STM5IPL Initial Report

Interpreting key player and team performances into AFL using data visualizations

Michael Le





1972 - 1975

1976 - 1989





1990 - 1999

2000 - now

August 2024

Abstract

AFL, commonly known as Australian Rule Football, where the sport was drafted in 1859 by "Hammersley, Smith, Thompson and Wills", who constructed the "rules" which has been the sport has been famous for in over "140+ years or more". Where the first clubs were formed in "1860" and "1866" in South Australia and Queensland respectively. Later, continued to expand in Victoria in "1877", forming "eight-team leagues" alongside with South Australia, forming VFA/VFL in "1897" but was renamed to AFL in 1990 expanded more teams up to AFL 2011-2012 Season where two new teams GWS Giants and Gold Coast Suns were added into the AFL official roaster. To understand the "draft system" has been a main goal building relationships between teams and players. The "selection process" requires intensive "scouting reports" and "player assessments" to inform decision-making. When drafting players, we must consider under two conditions fairness and talent amongst across multiple football clubs. One method using recent and up to date data from "previous drafts" to understand patterns of player and team performance. Hence, will be valuable for the player and team success and satisfaction of "drafting outcomes".

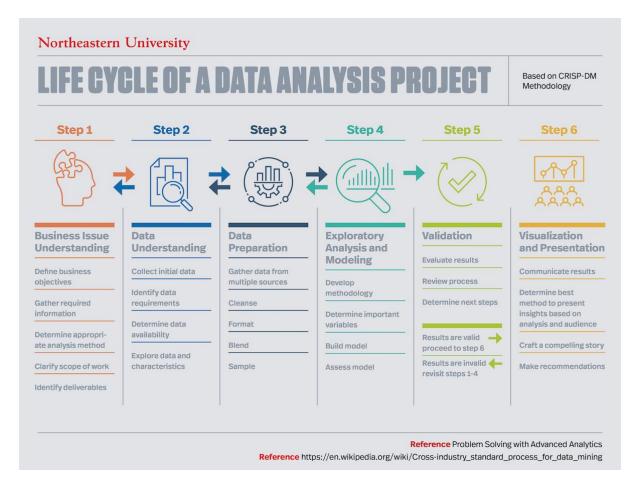


Figure 1. Life Cycle of a Data Analysis Project from Northeastern University

Introduction

The purpose of finding key performances in Australian Rules Football is to determine best talent among player candidates based on their "physical skills", "past performance in matches", "athletic abilities", and "psychological assessments". Most of the factors may include such as "speed", "growth", "endurance" and "strength" that is "quantifiable" to enable passionate and determined players to officially be drafted into the AFL Season. To enable decision making when it comes to their selection of players from the Sandringham Football Club at Foundry Athletic. The data was collected through email to discuss open-minded questions regarding key aspects to finding the best talent to provide an appropriate data visualization tool to demonstrate meaningful insights. Interpreting the "Business issue Understanding" and "Data Understanding" phases to determine on how well the team is performing. Includes, how well players are performing to easily process key talent and team performance during data analysis project. By understanding the data analytics lifecycle consists of six phases "based on the CRISP-DM methodology". Include, the "business issue", "understanding the data set, preparing the data, exploratory analysis, validation, visualization and presentation". To execute a well-informed data analysis project report.

Methodology

During the "Data Preparation" phase (seen Figure 1), in performing an explanatory analysis of the data collected on Australian Football games, understanding two key concepts talent and recruitment when drafting only 12 out of the 170 players from the Sandringham Football Club will be drafted into AFL. This can be achieved trends through data preparation, is the process of transforming and cleaning raw data by "standardizing data formats, enriching source data, or removing outliers." The data collection contains folders containing (seen Figure 2 below). After further discussion with the data team and supervisor during the meeting. We decided to divide the number of folders to focus only the folders from 2km Results, Combine Testing Data, GPS Data, Gym Strength Testing Data, Height & Weight Data, Max Speed Data and Player Football Match Statistics, without losing valuable information containing Excel Spreadsheets.

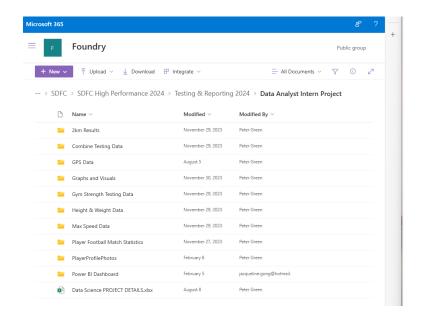


Figure 2. Supervisor's Folders containing all Player and Team Performance data from the Sandringham Football Club

Recommended technologies when necessarily used to perform these tasks using Microsoft Excel, combining multiple tables for each of the following folders without losing valuable information using Python programming language to merge. During the data collection process, up to the end of Week 3 of the placement, the data team have completed transformed and cleaned all raw data for Max Speed Data, Player Football Match Statistics (in Figures 4,5 and 6 respectively), and Combine Testing Data confirmed via chat while the GPS Data, while folders 2km Results and Heights and Weights are still in progress and lastly Gym Strength Testing Data (in Figure 3) is almost completed, where the cells are filled in red are the remaining entries needed to clean.

A	8	C	D E	F	G	H	1		K	L.	M	N	0	P Q	R	S	T	U	V W	X
Name		▼ Date_x	▼ Jump H ▼ ID	→ Weight →						Contac *	RSI (JH × J		oncer v l	OSI (CI - TYPE	Test IS -				t Ty · Test Ty	
2 Alfie Lambert	12/11/20			68.3				2457	36.57	0.171	2.16	28.9	1677	0.68 Neutral	ISO 30	234.75		15.55755 SJ	IMTP	68
3 Angus Phillips	12/08/20			82.1				2675	32.82	0.272	1.09	25.8	1892	0.71 Neutral	ISO 30	387.5		11.63056 SJ	IMTP	82
4 Angus Taylor	12/11/20	23 11/12/2	023 27.1 ATHLETE 6	80.8			19.3	2616	32.74	0.236	0.93	25	1575	0.6 Neutral	ISO 30	282.75		19.27195 SJ	IMTP	80
5 Archer Grant	12/11/20	23 11/12/2	023 27.9 ATHLETE 7	70.5	29	276	-5	2534	36.52	0.217	1.18	0	1461	0.58 Strong	ISO 30	290.25	275.75	-4.99569	IMTP	70
6 Archie Ludowyke	12/11/20	23 11/12/2	023 34.1 ATHLETE 8	78.8				2814	36.08	0.23	1.58	32.3	1781	0.63 Neutral	ISO 30	340.25		-0.36738 SJ	IMTP	7
7 Bennett Martin	12/11/20	23 11/12/2	023 29.4 ATHLETE 10	68.4			11.1	2389	35.03	0.251	1.41	30.4	1577	0.66 Neutral	ISO 30	264.25	297.25	11.10177 SJ	IMTP	6
8 Chartie Beaumont	12/11/20	23 11/12/2	023 33.9 ATHLETE 12	67.5			8.3	3068	45.93	0.186	1.79	0	1501	0.49 Strong	ISO 30	381.75	416.25	8.288288	IMTP	6
9 Chartie Rozenes	12/08/20	23 8/12/2	023 38.9 ATHLETE 13	75.8	421	366	-14	0	0	0	0	40.4	1886	0 Neutral	ISO 30	425.75	366	-14.0341 SJ	1000	7
O Christopher Kellaway	12/08/20	23 8/12/2	023 34.8 ATHLETE 14	77.6	383	2 400	4.6	3181	41.37	0.206	1.37	32	1872	0.59 Strong	ISO 30	381.5	399.75	4.565353 SJ	IMTP	7
1 Dexter Prime	12/08/20	23 8/12/2	023 31.9 ATHLETE 15	82.3	501	526	3.4	3231	39.7	0.215	1.6	32.8	1912	0.59 Strong	ISO 30	508	526	3.422053 SJ	IMTP	8
12 Elden Pitt	12/11/20	23 11/12/2	023 32 ATHLETE 16	83.3	36:	345	-4.6	3415	41.59	0.331	0.94	29.6	1997	0.58 Strong	ISO 30	361.25	344.75	-4.56747 SJ	IMTP	8
3 Eiden Pitt	12/11/20	23 11/12/2	023 32 ATHLETE 17	83.3	36:	345	-4.6	3415	41.59	0.331	0.94	29.6	1997	0.58 Strong	ISO 30	361.25	344.75	-4.56747 SJ	IMTP	8
14 Emmanuel Ganas	12/11/20	23 11/12/2	023 27.7 ATHLETE 18	85.8	471	624	24.6	3417	39.92	0.217	1.3	28.7	1941	0.57 Strong	ISO 30	470.25	623.75	24.60922 SJ	IMTP	8
5 Freddy Brayshaw	12/11/20	23 11/12/2	023 34.7 ATHLETE 21	63	283	3 367	22.9	2429	38.93	0.192	1.77	36.8	1505	0.62 Neutral	ISO 30	283	367.25	22.94078 SJ	IMTP	
6 Harvey Allan	12/11/20	23 11/12/2	023 36.4 ATHLETE 24	78.5	343	3 376	8.9	0	0	0.252	1.17	30.4	2058	0 Neutral	ISO 30	342.5	376	8.909574 SJ		7
7 Jack Cheep	12/08/20	23 8/12/2	023 36.5 ATHLETE 26	86.5	306	336	8.9	3210	37.54	0.183	1.99	35.1	2285	0.71 Neutral	ISO 30	306.25	336.25	8.921933 SJ	IMTP	. 8
18 Jack Dalton	12/11/20	23 11/12/2	023 41.7 ATHLETE 27	72.8	233	3 287	18.9	3113	42.7	0.211	1.88	32.3	1983	0.64 Neutral	ISO 30	232.5	286.75	18.91892 SJ	IMTP	7
19 Jack Hayter	12/11/20	23 11/12/2	023 34.5 ATHLETE 28	71.6	363	3 333	-8.2	2965	41.36	0.214	1.83	35.7	1649	0.56 Strong	ISO 30	362.5	332.75	-8.2069 SJ	IMTP	7
Jack Meredith	12/11/20	23 11/12/2	023 36.4 ATHLETE 29	68.9	483	1 400	-16.9	0	0	0.24	1.32	29.3	1505	0 Neutral	ISO 30	480.5	399.5	-16,8574 SJ		
1 Jake Matthews	12/08/20	23 8/12/2	023 32.9 ATHLETE 30	0	40	496	18.2	0	0	0.227	1.38	29.3	0	0 Neutral	ISO 30	405.75	495.75	18.15431 SJ	IMTP	
2 Jake Mehl	12/11/20	23 11/12/2	023 34.2 ATHLETE 31	68	357	7 377	5.4	2570	38.41	0.235	1.68	35.1	1621	0.63 Neutral	ISO 30	356.5	376.75	5.374917 SJ	IMTP	
3 James Arnold	12/11/20	23 11/12/2	023 35.1 ATHLETE 32	73.7	34	347	1.4	2583	35.62	0.271	1.29	30.1	1755	0.68 Neutral	ISO 30	342	347	1.440922 SJ	IMTP	7
4 James Cutler	12/11/20	23 11/12/2	023 26.5 ATHLETE 33	77.4	40	433	6.7	0	0	0.182	1.35	26.7	1623	0 Neutral	ISO 30	403.5	432.5	6.705202 SJ		7
25 James Georgiou	12/11/20			74.7	31			2942	39.6	0.224	1.73	35	1716	0.58 Strong	ISO 30	309.5		24.46614 SJ	IMTP	7
6 James Mikhael	12/11/20	23 11/12/2	023 34.1 ATHLETE 35	77.3	383	3 454	15.6	2331	30.35	0.191	2.1	38	1765	0.76 Neutral	ISO 30	383.25	454	15.5837 SJ	IMTP	7
7 Jhett Haeata	12/08/20	23 8/12/2	023 35.1 ATHLETE 36	76.3	31	3 397	21.2	0	0	0	0	33.4	1869	0 Neutral	ISO 30	313	397.25	21.20831 SJ	-	7
8 Jordan Tessier	12/11/20			77.7				2513	32.73	0.244	1.12	29.7	1592	0.63 Neutral	ISO 30	369.75		18.1969 SJ	IMTP	7
29 Joshua Dolan	12/08/20			75.1				0	0	0	0	38	1920	0 Neutral	ISO 30	287.75		12.27134 SJ		7
0 Kye Fincher	12/11/20			77.3				2935	38.26	0.151	2.32	32.5	2445	0.83 Powerful		348.75		20.42213 SJ	IMTP	7
1 Lenny Hoffman	12/08/20			81.8				3235	39.98	0.213	1.71	39.5	2117	0.65 Neutral	ISO 30	384		12.47863 SJ	IMTP	
2 Louis Fulcher	12/11/20			74.3				2861	38.76	0.226	1.51	33.7	1959	0.68 Neutral	ISO 30	365.5		16.78998 SJ	IMTP	7
3 Luka Pecer	12/08/20			87.5				2480	28.53	0.317	0.94	28.2	2093	0.84 Powerful		346.25			IMTP	
34 Luke McGinness	12/11/20			84.5				2823	33.93	0.252	1.14	26.2	1856	0.66 Neutral	ISO 30	421.75		15.69215 SJ	IMTP	8
5 Max Hoult	12/08/20			86.7				0	00.00	0.232	0	36.9	2199	0 Neutral	ISO 30	506		-16.6996 SJ	PHIE	8
6 Maximus Chalamandar				00.7	301	424	1,10.7	0	u	-	-	20.3	2133	Neutral	100 00	300	421.0	SI		7
7 Miles Tyrer	12/11/20			91.7	364	385	5.6	2826	31.02	0.278	0.84	25.1	2244	0.79 Neutral	ISO 30	363.5	205.05	5.645685 SJ	IMTP	9

Figure 3. Transformed Gym Strength Testing Data (shown only partially of it)

		В	С		Е		G		- 1
1	Player Na		D(vmax)	T(vmax)	90% Vmax		T(90%)	Speed (km	/hr)
2	Billy McGe					17.99	3	31.57	
3	Brodie Fin					21.1			
4	Charlie Ed	8.86	39.6	5.3	7.97	18.77	2.9	31.9	
5	Charlie Ee	8.64	46.61	6.5	7.78	19.3	3.3	31.1	
6	Charlton H	9.12	58.25	7.5	8.21	22.33	3.2	32.83	
7	Cooper Lo	8.83	35.43	4.9	7.95	21.48	3.3	31.79	
8	Ethan Will	8.63	46.96	6.3	7.77	15.83	2.6	31.07	
9	Harrison (8.6	31.22	4.6	7.74	22.66	3.6	30.96	
10	Harry Sulli	9.17	44.35	5.8	8.25	19.26	3	33.01	
11	Harvey Joh	8.49	38.69	5.5	7.64	18.66	3.1	30.56	
12	Jack Dalto	8.54	24.82	3.7	7.69	16.29	2.7	30.74	
13	Jeremy a'E	8.61	29.08	4.3	7.75	18.77	3.1	31	
14	Joshua Do	9.19	37.94	5.1	8.27	23.57	3.5	33.08	
15	Joshua Do	8.97	42.8	5.8	8.07	17.35	2.9	32.29	
16	Justin Kro	8.63	27.83	4.1	7.77	16.8	2.8	31.07	
17	Lachlan V	8.59	41.12	5.8	7.73	21.92	3.5	30.92	
18	Levi Ashcr	9.16	47.32	6.2	8.24	19.4	3.1	32.98	
19	Levi Young	8.16	37.65	5.6	7.34	17.74	3.1	29.38	
20	Luke Kenn	9.03	37.1	5	8.13	20.45	3.2	32.51	
21	Mason Sz	9.28	44.42	5.9	8.35	24.32	3.7	33.41	
22	Mitchell K	8.68	43.31	5.9	7.81	19.14	3.1	31.25	
23	Nathan Su	8.43	34.3	4.9	7.81	20.71	3.8	30.35	
24	Nathaniel	8.9	41.36	5.6	8.01	19.51	3.1	32.04	
25	Ned Magir	8.92	44.97	6.2	8.03	21.37	3.5	32.11	
26	Ollie Murp	8.1	42.06	5.9	7.29	17.23	2.8	29.16	
27	Ollie Wart	8.74	39.49	5.4	7.87	18.99	3	31.46	
28	Riely Colli	9.07	44.56	5.9	8.16	20.55	3.2	32.65	
29	Ryley Sand	9.2	43.35	5.8	8.28	18.89	3.1	33.12	
30	Samuel Li	8.39	42.98	6.1	7.55	18.34	3.1	30.2	
31	Taj Hotton	8.54	46.29	6.3	7.69	16.92	2.8	30.74	
32	Timothy P.	8.75	47.27	6.4	7.88	20.59	3.3	31.5	
33	Vigo Viser	8.37	40.53	5.6	7.53	16.56	2.7	30.13	
34	William B	8.57	37.96	5.4	7.71	17.66	3	30.85	
35	William N	9.07	51.16	6.8	8.16	20.58	3.4	32.65	
36									
37	Average	8.75	41.15	5.65	7.88	19.44	3.15	31.5	
	< >	Tran	sformed S	DEC Spec	d Data	+			

Figure 4. Transformed Sandringham Dragons Football Club Max Speed Data

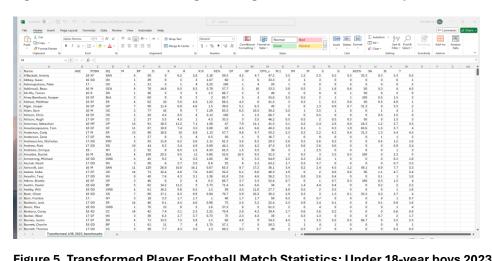


Figure 5. Transformed Player Football Match Statistics: Under 18-year boys 2023 BenchMarks

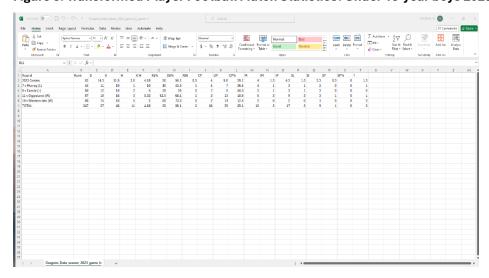


Figure 6. Transformed Player Football Match Statistics: Dragons Data season 2023 game by game

After enhancing and improving the data, we process only the "Exploratory Data Analysis", since we would not be modelling during the data analysis project if necessary, depending on the supervisor's proposal. We wanted to recognise and understand patterns of data using appropriate libraries to perform data manipulation, aggregation methods for statistical analysis such as computing their averages, standard deviations and z-scores to compute for the final dashboard. The supervisor prefers key statistics for computing average values from the GPS Data, 2km Results, and Combine Testing Data. (Seen in Figure 7 and 8) below, taking the maximum value as the supervisor proposed for each of the columns to solve for following z-scores, which will be later be used to form into a Rader Chart (See Figure 11 below) into the final dashboard.

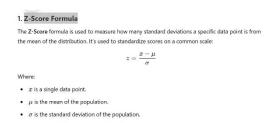


Figure 7. Z-Score Formula

		Weight		NORDBOARD-ISO	30		IMPT		DJ		SJ	С	MJ		
ATHLETEID	PLAYER NAME		NORDLEFT	NORD RIGHT	NORD ASSYM	Peak Vertical Farce	[t>ak Vortical Farco / BM [N/kq]	Jump Hoight (Imp-Mam) [am]	Contact Time [r]	Time)/Centec	Jump Hoight (Flight Time) [cm]	Jump Heigh (Imp-Mam) [cm]	t Cancentric PeakFarce [N]	DSI (OMJ Peak Farce)	TPF
ATHLETE 1	Aaron Taylor		327	313	-4.3	2662	33.83	30.1	0.201	1.5	28.5				
ATHLETE 2	Adrian Cale Alfie Lambert	60.3	434 235	459 270	5.4 15.6	2457	34.57	36.9	0.171	2,16	20.9	31.7	1020	0.74	
THLETE 4	Angur Boud	44.2	322	399	19.4	3265	42.62	24.9	0.111	6.19	44.7	26.1	114.1	0.14	
THLETES	Angur Phillips	82.1	388	439	11.6	2675	32.02	29.3	0.272	1.09	25.8	31.2	1928	0.72	
THLETE 6	Angur Taylor	80.8	293	350	19.3	2616	32.74	21.9	0.236	0.93	25	29.5	1592	0.61	4
THLETE?	Archer Grant	70.5	290	276	-5.0	2534	36.52	24.9	0.217	1.18		28.1	1486	0.59	Stong
THLETE 0	Archie Ludewyke Bailey McKenzie	70.0	340 351	339 346	-0.4 -1.3	2014 2515	36.00	36.2	0.23	1.50	32.3	34.6	1801	0.64	
THLETE 10	Bennett Martin	68.4	264	297	11.1	2389	35.03	35.4	0.251	1.41	30.4	30.3	1676	0.70	
THLETE 11	Bradie Findley		205	429	12.3			30.1	0.249	1.21					
THLETE 12	Charlie Beaumant	67.5	382	416	8.3	3068	45.93	33.3	0.186	1.79		36	1522	0.50	Stong
THLETE 13	Charlie Ruxener Christopher Kellowe:	75.8 77.6	426	366 400	-14.0 4.6	3181	41.37	27.9	0.206	1.37	40.4	39.6	1949	0.62	
THLETE 15	Dexter Prime	82.3	508	526	3.4	3231	39.7	34.3	0.215	1.6	32.8	33.3	1969	0.61	
THLETE 16	Eiden Pitt	03.3	361	345	-4.6	3415	41.59	30.9	0.331	0.94	29.6	32.9	2069	0.61	
THLETE 17	Emmanuel Ganar	85.8	470	624	24.6	3417	39.92	28.3	0.217	1.3	28.7	28.4	2002	0.59	Stong
THLETE 18	Flotcher Teelau		400	418	4.4	2787	35.42	33.9	0.257	1.34	39.5				
THLETE 19 THLETE 20	Flynn Graver	63	206	367 367	16.7 22.9	2429	38.93	33.9	0.192	1.77	36.8	35.8	1571	0.65	
THLETE 20	Freddy Brayzhau Harrison Oliver	63 70.7	283	367	22.9	2429	38.93 37.12	33.9	0.192	2.17	36.8	35.8	1571	0.65	
THLETEZZ	Herry Armetrena		364	397	8,3	2817	33.66	40.4	0.202	1,99	40,5			0.00	
THLETE 23	Harvey Allan	78.5	343	376	8.9			29.6	0.252	1.17	30.4	37.9	2197		
THLETE 24	Hunter Lynch		315	375	15.9	2650	24.46								
THLETE 25	Jack Choop Jack Dalton	86.5 72.8	306 233	336 287	8.9 18.9	3210 3113	37.54 42.7	36.3	0.183	1,99	35.1 32.3	38.9 43.1	2325	0.72	
THLETE 27	Jack Hayter	71.6	262	222	-0.2	2965	41.36	39.3	0.214	1.03	35.7	35.9	1689	0.57	Stone
THLETE 28	Jack More dith	68.9	481	400	-16.9	2,45	107	31.4	0.24	1.32	29.3	37.1	1526		D. Carrie
THLETE 29	Jake Mattheur		406	496	10.2			31.3	0.227	1.38	29.3				
THLETE 30	Jako Mohl	68	397	377	5.4	2570	38.41	39.2	0.235	1.60	35.1	34.8	1691	0.66	
THLETE31	James Arnald James Outles	73.7 77.4	342 404	347 423	1.4	2583	35.62	33.2 24.7	0.271	1.29	30.1	36.2 27.9	1799	0.70	
THLETE 32	James Georgiau	74.7	310	410	24.5	2942	39.6	38.8	0.102	1.73	25.7	41.7	1742	0,59	Stong
THLETE34	James Mikhael	77.3	383	454	15.6	2331	30.35	40.1	0.191	2.1	38	34.4	1835	0.79	Scand
THLETE 35	Jhott Hacata	76.3	313	397	21.2						33.4	37.3	1906		
THLETE36	Jardan Terrior	77.7	370	452	18.2	2513	32.73	26.7	0.244	1.12	29.7	31.1	1640	0.65	
NTHLETE 37 NTHLETE 38	Jarkus Dalen Julian Galbelly	75.1	200 375	320 450	12.3 18.1	3002	34.66				30	42.0	2015		
THLETE39	Kye Fincher	77.3	349	438	20.4	2935	38.26	35	0.151	2.32	32.5	38.5	2505	0.85	Pawerful
ATHLETE 40	Lenny Haffman	01.0	384	429	12.5	2225	39.90	36.3	0.213	1.71	39.5	40.0	2164	0.67	
ATHLETE 41	Louir Fulcher	74.3	366	439	16.8	2861	38.76	34.2	0.226	1.51	33.7	34.8	2111	0.74	
ATHLETE 42	LucarRiroloy		404	455	11.4	2513	30.8	32.4	0.235	1.39	28.4				
ATHLETE 43	Luka Pocor Luka Kannady	87.5	346	448 359	22.7 11.0	2480 2851	20.53	29.1	0.317	0.94 2.02	28.2	30.3	2317	0.93	Pawerful
ATHLETE 45	Luke McGinners	04.5	422	500	15.7	2023	33.93	20.7	0.252	1.14	26.2	27.4	1064	0.66	
STHLETE 46	MaxHault	86.7	506	422	-16.7						36.9	39.7	2273		
ATHLETE 47	Miles Tyrer	91.7	364	385	5.6	2826	31.02	23.3	0.278	0.84	25.1	31.6	2386	0.84	Pawerful
THLETE 40	Mitchell Kirkunnd-S	76.1	399	484	17.5						35.9	40.7	2120		
ITHLETE 49	Murphy Roid Oliver Green	70.5	353 400	413 393	14.6	2609	33.88	33.9	0.212	1.59	30.5	36.4	1957		
THLETE 51	Ollio Mandio	76.1	328	379	12.6						20.9	35.6	1970		
THLETE 52	Orcar Chootham		422	456	7.5	3737	41.43	32.5	0.205	1.61	42.5				
THLETE 53	Ouen Bater	91.4	363	499	27.3	3504	30.72				42.0	39.3	2134	0.61	
THLETE 54	Phoenix Janover Bhyz Hamzon	64.1	278 368	354 380	21.5	2396 2739	37.85	40.9	0.205	1.93	40	39.7 45	1855	0.77 0.78	
THLETE 55	Ricky Thomdoropoule	69.7	217	323	32.9	2739	33.89	41.5	0.191	1.93	37.1	41.3	1805	0.78	
THLETE 57	Riely Collins	78.6	293	330	11.2	2593	33.41	33.8	0.199	1.7	37.8	44.1	2098	0.81	Pawerful
THLETE 50	Bary Wright	75.6	292	280	-3.9	2284	30.37	34.7	0.289	1.21	30.1	34.7	1771	0.70	
THLETE 59	SachaLevine	79	362	373	3.1	2390	30.84	28.5	0.226	1.28	27.5	30.8	1859	0.78	
THLETE 60 THLETE 61	Sam Buck	86.3	361 317	409 339	11.7	2554 2696	29.83	26.5 26.7	0.207	1.3 0.94	30.3	34.5	1929	0.76	
THLETE 62	Sam Fanning Sam Linder		359	421	14.9	3020	37.38	34.5	0.205	1.46	31.1				
THLETE 63	Sanny Maare		344	402	14.4	3621	42.11		V.2.71	1.40	26.1				
THLETE 64	Toj Hetten	70.5	312	402	22.4	2842	38.67	40.1	0.223	1.02	33	45.6	1021	0.64	
THLETE 65	Ted Clayton	75.4	386	366	-5.2	2954	39.55	40	0.214	1.87	48,6	48.3	1957	0.66	
THLETE 66 THLETE 67	Tom Warhington Will Raillian	76.4	269	306	12.1 18.0	2601 2370	35.37 36.24	24.5	0.217 0.234	1.13	29.7	27.6	1012	0.60	
THLETE 68	William Finch	75	270	320	20.4	2784	37.67	34.1	0.234	1.55	35.2	37.3	1777	0.68	
THLETE 69	Zavier Bamert	70.0	295	391	24.6	2417	30.95	35.1	0.236	1.5	32.3	39.7	2145	0.09	Pauerful
THLETE 70	Sam Marzhall	78	289	321	9.8						33	42.5	1944		
			MORD LEFT	HORD RIGHT	HORD ASSTM	Peak Fertical Farc	ø Vørtical Farcø / BM [H/kq]	Jamp Height	Contact Time [r]	RSI (JH (Flight	Jump Height	Jump Height	Concest ric Peek	DSI (CMJ Pack Force / IMPT	
	TEAM AVERAGE		350	391	10.3	2798	36.20	33.0	0.226	1.51	(Flight	(Imp- 36.1	1910	Pauk Farca) 0.69	
	SD		61	65	10.5	351	4.01	5.0	0.0350	0.36	4.9	5.1	236	0.095	
	Z-SCORE		,	1	2	,	2	2	,	2	,	2	3	,	
	CMJ S	J DJ	IMPT	Nordb	_	ASHBOARD	+								

Figure 8. Gym Strength Testing Data: Dashboard Spreadsheet

After careful selection, intensive preparation and exploratory analysis from the First Four Phases during the data analysis project. The data team wanted to make sure all "the correct information" is obtained during the deliverables, ensure we do not have to repeat through an iterative process. Maintain all quality and security issues resolved to guarantee better outcomes when it comes to data visualizations into a dashboard using one of the two data visualization tools from either Tableau or Power-BI. After preparation and exploratory analysis stages is completed, the supervisor initialized what our final dashboards will be, shown in the figures below. During the placement, proposals may change periodically over time, since were still waiting for all data collection is completely finalised, likely due to the expansion for new recruits towards both boys and girls under 16 years of age. This will likely improve our results in terms of GPS averages, and Team GPS averages and comparisons (shown in Figure 10.) to "becoming more accurate" avoiding bias.

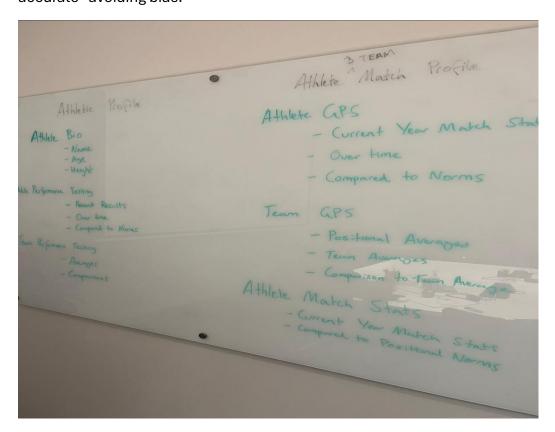


Figure 10. Supervisor's initial dashboard 1. Took place during the first day Week 1 during the placement

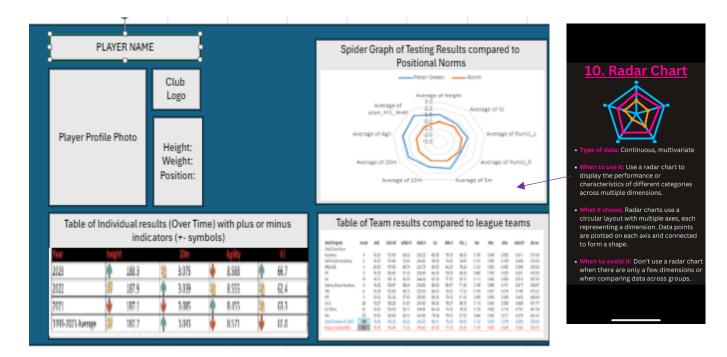


Figure 11. Supervisor's initial dashboard 2. Shown during via live chat during Week 3 of the placement.



Figure 12. Bar chart displaying key metrics for player performance from GPS data using PowerBI. Shown during via live chat during Week 3

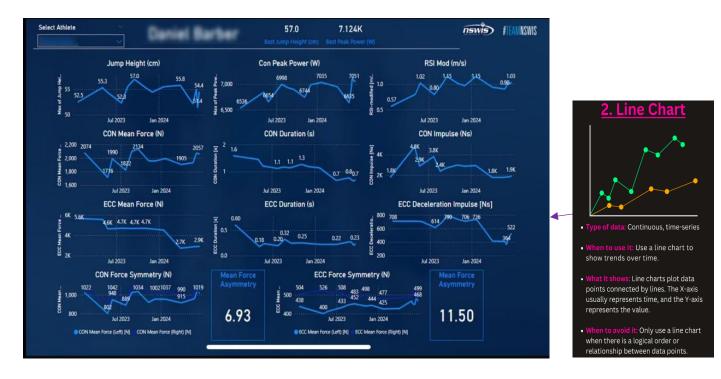


Figure 13. Line chart displaying key metrics for player performance growth from July 2023 to January 2024 using PowerBI. Shown during via live chat during Week 3

Displaying in onto the dashboards (from Figures 10-13 shown above) to tell relevant "highlights" of that story for the organization to secure trust and integrity that is required to accomplish their goals. To clarify better interpretations in terms of using the appropriate data to enable decision-making to drive key performances more effectively without being misinterpreted in a kindly manner. Without reinforcing bias and always consider fairness for the clients and what is required to the overall business to succeed for players to be eligible to be drafted into AFL. The organization at Foundry Athletic proposed one of two powerful tools in their domain to enable stakeholders and organizations to interact data. Deciding from Tableau or Microsoft Power BI which data and business analysts frequently use on the daily basis (seen in Figure 14).

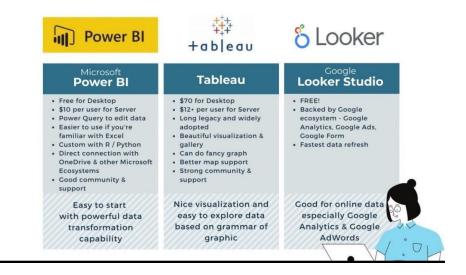


Figure 14. Comparison of data visualization tools

During the placement, when after the first phases of the data analysis project is completed, the data team proposed to use Microsoft Power-BI since it is free and convenient to use, making it suitable. Despite costs for each server are in USD not AUD, the data team will eventually have to pay these servers upfront to get familiarity and adapt with the new data visualization tool. Assuming the validation of the data is updated leaving no flaws or bias of our data during the 5th phase of the project. It has "the ability to analyze and share large datasets" to businesses. Enhances "sharing and collaboration aspects of business intelligence", like Tableau, Power-BI can integrate Microsoft Excel spreadsheets which it can be shared with colleagues and stakeholders effortlessly when creating dashboards and reports. Adjustments can be made with "the data being updated in real-time; businesses can identify and address issues promptly".

Overall, it enables coaches and stakeholders to interact with the visualizations through "charts, graphs and maps that brings data to life". To be satisfied with high expectations with their results in terms of finding key talent and recruitment from player and team performances. The reason the data team prefer Microsoft Power BI over Tableau because we want to perform more reports, since we wanted 2 pages at least to showcase the player key statistics and team performance statistics. Available "in Power BI Desktop" since we can build and view reports. Able to "filter data" to showcase data manipulation and aggregations more effectively and efficiently. Without using programming languages such as Python or R which can be integrated into Power-BI if necessarily to update more data visualizations. Our goal for the data analysis project was to allow more people to access more freedom of how they understand and handle the data to a huger audience and businesses overall. To conclude how the data team can best stories to clients about our data findings of how we can implement further strategies using player and team performances. To allow recruitment and finding key talent more effectively when drafting players into the Australian Football League for the Sandringham Football Club at Foundry Athletic.

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