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The Impact of Analytics Utilization on Team Performance: Comparisons Within and Across the U.S. Professional Sports Leagues

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ABSTRACT

Business analytics, defined as the use of data to make better, more relevant, evidence-based business decisions, has received a great deal of attention in practitioner circles. Organizations have adopted business analytics in an effort to improve revenue, product placement, and customer satisfaction. Professional sports teams are no different. While analytics has been used for over 30 years, the use of analytics by professional sports teams is a relatively new concept. However, it is unclear whether the teams that have adopted analytics are seeing any results. If not, then perhaps analytics is not the right solution. Analyses across the four, major U.S. sports leagues and within leagues show little to no competitive (on-field) or attendance (off-field) differences for the teams that have adopted analytics. Areas for additional research are provided in order to better understand the apparent disconnect between the hype in the sports industry and the lack of measurable results.

KEYWORDS: Analytics, Professional Sports, Analytics Adoption, Team Performance

ANALYTICS AND DECISION-MAKING

A hot topic in corporate Information Technology (IT) departments and board rooms over the last few years is business analytics (Gaines, 2013; White, 2013; Deutsch, 2014; Underwood, 2014). Business analytics, for this paper, is defined as the use of data to make better, more relevant, evidence-based business decisions. Business analytics includes the techniques and the technologies used to make these decisions.

A key component to successful business analytics is the availability of large quantities of high quality data.

Organizations and industries adopt analytics to improve revenue, product placement, customer satisfaction, customer returns, etc. Numerous studies (e.g., Elbashir et al., 2011; Shanks & Bekmamedova, 2012; and Seddon et al., 2012) have investigated how business analytics impacts and influences organizational performance. Like any new technology, tool, or process, organizations need to see its value (through improvements in efficiencies, effectiveness, or organizational performance) in order for its adoption to make sense; otherwise, the organization can achieve the same results without spending the extra time/money (White, 2013; Deutsch, 2014; Underwood, 2014). This can be viewed as business analytics' return on investment, a measure that can be difficult to calculate (James, 2014; McCann, 2014).

Industries and organizations outside the traditional players (retailing, manufacturing, and service industries) are also utilizing business analytics. Professional sports teams utilize analytics for game management, player development and personnel decisions, training and practice methods, marketing, ticket pricing, and financial decision-making (Maxcy & Drayer, 2014). With global revenues for professional sports teams expected near $150 billion (Clark, 2011), there is ample incentive to use analytics to maximize on-field performance and revenue (off-field performance) in an industry that is competitive by its very nature.

Sports teams, and matches (games) in particular, create an abundance of data and statistics, and the analysis of these data is as old as the sports themselves (Chadwick, 1867; Schumaker et al., 2010). A key component to any team is its ability to win and to do so consistently. Effective analysis of team and individual data provides owners, managers, trainers, scouts, and players with a better understanding of past performance.

The more recent advances and improvements in computing power and analysis tools have enabled decision-makers within the professional sports to apply analytics to the already vast quantity of data. However, analytics approaches across the sports industry and among the teams are diverse in terms of usage and underlying enthusiasm (Alamar, 2013). Recent works by Maxcy & Drayer (2014) and ESPN (2015) have shed light on the analytics usage and practices of professional sports teams, but the connection between analytics utilization and team performance/success is unclear.

This leads to the following research questions: 1) Do teams utilizing analytics perform better on and/or off the field? and 2) Is there a difference in performance by sport/league?

ANALYTICS AND PROFESSIONAL SPORTS

Analytics adoption and utilization by professional sports teams dates back to the late 1970s (Maxcy & Drayer, 2014; Schumaker et al., 2010), though the term "analytics" was not in use. In the late 1970s, Bill James led a revolution in sports statistics within professional baseball. James and his colleagues attempted to develop statistics and measures of performance that correlated directly with on-field performance (i.e., winning). New measures, such as OPS (On-Base Plus Slugging) and WAR/WARP (Wins Above Replacement Player), began as empirical evaluations by individual researchers and have since made their way into the mainstream of baseball reporting and analysis. As these measures emerged, some general managers and managers understood their value and their potential for improving performance.

Perhaps the most well-known example of this is from the Oakland A's in the late 1990s and early 2000s. Under general managers Sandy Alderson and then Billy Beane, the Oakland A's built their team using analytics and a modest budget/payroll. This story became a book – Moneyball: The Art of Winning an Unfair Game (Lewis, 2004) – and then a motion picture. While the A's never won the World Series, they did make the playoffs in four consecutive seasons. Their story inspired other teams to incorporate similar techniques, with the Boston Red Sox as the prime example of ultimate success – three World Series titles in a ten-year span from 2004-2013. However, even with the success stories of the Oakland A's and the Boston Red Sox, not all teams have embraced analytics. Many teams still employ large scouting offices for traditional player evaluation and assessment, and others feel that the emphasis on statistics and analytics has taken the focus away from the actual game of baseball (Kettmann, 2015).

While not nearly as well-known outside of the sport as the previous examples with baseball, professional basketball teams have been using Advanced Scout for nearly twenty years. This data mining software has been used most often to maximize substitution schemes (Bhandari et al., 1997).

The most common use of analytics in professional sports is not by the teams themselves but by individual researchers. These super-fans (like Bill James) have interests in sports statistics, history, and analytics that span all possible perspectives and motives. From baseball (Hirotsu & Wright, 2003; Freeman, 2004; Albert, 2008; Xu et al., 2015), soccer/football (Barros & Leach, 2006; Tovar, 2014), harness track racing (Schumaker 2013a, 2013b), hockey (Thomas, 2006; Pettigrew, 2014), and just about every other sport, professional sports continue to be scrutinized by individuals. However, this paper focuses on the adoption of analytics by professional sports teams, regardless of techniques, measures, or technologies used.

Maxcy and Drayer (2014) reported the following analytics adoption levels within the four, major U.S. sports leagues: Major League Baseball (MLB) – 97%, or 29 out of 30 teams; the National Basketball Association (NBA) – 80%, or 24 out of 30 teams; the National Football League (NFL) – 56%, or 18 out of 32 teams; and the National Hockey League (NHL) – 23%, or 7 out of 30 teams. A team was considered to have adopted analytics if the team employed analytics professionals as staff or consultants.

In early 2015, ESPN the Magazine and ESPN.com released an assessment of each of the 122 teams in the four, major U.S. sports leagues (ESPN, 2015). Each team, within each league, received a categorical ranking indicating "the strength of each franchise's analytics staff, its buy-in from execs and coaches, its investment in biometric data and how much its approach is predicated on analytics" (ESPN, 2015). Based on expert opinions, internal team sources, team evaluations, and statistical analysis, the categories are: 1-All-In, 2-Believers, 3-One Foot In, 4-Skeptics, and 5-Nonbelievers. Table 1 provides the categorizations for each of the leagues as well as the adoption percentages from Maxcy and Drayer (2014). In addition to the categorizations, ESPN (2015) ranked the overall top 10 and bottom 10 teams across all four leagues combined with the rest of the teams (#11-112) not ranked. The full categorization of each of the 122 teams as well as their ranking (if applicable) can be found in the Appendix.

League	**ESPN Category 1**	**ESPN Category 2**	**ESPN Category 3**	**ESPN Category 4**	**ESPN Category 5**	**Maxcy and Drayer**
MLB	9	7	6	6	2	97%
NBA	4	8	9	6	3	80%
NFL	0	9	7	12	4	56%
NHL	1	13	12	3	1	23%

Table 1: Team categorizations by league (ESPN, 2015) and adoption percentages (Maxcy & Drayer, 2014)

Table 1 shows that of all the teams ranked as Category 1 (All-In), over 60% are MLB teams. It appears that the NFL has been the slowest (most resistant?) to analytics implementation with exactly half of the 32 teams in Categories 4 and 5, while the NHL has a large number of teams (over 80%) that are either just getting started or on their way. It is difficult to reconcile the categorizations from ESPN (2015) with the percentages from Maxcy and Drayer (2014) since both used different techniques and processes. Regardless, given the thoroughness and level of research and data collection in ESPN (2015), these categorizations will be utilized throughout the remainder of this study.

HYPOTHESES

Perhaps the simplest to calculate and easiest to understand, a team's winning percentage is a clear indication of its on-field success. For most executives, managers, players, and fans, winning games is the primary goal. Nearly every aspect of sports is about finding ways to increase a team's winning percentage. This leads to the first hypothesis.

> H1 – Teams with higher analytics categorizations and rankings have higher winning percentages

In addition to a team's on-field performance measured by its winning percentage, a team's off-field performance can be measured by the number of fans watching the live games. This is considered an off-field performance measure as the primary impact of more fans is an increase in revenue from ticket sales, concession sales, and merchandise and souvenir sales. Across a full season, the total home attendance for any team can be measured against the potential seating capacity for that team's stadium/arena. Teams that perform better should draw more fans. This leads to the second hypothesis.

> H2 – Teams with higher analytics categorizations and rankings have higher attendance percentages relative to stadium capacity

Of the four leagues under consideration, none of them is new. While there are league differences in operating rules regarding issues such as salary caps, eligibility, free agency, and revenue sharing, no league has an unfair advantage or disadvantage utilizing technology, including analytics. Team owners are often some of the wealthiest individuals in a team's city, if not the country (Solomon, 2013), and should be able to afford additional technology and/or staff. This leads to the third hypothesis.

H3 – There is no difference in analytics' impact across the four leagues

ON-FIELD AND OFF-FIELD PERFORMANCE DATA

Using the tiered categorizations and the top 10 (1-10) and bottom 10 (113-122) rankings in ESPN (2015) as a starting point, additional data were collected.

For each of the 2013 and 2014 regular seasons, the number of victories were gathered from league-based season standings available from ESPN.com (e.g., http://espn.go.com/nhl/standings/_/year/2014). Given the differences across the leagues' schedules, team victories on their own do not provide comparable data. Therefore, winning percentages were calculated for each team in each year based on the team's number of victories divided by the number of games played. In the NFL, ties are possible – ties do not show up in the number of victories, but ties do count as "half" a victory when calculating a winning percentage. Additionally, in the NHL, winning percentages are traditionally calculated based on team victories and overtime/shootout losses. Therefore, using the point system in the NHL of two points for a victory (of any type) and one point for an overtime/shootout loss, the winning percentage is calculated as the number of points earned divided by the total points possible for the full season.

For each of the 2013 and 2014 regular seasons, the season's stadium attendance percentage was gathered from league-based attendance reports available from ESPN.com (e.g., http://espn.go.com/nhl/attendance/_/year/2014/). This number is derived by taking the total attendance at home games for each team and dividing that number by the stadium's capacity for all home games combined. Because stadiums oversell their official capacity and allow standing room only (SRO) tickets, it is possible for a team to have a seasonal attendance percentage greater than 100%. As a result, stadium attendance percentage treats filling a 40,000-seat baseball stadium to capacity as the same as filling a 19,000-seat hockey arena to capacity.

ANALYSES

The ESPN (2015) categorizations and rankings were published in early 2015 based on actual events, decisions, and work by each team during 2014. Therefore, the 2014 season is the most relevant season that will reflect the variance in the categorizations and rankings. Data from the 2013 season are also available, but this season occurred prior to the work of ESPN (2015). It is unknown how teams would have been categorized and ranked during the 2013 season.

In essence, using a categorization from year n, one can analyze performance in year n (or n+1). However, one cannot analyze performance in year n-1 based on the categorization in year n. The only use of data from year n-1 is to measure the change in performance from year n-1 to year n, thereby measuring the impact of the categorization in year n on both the performance in year n and the change in performance from year n-1.

WINNING PERCENTAGE

H1 states that teams with higher analytics categorizations and teams ranked in the top 10 (compared to the bottom 10) should have higher winning percentages than teams categorized or ranked lower. It is expected that teams in Category 1 (0.527) and Category 2 (0.540) would have winning percentages above 0.500, teams in Category 3 (0.496) would have winning percentages near 0.500, and teams in Category 5 (0.411) would have winning percentages below 0.500, but the high winning percentage (0.539) of Category 4 teams is not expected (see Table 2). In addition, Category 3 teams (0.021) showed the largest average change in winning percentage while Category 1 (-0.025) and Category 5 (-0.062) teams both had, on average, worse seasons in 2014 than in 2013, and Category 2 (0.009) and Category 4 (0.003) teams had only slightly better seasons in 2014. The combination of the 3rd best winning percentage and the 2nd worst change in winning percentage for Category 1 teams implies that analytics utilization is not helping these teams win more games. However, Category 5 teams had the worst winning percentage and the worst change in winning percentage (largest drop) which does support the hypothesis qualitatively.

Category	**Average 2014 Winning Percentage**	**Winning Percentage Standard Deviation**	**Average Change in Winning Percentage (2013-2014)**	**Change in Winning Percentage Standard Deviation**
1	0.527	0.125	-0.025	0.099
2	0.540	0.130	0.009	0.113

3	0.496	0.154	0.021	0.131
4	0.539	0.119	0.003	0.153
5	0.411	0.170	-0.062	0.184

Table 2: Descriptive statistics of winning percentage and change in winning percentage

Due to the categorical nature of the ESPN (2015) categorizations, correlations could not be performed with these data against winning percentage, but regression analysis showed a non-significant relationship in 2014 (p=0.130) and in the change between 2013 and 2014 (p=0.654). Correlations were performed with the rankings (top 10 and bottom 10) against winning percentage, but no significant correlations existed for 2014 (p=0.137) or for the change in winning percentage between 2013 and 2014 (p=0.640).

The scatter plot of the teams' winning percentages against their categorization (Figure 1a) provides the best visualization of the lack of difference across categories. Similarly, Figure 1b shows the scatter plot of the change in winning percentage between 2013 and 2014 against the teams' categorization.

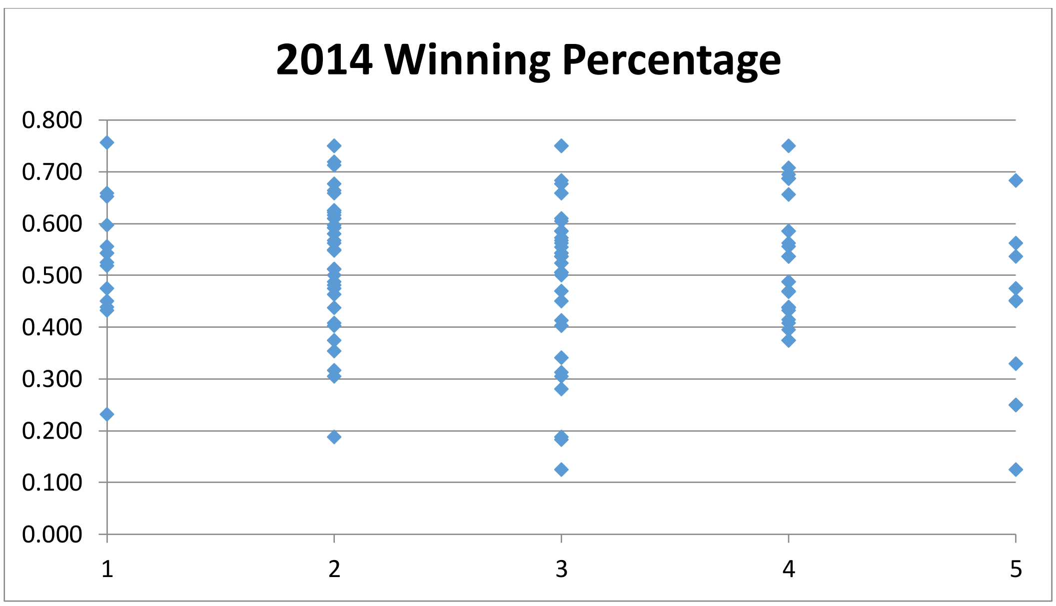

Figure 1a: Scatter plot of winning percentage against categorization

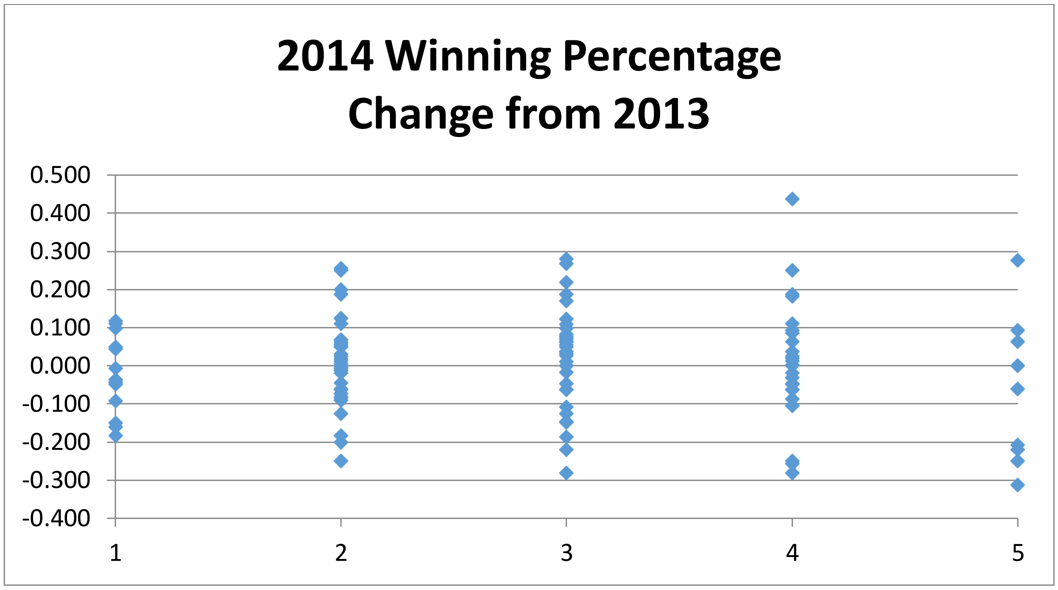

Figure 1b: Scatter plot of change in winning percentage between 2013 and 2014 against categorization

In both figures, there is a relatively equal distribution across all five categories. ANOVA tests show no significant difference across the five categories for winning percentage or change in winning percentage ($p=0.086$ and $p=0.453$, respectively). In Figure 1a, while the highest winning percentage is from Category 1 and the lowest winning percentage is from Category 5 (and tied with a team from Category 3), the rest of the winning percentages are spread across all five categories. In fact, the average winning percentage for Category 1 is the third highest at 0.527 with Category 2 at 0.540 and Category 4 at 0.539. In Figure 1b, the biggest improvement in winning percentage is from Category 4. The Category 1 teams had the narrowest range of change in winning percentage, and the biggest change for any Category 1 team was far below the biggest change in the other categories. Perhaps the one consolation is that Category 1 teams tended not to have substantially worse follow-up seasons as teams in the other categories.

The evidence does not support H1 – teams with higher analytics categorizations and rankings do not have higher winning percentages than the other teams.

STADIUM ATTENDANCE

H2 states that teams with higher analytics categorizations and teams ranked in the top 10 (compared to the bottom 10) should have higher attendance percentages than teams categorized or ranked lower. Even if a team fails to win more games, the team's usage of analytics should make the games more competitive and therefore more attractive to the fans. Of course, if the team does win more games, the team will be even more attractive to fans.

The attendance percentage of Category 1 teams (82.14%) is the lowest among all five categories, and the attendance percentages for Categories 2-5 (90.43%, 89.51%, 89.20%, and 89.07%, respectively) are nearly identical to each other (see Table 3). However, Category 1 teams (1.828) had the largest increase in attendance percentage between 2013 and 2014 (implying 2013 was that much worse than 2014 in terms of attendance), and all other Categories had an average change in attendance percentage between -1.000 and 1.000 (with Category 5 showing the 2nd largest increase at 0.890). The correlation (non-significant) between winning percentage and attendance percentage is 0.18.

Category	**Average 2014 Attendance Percentage**	**Attendance Percentage Standard Deviation**	**Average Change in Attendance Percentage (2013-2014)**	**Change in Attendance Percentage Standard Deviation**
1	82.14	22.50	1.828	5.820
2	90.43	13.70	0.232	4.874
3	89.51	13.59	-0.018	7.225
4	89.20	14.06	-1.059	4.696
5	89.07	14.47	0.890	6.645

Table 3: Descriptive statistics of attendance percentage and change in attendance percentage

As with winning percentages, due to the categorical nature of the ESPN (2015) categorizations, correlations could not be performed with these data against attendance percentage, but regression analysis showed a non-significant relationship in 2014 (p=0.449) and in the change between 2013 and 2014 (p=0.348). Correlations were performed with the rankings (top 10 and bottom 10) against attendance percentage, but no significant correlations existed for 2014 (p=0.591) or for the change in attendance percentage between 2013 and 2014 (p=0.774).

The scatter plot of the teams' attendance percentages against their categorization (Figure 2a) provides the best visualization of the lack of difference across categories. Similarly, Figure 2b shows the scatter plot of the change in attendance percentage between 2013 and 2014 against the teams' categorization.

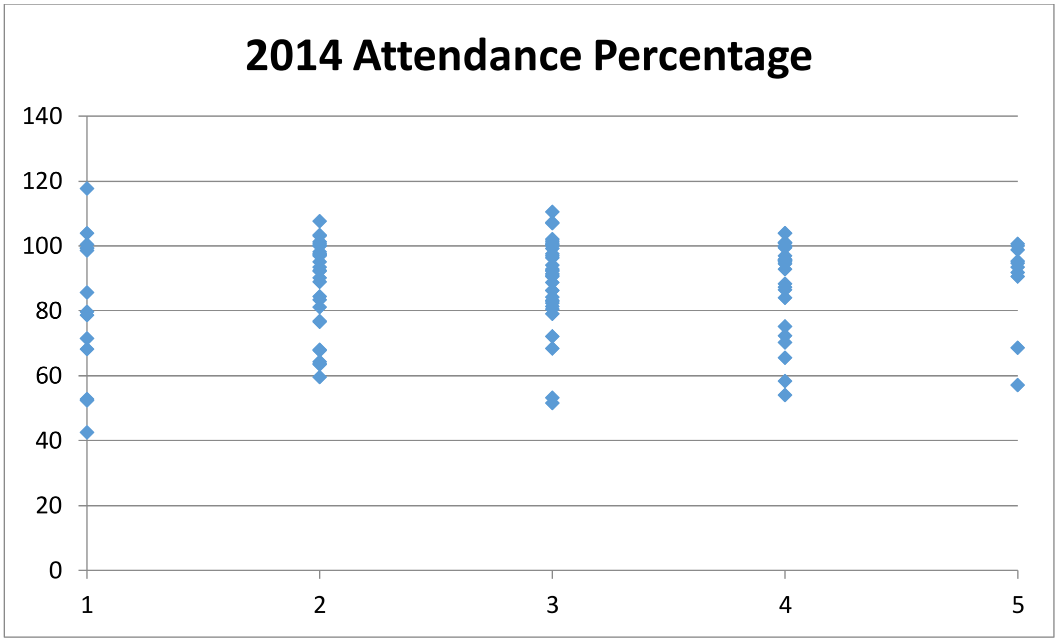

Figure 2a: Scatter plot of attendance percentage against categorization

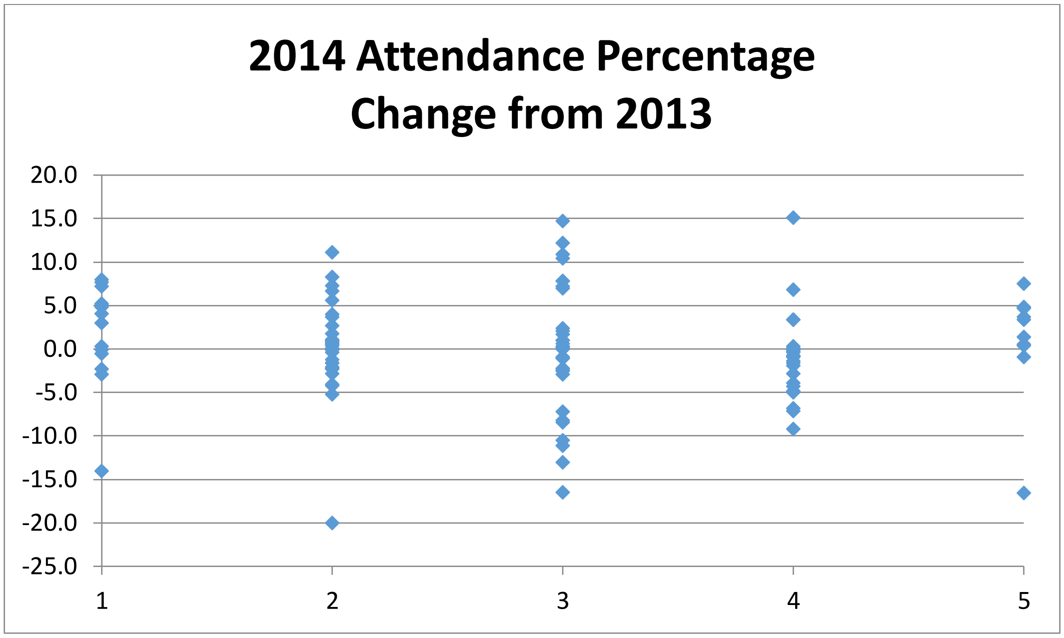

Figure 2b: Scatter plot of change in attendance percentage between 2013 and 2014 against categorization

In both figures above, there is a relatively equal distribution across all five categories. ANOVA tests show no significant difference across the five categories for attendance percentage or change in attendance percentage (p=0.516 and p=0.644, respectively). In Figure 2a, the highest attendance percentage and the lowest attendance percentage are both from teams in Category 1. This impacts the average attendance percentage for Category 1 which was the lowest among the five categories. In Figure 2b, the biggest improvement in attendance percentage is from Category 4 (also the case with winning percentage).

The evidence does not support H2 – teams with higher analytics categorizations and rankings do not have higher attendance percentages than the other teams.

LEAGUE COMPARISONS

H3 states there is no difference in analytics' impact across the four leagues. Table 4 presents the descriptive data for the 2014 season for the four leagues across the two previously discussed variables of winning percentage and attendance percentage. For the NHL, the average winning percentage is greater than 0.500 due to the winning percentage calculation formula (described earlier) where overtime/shootout losses are counted.

First impressions from Table 4 reveal some interesting observations. Only in the NBA does the highest winning percentage belong to the highest category (Category 1). In the other leagues, the highest winning percentage belongs to Category 2 (MLB), Category 4 (NFL), and Category 5 (NHL). While Category 1 teams in the NFL and NHL have the second highest winning percentage, Category 1 teams in the MLB have the third highest winning percentage. Keep in mind that in Categories 1 and 5 in the NHL, there is only one team.

League (Category)	**Count of Category**	**Average 2014 Winning Percentage**	**Average 2014 Attendance Percentage**
MLB	**30**	**0.500**	**70.40**
1	9	0.498	73.42
2	7	0.541	68.41
3	6	0.509	73.13
4	6	0.458	67.97
5	2	0.463	62.85
NBA	**30**	**0.500**	**90.90**
1	4	0.561	92.90
2	8	0.517	89.18
3	9	0.461	88.96
4	6	0.526	91.23
5	3	0.439	98.03
NFL	**32**	**0.500**	**96.95**
1	0	n/a	n/a

2	9	0.535	98.13
3	7	0.455	96.56
4	12	0.568	96.91
5	4	0.297	95.10
NHL	**30**	**0.562**	**96.57**
1	1	0.652	117.6
2	13	0.556	97.72
3	12	0.540	94.01
4	3	0.610	96.80
5	1	0.683	90.50

Table 4: Summary data by league

Regression analyses performed for each league separately on winning percentage and attendance percentage yielded no significant results (see Table 5). The lack of significant differences is further evident in the scatter plots (Figure 3).

League	**Regression p-value of Winning Percentage versus Category**	**Regression p-value of Attendance Percentage versus Category**
MLB	0.118	0.432
NBA	0.423	0.539
NFL	0.333	0.354
NHL	0.504	0.100

Table 5: Regression analyses by league

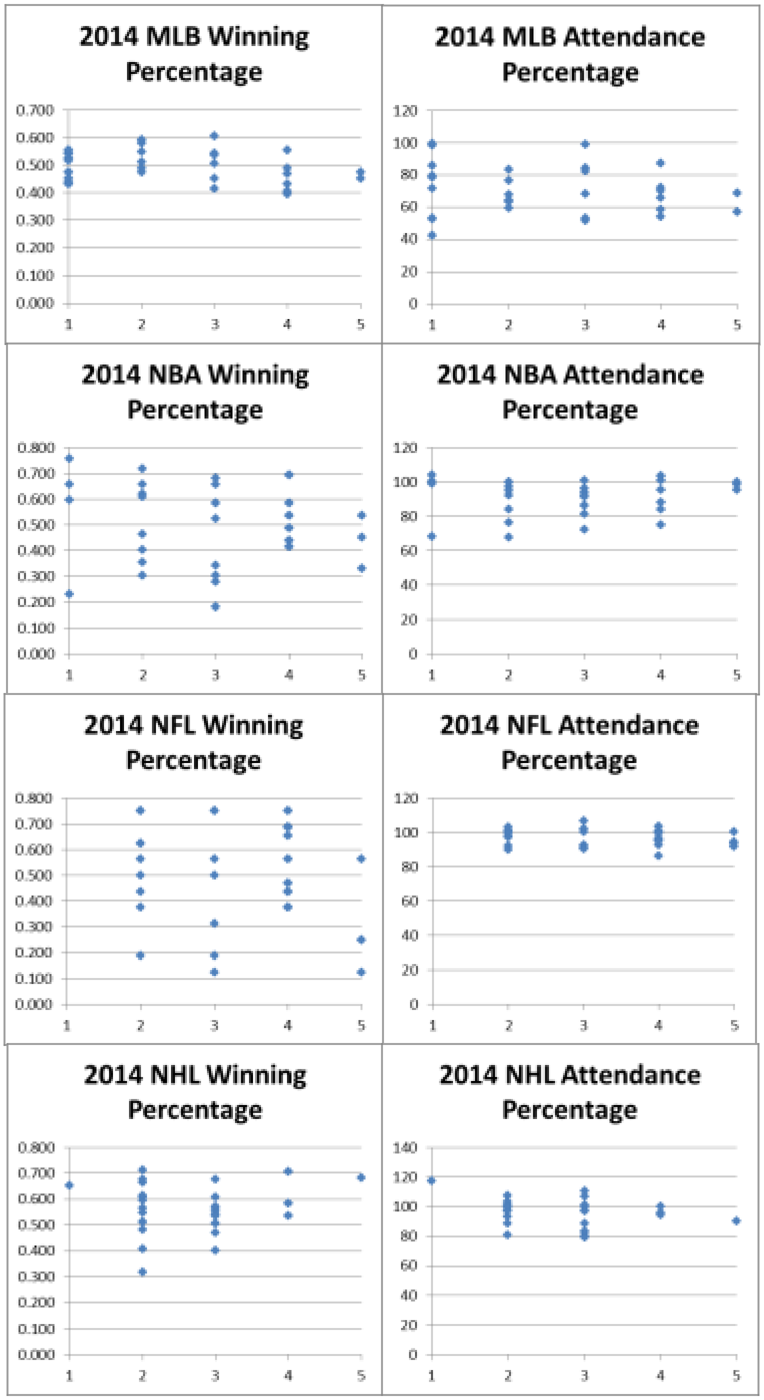

Figure 3: Scatter plots of MLB winning percentage and attendance percentage against categorization for all four leagues

The four sets of scatter plots in Figure 3 show relatively even distributions. In the MLB, the highest winning percentage for a single team is from Category 3, and the scatter plot clearly shows Category 2 teams with higher winning percentages than Category 1 teams. The wider distribution of attendance percentages for Category 1 MLB teams includes the teams with both the highest and lowest individual attendance percentages. In the NBA, there is the general trend of lower categories associated with lower winning percentages (though not significantly so) as well as the Category 1 outlier and the much wider range than in the MLB. The NBA attendance percentages are nearly identical for Categories 2-4, and there is again an outlier in Category 1 (the same outlier team in winning percentage – Philadelphia 76ers). The NFL scatter plots are more condensed with more teams in fewer categories. Categories 2, 3, and 4 all have teams with very high winning percentages (three of the five highest winning percentages are from Category 4 teams), and only Category 4 teams are excluded from any of the lowest winning percentages. NFL games consistently have near-capacity attendance due to the popularity of the sport. This is evident in the scatter plot of attendance percentage which shows high percentages and narrow ranges for teams from every category. Most of the teams in the NHL (25 out of 30) are in Categories 2 and 3, so there is a heavy concentration in the scatter plots. However, every team in Categories 4 and 5 had a winning percentage over 0.500 and, like the NFL, the attendance percentage for all teams is high. Due to the small and unbalanced team counts within the categories within each of the leagues, additional statistical tests (such as ANOVA) could not be performed.

In the end, the evidence does not support H3 – there is no difference in the impact of analytics adoption across the four leagues.

DISCUSSION, LIMITATIONS, AND FUTURE RESEARCH

Across the three hypotheses, no statistically significant results were found. However, professional sports teams in these four leagues continue to adopt and improve their analytics utilization. How can this trend be explained if there are no empirical data to support such investments in staff, technology, and time? Where is the return on investment for these teams who have spent time and money on analytics efforts?

Perhaps it is unfair to expect results in such a short period of time. This could potentially explain why there are no significant results using the ESPN (2015) categorizations and the performance data from the 2014 season. Unfortunately, categorizations for the 2013 season or the 2012 season (or any prior) are not available to use against the performance results in the 2014 season. The question remains, therefore, how long must a team wait before it will see measurable and

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consistent results in either winning percentage or attendance percentage, assuming improvements will be seen at all? In other words, is there a measurable "lag time" between analytics adoption/implementation and improvements in on-field or off-field performance? With most technology implementations, immediate results and improvements are not possible. Time is required between planning, implementation, and some later point when the results of the technology utilization can be realized. This could take weeks or months for a new social media effort, and it could take years for a fully integrated ERP system. Analytics implementation by professional sports teams is no different. Results may not be seen immediately.

Additionally, given the myriad of variables at play during any single game/match, let alone an entire season, is it even fair to expect consistent improvements in any of the measures used here? And if enough teams are utilizing analytics techniques, will a measurable difference in performance be possible or is the competitive advantage of analytics lost in its ubiquity? This is all assuming that teams who have adopted analytics are utilizing analytics to their full potential, something that needs further investigation.

LIMITATIONS

The primary limitation of this study is the reliance on the ESPN (2015) rankings and categorizations. While based on descriptive data and the opinions of internal and external experts, the rankings and categorizations are not perfect. Some would argue that these rankings and categorizations are no better than subjective opinions as the methodology for their creation is not available. Perhaps, but ESPN (the network, the magazine, or the website) is seen as an authority.

A second limitation is the availability of only one year's worth of performance data since the rankings and categorizations were created. Although this is addressed in the *Future Research* section below, it is a limitation in that the quantity of usable, longitudinal data is limited.

Finally, winning percentage and attendance percentage were chosen for their applicability to all of the leagues as well as their relative importance as measures of on-field and off-field success. However, many more performance statistics exist beyond these variables. Some of these statistics are applicable to all of the professional leagues – point differential (points scored minus points allowed), home vs away (home winning percentage minus away winning percentage), playoff appearances or league championships, and team revenue – while many, if not most, are sport-specific – team ERA or team OBP in baseball, team field-goal percentage or team rebound differential in basketball, team tackles-for-loss or team total yards from scrimmage in football, and team scoring chances or team power play efficiency in hockey. The full list of potential performance measures, especially when sport-specific measures are included, is quite large and this study only scratches the surface. However, whether a team scores more points than its opponents or whether a team performs better at home or on the road is secondary to overall wins.

FUTURE RESEARCH

Considering the unexpected results of the analyses, further research is warranted to better understand the impact of analytics adoption by professional sports teams. Attention should be paid to both the reasons and causes for analytics adoption as well as the performance results stemming from analytics adoption.

Many possible approaches exist to better understand analytics adoption by professional sports teams, but some of the possibilities include:

- Look at how teams are utilizing analytics, and assess whether teams are utilizing analytics to their full potential. Do teams with greater utilization towards potential have greater on-field and off-field performance success? Is there a difference between back-office (general manager) utilization and on-field (coach or manager) utilization?
- Look at more in-depth data regarding how long teams have been utilizing analytics, and assess the number of championships won as a result of when analytics were adopted. Have teams who adopted analytics before others won more championships (perhaps as a result of time instead of utilization differences)?
- Look at city (or metro area) population, and assess the impact of population and market size on analytics adoption. Do teams in smaller cities or markets have to utilize more analytics to field a winning team and attract fans? Do teams in such markets adopt analytics earlier than other teams in order to stay ahead?
- Look at team value, and assess its impact on analytics adoption. Do teams with lower value have to utilize more analytics to field a winning team and attract fans (and hopefully increase their value)?
- Look at performance measures in future seasons (2015, 2016, and beyond), and assess the impact of the 2014 categorizations on future performance. Do significant differences in on-field and off-field performance arise in future seasons based on current analytics adoption levels? Is there a measurable lag between adoption and performance results?

CONCLUSION

There is an apparent disconnect between the analytics hype in the professional sports industries and the lack of measurable and significant performance results by the teams. No significant differences were found in terms of winning percentage or attendance percentage, and no significant differences were found within the individual leagues. More research is needed (especially longitudinally) to further understand this phenomenon, but until then, these data and analyses indicate analytics adoption provides no on-field or off-field performance improvements.

APPENDIX

A listing of all 122 teams and their categorizations by ESPN (2015). Each league is ordered first by category (1-5) and then alphabetically by team within each of the five categories. Numbers in parentheses represent top 10 and bottom 10 rankings out of all 122 teams.

MLB	**NBA**	**NFL**	**NHL**
Boston Red Sox – 1 (5)	Dallas Mavericks – 1 (8)	Atlanta Falcons - 2	Chicago Blackhawks – 1 (10)
Chicago Cubs – 1	Houston Rockets – 1 (3)	Baltimore Ravens - 2	Boston Bruins - 2
Cleveland Indians – 1	Philadelphia 76ers – 1 (1)	Cleveland Browns - 2	Buffalo Sabres - 2
Houston Astros – 1 (2)	San Antonio Spurs - 1 (7)	Dallas Cowboys - 2	Columbus Blue Jackets - 2
New York Yankees – 1 (6)	Atlanta Hawks - 2	Jacksonville Jaguars - 2	Edmonton Oilers - 2
Oakland A's – 1 (9)	Boston Celtics - 2	Kansas City Chiefs - 2	Los Angeles Kings - 2
Pittsburgh Pirates – 1	Cleveland Cavaliers - 2	New England Patriots - 2	Minnesota Wild - 2

St. Louis Cardinals – 1	Detroit Pistons - 2	Philadelphia Eagles - 2	New York Islanders - 2
Tampa Bay Rays – 1 (4)	Golden State Warriors - 2	San Francisco 49ers - 2	Pittsburgh Penguins - 2
Baltimore Orioles – 2	Memphis Grizzlies - 2	Buffalo Bills - 3	St. Louis Blues - 2
Kansas City Royals – 2	Oklahoma City Thunder - 2	Chicago Bears - 3	Tampa Bay Lightning - 2
Los Angeles Dodgers – 2	Portland Trail Blazers - 2	Green Bay Packers - 3	Toronto Maple Leafs - 2
New York Mets – 2	Charlotte Hornets - 3	Miami Dolphins - 3	Washington Capitals - 2
San Diego Padres – 2	Indiana Pacers - 3	Oakland Raiders - 3	Winnipeg Jets - 2
Toronto Blue Jays – 2	Miami Heat - 3	Seattle Seahawks - 3	Arizona Coyotes - 3
Washington Nationals – 2	Milwaukee Bucks - 3	Tampa Bay Buccaneers - 3	Calgary Flames - 3
Chicago White Sox – 3	Orlando Magic - 3	Arizona Cardinals - 4	Carolina Hurricanes - 3
Los Angeles Angels – 3	Phoenix Suns - 3	Carolina Panthers - 4	Dallas Stars - 3
Milwaukee Brewers – 3	Sacramento Kings - 3	Cincinnati Bengals - 4	Detroit Red Wings - 3
San Francisco Giants – 3	Toronto Raptors - 3	Denver Broncos - 4	Florida Panthers - 3

Seattle Mariners – 3	Utah Jazz - 3	Detroit Lions - 4	Montreal Canadiens - 3
Texas Rangers – 3	Chicago Bulls - 4	Houston Texans - 4	Nashville Predators - 3
Arizona Diamondbacks - 4	Denver Nuggets - 4	Indianapolis Colts - 4	New Jersey Devils - 3
Atlanta Braves – 4	Los Angeles Clippers - 4	Minnesota Vikings - 4	Philadelphia Flyers - 3
Cincinnati Reds – 4	Minnesota Timberwolves - 4	New Orleans Saints - 4	San Jose Sharks - 3
Colorado Rockies – 4	New Orleans Pelicans - 4	New York Giants - 4	Vancouver Canucks - 3
Detroit Tigers – 4	Washington Wizards - 4	Pittsburgh Steelers - 4	Anaheim Ducks - 4
Minnesota Twins - 4	Brooklyn Nets – 5 (118)	St. Louis Rams - 4	New York Rangers - 4
Miami Marlins – 5 (115)	Los Angeles Lakers – 5 (113)	New York Jets – 5 (114)	Ottawa Senators - 4
Philadelphia Phillies – 5 (122)	New York Knicks – 5 (121)	San Diego Chargers – 5 (119)	Colorado Avalanche – 5 (117)
		Tennessee Titans – 5 (116)	
		Washington Redskins – 5 (120)	

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