Athletic Training Educators' Conference
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# New Knowledge Required for Continuous Quality Improvement in Patient Outcomes

Gary B. Wilkerson, EdD, ATC

THE UNIVERSITY OF TENNESSEE CHATTANOOGA

## Conflict of Interest:

*In compliance with continuing education requirements, all presenters must disclose any financial or other associations with companies to which they have a direct link and/or financial relationship that is related to the topic/content of their presentation.*

ATEC ATHLETIC TRAINING EDUCATORS' CONFERENCE EDUCATION DRIVING CLINICAL PRACTICE

*Nothing relevant to disclose*

## Objectives:

1. Demonstrate the *importance of data collected in the clinical setting* to continuous improvement in the quality of patient outcomes.
2. Discuss *evolving changes in the conceptualization of evidence-based practice* and patient-centered care.
3. Review the *relevance of predictive algorithms derived from machine learning* to the delivery of individualized care.

# Continuous Quality Improvement (CQI)

- What is it?
- Where did it come from?
- Why does it matter?
- How is it done?

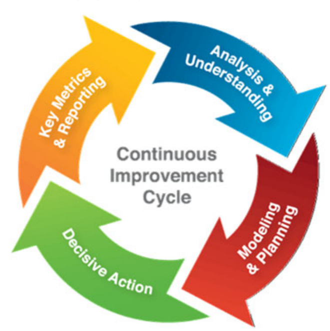


# What is CQI?

- The systematic process of identifying, describing, and analyzing problems, and then testing, implementing, learning from, and revising solutions

... <u>an ongoing cycle</u> of collecting data and using it to make decisions to gradually improve processes

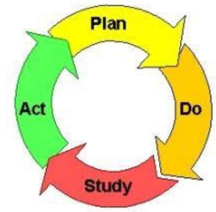
U.S. Department of Health & Human Services



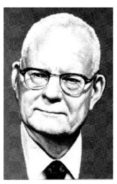
# Where did CQI come from?

- Walter Shewhart (1891-1967)

  - *Assigned to improve voice clarity of Bell Telephone handsets*
    Western Electric Company – Hawthorne Works, Cicero, IL
  - *Consultant to US War Department during WWII*
    - Statistical Process Control (1925)




- W. Edwards Deming (1900-1993)

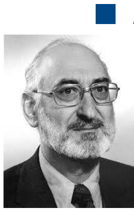


  - *US Department of the Census & Bureau of Labor Statistics*
  - *Consultant to US War Department during WWII*
  - *Consultant to Japanese industry (1950)*
    - Total Quality Management – Continuous Quality Improvement

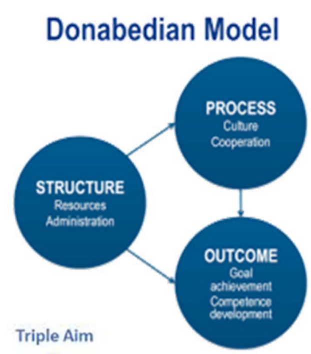


# Concern About Quality in Healthcare

- Avedis Donabedian (1919-2000)



  - *Evaluating the quality of medical care. Milbank Mem Fund Q. 1966;44(3)*
    - University of Michigan School of Public Health




- Donald W. Berwick (1946- )

  - *Continuous improvement as an ideal in health care. New Eng J Med. 1989;320(1)*
    - Harvard Medical School
    - CEO – Institute for Healthcare Improvement
    - Administrator of CMS

# Core Competencies for Health Professionals*

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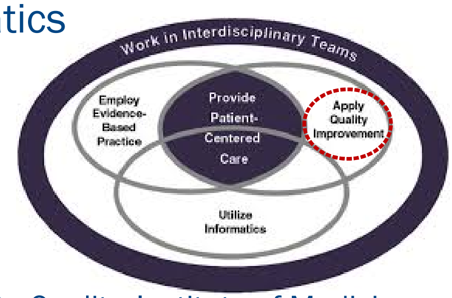
1. Evidence-Based Practice
2. Patient-Centered Care
3. Inter-professional Education & Collaborative Practice
4. Effective Use of Healthcare Informatics
5. Continuous Quality Improvement




* 2003: Health Professions Education: A Bridge to Quality, Institute of Medicine



# Why does CQI matter to AT educators?

- New Standards for Professional (Masters' Level) Athletic Training Programs – 2020

| Curricular Content Standards | BOC Practice Analysis, 7th Edition | NATA Educational Competencies, 5th Edition |
|---|---|---|
| 63. Use systems of quality assurance and quality improvement to enhance client/patient care. | 0401, 0501, 0502, 0503, 0504 | EBP-4, EBP-11, EBP-12, EBP-13, EBP-14, PHP-4 |

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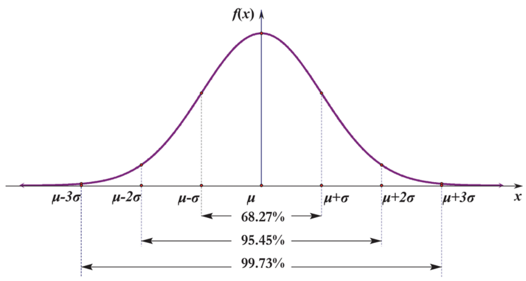
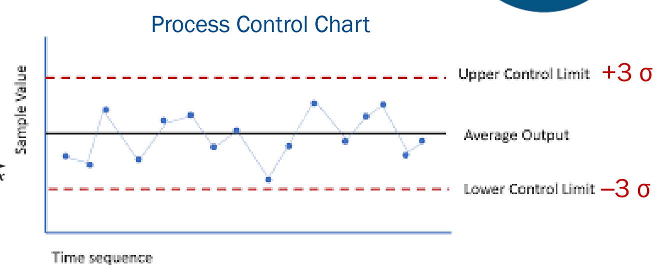
# How is CQI done?

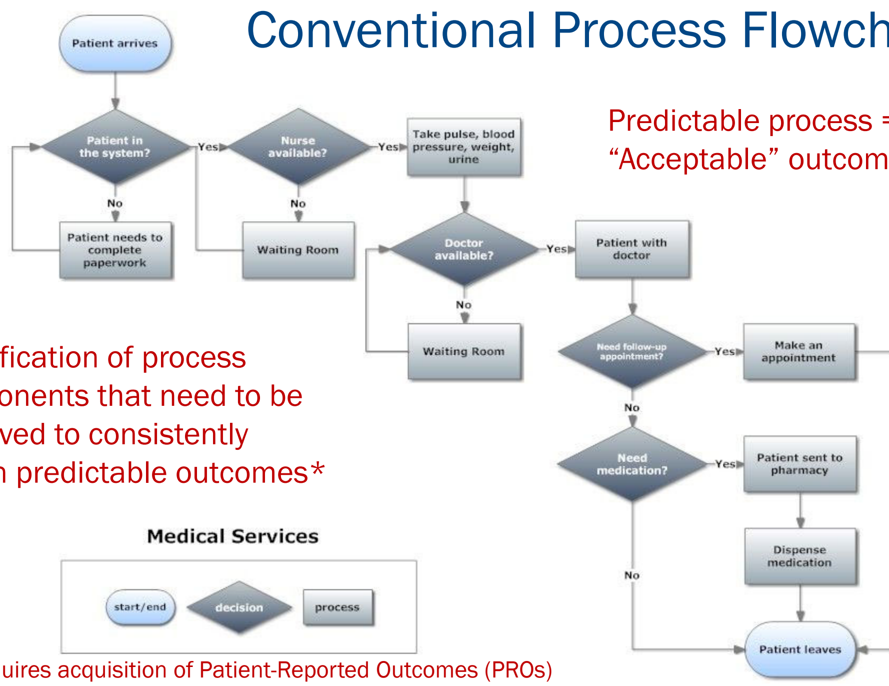




- "Common Cause Variation" – Associated with a "normal" distribution of values
- "Special Cause Variation" – Values outside the range of ± 3 σ (99.7% of all cases)
- "Six Sigma" Data-Driven Approach to Problem Solving – Motorola 1980

  99.99% of all cases within ± 6 σ



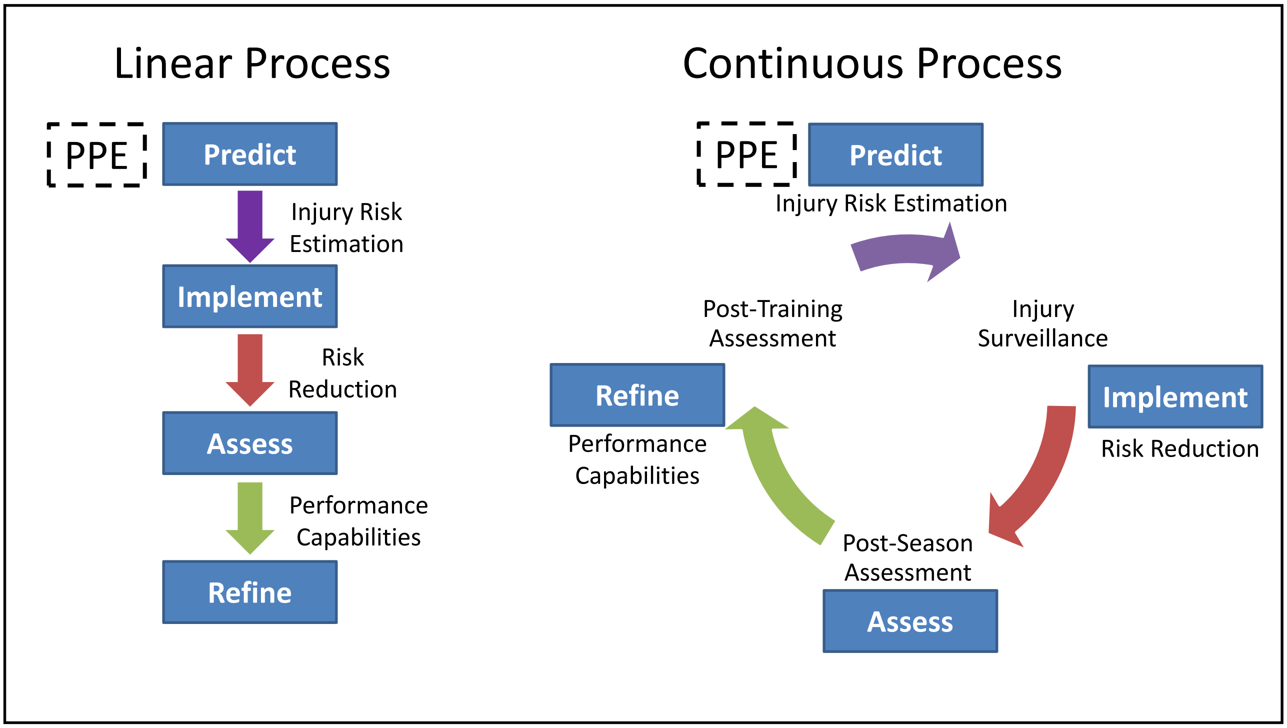
# Conventional Process Flowchart




Predictable process =
"Acceptable" outcome variability

Identification of process components that need to be improved to consistently obtain predictable outcomes*

* Requires acquisition of Patient-Reported Outcomes (PROs)




# Rapid Learning

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- 2007: The Learning Healthcare System
  - *Roundtable on Evidence-Based Medicine*
- 2013: Best Care at Lower Cost
  - *Committee on the Learning Health Care System in America*

1. The prevailing approach to generating clinical evidence is inadequate
2. Knowledge generation imbedded in practice leads to continual improvement in care
3. A completely new approach - changes in how we define the roles of health professionals

# Rapid Learning

- Purposes:
  1. Generate and apply the best evidence relevant to each patient
     - Patient-centered care
  2. Propel scientific discovery as a natural outgrowth of patient care
     - Data collected during the process of care delivery
  3. Support quality assessment and improvement
     - Benchmarking clinic/clinician performance relative to aggregated dataset

Abernethy AP, Ahmad A, Zafar SY, Wheeler JL, Reese JB, Lyerly HK. Electronic patient-reported data capture as a foundation of rapid learning cancer care. *Medical Care*. 2010;48(6):S32-S38



# Benchmarking:
## # Injuries per 1000 Athlete-Exposures
## # Days Time Loss per 1000 Athlete-Exposures

NCAA | SPORT SCIENCE INSTITUTE™

Injury Surveillance Program

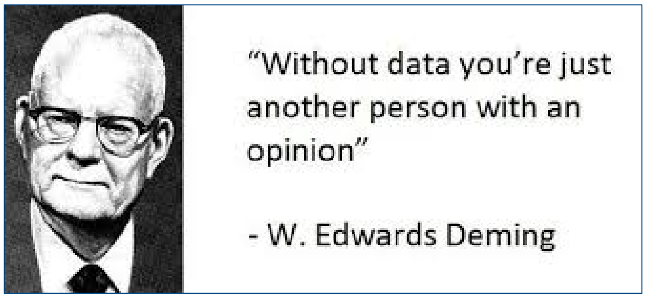
DATALYS CENTER.
NCAA® Injury Surveillance Program
Powered by ATHLETIC TRAINERS

AT PBRN
Athletic Training Practice Based Research Network

RIO
REPORTING INFORMATION ONLINE

NATION:
National Athletic Treatment, Injuries, & Outcomes Network

# What is currently measured? What else needs to measured?



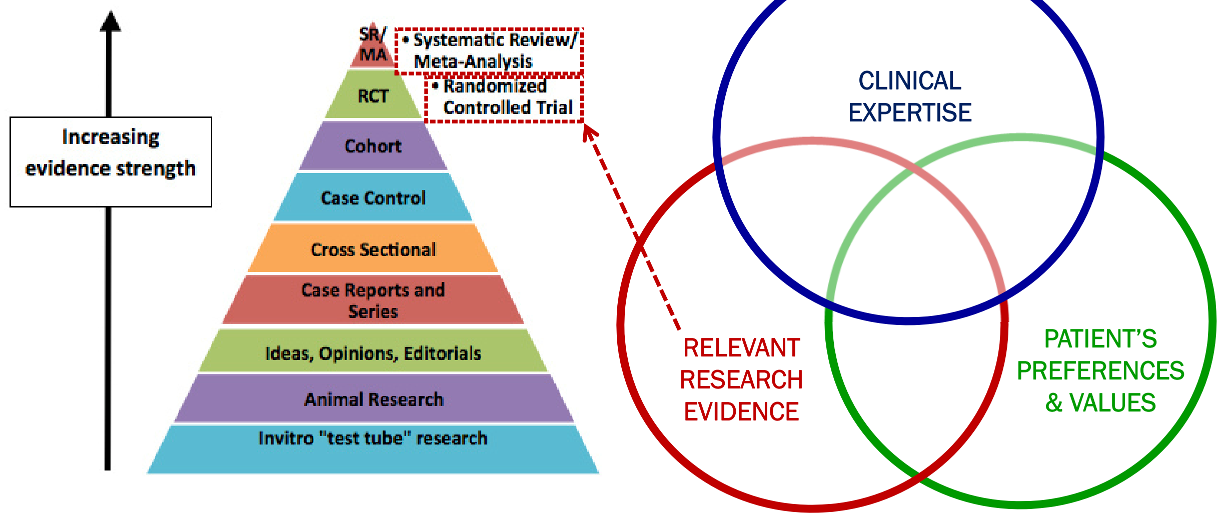

- How many athletic programs are currently collecting enormous amounts of data that are not being effectively utilized for maximum benefit?



# Mobile Health – mHealth

- The use of mobile and wireless technologies to support the achievement of health objectives.
  - *mHealth: New Horizons for Health through Mobile Technologies*
    - World Health Organization, 2011

## Original Conceptualization of Evidence-Based Practice




Sackett DL, Rosenberg WMC, Gray JAM, Haynes RB, Richardson WS. Evidence-based medicine: what it is and what it isn't. *BMJ*. 1996;312:71-71.



## Evidence-Based Practice: Changing Perspective

- Clinical presentation (history & physical exam findings) and patient preferences should be considered prior to application of research evidence
- Strength versus weakness of the RCT for decision support:
  - Good to assess intervention efficacy in patient groups (ideal conditions)

    *"Arguably, the worst way to assess who will benefit from an intervention"*

Schattner A, Fletcher RH. Research evidence and the individual patient. QJM. 2003;96:1-5.

## Evidence-Based Practice: Changing Perspective

- Q: Why do so many colleges and grad schools teach $p = 0.05$?

  A: Because that's still what the scientific community and journal editors use

- Q: Why do so many people still use $p = 0.05$?

  A: Because that's what they were taught in college or grad school

- The widespread use of "statistical significance" ("$P \leq 0.05$") as license for making a claim of a scientific finding (or implied truth) leads to considerable distortion of the scientific process

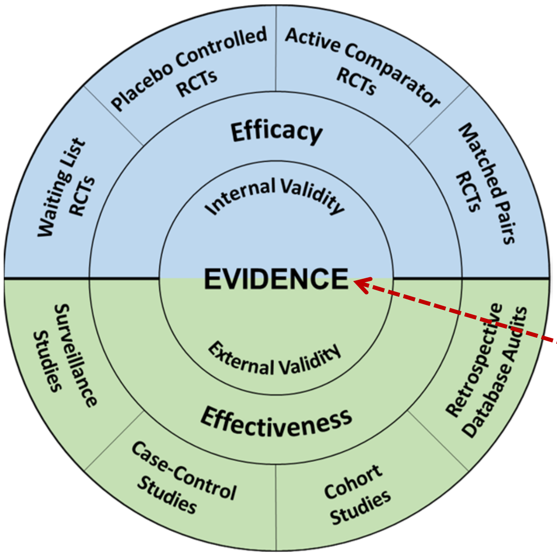
Wasserstein RL, Lazar NA. The ASA's statement on p-values: context, process, and purpose. Am Stat. 2016;70(2):129-133.

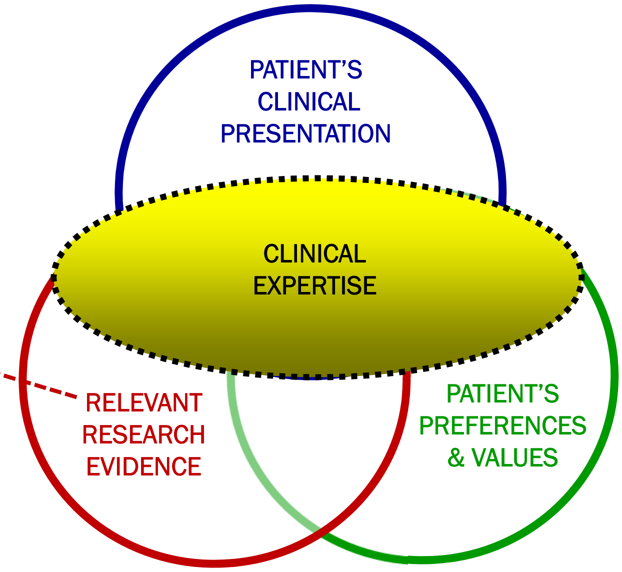


## Distinctly different inferential frameworks:

- "Frequentist" interpretation of probability (*P*-value):
  - *Expected frequency* of observed result with repeated random sampling
- "Bayesian" interpretation of probability:
  - *Degree of certainty* that same outcome will be observed in a similar cohort

## Changing Perspective on Evidence-Based Clinical Decision Making




Tugwell P, Knotterus JA. Is the evidence pyramid now dead? J Clin Epidemiol. 2015;68:1247-1250

Hanynes RB, Devereaux PJ. Guyatt GH. Clinical expertise in the era of evidence-based medicine and patient choice. *EBM.* 2002;7:30-38.



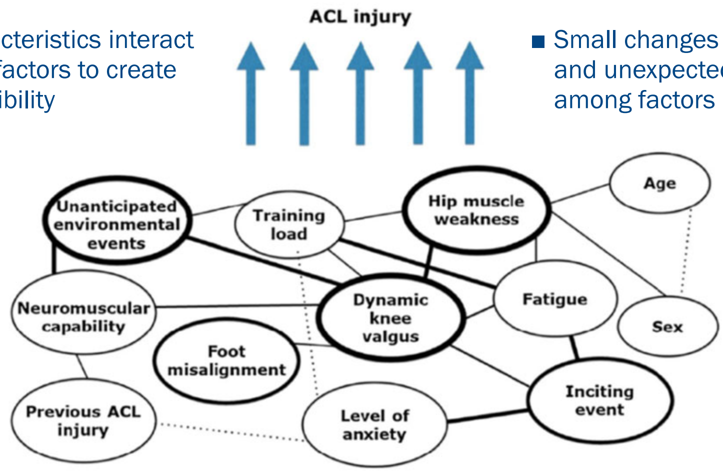
## Changing Perspective

- Limitations of parametric (frequentist) statistical analyses:
  - Random assignment and group averaging mask individual differences
  - Reductionist approach severely limits identification of interactions
  - Incapable of detecting non-linear relationships
- Complex Systems Approach (Dynamical Systems Theory):
  - Recognition of pattern of risk factor interactions over time
  - Small change in one variable may have large effect on another
  - Emergence: Abrupt change in non-linear system configuration

Bittencourt NF, Meeuwisse WH, Mendonça LD, Nettel-Aguirre A, Ocarino JM, Fonseca ST. Complex systems approach for sports injuries: moving from risk factor identification to injury pattern recognition—narrative review and new concept. *Br J Sports Med*. 2016;50(21):1309-1314.

## Every athlete (Complex System) has a unique injury predisposition

- Intrinsic characteristics interact with extrinsic factors to create injury susceptibility

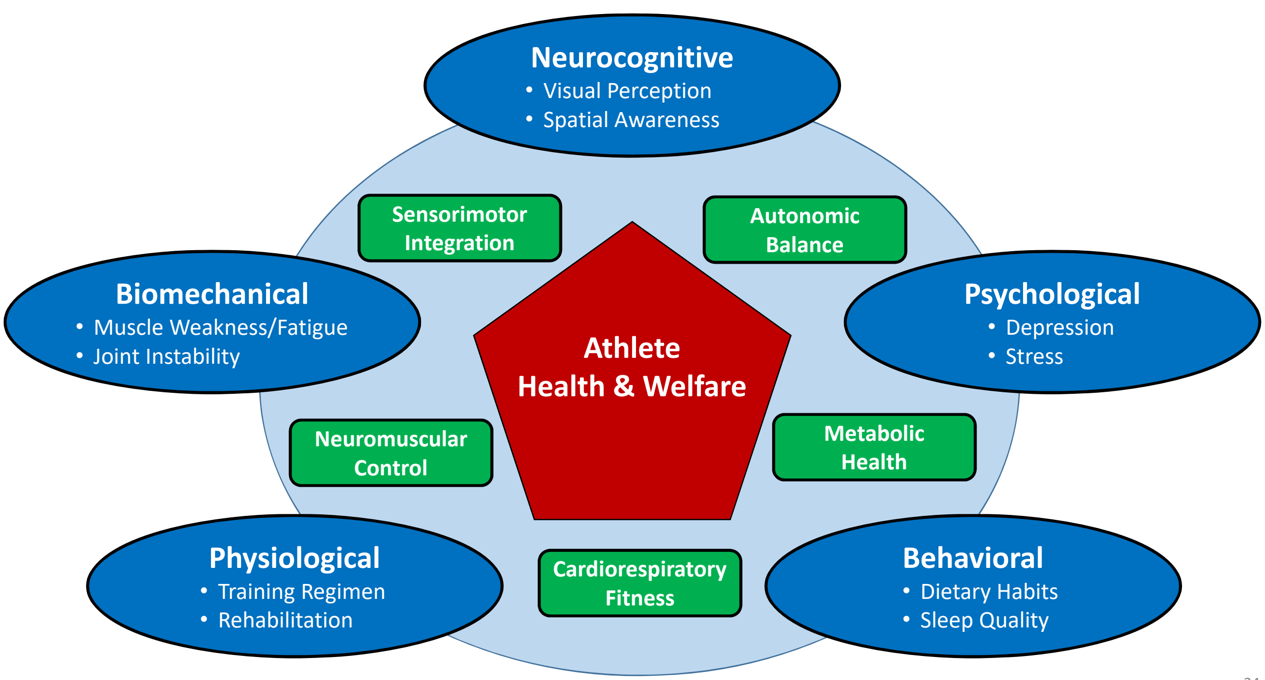



- Small changes can produce large and unexpected interaction effects among factors


Benjaminse, A., Webster, K.E., Kimp, A., Meijer, M. and Gokeler, A. Revised approach to the role of fatigue in anterior cruciate ligament injury prevention: a systematic review with meta-analyses. *Sports Med.* 2019; https://doi.org/10.1007/s40279-019-01052-6.

Bittencourt NF, Meeuwisse WH, Mendonça LD, Nettel-Aguirre A, Ocarino JM, Fonseca ST. Complex systems approach for sports injuries: moving from risk factor identification to injury pattern recognition—narrative review and new concept. *Br J Sports Med*. 2016;50(21):1309-1314.



# Rapid Learning

- Big Data is the essential fuel

Etheredge LM. Rapid learning: a breakthrough agenda. *Health Affairs*. 2014;33(7):1155-1162

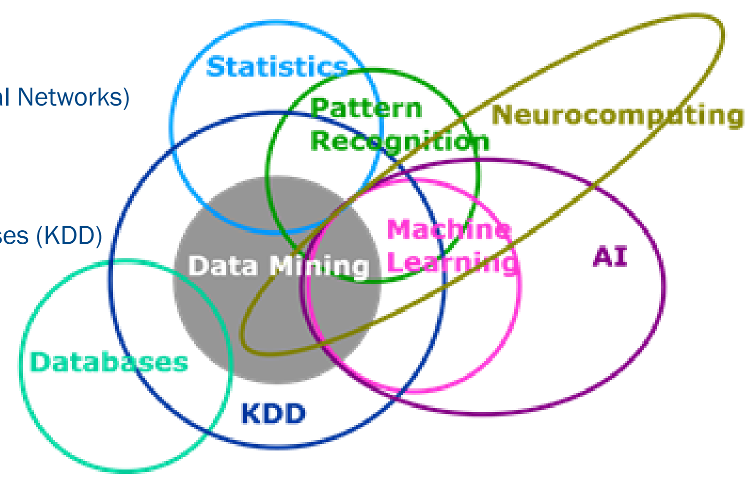
- Data Science → Predictive Analytics

1. Traditional Statistics (overlap with machine learning)
   - Logistic Regression
   - Cox Regression (Survival Analysis)
2. Supervised Machine learning (outcome specification)
   - Classification and Regression Trees (CARTs)
   - Artificial Neural Networks
3. Unsupervised Machine learning (exploratory data mining)
   - Cluster Analysis
   - Principal Components Analysis



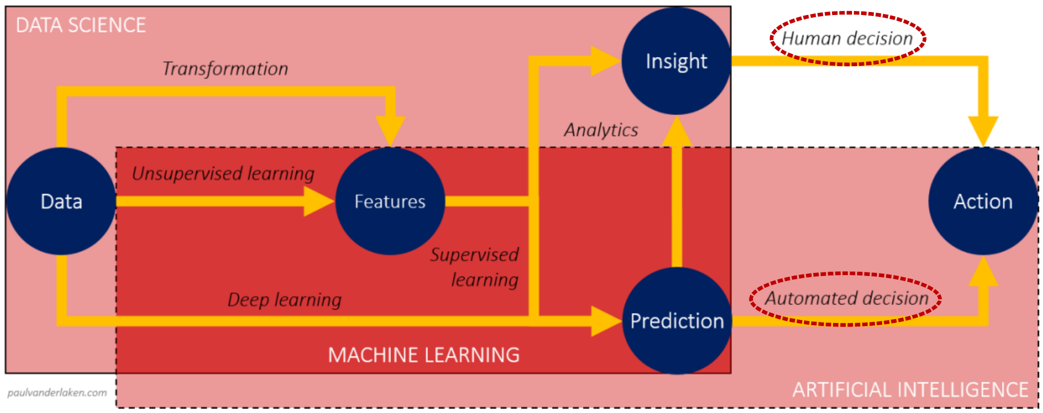
# Overlapping "Data Science" Components

- Statistics
- Machine Learning
- Artificial Intelligence (AI)
- Neurocomputing (Artificial Neural Networks)
- Databases
- Data Mining
- Knowledge Discovery in Databases (KDD)
- Pattern Recognition

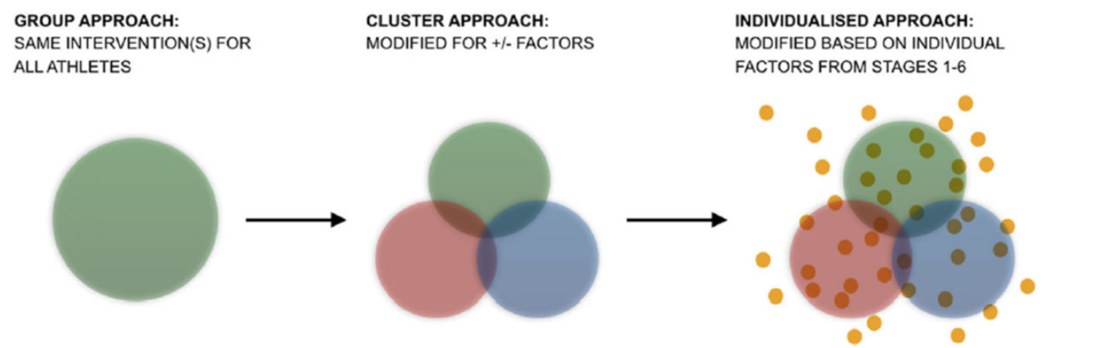



https://blogs.sas.com/content/subconsciousmusings/2014/08/22/looking-backwards-looking-forwards-sas-data-mining-and-machine-learning/

# Data Science – Machine Learning – Artificial Intelligence

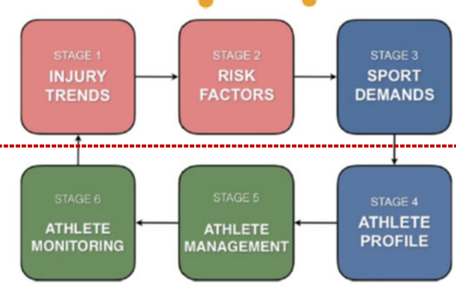



https://paulvanderlaken.com/2018/01/16/ai-datascience-machinelearning/amp/



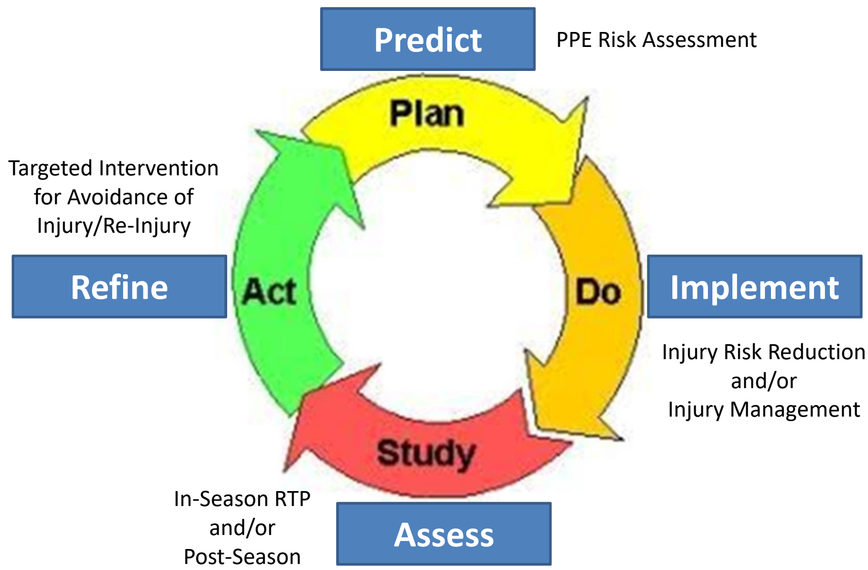

**Group-Level Analyses:**
- Injury Trends: Injuries per 1000 Athlete-Exposures
- Risk Factors: Association of screening results with injury occurrence
- Sport Demands: Internal/External load (adaptation vs. overload)

**Individual-Level Health Management:**
- Athlete Profile: Clustering of injury resistance vs. injury risk factors
- Athlete Management: Targeted interventions for risk reduction
- Athlete Monitoring: Longitudinal tracking of each athlete's status

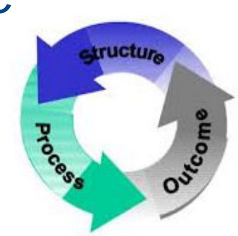



Roe M, Malone S, Blake C, et al. A six stage operational framework for individualizing injury risk management in sport. *Inj Epidemiol*. 2017;4:26.

## Shewhart Concept Application to Athletic Training




## CQI Application to AT Practice




- What outcomes need improvement?
  - *Lateral Ankle Sprain Re-Injury: ~ 70%*
  - *Anterior Cruciate Ligament Tear: ~ 30%*
- How does the injury management process need to be modified to improve outcomes?
- Does structure interfere with implementation of process changes that could improve outcomes?

# How should CQI be applied to AT practice?

- Outcome
  - *Individualized health management*
    - Complex systems approach – machine learning
- Process
  - *Evidence-based protocols and RTP criteria*
    - Rapid Learning (mHealth)
- Structure
  - *Medical model for delivery of AT services*
    - Delivery of patient-centered care




# Summary

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1. A critical need for improved healthcare quality still exists
2. Technology is facilitating acquisition of large datasets
3. Machine learning is increasingly used for data analysis
4. Cultural factors that have historically influenced structure and process may impede effective implementation of CQI

Gary-Wilkerson@utc.edu