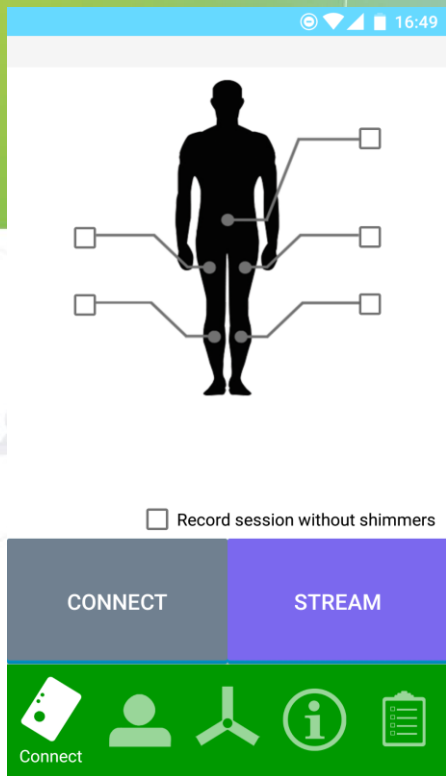
HIA3

RTP

Baseline

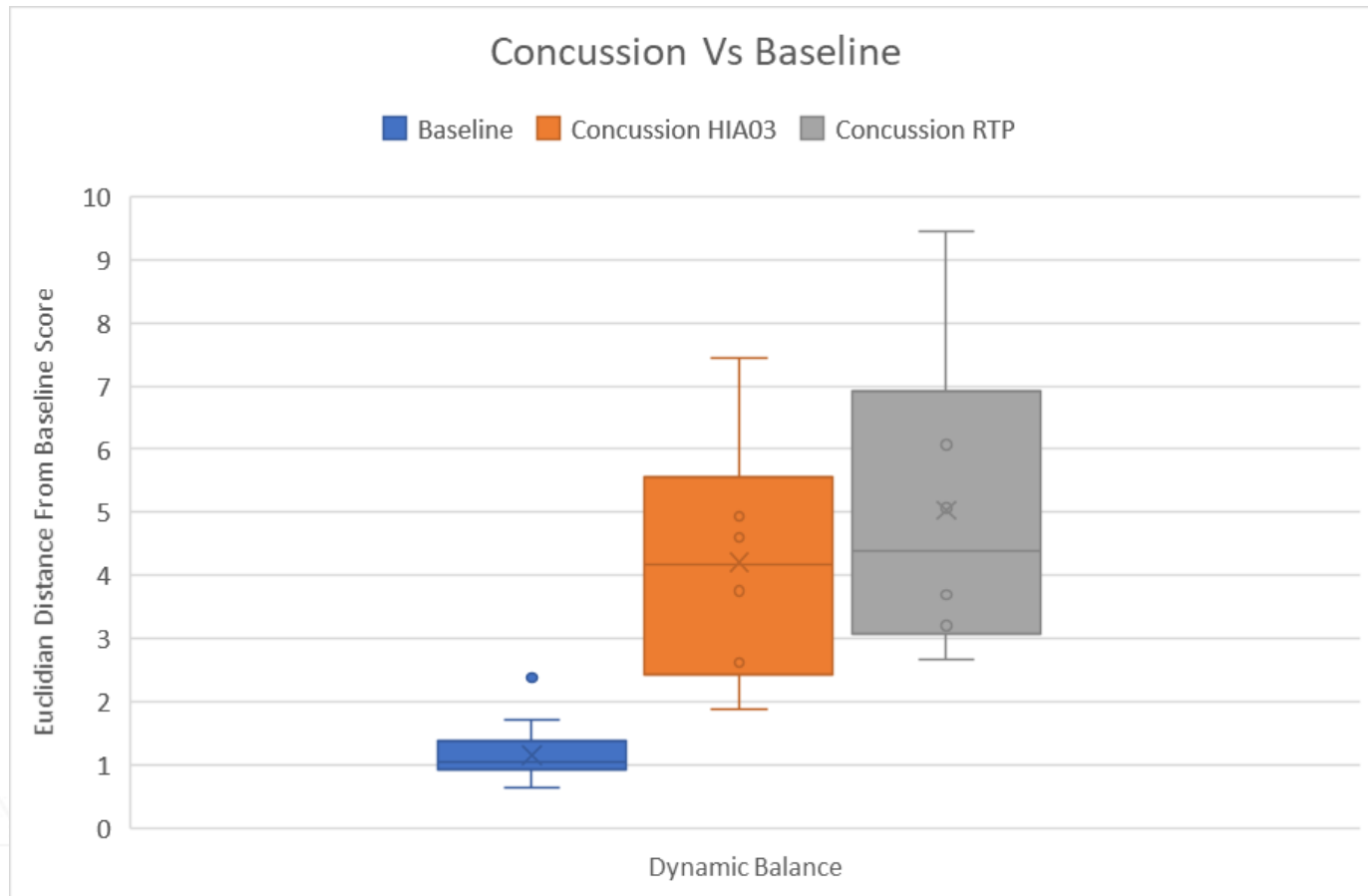
'traditional' YBT n=268

'quantified' YBT N=109



creating a data-driven society

Can inertial sensor data capture dynamic balance control deficits following a concussive head injury?



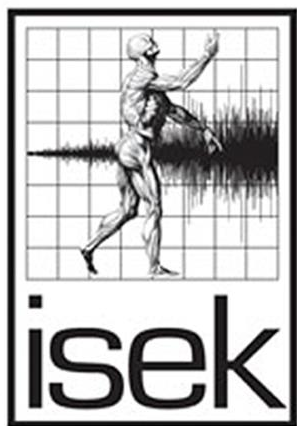
Are dynamic balance control deficits at pre-season associated with an increased risk of sustaining a concussion?

simple
answer.....YES



Players with sub-threshold q-YBT performance at baseline **3 times** more likely to sustain concussive injury throughout the season, controlling for previous history of concussion.....

Thank You!



international society of
electrophysiology and kinesiology

UCD / Dublin / Ireland

30th June-2nd July 2018

www.isek.org

Call for Abstracts now open!



Bringing together researchers in human movement and the neuromuscular system

@caulfieldbrian

Anterior

Regression Model	Predictors	P Value	Odds Ratio	LOWER	Upper
Model 1	Concussion History	0.03	2.94	1.10	7.85
	Constant	<0.01	0.14		
Model 2	ANT_R_GyromagApproxEntropy	0.015	3.84	1.29	11.40
	Constant	<0.01	0.104		
Model 3	Concussion History	0.045	2.81	1.024	7.736
	ANT_R_GyromagApproxEntropy	0.023	3.63	1.198	10.971
	Constant	<0.01	0.07		
Model 4	Concussion History	0.27	2.91	0.44	19.2
	ANT_R_ApproxEntropy	0.13	3.72	0.69	20.10
	ANT_R_GyromagApproxEntropy*Con Hx	0.97	0.96	0.10	8.9
	Constant	<0.01			

Regression Model	Predictors	P Value	Odds Ratio	LOWER	Upper
Model 1	Concussion History	0.03	2.94	1.10	7.85
	Constant	<0.01	0.14		
Model 2	PL_R_lumbar_pitch_f95%_22.03	<0.01	5.962	2.08	17.07
	Constant	<0.01	0.097		
Model 3	Concussion History	0.04	3.07	1.07	8.79
	PL_R_lumbar_pitch_f95%_22.03	<0.01	6.04	2.05	17.80
	Constant	<0.01	0.07		
Model 4	Concussion History	0.77	0.77	0.13	4.54
	PL_R_lumbar_pitch_f95%_22.03	0.38	1.95	0.44	8.66
	PL_R_lumbar_pitch_f95%_22.03*ConHx	0.05	9.68	0.99	94.82
	Constant	<0.01	0.12		

Regression Model	Predictors	P Value	Odds Ratio	LOWER	Upper
Model 1	Concussion History	0.03	2.94	1.10	7.85
	Constant	<0.01	0.14		
Model 2	PM_L_lumbar_gyroY_approxDW_185	0.037	2.84	1.06	7.59
	Constant	<0.01	0.143		
Model 3	Concussion History	0.043	2.82	1.03	7.70
	PM_L_lumbar_gyroY_approxDW_185	0.043	2.82	1.03	7.70
	Constant	<0.01	0.09		
Model 4	Concussion History	0.03	6.33	1.16	34.52
	PM_L_lumbar_gyroY_approxDW_185	0.21	0.26	0.03	2.17
	PM_L_lumbar_gyroY_approxDW_185* onchx	0.03	6.33	1.162	34.52
	Constant	<0.01	0.53		