NSCA COACHES CONFERENCE 2023

JANUARY 4 – 6, 2023

Charlotte, NC & Online | 2.0 CEUs

#NSCACoaches23

CONFLICT OF INTEREST STATEMENT

I have no actual or potential conflict of interest in relation to this presentation.

Simple Data Analysis for Coaches

Using Basic Statistics to Optimize Your Data

Learning Outcomes:

- In this presentation we will:
  - Review the *practical* meaning of common statistical methods for coaches, including:
    - *Measures of central tendency & variation*
    - *standard scores (Z-scores)*
    - *Smallest worthwhile change (SWC)*
    - *correlation (Pearson's r)*
    - *effect size (Cohen's D)*

Learning Outcomes:

- In this lecture we will:
  - Learn a new concept for operationalizing data, involving the 3-step process of monitor, evaluate, and operationalize (M.E.O.)
    - *Monitor: get beyond testing batteries with invisible monitoring opportunities*
    - *Evaluate: employ statistical procedures to better understand and visualize your data*
    - *Operationalize: create simple shortcuts that transform numbers into action and improve informed decision-making*

Learning Outcomes:

- In this lecture we will:
  - Explore how M.E.O. can be used to drive performance and create buy-in
    - *Performance within and between athletes*
    - *Communication with coaching staff, admin, and athletes*
  - Follow along with worked-problem examples that illustrate the M.E.O. process

About Me

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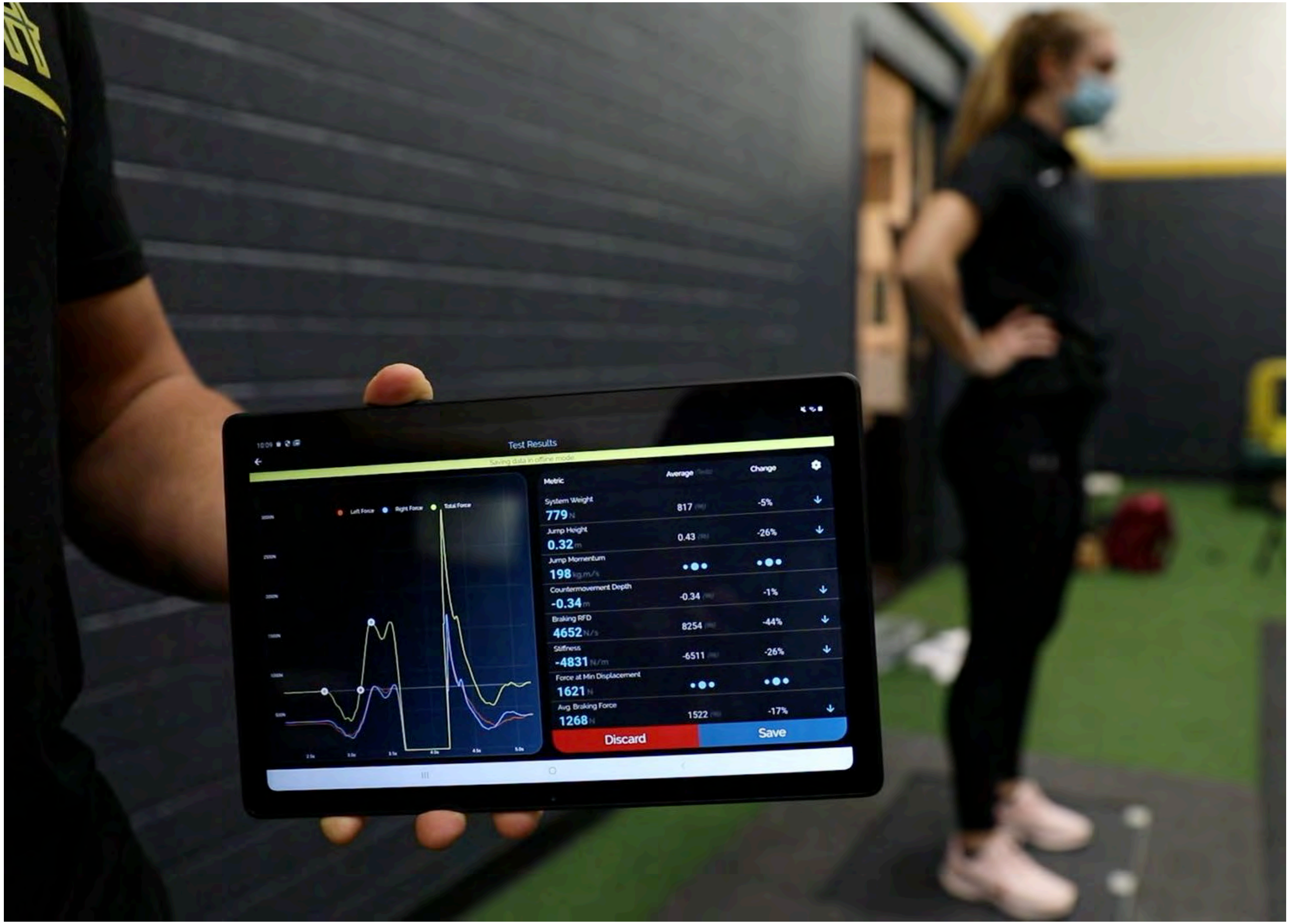

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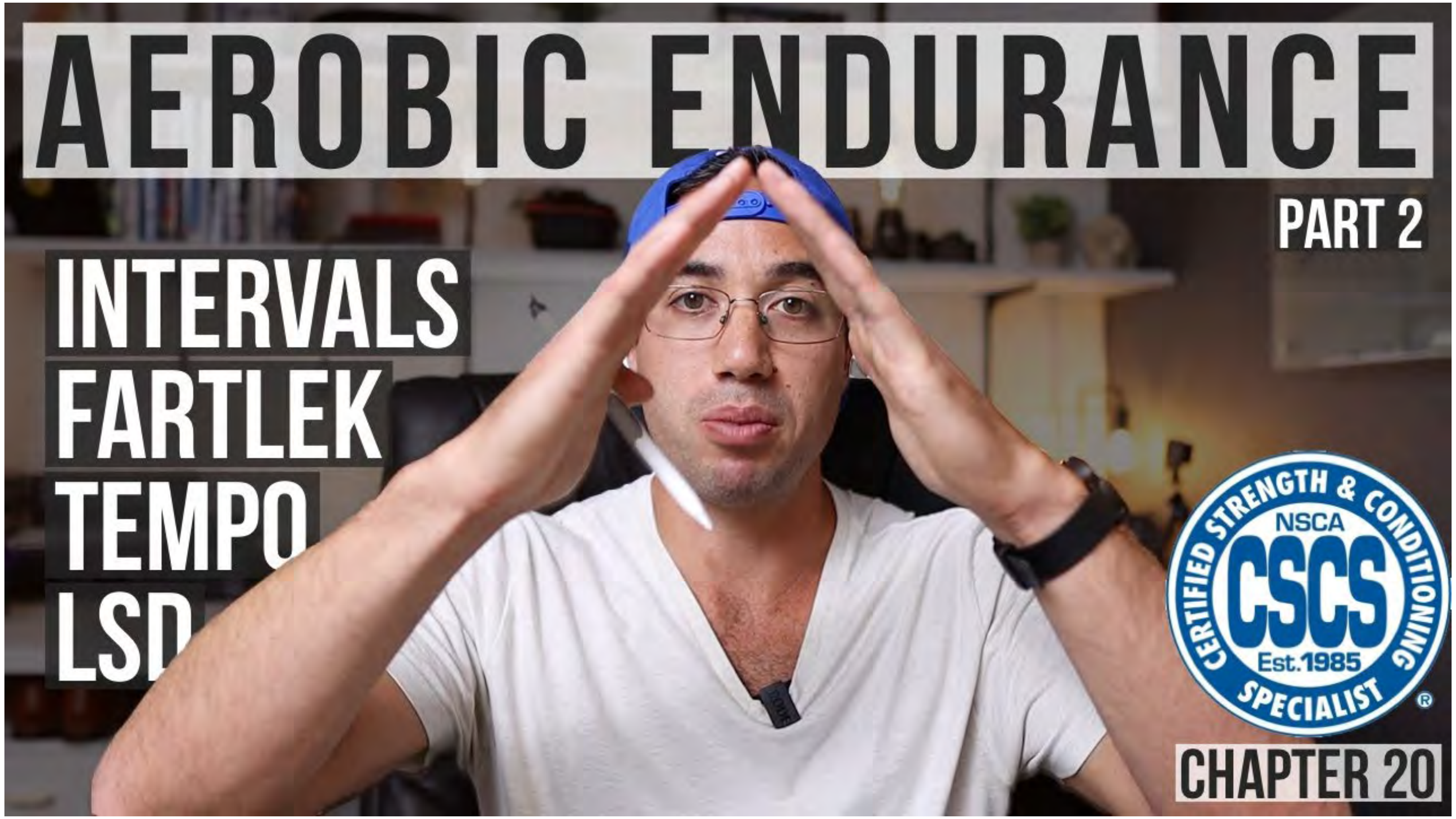

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- Husband & Father

Scenario

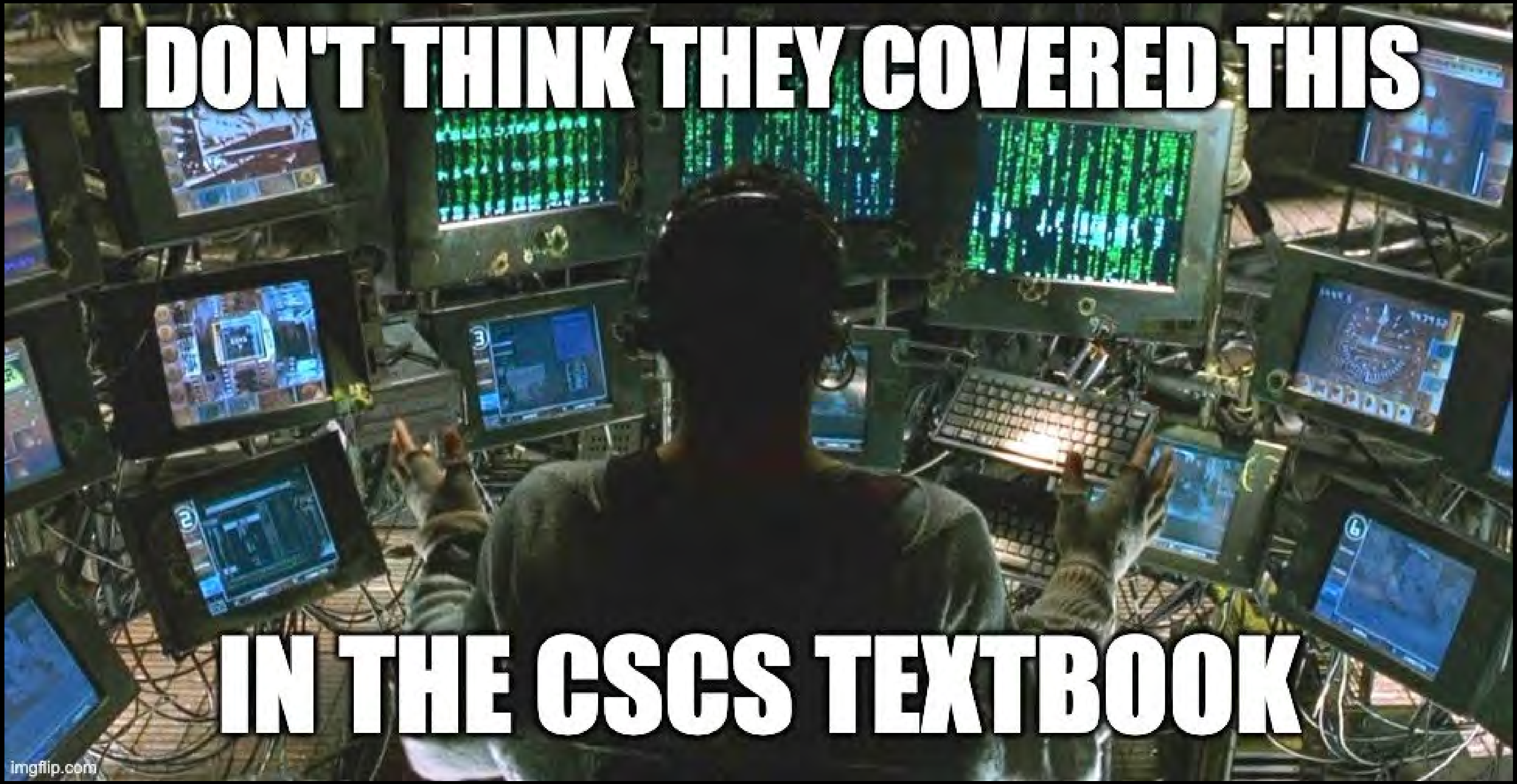
- The typical pre-season performance test
    - 30 athletes
    - 3 performance tests
    - Dozens of collected variables

What the Athlete Sees

What the Sport Coach Sees

What the Athletic Director Sees

What the Strength Coach Sees



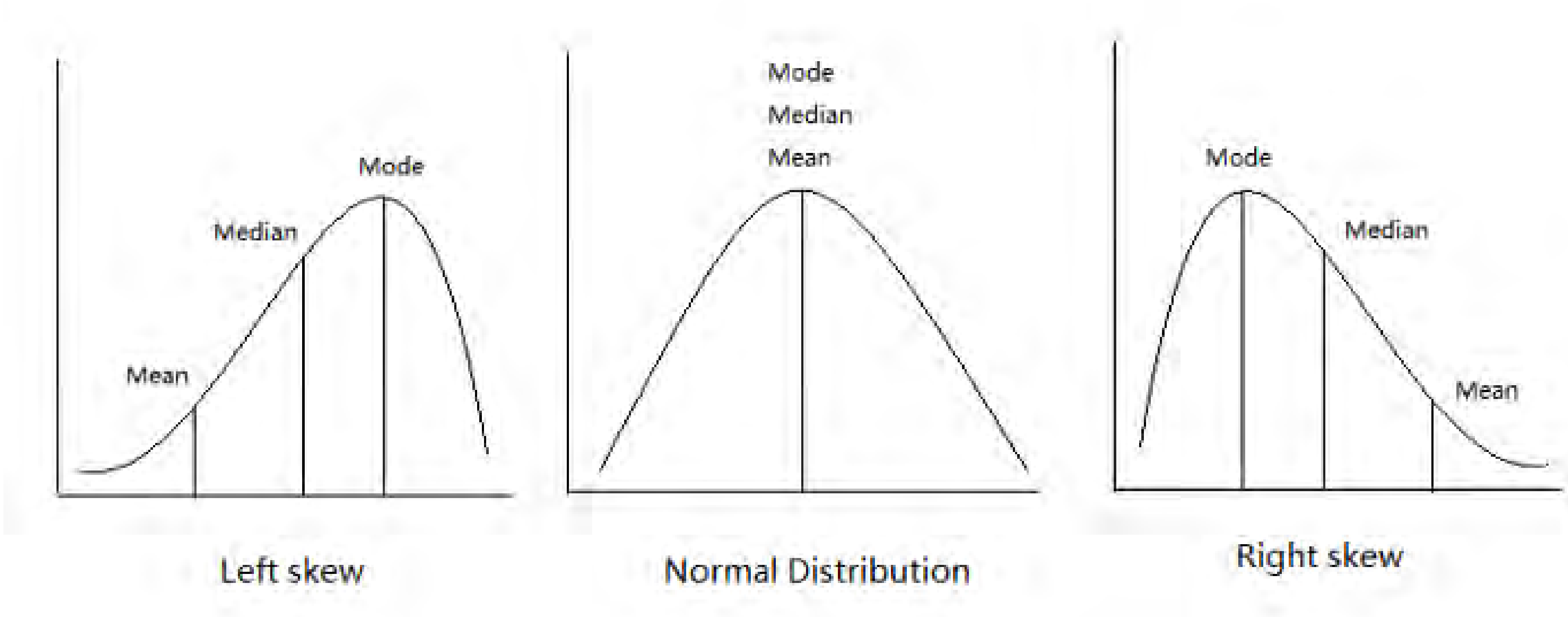
Our Goal Today

A miracle happens

But First, Statistics

- *Practical* meaning of common statistical methods (that coaches might actually use)
  - Central tendency: Mean, median, & mode
  - Variation: standard variation & coefficient of variation
  - Change scores: Smallest Worthwhile Change
  - Standard scores: Z-scores
  - Relationships: Pearson correlation coefficients, coefficient of variation
  - Effect size: Cohen's D

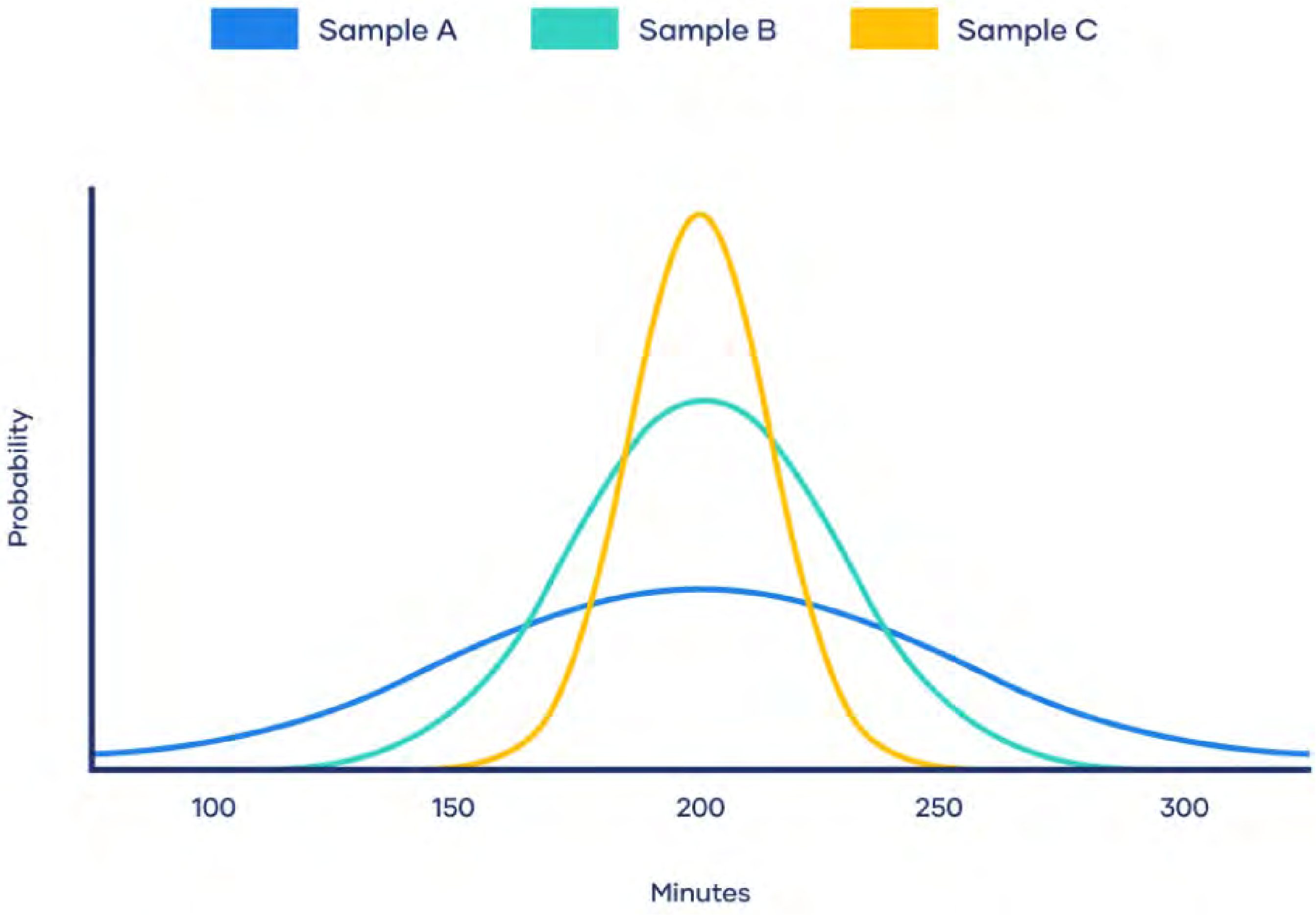
Central tendency: Mean, median, & mode



- This is a simple and common statistic, but very important. The mean allows you to simplify an entire dataset into a single representative statistic.
- e.g. the average jump height for our starts is 51 cm
- e.g. the average session RPE for today was 7.5

Variation: standard variation & coefficient of variation

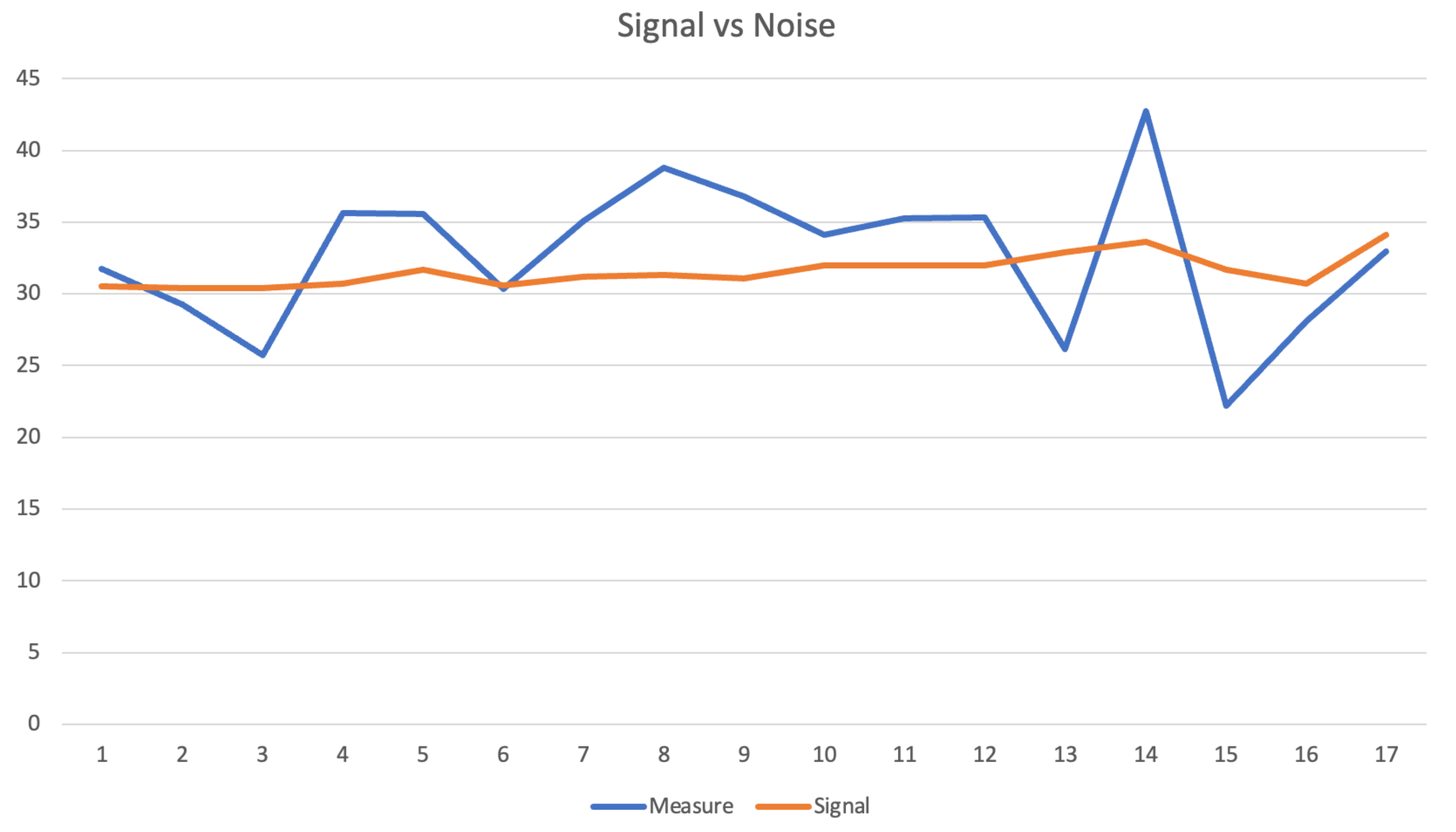
- Measures of spread give you information into the variability within a group, as well as into the reliability of your testing measures
- e.g. the jump heights in our group ranges from 39 to 61 cm
- e.g. the average CV for repeated vertical jumps was 8.4%



Change scores: Smallest Worthwhile Change

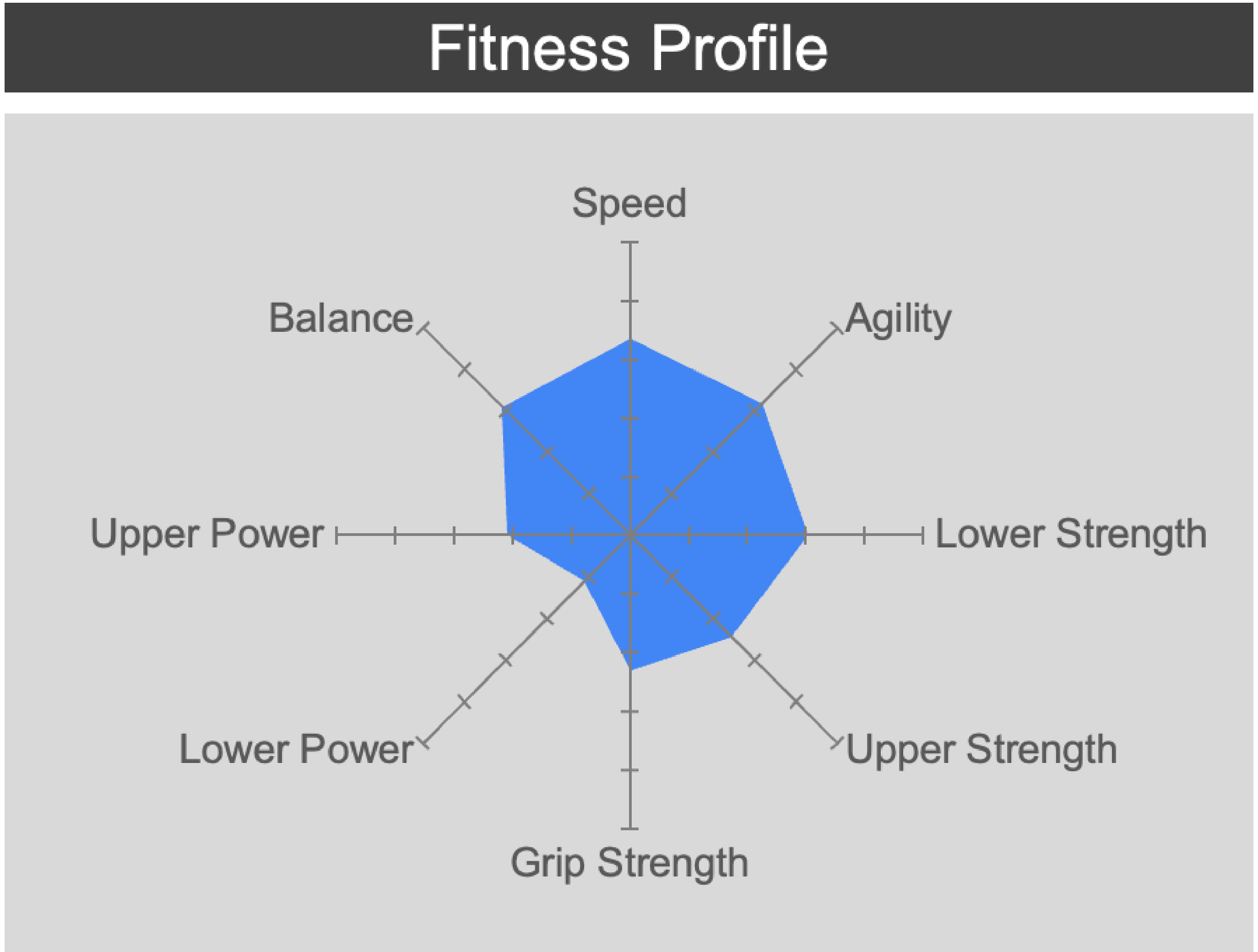
- Oftentimes, we want to know the difference between the means from two different groups, say starters vs nonstarters, OR we want to know whether an athlete has made meaningful progress
- In these cases, we need to identify the signal through the noise
- Measured score = signal
- Variation in scores = noise

Change scores: Smallest Worthwhile Change



Standard scores: Z-scores

- Converts all scores to a standard unit that allows comparison between individuals and across variables within a group
- Allows for better holistic visualizations



Effect size: Cohen's D

- An effect size tells us the practical importance, or magnitude of an observed change
- Sometimes called "clinical significance"

Relationships: Pearson correlation coefficients

- A correlation refers to the relationship between two variables.
- In this instance, we are not interested in changes between time points or differences between groups

Relationships: Pearson correlation coefficients

- Instead, we are asking, how does one variable change in response to another variable?
- In other words, how much variance in X is explained in Y?

Monitor, Evaluate, and Operationalize (MEO)

- Monitor
- Evaluate
- Operationalize
- Win?

Monitor

“You can’t improve what you don’t measure”

Monitor

- Monitor: the process of observing, measuring, and recording the training process
- This is a topic that we could dive deeply into another time
- We are going to assume that you are already doing this, but I will give you a few suggestions for how to start if you haven't already:

Monitor

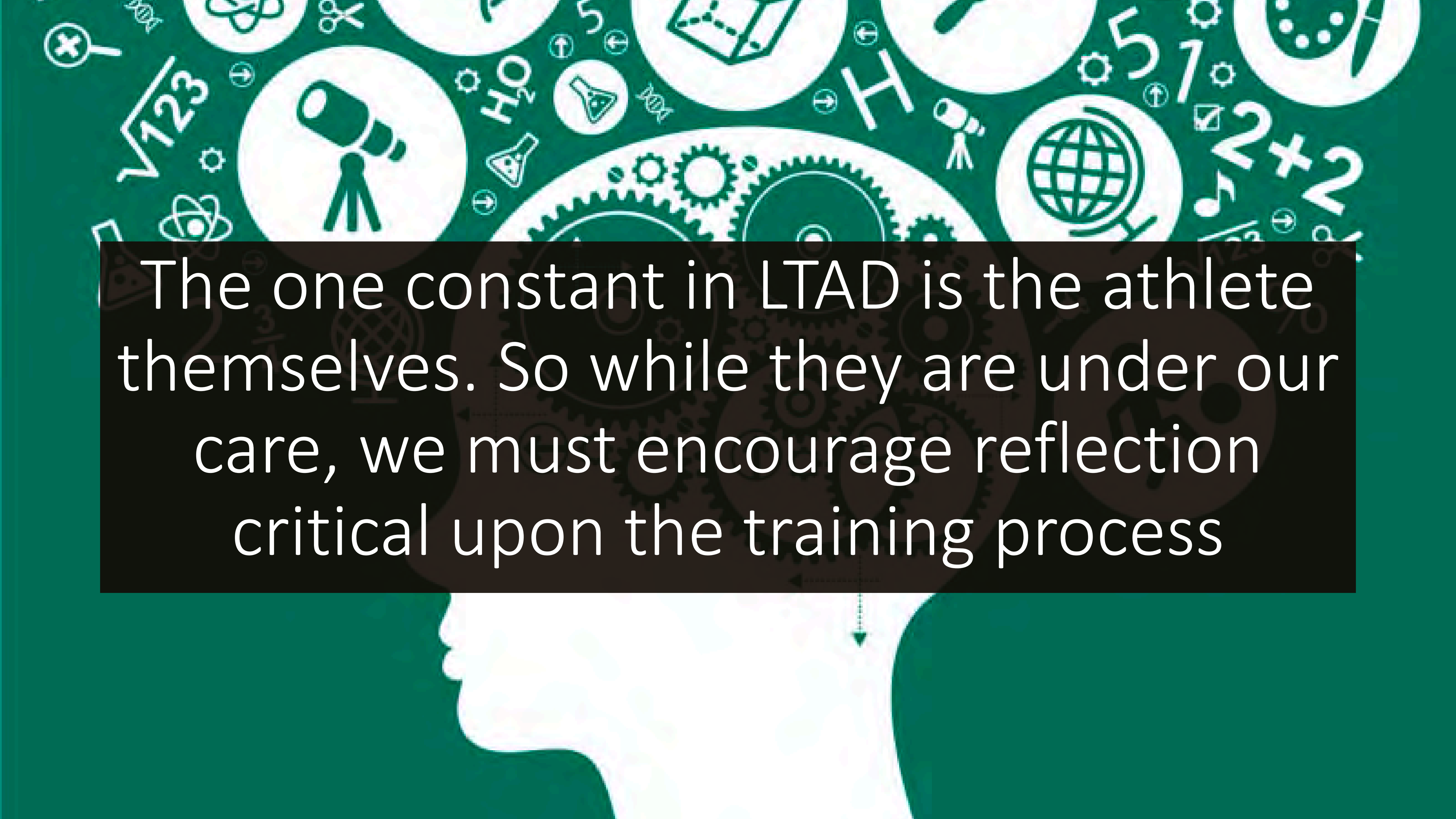
- Getting started
  - Low hanging fruit
  - Impart ownership
  - Encourage a culture of reflection and metacognition

Testing vs Monitoring

Single timepoint testing

vs.

Ongoing data collection integrated with the training process



The one constant in LTAD is the athlete themselves. So while they are under our care, we must encourage reflection critical upon the training process

Invisible Monitoring


BIG BROTHER
IS WATCHING YOU

Invisible Monitoring

- to assess the readiness of athletes to undertake further loading is the use of actual training drills
- assess fatigue via protocols that occur within the normal training and competition process
- Example: “Benchmark sets” Popularized by Mike Tuchscherer

Benchmark Sets:

- The use of a top set at a prescribed relative intensity
- Can be used to estimate weekly 1RM changes
- No added fatigue—it’s part of the prescribed training stimulus for the day

Evaluate

- Employ statistical procedures to better understand and visualize your data
- Turn wall of text into data visualization
- Pro-tip: automation & repeatability are important!

Evaluate

- The boring part
  - Data organization
  - Data screening
  - Data cleaning

Evaluate: SBAT Method

- Single Big-A$$ Table
- Important for leveraging table functionality in Excel or for importing into other programs

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
1	Name	Sex	Age	Height	Weight	10m	20m	30m	Avg. Braking	Avg. Braking	Avg. Braking	Avg. Landing	Avg. Propulsi	Avg. Propulsi	Avg. Propulsi	Avg. Relative	Avg. Relative	Avg. Re
2	Athlete 1	male	20.46	162.98	65.2	1.885	3.125	4.24	1051.96715	-809.92765	-0.85685	891.32295	1391.3204	2279.75715	1.74035	164.51595	-12.42565	217.
3	Athlete 2	male	19.31	183.95	81.4	1.73	2.915	3.975	1568.8289	-1255.1264	-0.90885	1097.21845	1827.59365	3063.64315	1.8408	196.57255	-15.4276	228.9
4	Athlete 3	male	19.18	165.46	74.3	1.87	3.07	4.25	1650.8672	-1462.3211	-0.9862	979.8232	1622.4097	2419.2686	1.6583	226.6269	-19.693	222.
5	Athlete 4	female	17.46	157.63	54.6	1.975	3.5	4.93	956.3294	-736.60435	-0.8477	679.10275	972.1768	1224.1556	1.34995	178.45205	-13.4839	181.
6	Athlete 5	female	22.05	150.58	59.6	2.12	3.62	5.12	939.08765	-528.626	-0.61965	714.6257	1173.76705	1467.6082	1.3838	160.66765	-8.8721	20
7	Athlete 6	female	20.19	165.24	56.7	2.21	3.65	5.06	1026.14885	-752.66555	-0.8114	695.303	1136.2032	1509.85365	1.45375	184.3575	-13.26545	20
8	Athlete 7	female	23.81	170.76	61.7	1.845	3.38	4.81	1137.21515	-762.12665	-0.75445	744.8648	1241.167	1595.93765	1.44295	187.9936	-12.35935	205.1
9	Athlete 8	female	21.28	180.43	78.7	2.06	3.575	4.995	1313.35135	-946.44535	-0.7934	926.3439	1373.6124	1760.3647	1.38325	170.0586	-12.02215	177.
10	Athlete 9	female	18.52	176.03	66.6	2.05	3.475	4.845	1369.80135	-1094.7143	-0.89795	864.1129	1251.76425	1684.5667	1.48575	209.56635	-16.42995	191.
11	Athlete 10	male	20.92	175.21	69.4	1.87	3.03	4.205	1424.344	-1415.1681	-1.1091	1016.43055	1395.6655	2282.03635	1.80895	209.19655	-20.38905	204.
12	Athlete 11	female	23.59	158.53	61.9	1.915	3.42	4.865	1046.58205	-646.8099	-0.69255	742.5967	1213.19695	1641.36625	1.53	172.276	-10.44475	199.6
13	Athlete 12	male	21.89	188.72	82.3	1.95	3.05	4.175	1509.6704	-1276.4505	-0.942	1050.09345	1674.10495	2612.7747	1.6846	186.8963	-15.50005	207.2
14	Athlete 13	male	19.59	167.51	69.6	1.695	2.94	4.1	1222.6773	-803.91435	-0.74205	811.82105	1781.06545	2862.09325	1.7732	179.03715	-11.5479	260.
15	Athlete 14	female	21.42	168.34	64.6	1.815	3.21	4.48	1031.62105	-714.43175	-0.7456	748.3094	1199.29045	1643.6346	1.4256	162.69415	-11.05295	189.
16	Athlete 15	female	20.05	156.06	65.9	2.07	3.52	4.885	1226.6394	-915.7779	-0.82905	841.18845	1299.4211	1756.45805	1.4737	189.86585	-13.9054	201.1
17	Athlete 16	male	22.38	157.56	66.5	2.015	3.335	4.525	1227.14075	-768.4021	-0.7066	826.7125	1471.1127	2164.51575	1.61505	188.1859	-11.5599	225.6
18	Athlete 17	male	18.27	178.99	85.8	1.735	2.945	4.035	1684.61335	-1029.8226	-0.703	1085.7092	2134.77565	3322.61	1.7691	200.1727	-12.00425	253.6
19	Athlete 18	female	19.89	151.39	59.8	1.99	3.885	4.795	1130.86215	-816.0448	-0.80825	769.73775	1220.60145	1634.2705	1.49245	192.80435	-13.6485	208.1
20	Athlete 19	female	19.75	198.46	93.6	2.29	3.835	5.25	1633.37165	-1256.3615	-0.85085	1134.03075	1640.41095	2121.52195	1.38155	177.96645	-13.4283	178.
21	Athlete 20	male	20.06	169.46	71.4	1.765	2.97	4.16	1450.15425	-1262.3506	-0.98495	929.3604	1491.6042	2359.58165	1.77065	207.3773	-17.77055	212.6
22	Athlete 21	female	17.74	141.71	51.1	1.955	3.495	4.895	876.9304	-590.8851	-0.7522	646.54195	1034.58205	1344.80355	1.4191	174.8802	-11.55955	206.
23	Athlete 22	female	18.51	168.03	65.8	2.125	3.65	5.135	1129.0859	-743.3242	-0.7309	811.61155	1194.9837	1531.3798	1.42335	174.84145	-11.2918	185.
24	Athlete 23	female	20.22	161.27	63.4	1.97	3.455	4.805	942.0694	-468.58705	-0.5418	811.7258	1248.25205	1568.34575	1.39595	151.5463	-7.39435	200.8
25	Athlete 24	male	20.69	169.29	61.0	1.53	2.71	3.83	1068.6568	-822.41425	-0.85065	787.4939	1321.96505	2044.494	1.6754	178.61855	-13.48515	220.
26	Athlete 25	male	18.33	169.91	66.4	1.83	3.1	4.295	1227.2111	-1081.0618	-1.0114	796.0239	1412.2009	2286.18245	1.7614	188.34445	-16.27405	216.7
27	Athlete 26	male	17.44	175.64	80.6	1.765	3.04	4.185	1289.46795	-977.56095	-0.86025	1051.96555	1746.17105	2937.8801	1.8617	163.00355	-12.1223	220.
28	Athlete 27	male	22.28	172.32	76.4	1.845	3.125	4.275	1352.64185	-1189.8029	-0.9875	656.47185	1454.2323	2313.39675	1.7538	180.4174	-15.5682	193.
29	Athlete 28	male	20.06	176.34	66.5	1.615	2.775	3.935	1360.366	-1260.0491	-1.03595	964.6764	1432.25385	2325.3273	1.79905	208.41375	-18.9377	219.
30	Athlete 29	male	19.95	168.42	69.0	1.705	3	4.515	1264.5653	-1239.9664	-1.09135	872.31955	1291.89965	1926.45345	1.6326	186.7795	-17.9673	190.
31	Athlete 30	male	17.18	171.05	72.0	1.72	2.975	4.1	1151.9551	-978.511	-0.9481	760.53295	1419.09375	2282.13465	1.7321	163.19385	-13.59805	201.0
32	Athlete 31	female	17.14	177.45	71.9	1.7	3.11	4.495	1179.7173	-833.348	-0.78265	950.7929	1330.3023	1694.3454	1.4046	167.37445	-11.5984	188.7
33	Athlete 32	female	23.31	154.90	54.6	1.98	3.355	4.6	874.78795	-673.11505	-0.8505	653.126	973.24545	1263.74685	1.3763	163.32965	-12.32815	181.
34	Athlete 33	female	20.11	169.24	59.9	2.425	3.805	5.14	1003.32435	-729.67035	-0.806	664.7869	1110.65355	1578.89165	1.5425	170.6409	-12.17395	188.8
35	Athlete 34	male	19.44	192.98	86.6	1.76	3.045	4.18	1755.2459	-1547.5327	-1.01225	1052.1314	1819.99265	3107.6993	1.8621	206.66355	-17.87435	214.
36	Athlete 35	male	22.22	156.13	64.6	1.935	3.19	4.32	1105.23845	-890.0361	-0.8945	788.5764	1304.78105	1965.55215	1.61025	174.32555	-13.77145	205.7
37	Athlete 36	male	18.38	165.00	68.8	1.665	2.905	4.11	1313.60075	-1288.8236	-1.1266	940.57165	1622	3011.7213	2.0396	194.6323	-18.7335	240.3
38	Athlete 37	male	18.61	178.40	75.2	1.87	3.41	4.3	1606.0785	-1464.9437	-1.02035	1133.49695	1601.06535	2489.1107	1.6764	217.69655	-19.4801	217.0
39	Athlete 38	male	22.56	177.13	81.2	1.855	3.055	4.245	1558.91915	-1328.2605	-0.95495	881.1544	1610.9374	2486.8054	1.69895	195.6437	-16.35295	202.

Evaluate: Statistical Processing

- Statistics = Answers to Questions
  - How high = score
  - How high on average = mean
  - How much variability = SD, CV
  - How reliable = CV
  - Was change significant = SWC, CV
  - How much change = ES, %diff
  - How much change compared to team = Z-scores
  - Was there a relationship with other fitness characteristics = Pearson r correlation

Evaluate: Data Visualization

- This is one of the most important, and yet most individualized pieces of the process
- Key Points
  - Maintain a high info-to-ink ratio
  - Utilize blank space
  - Beware of hidden connotations
  - Follow universal design principles

For Further Guidance…

NSCA's Essentials of Sport Science

Expand | **Collapse**

CHAPTER 21

Data Delivery and Reporting

Tyler A. Bosch, PhD
Jacqueline Tran, PhD

Data Visualization Examples

Data Visualization Examples

Operationalize

- Transform numbers into action and improve informed decision-making
  - Why go through all this trouble if it doesn't contribute to the training process??

Operationalize

- Only you and your performance team can ultimately decide how to use the data
- That said, I do have at least 7 suggestions

7 Tips to Operationalize Data

- Tip 1: Create a Plan
  - Decide ahead of time what your actionable steps will be
  - Example: Establish dynamic strength index benchmark & adjust training emphasis accordingly

7 Tips to Operationalize Data

- Tip 2: Establish Ownership
  - Create a training culture of ownership and excellence among the athletes
  - Example: create player cards that display relevant performance data, and set individualized goals with each athlete

7 Tips to Operationalize Data

- Tip 3: Educate Stakeholders
  - Take time to educate the performance staff
  - Example: show the sport coach the correlations between strength, power, and speed measures to establish buy-in for the resistance training program

7 Tips to Operationalize Data

- Tip 4: One Graph to Rule Them All
  - Use Z-scores to create comprehensive athlete profile
  - Example: radar plot showing relevant KPIs. This can guide performance staff in making training decisions

7 Tips to Operationalize Data

- Tip 5: Stoplight System
  - Use SWC to identify signs of overtraining
  - Example: daily jump monitoring as a surrogate measure of readiness vs fatigue, or as a component of a larger readiness assessment

7 Tips to Operationalize Data

- Tip 6: Celebrate small wins
  - Use SWC to celebrate small wins in the training process
  - Example: Submaximal RPE PRs provide positive reinforcement with limited fatigue

7 Tips to Operationalize Data

- Tip 7: Leave the Human in the Loop
  - Remember that all the data in the world will not replace a face-to-face conversation with your athlete, or the intuition of a veteran coach.
  - Example: Use the MEO process as a way to drive further communication and relationship between all members of the performance staff and the athletes under your care.

Resources

- Resources that I have found exceedingly helpful
  - Dr. Will Hopkins' Website: https://sportscience.sportsci.org/resource/stats/index.html
  - Dr. Adam Virgile's work: https://adamvirgile.com/
  - Excel Tricks for Sports: https://www.youtube.com/@ExcelTricksforSports
  - NSCA's Essentials of Sport Science
  - Google
  - YouTube

Resources I've Created

- Statistics Theory and Application Playlist
- Essentials of Sport Science Playlist

References

- Hopkins, W. G. (2004). How to interpret changes in an athletic performance test. *Sportscience*, *8*, 1–7.
- Hopkins, W. G., Marshall, S. W., Batterham, A. M., & Hanin, J. (2009). Progressive statistics for studies in sports medicine and exercise science. *Medicine and Science in Sports and Exercise*, *41*(1), 3–13. https://doi.org/10.1249/MSS.0b013e31818cb278
- Magnusson, K. (n.d.). Understanding Correlations. Retrieved December 16, 2022, from https://rpsychologist.com/correlation/
- Magnusson, K. (n.d.). Interpreting Cohen's d. Retrieved December 16, 2022, from https://rpsychologist.com/cohend/
- Rhea, M. R. (2004). Determining the magnitude of treatment effects in strength training research through the use of the effect size. *Journal of Strength and Conditioning Research*, *18*(4), 918–920. https://doi.org/10.1519/14403.1
- Turner, A., Brazier, J., Bishop, C., Chavda, S., Cree, J., & Read, P. (2015). Data Analysis for Strength and Conditioning Coaches: Using Excel to Analyze Reliability, Differences, and Relationships. *Strength & Conditioning Journal*, *37*(1), 76. https://doi.org/10.1519/SSC.0000000000000113