"STEAMS" Methodology of NBA Draft Player Position

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Abstract

This paper adopts STEAMS (Science, Technology, Engineering, Artificial Intelligence, Math, Statistics) methodology. The objective of this paper is to introduce the benefits of integrating all 6 "STEAMS" elements, especially living in the Big Data World. The NBA Draft Position case study was demonstrated to present this novel "STEAMS" concept as compared to the current "STEM" or" STEAM" approach. There are three core visions of this "STEAMS" methodology: (1) replace "Art" with "Artificial Intelligence", (2) separate "Statistics" from "Math", and (3) integrate all six "STEAMS" elements. Adding the "Artificial Intelligence" element can trigger and enhance the effectiveness of "Sports" science research and "Math" algorithms. Separating the "Statistics" element can conduct more effective risk management and draw practical conclusions. Due to the previous two benefits, integrating all 6 "STEAMS" elements is becoming a widespread methodology for most scientists and engineers working in the modern Big Data era. Several techniques are used to help determine the NBA Player position and identify the similar NBA players for the benchmarking objective. It's critical and urgent for educators and teachers to abandon the traditional STEM approach to adopt the new "STEAMS" approach to educate our next generations in their early school learning and career development.

Keywords
JMP, Modeling, Simulation, Statistics, Sports Analytics

1. Introduction

"STEM" (Science, Technology, Engineering, Math) or "STEAM" (Science, Technology, Engineering, Art, Math) are popular in School Education is a term used to group together these academic disciplines (Fas 2017, Colwell 2016). This term is typically used when addressing education policy and curriculum choices in schools to improve competitiveness in science and technology development. It has implications for workforce development, national security concerns and immigration policy. The acronym came into common use shortly after an interagency meeting on science education held at the US National Science Foundation. In the early 1990's, a summer program called STEM Institute is arranged for talented under-represented students in the Washington, DC area. Based on the program's recognized success and expertise in STEM education (NSF 2018), that NSF was first introduced to the acronym STEM.

1.1 Criticism of STEM

The focus on increasing participation in STEM fields has attracted many criticisms. The efforts of the U.S. government to increase the number of STEM graduates, the science and engineering occupations have been flat or slow-growing, and unemployment as high or higher than in many comparably-skilled occupations (Teitelbaum 2014). There was a "mismatch between earning a STEM degree and having a STEM job in the United States, with only around ¼ of STEM graduates working in STEM fields, while less than half of workers in STEM fields have a STEM degree (Charette 2013). Based on the data, science should not be grouped with the other three STEM categories, because, while the other three generally result in high-paying jobs, "many sciences, particularly the life sciences, pay below the overall median for recent college graduates (Casselman 2014). Efforts to remedy the perceived domination of STEM subjects has led to intense efforts to diversify the STEM workforce. Some critics feel that this practice in higher education, as opposed to a strict meritocracy, causes lower academic standards (MacDonald 2018).

1.2 STEAM vs STEM

STEAM fields are Science, Technology, Engineering, Art (Slate 2016), and Math (Virginia Tech 2012). STEAM is designed to integrate STEM subjects into various relevant education disciplines. These programs aim to teach students innovation, to think critically and use engineering or technology in imaginative designs or creative approaches to real-world problems while building on students' mathematics and science base (Jolly 2016). STEAM programs add art to STEM curriculum by drawing on design principles and encouraging creative solutions (Pomeroy 2016, Eger 2016, CBS 2016, Schank 1991).

1.3 Artificial Intelligence and Digital Art

In the modern Big Data Society, Artificial intelligence (AI) is becoming a new dominant Data Science. AI is intelligence demonstrated by machines, in contrast to the natural intelligence displayed by humans. In computer science AI research is defined as the study of "intelligent agents": any device that perceives its environment and takes actions that maximize its chance of successfully achieving its goals (Garvey 2018).

Digital art is an artistic work or practice that uses digital technology as an essential part of the creative or presentation process. Since the 1970s, various names have been used to describe the process, including computer art and multimedia art (Christiane 2016, Lieser 2017). Recently, a lot of articles are about AI in art and design, especially the feature imagery, unsurprising as they're largely created by people from a science rather than arts background, and their research is often presented in the ultra-detailed format of scientific papers - heavy on words and, strange to us. This digital art application of AI is being referred to as 'generative'. Generative AI will drive the next generation of apps for auto-programming, content development, visual arts, and other creative, design, and engineering activities. In generative graphics, AI can abstract visual patterns from artwork and then apply those patterns in the fanciful re-rendering of photographic images with the hallmark features of that artwork (Kobielus 2017).

2. Break Down of Six STEAMS Elements

Instead of using classical STEM or STEAM, here, a new holistic “STEAMS” methodology is introduced. There are several novel concepts embedded in this new “STEAMS” methodology: (1) replace “Art” with “Artificial Intelligence”, (2) separate “Statistics” from “Math”, and (3) integrate all six “STEAMS” elements. “STEAMS” (Science, Technology, Engineering, Artificial Intelligence, Math, Statistics) methodology will be demonstrated through a basketball player case study. The authors will break down six STEAMS elements in the following sections.

2.1 Understand Basketball Sports “Science”

NBA draft pick has always been ambiguous. Annual draft pick event is extremely important since underdog team can immediately become a champion contender after hiring a star player. The objective of this paper is to apply STEAMS methodology on choosing the appropriate player position. First, a NCAA Stanford University basketball player KZ Okpala will be compared to top 50 NBA players for swing guard and small forward positions to find out whether this player has a greater NBA potential for either of these positions. In Figure 1, 12 characteristics are listed about each draft NBA candidate. Okapala received 94 points and is stronger on size, jump shot, but weaker on defense, strength, and “NBA ready and passing.” One NBA scout reports his weakness as “defense could improve, doesn’t block a lot of shots, needs to be more disruptive in defense, doesn’t do well when in contact, free throw percentage needs to improve, and sometimes a bit too afraid to pick up a foul.”

Basketball players’ strength can be categorized as SPARQ (Speed, Power, Agility, Reaction, Quickness). The researchers used data from 234 of the 1092 players who participated in the NBA combined draft from 2010-2015. The study then relates that player data to subsequent on-court NBA performance in each participant's first and third years. Using Principal Component Analysis, a statistical analysis that finds the main or principal components of a dataset with a lot of variables, the authors identified three principle factors - Body Length-size (height, standing reach, weight, wingspan, hand length, hand width), Power-Speed-Agility-Quickness (standing vertical jump, maximal vertical jump, ¾-court sprint, lane agility, body fat %), and Upper-Body Strength (bench press).

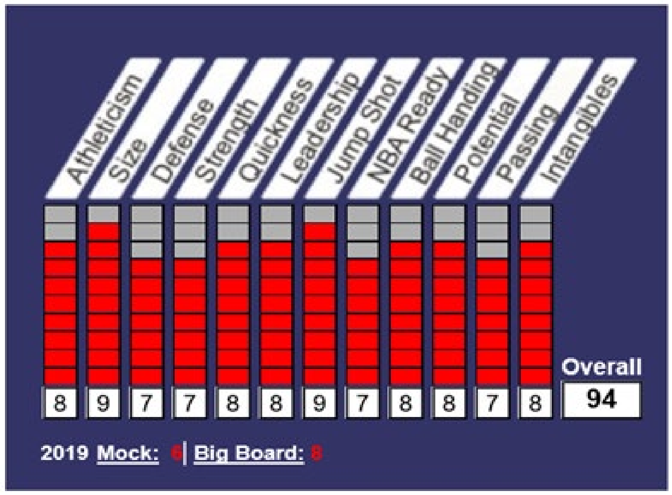


Figure 1. 12 NBA Draft Characteristics

2.2 Combine Measurement and Testing “Technology”

In Figure 2, nbadraft.net released the potential draft mock results each week. Okpala player was listed 13th as SF/SG on Jan.4, 2019 release. NBA Pre-Draft Combine Measurement and Athleticism Test includes Seed: ¾ Court Sprint, Power: Vertical Jump, 185 Pound Bench Press, and Agility/Reaction/Quickness: Lane Agility Drill, Reactive Shuttle Run.

What kind of strength training program for KZ Okpala to improve his defense skills particularly on Speed, Lane Agility Drill, and Reactive Shuttle Run? 3/4 court sprint is a bit of a misnomer, as the distance covered in this drill is actually 75 feet despite the fact that an NBA court is 94 feet in length, the 3/4 court sprint is the basketball equivalent to football’s 40-yard dash. The drill is primarily a measure of acceleration rather than top-line speed, and times typically fall between the low- to mid-three second range. The lane agility drill is designed to measure a player’s lateral quickness and ability to change direction. Cones are placed along the four corners of the key, and players follow a square path around them, first clockwise and then counterclockwise, peddling forwards, backwards, and side to side in the process.

2019 Mock Draft

Updated: 1/4/19 2:45 pm

#	Team	Player	H	W	P	School	C
1	*Cleveland	RJ Barrett	6-6	210	SG	Duke	Fr.
2	Phoenix	Zion Williamson	6-6	280	PF	Duke	Fr.
3	New York	Ja Morant	6-3	175	PG	Murray St.	So.
4	Chicago	Bruno Fernando	6-10	245	C	Maryland	So.
5	Atlanta	Keldon Johnson	6-6	215	SG/SF	Kentucky	Fr.
6	Washington	Cameron Reddish	6-7	215	SG/SF	Duke	Fr.
7	New Orleans	Rui Hachimura	6-8	235	SF/PF	Gonzaga	Jr.
8	Minnesota	Charles Bassey	6-10	245	C	Western Kentu...	Fr.
9	Orlando	Kevin Porter	6-5	220	SG/SF	USC	Fr.
10	Brooklyn	Nickeil Alexande...	6-5	205	SG	Virginia Tech	So.
11	Utah	Jontay Porter	6-11	240	C	Missouri	So.
12	*Atlanta	Bol Bol	7-2	235	C	Oregon	Fr.
13	*Boston	KZ Okpala	6-8	195	SG/SF	Stanford	So.
14	*Boston	Nassir Little	6-6	220	SF	North Carolina	Fr.

Figure 2. 2019 NBA Mock Draft

In Figure 3 below: KZ Okpala's combine measurement is listed against the top forwards. Okpala's physique is relatively shorter, weaker, and slower.

Forwards

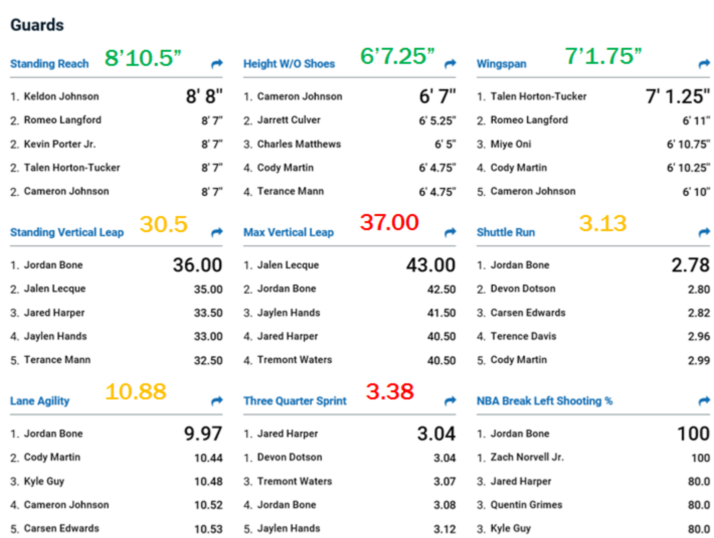
Standing Reach	8'10.5"	Height W/O Shoes	6'7.25"	Wingspan	7'1.75"
1. Jaxson Hayes	9' 2.5"	1. Jaxson Hayes	6' 10.25"	1. Eric Paschall	6' 11.75"
2. Daniel Gafford	9' 2"	2. Jontay Porter	6' 9.75"	2. Jaxson Hayes	7' 3.5"
3. Jontay Porter	9' 1.5"	3. Luka Samanic	6' 9.5"	3. Naz Reid	7' 3.25"
3. Mfiondu Kabengele	9' 1.5"	4. Daniel Gafford	6' 9.25"	4. Mfiondu Kabengele	7' 3"
5. Naz Reid	9' 1"	5. Mfiondu Kabengele	6' 8.75"	5. P.J. Washington	7' 2.25"

Standing Vertical Leap	30.5	Max Vertical Leap	37.00	Shuttle Run	3.13
1. O'Shae Brissett	34.00	1. Brandon Clarke	40.50	1. Admiral Schofield	2.87
1. Brandon Clarke	34.00	2. Terance Mann	38.50	2. Dylan Windler	2.94
3. Eric Paschall	33.00	2. Nassir Little	38.50	3. Darius Bazley	2.95
4. Terance Mann	32.50	4. Eric Paschall	38.00	4. Luka Samanic	3.03
4. Daniel Gafford	32.50	4. Luka Samanic	38.00	5. Marial Shayok	3.04

Lane Agility	10.88	Three Quarter Sprint	3.38	NBA Break Left Shooting %	
1. Kris Wilkes	10.39	1. Brandon Clarke	3.15	1. Jalen McDaniels	83.3
2. Brandon Clarke	10.61	2. Nassir Little	3.24	2. O'Shae Brissett	80.0
3. Isaiah Roby	10.63	3. Daniel Gafford	3.25	2. Reggie Perry	80.0
4. Dylan Windler	10.70	3. Mfiondu Kabengele	3.25	2. Ignas Brazdeikis	80.0
5. Admiral Schofield	10.77	3. Isaiah Roby	3.25	2. Mfiondu Kabengele	80.0

Figure 3. 2019 NBA Pre-Draft Combine Measurements and Testing in Forwards

Since Okpala's NBA position is still undecided between SF and SG. In Figure 4 below: KZ Okpala's combined measurement is listed against the top guards. Okpala's body is relatively larger, weaker, and slower. Okpala fits to the small forward position better based on the Combine Measurement and Testing results.



Guards

Standing Reach	8'10.5"	Height W/O Shoes	6'7.25"	Wingspan	7'1.75"
1. Keldon Johnson	8' 8"	1. Cameron Johnson	6' 7"	1. Talen Horton-Tucker	7' 1.25"
2. Romeo Langford	8' 7"	2. Jarrett Culver	6' 5.25"	2. Romeo Langford	6' 11"
2. Kevin Porter Jr.	8' 7"	3. Charles Matthews	6' 5"	3. Miye Oni	6' 10.75"
2. Talen Horton-Tucker	8' 7"	4. Cody Martin	6' 4.75"	4. Cody Martin	6' 10.25"
2. Cameron Johnson	8' 7"	4. Terance Mann	6' 4.75"	5. Cameron Johnson	6' 10"

Standing Vertical Leap	30.5	Max Vertical Leap	37.00	Shuttle Run	3.13
1. Jordan Bone	36.00	1. Jalen Lecque	43.00	1. Jordan Bone	2.78
2. Jalen Lecque	35.00	2. Jordan Bone	42.50	2. Devon Dotson	2.80
3. Jared Harper	33.50	3. Jaylen Hands	41.50	3. Carsen Edwards	2.82
4. Jaylen Hands	33.00	4. Jared Harper	40.50	4. Terence Davis	2.96
5. Terance Mann	32.50	4. Tremont Waters	40.50	5. Cody Martin	2.99

Lane Agility	10.88	Three Quarter Sprint	3.38	NBA Break Left Shooting %	
1. Jordan Bone	9.97	1. Jared Harper	3.04	1. Jordan Bone	100
2. Cody Martin	10.44	1. Devon Dotson	3.04	1. Zach Norvell Jr.	100
3. Kyle Guy	10.48	3. Tremont Waters	3.07	3. Jared Harper	80.0
4. Cameron Johnson	10.52	4. Jordan Bone	3.08	3. Quentin Grimes	80.0
5. Carsen Edwards	10.53	5. Jaylen Hands	3.12	3. Kyle Guy	80.0

Figure 4. 2019 NBA Pre-Draft Combine Measurements and Testing in Guards

2.3 Systematic Engineering Problem Solving

Since the Okpala's NBA position is still not fully determined. This paper will use Engineering Problem Solving Approach to help determine Okpala's position. In Figure 5, Player Okpala's college basketball statistics was listed. The author would use his 2018-2019 season college statistics to predict which position would fit him better in NBA career.

		Games		Field Goals			Three Points			Free Throws			Rebounds			Miscellaneous				
Season	Team	G	Min	FGM	FGA	FG%	3PM	3PA	3P%	FTM	FTA	FT%	OR	DR	Reb	Ast	TO	Stl	Blk	Pts
2017-18	STAN	19	529	61	153	39.9	6	27	22.2	59	90	65.6	21	47	68	30	45	12	12	187
2018-19	STAN	14	452	78	168	46.4	19	41	46.3	58	78	74.4	21	70	91	28	41	13	12	233
Total	-	33	981	139	321	43.3	25	68	36.8	117	168	69.6	42	117	159	58	86	25	24	420

Figure 5. Okpala's College Basketball Statistics

In Table 1: Okpala's 2019 season statistics is compared to 2019 NBA top 50 Players' average statistics based on 48mins. Okpala was performing better in most categories as highlighted in Green Color but also weaker in several categories in Yellow Color. In general, Okpala fits to the SF position more than SG position which is consistent with his 2019 Combine Measurement and Testing results. Preferable Position is chosen based on whether KZ's statistics can outperform the average of top 50 players for that position.

Table 1. KZ Okpala's Statistics against top NBA 50 players in SF and SG

Player	POSITION	FG%	3P%	FT%	OR/48mins	DR/48mins	Ast/48mins	TO/48mins	Stl/48mins	Blk/48mins	Pts/48mins
Position		Either	Either	SF	Either	Either	SF	Either	SF	Either	SF
KZ Okpala	SG-SF	46.4	46.3	74.4	2.2	7.4	3.0	4.3	1.4	1.3	24.6
Top 50 Payers	SF	45.1	35.9	79.5	1.3	6.6	3.9	2.6	1.6	0.7	24.4
Top 50 Players	SG	44.2	35.8	81.5	1.1	5.1	5.8	3.2	1.7	0.6	26.7

2.4 Artificial Intelligence

To further assess whether player Okpala should play at SF or SG position, a Hierarchical Clustering and Dendrogram analysis was conducted among the Okpala and the other top 50 Forwards and Guards. Player Okpala (ID=1) is grouping with the other 3 players ID-25, ID-53, ID-37 in the top group.

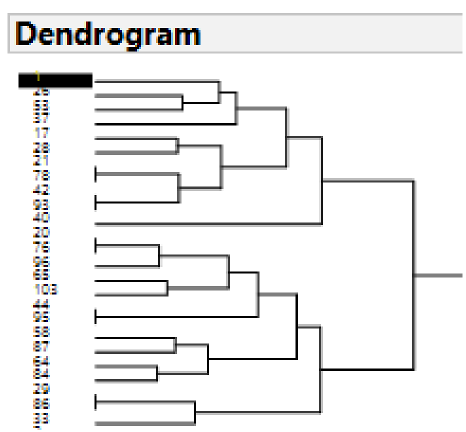


Figure 6. Hierarchical Clustering Dendrogram among top NBA Forwards and Guards

These three similar players are Aaron Gordon (Small Forward), Marvin Williams (Small Forward), and Jerami Grant (Small Forward) respectively which has indicated that KZ Okpala should play small forward in his NBA career.

2.5 Mathematics

The Section 2.4 “Artificial Intelligence” clustering patterns were identified based on clustering distance math of calculating the dissimilarity of nutritions among chocolate products. There are several cluster math algorithms: (1) Average, (2) Centroid, (3) Ward, (4) Single, and (5) Complete (Milligan 1980). Will these 5 different clustering algorithms have the same results? If there is any difference, how do we to select which algorithm to explore the clustering patterns best? In Figure 7, there are three existing clusters (Green, Yellow, Red). Which two clusters should bond first? The joining sequence is determined by the clustering distance algorithms. Centroid, Single, and Complete algorithms are compared. The Centroid algorithm connects Green cluster and Yellow cluster through the purple line connecting the two cluster means (purple triangles). The Single algorithm groups Green cluster and Red cluster by the closest points between these two clusters. The Complete algorithm groups Yellow cluster and Green cluster by the farthest points between these two clusters. Depending on which distance algorithm is chosen, the clustering sequence and pattern may be different. We must dive into the mathematical calculations for each clustering distance algorithm and understand the benefits and limitations of each math algorithm to choose the best algorithm to draw reliable clustering patterns and results.

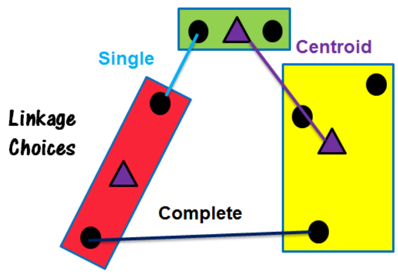


Figure 7. Diagram of the Centroid, Single, and Complete Clustering Methods

Here, five major clustering distance algorithms will be compared. The calculations of the five different clustering algorithms are shown in Figure 8. The basic Algebra “Math” algorithms are utilized in the modern “Artificial Intelligence” clustering method. In the new “STEAMS” approach, “Math” is the foundation of evolving the modern “Artificial Intelligence”. Adding the “Artificial Intelligence” element can trigger the exploration of the Math elements and Science research.

Average Linkage Distance for the average linkage cluster method is:

$$D_{KL} = \sum_{i \in C_K} \sum_{j \in C_L} \frac{d(x_i, x_j)}{N_K N_L}$$

Average

Centroid Method Distance for the centroid method of clustering is:

$$D_{KL} = \|\overline{x}_K - \overline{x}_L\|^2$$

Ward's Distance for Ward's method is:

$$D_{KL} = \frac{\|\overline{x}_K - \overline{x}_L\|^2}{\frac{1}{N_K} + \frac{1}{N_L}}$$

ANOVA

Single Linkage Distance for the single linkage cluster method is:

$$D_{KL} = \min_{i \in C_K} \min_{j \in C_L} d(x_i, x_j)$$

Minimum

Complete Linkage Distance for the Complete linkage cluster method is:

$$D_{KL} = \max_{i \in C_K} \max_{j \in C_L} d(x_i, x_j)$$

Figure 8. JMP Clustering Distance Algorithms

2.6 Statistics

In Table 2, Okpala's basketball statistics was compared against three identified players in the Clustering Dendrogram analysis. This similarity analysis can help prove that Okpala is fit more for the small forward position and also can help develop his NBA functions by benchmarking to three similar players.

Table 2. Okpala's statistics benchmarked to three Similar NBA Players

Player	POSITION	FG%	3P%	FT%	OR/48mins	DR/48mins	Ast/48mins	TO/48mins	Stl/48mins	Blk/48mins	Pts/48mins
KZ Okpala	SG-SF	46.4	46.3	74.4	2.2	7.4	3.0	4.3	1.4	1.3	24.6
Aaron Gordon	SF	44.3	35.8	68.1	2.4	8.3	4.7	2.6	1.1	1.0	21.6
Jerami Grant	SF	52.7	36.2	68.3	1.5	5.9	1.4	1.4	1.2	1.9	19.2
Marvin Williams	SF	42.4	38.3	71.7	1.7	8.0	1.9	1.0	1.6	1.2	17.6

2.7 Model Validation

Based on our STEAMS study, player Okpala should have a greater potential to play the SF position over the SG position. Okpala is currently playing in the Miami Heat in 2019-2020 season as a rookie. Here is the NBA scout report on his current NBA status: Okpala is likely going to be a very solid player in the NBA. His collegiate statistics stack up nicely against the likes of Paul George and Kawhi Leonard, and so does his frame. However, it might be hard for the 6'9" rookie from Stanford to earn a huge chunk of playing time this summer. Our STEAMS study has successfully predicted his NBA SF position over SG position.

3. Conclusions

"STEAMS" methodology is very successful on understanding Basketball Sports Science. Understanding the NBA Pre-Draft Combine Measurement and Testing can be done effectively through a systematic "Engineering" problem solving framework. Modern "Artificial Intelligence" methods can help determine player's NBA preferable SF position and similar players. Hierarchical clustering distance mathematics is critical to determine the clustering dendrogram patterns. Benchmarking players' statistics can be compared by using the descriptive statistics. In the modern Big Data era, most scientists and engineers shall adopt this "STEAMS" methodology and integrate all 6 elements seamlessly and collectively.

Acknowledgements

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Biography

Mason Chen is currently a student at Stanford OHS and serves as the student ambassador and webmaster for STEAMS. Having started STEAMS since its inception in 2014, he has held various roles such as President of the Student Chapter from 2017 to 2019. Through STEAMS, he has published more than 20 conference proceeding papers as first, second, or third author. As first author, he has won numerous awards including the Best Conference Proceeding Paper Award in the 2018 JMP Discovery Summit as well as finishing 1st Place three times for the STEM presentation competition at IEOM conferences. He has also certified the IBM SPSS Statistics Level I, II, Modeler Level I, and IASSC Yellow Belt, Green Belt, and Black Belt.