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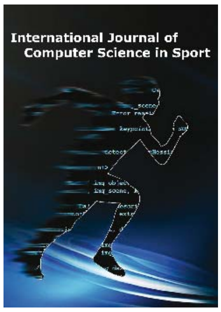

A Team-Compatibility Decision Support System for the National Football League

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Abstract

Many factors are considered when making a hiring decision in the National Football League (NFL). One difficult decision that executives must make is who they will select in the offseason. Mathematical models can be developed to aid humans in their decision-making processes because these models are able to find hidden relationships within numeric data. This research proposes the **H**euristic **E**valuation of **A**rtificially **R**eplaced **T**eammates (HEART) methodology, which is a mathematical model that utilizes machine learning and statistical-based methodologies to aid managers with their hiring decisions. The goal of HEART is to determine expected and theoretical contribution values for a potential candidate, which represents a player's ability to increase or decrease a team's forecasted winning percentage. In order to validate the usefulness of the methodology, the results of a 2007 case study were presented to subject matter experts. After analyzing the survey results statistically, five of the eight decision-making categories were found to be "very useful" in terms of the information that the methodology provided.

KEYWORDS: DECISION SUPPORT SYSTEMS, LEARNING SYSTEMS, MACHINE LEARNING, PREDICTION METHODS, NEURAL NETWORKS

Introduction

The focus of this research is on the National Collegiate Athletic Association (NCAA) and the National Football League (NFL). Since its conception, both the collegiate and the professional game have changed dramatically. Today, football is not only a game; it is a major revenue-generating business in the United States. For example, the average revenue generated by an NFL team in 1998 was $109M; in 2018, the average revenue per team grew to $427M (Forbes, 2018). One of the most important decisions a team from the NFL will make is who they will hire to play the game. In terms of this decision, the majority of hiring decisions are made during the NFL’s annual draft or during the free-agent signing period. To make good hiring decisions in the NFL, managers must try to estimate how well an individual can play a particular position on the field. This is an arduous task since a player’s performance is dependent upon other players on the field. To complicate hiring decisions further, teams must also obey roster size limits and a salary cap. Teams employ general managers, scouts, and other personnel to evaluate a player’s ability to play football. To aid these experts, statistics are collected during games. However, there is not a universal understanding of the importance of how these statistics affect individual performances and, ultimately, the team’s performance (Hartman, 2011).

Football falls behind other sports, most notably professional baseball when it comes to using analytics to assist in hiring decisions (Birnbaum, 2019). There are many reasons why football is difficult to analyze from a quantitative perspective (Stern, 1998). One reason is simply that teams in the NFL only play 16 regular-season games. From a sample size perspective, the number of games played in the NFL regular season is considerably fewer than in other professional sports. It is also difficult to find detailed play-by-play information for *all* playing positions in football.

There is an inherent difficulty in determining a player's contribution to his team’s performance. Even outside of the scope of football, very few methodologies address this issue from a quantitative perspective. However, one example which attempts to assess an individual player's impact on a team’s chances of winning in a game in the National Basketball Association (NBA) utilizes Bayesian regression (Deshpande & Jenson, 2016). However, most of the literature associated with player evaluation focus on evaluating one particular playing position rather than methods derived for all playing positions. For example, quantitative methods have been employed to predict the career success of tight ends in the NFL (Mulholland & Jensen, 2014). Another example includes an investigation of how important a quarterback’s cognitive ability impacts their NFL Draft position and career outcomes (Pitts & Evans, 2018).

Football is a system that is comprised of interacting forces, theories, strategies, and rules. For this reason, it is plausible that some of the aspects related to this system can be modeled mathematically (Larsen & Fenn, 2006). Thus, if models are created with a sufficient amount of allowable error, methodologies can be developed that can provide insight to hiring managers in the NFL. Data-driven models are able to find hidden relationships within numeric information. The practice of developing data-driven models to understand game dynamics is an emerging field of study within sports (Perl & Memmert, 2017; Clemente & Martins, 2017). The aim of this article is to disseminate the development and the applications of a methodology called HEART, which is short for **H**euristic **E**valuation of **A**rtificially **R**eplaced **T**eammates. HEART is a model derived from artificial intelligence and statistical analysis that aims to isolate an individual’s contribution towards team success so that better hiring decisions can be made. To develop this decision support tool, HEART incorporates the effects that aging may have on a player’s physiological ability to play football, as well as a player’s historical on-the-field performance indicators. In particular, HEART aims to provide insights to NFL hiring managers with the following aspects related to hiring:

- Determine which playing positions a team should target in the off-season.
- Determine which specific players a team should target in the off-season.
- Evaluate the effectiveness of potential trades that might occur within the off-season.
- Identify the amount of risk associated with hiring players in the off-season.

The HEART methodology will be presented in four sections. The first section, called **HEART Model,** will introduce the data that was used to develop the predictive models that help estimate a team's future winning percentage. The second section, called **HEART Simulation,** will describe how two metrics, which are called expected and theoretical contribution values, were derived. A third section, called **HEART Selected Results,** provides specific examples of how HEART can be used by player evaluators and hiring managers to make better decisions in the NFL Draft and free agency signing periods. Finally, a fourth section, called **HEART Validation,** will present the results of a survey that was sent to experts in order to determine whether the HEART methodology produced useful results to hiring managers in the NFL.

Literature Review

The quality of human capital plays a critical role within any industry. This is because the quality of human capital relates to an organization's competitive advantage. This is especially true for an NFL organization. The use of data mining methodologies for human resource management decisions related to staffing, development, performance management, and compensation is now considered by researchers as a relatively new application area within analytics (Strohmeier & Piazza, 2013). Developing predictive models for organizations with high turnover rates, like the NFL, is a complicated task. However, various traits about employees have been used to predict job performance in a number of industries (Rothstein & Goffin, 2006; Clark & Jones, 2007; Chien & Chen, 2007; Chien & Chen, 2008).

HEART is a methodology that attempts to overcome deficiencies within the scope of quantitative analysis within American football with respect to player evaluations and hiring. Evaluating an individual player's football ability accurately has many benefits for a sports organization and even the cities in which NFL teams are located (Coates, 2002). If a methodology was created that evaluates a player's football ability accurately, an organization could make better decisions when formulating members for a team and the financial contracts that pursue (Pitts & Evans, 2018). The financial aspects of signing players to play for a professional sports organization is an extremely important decision (Yaldo & Shamir, 2017). Though researchers have started to address this particular problem outside of American football (Gavião, Sant'Anna, Lima, & Garcia, 2019), the amount of literature related to the NFL is still somewhat limited. In this section, a review of literature related to player evaluation models and hiring methodologies inside and outside of football is presented. In addition, comments will be provided in order to explain the contributions of the presented methodology.

Data Mining Challenges, Applications, and Research Gaps in Football

In 1902, David Hilbert, an influential mathematician, outlined 23 major issues that he thought the mathematical community should address over the next century (Hilbert, 1902). Just as the mathematical community once had an outline of issues to overcome, football also has a set of related issues. This list of problems has been described by Schatz (2005) as Football's Hilbert Problems. In his report, Schatz outlines ten issues that warrant further analysis from the quantitative research community. The following list summarizes the issues outlined by Schatz that relate to the scope of the research presented in this article.

1. **Player Comparisons**: Although there have been efforts to determine metrics that allow for the comparison of players within a certain playing position (Stern, 1998; Schatz, 2004; Wolfson, Addona, & Schmicker, 2011) there is currently a gap within the literature with respect to deriving metrics that allow players of *any* playing position to be compared within a particular sport. One approach that researchers have taken to evaluate individual players on a team regardless of their playing position is often referred to as a plus-minus rating system (Hvattum, 2019). These systems date back to the 1950s and they attempt to distribute credit to an individual player based on the players' team performance. Though these methods have evolved considerably over time, HEART attempts to contribute to this gap of literature by presenting a methodology that is quite different from other methods that have been published. Ultimately, two metrics, which are called the expected and theoretical contribution values, are generated by the HEART methodology. These metrics can be used by NFL player hiring managers to compare players of the *same* or *different* playing positions.

2. **Roster Composition:** Until recently, the use of analytical modeling techniques has been limited with respect to decisions related to roster compositions within the NFL. These decisions have historically relied on human judgment when it comes to evaluating a player's contextual performance on the field (Whiting & Maynes, 2016). However, data-mining methods such as classification trees, logistic regression, generalized additive models, and multivariate adaptive regression splines have been used to evaluate and manage the risk of selecting players to play for an organization (Demir, 2014). NFL rosters are primarily constructed during the NFL Draft and free agency signing periods. The literature related to composing rosters based on data-driven methodologies with respect to American football is limited. Examples exist of researchers tackling this particular problem in other sports (Saikia, Bhattacharjee, & Radhkrishnan, 2016). For example, stochastic programming has been leveraged within a methodology for the English Premier League (Pantuso, 2017). This particular methodology attempts to ensure that a team has a certain mix of skills, that certain league-specific regulations are met, and that a team's budget limits are not violated. It is imperative for managers to understand when risky hiring decisions are being made. This is especially true given the large and long financial commitments that teams make to players they sign. To address these types of constraints, researchers have explored various efficiencies ratings related to player performance in order to create optimal lineups in the NBA (Nagarajan & Li, 2017; Hsu, Galsanbadam, Yang, & Yang, 2018). The expected and theoretical contribution values derived by HEART can provide insight into when a risky hiring decision might be made. This contribution is significant because research shows that it is very difficult and time-consuming for teams to recover from making risky decisions that do not turn out well (Hendricks, DeBrock, & Koenker, 2003).

3. **Player Replacement:** Another limitation of quantitative analysis within football includes replacement strategies. This is a key component when identifying whether it is advantageous for a team to cut a certain player from a team's roster and replace the player with another individual from the NFL Draft or free agency. In addition, replacement strategies provide insight to managers when it comes to evaluating trades that are proposed during the off-season. Many types of trade offers are considered by NFL managers. The first type involves one team that is willing to trade one of their players for

another player on another team. The contribution values provided by HEART can assist an NFL manager in determining whether to accept or reject a trade offer. The second type of trade occurs in the NFL Draft when a team wants to trade draft picks in order to move up or down in their draft position. This type of trade can be advantageous when a team covets a certain player in the draft and wants to make sure that they are in a position in which they can select the player. In addition, if a team does not covet a certain player when they are scheduled to make a selection in the draft, they might consider trading their draft selection away to another team. Though literature is limited in this area of study, one proposed method incorporates nonparametric regression in order to help managers identify the trading value of draft picks (Schuckers, 2011). Another concept associated with player replacement involves decisions related to immigrating the risk associated with injuries. Given how physically demanding football is, injuries are inevitable. Data-driven decision support systems have been developed that predict athletic injuries (Peterson & Evans, 2019). However, this particular area of research has not received much attention within the NFL.

4. **Draft and Player Development:** Each team has an opportunity to select and hire players from the NFL Draft. However, as stated earlier, there is a limited amount of research in regard to quantitative methods related to making optimal decisions in the NFL Draft. However, examples can be found outside of the NFL. For example, researchers have explored the career longevity of NBA prospects (Abrams, Barnes, & Clement, 2008). Another example that can be found in the literature includes the use of dynamic programming to improve a sports league draft (Fry, Lundberg, & Ohlmann, 2007). Though this methodology has promising results, it relies on knowing the valuation of the players on an existing roster and the valuation of players on opposing teams as well as knowing every team’s need, which is normally a subjective process based upon expert opinions and not quantitative metrics. HEART not only provides quantitative metrics that could be used in conjunction with this type of approach, but it also provides a way to determine a team’s positional area of need. Similarly, younger players, especially those taken in later rounds of the draft, may require more time to develop into contributing players on an NFL roster. Based on the financial structures that are in place in the NFL, players that are selected earlier in the draft are paid more than those who are selected in later rounds (Macey, 2005). Given this, more time is spent evaluating players that are projected to be chosen earlier in the draft. Another contribution of the HEART methodology relates to the data-driven nature in which it was constructed. In other words, thousands of players can be assessed quickly. This could potentially draw attention to talent that has gone unnoticed by player evaluators.

5. **College and Pro Translation:** Although there are several similarities between the two levels of competition, research is needed to evaluate how players translate from the NCAA to the NFL. HEART provides a way to forecast how well a college’s prospects will influence a team’s predicted winning percentage in the NFL, which is perhaps the HEART methodology’s biggest contribution. This ability is quintessential for making better decisions in the NFL Draft. For example, NFL general managers must decide on which playing positions will help their team the most, which players should be taken, and when those players should be taken if they are available during the NFL draft. Being able to predict how well a college prospect might perform in the NFL is also beneficial for college players who are trying to decide if they should leave college early and turn pro. Quantitative approaches for recruiting players have been found outside of the NFL (Barron, Ball, Robins, & Sunderland, 2018). This particular system leverages proprietary

data as well as artificial neural networks in order to forecast a player's career trajectory in professional soccer. Research contributions related to the NFL Draft can be found in the literature. For example, researchers have investigated the selection bias related to a player's age with respect to when a particular player was selected in the NFL Draft (Beyer, Fukuda, Redd, Stout, & Hoffman, 2016). Other examples employing quantitative techniques related to the draft have also been studied. For example, various heuristics have been developed to automate the player selection process sport's league draft (Uzochukwu & Enyindah, 2015; Al-Shboul, Syed, Memon, & Khan, 2017).

HEART Model

The focus of this section is on describing how the HEART model was developed. The goal of the HEART model was to predict a dependent attribute for football called the Pythagorean Theorem winning percentage. Further discussion about the development of this dependent attribute will be discussed in later sections. However, it is important to know that the development of this particular metric is considered a contribution of the presented research because it has not been previously defined for the NFL, even though it has been defined for other professional sports like baseball, basketball, and hockey. After presenting the development of the dependent attribute of HEART, discussions related to the input attribute that was used in HEART will follow.

Football's Pythagorean Theorem Winning Percentage

In 1979, Bill James derived an empirical formula that estimated team winning percentages for Major League Baseball (MLB) (James, 1979). Later, he revised his initial work to predict a team's winning percentage for a given season based on the team's ability to score as well as the team's inability to keep opponents from scoring (James, 1985). James hypothesized that teams would win more than half of their games if they were able to score more points than they gave up. James named his formula the Pythagorean Theorem winning percentage, which is shown in Equation 1, because of how similar the derivation resembled the Pythagorean Theorem.

$$\text{Pythagorean Winning\%} = \frac{\text{Runs Scored}^{\text{X}}}{\text{Runs Scored}^{\text{X}} + \text{Runs Allowed}^{\text{X}}} \tag{1}$$

Evaluating team performance through the Pythagorean winning percentage is attractive because it encompasses team success in terms of three aspects of football, which include offensive, defensive, and special teams. The Pythagorean winning percentage eliminates "luck" from the traditional way that winning percentage is normally calculated (Moy, 2006).

To develop football's Pythagorean winning percent relationship, a historical database was acquired from Pro-Football Reference (2009) that included team statistics such as points scored (PS) and opponent points scored (OPS) from 1988 to 2007. In total, 601 samples were randomized and partitioned into training and testing datasets. Based on the randomized data, 80% of the data was used to determine the exponent of *x,* and the remaining 20% of the data was used for independent testing. StatSoft's Statistica 10 was used to minimize the squared error between the actual and estimated winning percentages in the training dataset. The least-squared estimate of football's Pythagorean winning percentage exponent (i.e. *x*) was found to be 2.49. According to the results of the minimization, the parameter was significant, since the p-level was well below an alpha value of 0.05. In addition, the lower and upper confidence limits for the estimate were found to be 2.36 and 2.62, respectively. In terms of the testing results, the coefficient of determination (R^2) was 85.2%, and the confidence limit was found to be ±0.147 in terms of winning percentage, or ±2.36 games in an NFL regular season.

Performance-Aging Curves

Inputs that reflect a player's physical ability were used to develop HEART. This is significant because aging and the physical nature of playing football has a negative effect on an athlete's ability to play the game (Robbins, 2011). In order to use inputs that relate to an athlete's physical abilities, performance-aging curves were developed for eight events that were measured during the NFL Combine. These events include how fast a player can run a 10, 20, and 40-yard dash; how far a player can jump horizontally or vertically; how many times a player can bench press 225 pounds; and how long it takes a player to complete the cone and shuttle drills. The combine events were selected as physical assessments because they are recorded in a standardized manner, nearly all NFL players have been measured for these events at the NFL Combine, and the events directly related to the skills that are required to play football (Ebben & Blackard, 2001). A fixed-effects model, which is shown in Equation 2, was developed to predict a player's performance in NFL Combine events at *any* age. To utilize this equation, the three coefficient values (i.e. f_1, f_2, and f_3) were determined through nonlinear optimization. Assuming these factors are known, the only information that is required to make a prediction of a player's performance in a combine event is the player's age when he was first measured at the combine, the measurement of the specific event in question, and the current age of the player.

$$Combine\ Value_{x_{Age}} = f_1 \cdot Combine\ Value_{x_0} + f_2 \cdot (x_{Age} - x_0) + \left(f_3 \cdot (x_{age} - x_0)\right)^2 \quad (2)$$

Equation 2 resembles a second-order polynomial equation and has the ability to capture three periods of performance that football players are likely to experience while playing in the NFL. These periods include increasing, peak, and decreasing performance periods.

To determine the fixed-effect coefficients, a historic NFL Combine dataset was obtained from the Sports Xchange that covered the years 1996 to 2006. Though this dataset was rife with information, it by itself was not enough to develop the performance-aging curves. This is due to the nature and purpose of the NFL Combine. In general, only around 300 players are invited into the NFL Combine each year. The purpose of the event is to allow NFL player evaluators and hiring managers to watch draft-eligible players compete in events, obtain medical information, and engage them in interviews. For this annual event, the athletes tend to range in age from 21 to 24 years. This range is simply not long enough to create desirable performance-aging curves since veterans in the league can be much older than 24 years of age. In order to overcome this limitation, a second dataset was needed.

The second historical database was obtained from a software developer called Electronic Arts (EA), which develops an extremely popular video game series called Madden NFL. This database contained a myriad of attributes, which include, but are not limited to, speed, strength, agility, jumping, stamina, and injury, and each rating is assigned a value between zero and one hundred. EA has an incentive to make their game as realistic as possible, so the premise of the performance-aging curve development was to build models using Madden NFL ratings as inputs in order to simulate actual NFL Combine event performances. Then, after these models were developed, they could be used to forecast combine event performance for all players that appeared in the Madden NFL datasets. This is significant because if a player was under contract with the NFL, their ratings were included in the Madden NFL databases.

A dataset was constructed which matched players' NFL Combine performance values with appropriate ratings in the Madden NFL dataset. Once these datasets were constructed, each dataset for each combine event was randomly partitioned. The random partition used 60% of the data for training, 15% for cross-validation, and 25% for testing. To demonstrate the performance-aging curve methodology, an example will be presented using the 40-yard dash.

In total, 64 performance-aging curves were developed for HEART. It should be noted that these results are presented in the appendix. In developing the performance-aging curve for the 40-yard dash, the total sample size was 929 and NeuroDimension's NeuroSolutions v5 software was used to develop the artificial neural networks. In terms of the training, a mean squared error (MSE) of 0.011 and an R^2 of 88.2% were obtained. Based on the independent testing data, this model achieved an MSE of 0.013 and an R^2 of 87.7%.

After NFL Combine performances were forecasted from the ratings from the Madden NFL dataset, nonlinear optimization was used in order to determine the fixed-effect coefficients (i.e. f_1, f_2, and f_3) by minimizing the sum of the squared error between the forecasted event measures and the estimate generated by the fixed-effects model shown in Equation 2. The nonlinear optimization was conducted through Frontline System's Premium Solver Platform v7 software. Models were constructed either for single playing positions or for a small group of playing positions. The summary of the performance-aging curve for the 40-yard dash for the running back position is shown in *Table 1*.

Table 1. Aging Curve Model Parameters and Values for RB

Parameter	Estimate	Standard Error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	1.01	0.01	184.64	0.00	1.00	1.02
f_2	-0.05	0.01	-6.22	0.00	-0.07	-0.04
f_3	0.01	0.00	9.55	0.00	0.01	0.01

Additional insight can be extracted from the results found in *Table 1*. For example, in terms of averages for the running back position for the 40-yard dash, the peak age was found to be 28 years. In addition, the peak performance was found to be 4.55 seconds. Finally, an average player improved 0.87% per year until peak performance was obtained, and then a player declined by 2.69% per year after peak performance was obtained.

It should be noted that not all players that attend the NFL Combine compete in all of the events. In this case, missing values were handled using regression-based multiple imputations, since the literature suggests that this method produces estimates for missing values with little to no bias after the results are pooled (Scheffer, 2002; Young, Weckman, & Holland, 2009). Examples of using regression-based multiple imputations can be found in contributions made by Newman and Sin (2009) and Ng, Rouse, and Harrison (2016).

On-the-Field Attributes

Up to this point, the output of the HEART model has been defined as football's Pythagorean winning percentage. In terms of inputs into the HEART model, eight attributes have been defined thus far. These inputs include the estimated physical performances of eight NFL Combine events for any age of a player's career. The remaining input attributes used for the HEART model will be described as on-the-field input attributes. In total, 66 basic and advanced on-the-field input attributes were requested from STATS (2007) for all players that played in NCAA college football or the NFL from 1991 through 2007. This dataset was quite large, given the number of teams and players that appeared in both leagues during this timeframe. The dataset can be briefly summarized based upon whether a player was considered an offensive, defensive, or special teams player, however; a complete list of on-the-field attributes that were used in conjunction with the estimated NFL Combine performance inputs can be found in the appendix.

Ten attributes were common to all offensive, defensive, and special-team players. These included basic attributes, like the player's name, team, age, games started or played, and his height and weight. Thirty-two attributes were offensive playing statistics, with some considered basic and others advanced. Basic attributes include pass yards, rushing receptions, and receiving yards. More advanced statistics include passing yards to the catch, rushing yards before and after contact, the number of receiving targets, and blocking penalty yards or the number of sacks allowed. Defensive attributes also contained basic and advanced statistics. Examples include the number of tackles, interceptions, and quarterback knockdowns. Examples of special team statistics included punt return yards, the number of punts inside the 20-yard line, kickoff return yards, and field goals made at certain distance intervals (i.e. 0-35 yards, 35 or more yards).

Coaching Input Attributes

The final set of input attributes to the HEART model included career statistics from the head coach of an NFL team. To capture these attributes, data was collected from Pro-Football Reference (2009). The attributes for coaches were limited, but included age, the number of divisional and league championships, the number of games coached, and the divisional rank (i.e. first place, second place, etc.) in which the coach's team placed in a given NFL season.

Moving Average Attributes

Simple moving averages were calculated for all of the players' on-the-field input attributes as well as the coaching input attributes. This smoothing technique was used because we assumed a player's historical performance might be significant in predicting a player's future performance in the NFL. Likewise, it was assumed that a coach's historical performance might influence a team's future performance in the NFL. A maximum of four periods was chosen based on the maximum amount of time a player can play college football. The NCAA stipulates that a collegiate athlete can play up to four seasons of football before they are considered ineligible. The on-the-field databases contained information that was aggregated in a per season manner. Moving averages were computed based on the average of the current and immediate prior seasons (i.e. MA1), the current and prior two seasons (i.e. MA2), and the current and prior three seasons (i.e. MA3). Longer periods of moving averages could have been computed in some situations. However, this would have increased the frequency of missing data because not all players have played more than four years of college or professional football. Thus, the four-period moving average (i.e. MA3) represents the maximum amount of information that would be available if a player has no NFL experience.

HEART Model Player Selection

Now that the dependent attribute (i.e. football's Pythagorean winning percentage) and the independent attributes (i.e. estimates from the performance-aging curves, on-the-field statistics for players and coaches) have been introduced, the framework that was used in order to create the dataset that was used to train and test the HEART model will be discussed. The framework, which is shown in *Figure 1*, was needed in order to construct the dataset for the HEART model. For example, it is common for teams in the NFL to have multiple quarterbacks (i.e. QB1 and QB2) or even several running backs (i.e. RB1 and RB2) on a team's roster in a given season. *Figure 1* represents which playing positions, and how many of the same playing positions, were considered when constructing the dataset for the HEART model.

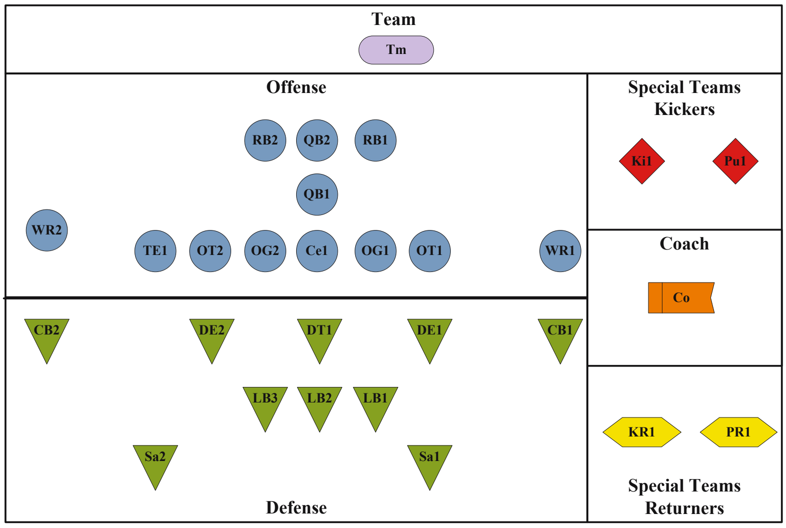

Figure 1. HEART Positions and Abbreviations

Choosing the playing positions for the HEART model was not a trivial task, due to defensive and offensive schemes used in the NFL. The positions shown in Figure 1 represent a "generic" scheme for both the offense and defensive. Additional schemes could have been created, but they would have reduced the sample size of the datasets that were needed to create the HEART model. Unfortunately, the data available at the time of this study was limited. Therefore, in order to maximize the data that was used, the "generic" scheme was chosen. More about this limitation will be discussed in the validation section, where experts were asked to provide feedback on the usefulness of the information provided by the HEART methodology.

Even with the playing positions identified, an additional strategy was needed in order to decide which particular play would be designated as the started (i.e. 1) or the backup (i.e. 2) for a particular playing position. To make this distinction, a set of rules was created for all playing positions. For example, consider the quarterback position. Given a team's roster, the quarterback that had the most games started was considered QB1, and the quarterback with the second-most games started would be considered QB2. Once this designation was determined, all of the input attributes associated with a particular player were used in order to construct the dataset. However, this simple rule is not sufficient if numeric ties occurred within the data. In this case, additional comparisons were needed. For the quarterback position, the second statistic that was considered as the number of games played. Thus, the quarterback with the most games played, given that the first comparison was a tie, was considered QB1, and the second-most games played, given that no further ties occurred, was considered QB2. Similar rules were created for all playing positions, and they can be found in the appendix.

HEART Model Dataset Creation

Now that the team, players, coach inputs, and team output attributes have been presented, the following section will describe how the dataset was created in order to develop the final HEART model. The strategy used for the HEART model represents all of the information that would be known by hiring managers after the completion of an NFL season and before free agency signing periods, as well as the NFL Draft. To create this dataset, inputs from a given season (i.e. n) were used to forecast the output for the following season (i.e. n+1). This framework is demonstrated by a small example shown in *Table 2*, which by no means is meant to be complete and comprehensive. For this example, Tim Couch was assigned as QB1 for the Cleveland Browns for the 2000 season. In addition to Couch, who was the clear starter in the 2000 season, the remaining players for HEART's roster were identified and their associated input attributes were used to forecast the number of games Cleveland would win in the 2001 season. Based on the input values for this particular roster, the football Pythagorean Theorem (FPT) winning percentage value was forecasted to be 8.4%. This value suggests that the Cleveland Browns would win 8.4% of their regular-season games in 2001. To be more specific, 8.4% of a 16 game regular season equates to a forecasted value of 1.344 wins for the Browns in 2001. This value, which was rather low in comparison to other values shown in *Table 2*, was not a surprise given that the Brown's were an expansion team in 1999 and based on the fact that they won only three games in 2000 and two games in 1999. It should be noted that this value does not represent Couch's contribution towards team winning percentage, but rather, it represents the baseline forecast for the number of games the Brown's were forecasted to win in 2001 if no other changes were made to their roster going into the 2001 season.

Table 2. HEART Model Database Example

Team	**Year (n)**	**QB1**	**Passing Attempts**	**Passing Yards to Catch**	**Cone**	**…**	**Year (n+1)**	**FPT Winning%**
CLE	2000	Couch	215	1347	7.360	…	2001	8.4
CLE	2001	Couch	454	835	7.382	…	2002	43.0
CLE	2002	Couch	443	1756	7.403	…	2003	54.5
CLE	2003	Holcomb	302	549	7.540	…	2004	35.6
CLE	2004	Garcia	252	1499	7.466	…	2005	29.7
CLE	2005	Dilfer	333	136	7.550	…	2006	34.3
CLE	2006	Frye	393	623	6.949	…	2007	26.8

Artificial Neural Network Modeling w/ Genetic Algorithm Optimization

In total, 16 NFL seasons were used to construct the dataset used to create the HEART model. This section will review the training and testing results of a small committee of three artificial neural networks (ANNs) that were used to model the database that was constructed for the HEART model. Even simple processes, such as taking the mean of the outputs that are generated by a committee of models, have significant advantages (Shadabi, Sharma, & Cox, 2006). This is especially true when it comes to reducing the negative effects of modeling data with a relatively low sample size (Thieme, Song, & Calantone, 2000), which is the case for the development of the HEART model. This limitation is not considered a limitation of HEART but is considered a limitation of the data that was available at the time HEART was developed. This limitation will also be discussed in the validation section of the manuscript.

To determine the neural network models used in the committee, a trial-and-error training procedure was used. In terms of software, NeuroSolutions v5 was used to develop and test the ANNs. The training process started by normalizing all input and output attributes between zero and one. Then, the dataset was randomly partitioned into 60% training, 20% cross-validation, and 20% testing. During the ANN training phase, the number of neurons in the network's hidden layer was varied from one to 50. Each network was configured to train for a maximum of 100,000 epochs for 1,000 generations of the genetic algorithm (GA) tuning. This deep-learning process required several hundreds of thousands of candidate ANN models to be trained and tested. Ultimately, the three ANNs that produced the lowest MSE in terms of the cross-validation dataset were used to forecast a player's expected and theoretical contribution values.

Overall, a committee of three neural network models (i.e. ANN A, B, and C) was used to predict a team's future winning percentage. Table 3 provides a summary of the goodness-of-fit statistics for the training, validation, and testing partitions from the best-performing ANN model that was found (i.e. ANN C). According to the coefficient of determination (R2) value, the model explains around 70% of the variations within all partitions. In addition, the 95% prediction interval for a team's future winning percentage is about ±2.5 games.

Table 3. Goodness-of-fit Summary for ANN C

Partition	MAE	Min |Error|	Max |Error|	R^2	Win% ±	Game ±
Training	0.042	0.001	0.231	0.743	0.172	2.755
Validation	0.072	0.004	0.213	0.725	0.167	2.676
Testing	0.072	0.004	0.204	0.686	0.144	2.306

HEART Simulation

In order to determine a player's contribution towards a team's future winning percentage, an iterative replacement strategy was used. The replacement strategy was dependent upon the model's three ANNs that were created. For example, assume that a general manager has an up-to-date roster and that all the HEART playing positions (i.e. QB1 and QB2) were defined. All of the associated input attributes for the players on the roster could then be used to forecast the team's future winning percentage. A general manager might want to know how a team's predicted winning percentage might change if one player's set of input attributes were replaced with another player's set, provided the two players shared the same playing position. This is exactly what the HEAT simulation does. However, the data used for the HEART model can be pre-processed in several ways in order to evaluate the change in the predicted winning percentage. From this perspective, the development of two metrics, called the expected and theoretical contribution values, will be discussed in the next section. It should be noted that these results, among other applications of the HEART methodology, were presented to NFL hiring experts in order to validate the HEART methodology.

Expected and Theoretical Contribution Values

As noted, the input data for the players used in the HEART model can be pre-processed in a variety of ways in order to make a forecast of a team's future winning percentage. For this research, two different contribution metrics were explored. These metrics are called the expected and theoretical contribution values. From a modeling perspective, the only difference between these two values was how the on-the-field input data was prepared and applied to the HEART models.

The original on-the-field data that was obtained was aggregated in a per-season manner, and none of the input attributes were calculated by taking ratios of other on-the-field statistics. An example of a calculated statistic would be a quarterback's passing yards per passing attempt, or rushing fumbles per rushing attempt, or receiving touchdowns per receiving targets. Of course, these attributes could have been calculated. However, the expected contribution estimates were generated with data that was not adjusted by taking ratios of other on-the-field statistics.

An argument could be made that would support adjusting the original data. For example, players in football are often injured during a season, and as a result, they do not play every game within an NFL regular season. In this case, a player's on-the-field statistic could be adjusted by knowing how many games the athlete played in a given season. This information could be used to extrapolate what the on-the-field statistic would have been if the player had played all 16 games of an NFL regular season. As a result, the contribution associated with this type of adjustment is called the theoretical contribution value.

Table *4* provides an example of how the contribution values were determined for a specific player on a specific team for a given season. For this example, Darrelle Revis, a cornerback from the University of Pittsburgh, was a prospect in the 2007 NFL Draft. In order to calculate the effect the contribution values for Revis would have had on the Cleveland Browns, a baseline must be determined. In regard to this example, the baseline winning percentage was estimated to be 51.2%, 47.7%, and 53.4% for each of the three respected ANN models (A, B, and C). The baseline values represent the predicted winning percentage, given the Brown's roster for the 2007 season, in other words, the players on the roster right before the 2007 NFL Draft. To generate the expected contribution values, Darrelle's non-adjusted input attributes were replaced with Leigh Bodden's, who was originally assigned as the Brown's CB1, and estimates from the three ANN models were made. The expected replacement contribution value from ANN A suggests that Revis would increase the Brown's estimated winning percentage to 9.7%, whereas models B and C suggest the team's performance would decrease by 0.2% and 0.58%, respectively. However, the changes in the theoretical values, which were 20.4%, 0.1%, and 7.8%, suggested that Revis would improve the Brown's 2007 winning percentage.

Table 4. Expected and Theoretical Team-Specific Example

HEART Model	Team City	Baseline (win%)	Expected Replacement (win%)	Expected Delta (win%)	Theoretical Replacement (win%)	Theoretical Delta (win%)
A	Cleveland	51.2	60.9	9.7	71.6	20.4
B	Cleveland	47.7	47.5	-0.2	47.9	0.1
C	Cleveland	53.4	47.6	-5.8	61.2	7.8

If the expected contribution values for Revis on the Browns were averaged, the difference would be 0.012, which means that Revis would increase the Brown's seasonal wins by 0.2 games. However, as anticipated, the final theoretical value was much higher. This higher value was anticipated because Revis did not play many games during his first year at Pittsburgh. The theoretical contribution value for Revis on the Brown's roster in 2007 was calculated to be 9.4%, which would suggest that if he were drafted, he would have increased the Brown's number of games won by 1.51.

HEART-Selected Results

The following sections present applications that were derived from the HEART methodology that relates to evaluating players or supporting other decisions that were made by NFL managers. In particular, the results of a 2007 free agent and NFL Draft case study will be presented. Therefore, the following sections will describe the datasets that were used for the case study.

NFL Draft and a Free Agent Player-Data

In order to validate the results of the HEART methodology, a dataset of the top 100 draft-eligible players for the 2007 NFL Draft, as well as the top 100 free agent players that were available after the 2006 season, was created (Football's Future, 2007). Once the players were identified and the players' statistical information was obtained, the input values were simulated through the HEART models for each NFL team.

Team-Specific Ratings for Draft Class

The NFL Draft is extremely important for NFL decision-makers. In the 2007 NFL Draft, the Oakland Raiders owned the first pick. After simulating all draft-eligible players through the HEART model and simulation, an NFL general manager could evaluate the expected and theoretical contributions values of all players that were eligible to hire. If this was done well before the NFL Draft, a team could ensure that they were sending scouts to evaluate a potential player with a high contribution value that they might have otherwise overlooked. The results could also be used to support evaluations that had already taken place, or they could be used to identify when it might have been advantageous to reevaluate a player if their contribution values differed from their own, independent evaluations.

Table 5 provides the results of five players who had the highest expected and highest theoretical contribution values for the Oakland Raiders leading up to the 2007 NFL Draft. The model suggests that the Raiders should have avoided drafting JaMarcus Russell using their first overall pick, a move which some have suggested was one of the biggest busts in NFL Draft history (CBS Sports, 2016). In fact, HEART recommended that the Raiders should have selected Patrick Willis, who would later become the 2007 Defensive Rookie of the Year Award winner, who was selected to 7 Pro Bowls, and who is very likely to become a member of the NFL Hall of Fame. This type of career is much different from Russell's career, which lasted just three NFL seasons, in which where he started 25 games.

Table 5. Team-Specific Ratings for Oakland Raiders' 2007 Top 5 Draft Prospects

Pos.	Name (Last, First)	Act. Draft Selection	Expected (games)	Theoretical (games)	Expected Rank	Theoretical Rank
LB	Willis, Patrick	11	3.00	3.27	1	1
RB	Peterson, Adrian	7	2.53	3.03	2	2
QB	Quinn, Brady	22	2.40	2.43	3	3
QB	Russell, JaMarcus	1	2.23	2.27	4	4
CB	Revis, Darrelle	14	1.23	1.90	7	5

2007 NFL Mock Draft with Team-Specific Contribution Values

The NFL Draft is extremely important to NFL teams, and deciding whom to select is extremely difficult. Player evaluators on one team simply have different opinions about a player's value and their fit on the team. After simulating all draft-eligible players through all 32 NFL teams, a mock draft can be generated. Mock drafts are useful when hiring managers are trying to create a strategy regarding whom they or other teams in the league will target with draft picks. For example, a mock draft consisting of the first 10 picks of the 2007 NFL Draft is shown in *Table 6*.

Table 6. First 10 Picks for the 2007 Mock Draft based on Team-Specific Contribution Values

Draft Pick	Team Name	Act. Player Selected in the Draft	Player's Pos.	Player Selected by HEART	Player's Pos.	Actual Pick
1	Oakland Raiders	Russell, JaMarcus	QB	Willis, Patrick	LB	11
2	Detroit Lions	Johnson, Calvin	WR	Quinn, Brady	QB	22
3	Cleveland Browns	Thomas, Joe	OT	Peterson, Adrian	RB	7
4	Tampa Bay Buccaneers	Adams, Gaines	DE	Carriker, Adam	DT	13
5	Arizona Cardinals	Brown, Levi	OT	Revis, Darrelle	CB	14
6	Washington Redskins	Landry, LaRon	Sa	Branch, Alan	DT	33
7	Minnesota Vikings	Peterson, Adrian	RB	Thomas, Joe	OT	3
8	Atlanta Falcons	Anderson, Jamaal	DE	Yanda, Marshal	OG	86
9	Miami Dolphins	Ginn Jr., Ted	WR	Russell, JaMarcus	QB	1
10	Houston Texans	Okoye, Amobi	DT	Johnson, Calvin	WR	2

As noted, Patrick Willis was the highest-rated player for the Oakland Raiders in the 2007 Draft. The second pick of the 2007 NFL Draft was owned by the Detroit Lions. The model suggested that Brady Quinn should have been taken by the Lions because of his high theoretical contribution value. As it turns out, the Lions selected Calvin Johnson, who would later become one of the most prolific receivers in the draft and will likely become a future NFL Hall of Fame member. Quinn, on the other hand, only started 20 games during his four-year career in the NFL. Some might say that taking Quinn was overvalued based on the HEART methodology, while others have been on record saying that Quinn was the most NFL-ready quarterback in the draft based on his collegiate experience (Lewin, 2007). Regardless, if a team like the Lions had Quinn projected as a late first-round or second-round pick, the discrepancy in the results might have started conversations within the organization if their evaluation had been accurate.

The third selection in the 2007 NFL Draft was owned by the Cleveland Browns. According to the theoretical results, Adrian Peterson should have been selected with this pick. Peterson has had a fruitful career, winning the Offensive Rookie of the year award in 2007, Player of the Year Award in 2008, and Offensive Player of the Year Award in 2012. In addition, Peterson has been selected for the NFL Pro Bowl seven times and is likely to become a future member of the NFL Hall of Fame. Even with Peterson's successful career, the results do not imply that the Cleveland Browns made a mistake in drafting Joe Thomas. Thomas has been selected to 10 Pro Bowls and is likely to be a first-ballot NFL Hall of Fame member.

Based on the mock draft provided in *Table 6*, other interesting outcomes emerged. For example, Darrelle Revis was selected by HEART nine spots ahead of when he was actually taken in the Draft. He, too, will likely be considered for the NFL Hall of Fame, since he has been selected to seven Pro Bowls. Another interesting outcome relates to the eighth overall player selected by HEART, which was Marshal Yanda. This particular player was actually taken with the 86th overall pick (i.e. 3rd round) in the 2007 NFL Draft. Perhaps NFL scouts and general managers overlooked or undervalued Yanda since, as of 2018, Yanda has made seven Pro-Bowl appearances. Clearly, one application of HEART is to identify "diamonds in the rough." When these situations occur, expert player evaluators can dig deeper into the available information. They can also build strategies for later rounds since teams might want to select players that are rated highly by HEART but are still available to select.

Draft Value Chart

During the NFL Draft, teams propose trade offers that often include teams trading draft positions. Teams may want to trade up or down in terms of their draft position. In this case, in order to move up and obtain a player, teams are often willing to give up multiple picks. Before NFL managers make or accept trade offers, they often consult a draft-pick value chart (ESPN, 2004), which assigns each draft selection with a numeric value that can be used to determine if the trade is fair. For example, the number one overall pick in the draft is worth 3,000 points. In order for a team to give up this position, they must acquire picks that are reasonably equal to the value of the number one pick. Based on the HEART methodology, contribution values can also be used to derive values for draft picks. *Figure 2* shows the traditional system used in comparison to the one derived from the HEART methodology. Teams could use HEART to create a pre-draft or live draft-value chart, which would represent the current talent in a given draft, as opposed to one that has been aggregated over time.

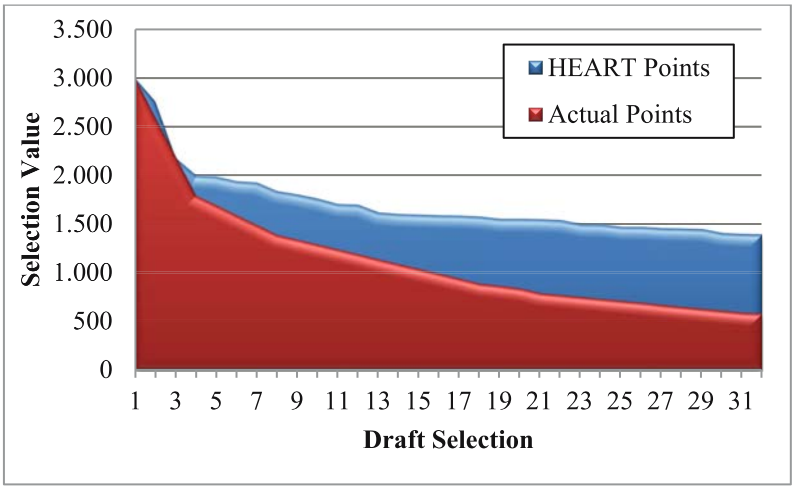

Figure 2. First Round Draft Selection Value Chart

Figure 2 shows that the HEART values are nearly identical to the historical chart for the first three selections. However, the point values for the remaining picks in the first round differ greatly. Based on the derived values, the results suggest that teams undervalue first-round draft picks, which is consistent with other research findings (Massey & Thaler, 2005; Mirabile, 2007).

HEART Validation

A survey that included the results of a 2007 case study was sent to a targeted audience in order to validate that the HEART methodology produced useful information to hiring managers in the NFL. The overall objective of the survey was to gain an additional perspective as to the benefits and limitations of the methodology and the results of HEART. In addition, it was also given in order to determine if a statistical claim could be made that the methodology produced "useful" information to player evaluators and hiring managers. The following sections describe the design of the survey, summarize the results of the survey, and discuss the open-ended feedback that was obtained via the survey. It should also be noted that the complete responses obtained from the survey are shown in the appendix.

Participant Information

The first set of questions that appeared in the survey related to the participant. For this research, it was desired to use this information in order to classify a participant as a novice or an expert player evaluator in the NFL. Ultimately, the survey was sent to 400 potential participants. The group of invited participants included people who worked for an NFL team (i.e. general managers, scouts, directors of player development, and coaches) or who worked for a company that focused on supplying information to paying customers. In order to determine if the participant was an expert, a question was used which asked the survey participant to indicate how much of their financial livelihood (i.e. none, very little, some, a lot, a great deal) depended upon their ability to evaluate NFL players. As long as a participant did not indicate "none," they were considered an expert within this domain. If a participant was not considered an expert, their results were not used. From the 400 potential participants, 40 met the criteria of being an expert in the field. Thus, the survey results were based on these participants' responses.

Player Evaluation Questions

The survey was designed to explore the eight decision-making categories that NFL managers must make during each NFL off-season. The eight questions that survey participants were asked to respond to are shown in *Table 7*. The participants were given the flexibility of evaluating the expected and theoretical contribution results for a specific team in the NFL (i.e. team-specific results), or the average expected and theoretical contribution values across all teams in the NFL (i.e. league-wide results) for the 2007 NFL Draft and free agency signing periods. In addition, participants were also given the chance to provide open-ended feedback about the results.

Table 7. How useful would this additional information have been during the 2007 NFL off-season?

Decision Categories	Not Useful (1)	Somewhat Useful (2)	Useful (3)	Very Useful (4)	Extremely Useful (5)	Average Rating
which positions should be targeted	1	11	6	15	12	3.58
which players should be targeted	0	9	10	18	8	3.56
player trades	1	11	22	11	0	2.96
Draft selection trades	1	10	17	14	3	3.18
assessing the risk of injuries	8	15	15	6	1	2.49
financial contracts	5	21	12	7	0	2.47
overall decisions for NFL Draft	2	6	9	20	8	3.58
overall decisions for NFL FA	0	7	15	16	7	3.51

Based on the results provided by the HEART methodology, survey participants were to rate on a 5-point Likert scale how "useful" the information would have been prior to the 2007 NFL Draft or free agent signing periods. This linear scale ranged from not useful (1), somewhat useful (2), useful (3), very useful (4), to extremely useful (5). In total, 20 of the 32 teams in the league were evaluated by at least one respondent. In total, 45 evaluations were made, which means that five participants chose to go through the survey more than once. The aggregated results from the team-specific and league-wide evaluations are shown in *Table 7*.

In order to summarize the results found in *Table 7* statistically, a one-sample t-test and one-sample sign test were performed. Both results are presented based upon differing opinions on how Likert survey data should be summarized (Sisson & Stocker, 1981; Goldstein & Hersen, 1984; Clason & Dormody, 1994; Lubke & Muthen, 2004; Jamieson, 2004). In order to determine if a certain hypothesis was accepted or rejected, an alpha value of 5% was used and compared to a computed p-value. *Table 8* shows a summary of the results for both tests that were performed and the survey responses. The table provides a 95% confidence interval (CI) for the test statistics for both the mean and median values.

Table 8. Validation Summary

Likert Item	1-Sample t-test		1-Sample Sign Test	
Decision-Making Categories	**95% CI**	**Usefulness CI**	**95% CI**	**Usefulness CI**
1. which position should be targeted	(3.2, 3.9)	(Useful)	(3.0, 4.0)	(Useful, Very Useful)
2. which players should be targeted	(3.3, 3.9)	(Useful)	(3.0, 4.0)	(Useful, Very Useful)
3. player trades	(2.7, 3.2)	(Useful)	(3.0, 3.0)	(Useful)
4. draft selection trades	(2.9, 3.5)	(Useful)	(3.0, 4.0)	(Useful, Very Useful)
5. assessing the risk of injuries	(2.2, 2.8)	(Somewhat Useful)	(2.0, 3.0)	(Somewhat Useful, Useful)
6. financial contracts	(2.2, 2.7)	(Somewhat Useful)	(2.0, 3.0)	(Somewhat Useful, Useful)
7. overall decisions for NFL Draft	(3.3, 3.9)	(Useful)	(3.0, 4.0)	(Useful, Very Useful)
8. overall decisions for NFL FA	(3.2, 3.8)	(Useful)	(3.0, 4.0)	(Useful, Very Useful)

The results shown in *Table 8* indicate that HEART was at least "useful" for six decision-making categories, regardless of the statistical tests performed. Based on the t-test, which tests a sample's mean, all but two decision-making categories were deemed "useful." However, the results look more promising when based on the nonparametric sign tests that were performed on the survey responses. For example, the one-sample sign test, which tests a sample's median, indicated that five of the eight decision-making category's highest level of "usefulness" could be classified as "very useful." These decision-making categories included "which playing positions should be targeted," "which players should be targeted," "draft selection trades," "overall decisions for the NFL Draft," and "overall decisions for NFL free agency."

Benefits and Limitations

Developing and evaluating a decision support model for NFL player-selection is an inherently challenging task. Factors that increase the complexity of developing and evaluating the usefulness of a data-driven decision support systems include a team's existing roster, coaching philosophies, salary cap, the lack of detailed play-by-play data, the limited number of games played per season, or factors such as a player's history of injury or lack of playing time. Although the survey results were favorable, it certainly does not mean that the proposed methodology is free of limitations. However, as it has been shown, methodologies like HEART also have their benefits from a decision-making perspective. In the following section, the benefits and limitations are discussed.

One limitation of HEART is based on its inherent design. For example, HEART is a data-driven decision support system. The system does not leverage expert opinion or preferences into the heuristics that were used to generate player-selection recommendations. This type of limitation could have been overcome if a more sophisticated design was created and experts were available to consult. However, given that data-driven support systems are inherently dependent upon the quality of data used, it could also be viewed by some as a benefit. This is because data-driven decision support systems can provide additional evidence that a decision-maker could consult given that they can often uncover insights that are not obvious to a decision-maker. The additional insight that a data-driven model could provide could augment a manager's perspective in terms of which players are ultimately selected.

From a data perspective, advanced on-the-field statistics were used to develop HEART. The particular attributes used within the HEART methodology are not widely available for the general research community to explore or replicate the research approach presented in this article. Detailed play-by-play information is slowly becoming more widely available, but currently, this information can be difficult or costly for researchers to obtain. Even if more advanced information is becoming available to the research community, there is a limitation associated with the information that is available for certain playing positions. In other words, that amount of on-the-field statistics for each playing position is disproportionate. From a data-driven decision support system standpoint, this can lead to the methodology having a bias when determining the overall impact of certain playing positions. The disproportionate amount of information available for some playing positions most likely would result in HEART overvaluing or undervaluing certain playing positions given the abundance or scarcity of the information that is available for each playing position.

The intent of HEART's expected and theoretical contribution values was to provide decision-makers a way to assess the risk associated with selecting a particular player. While this was perceived as a benefit of the methodology, there are, of course, limitations with the approach that was taken. For example, the forecasted values for the expected and theoretical values only use attributes that can be measured or that can be derived from a player's playing record. Based on the HEART methodology, risky decisions are associated with a significant difference between a player's expected and theoretical contribution value. However, these values are derived from a very limited window of a player's playing career, which of course, can be disrupted by injury, suspensions, or even because certain players do not have an opportunity to play given the talent of other players of the same playing position on their team. From a player selection standpoint, NFL decision-makers constantly assess the risk associated with selecting players. Managing risk of this nature is complicated by roster limits, contracts, salary caps, and even the supply and demand of players that are available within the NFL Draft and free agency. HEART does not incorporate all of the information that NFL decision-makers use in order to immediate the risk associated with selecting players. For example, decision-makers consider a player's character, work ethic, leadership characteristics, ability to learn new offensive and defensive schemes, marketability, upside, or other factors that difficult to quantify.

One unique contribution of HEART is that it provides a way to compare players of any playing position, due to the nature in which the expected and theoretical contribution values were determined, which represent a forecast of a team's winning percentage. This overcomes some of the limitations with respect to the available literature where methods tend to focus on developing metrics that can only be used to compare players that share the same playing position. However, HEART does not incorporate a sophisticated way of addressing different offensive and defenses playing philosophies. For example, from a defensive perspective, two common defensive strategies include the 4-3 and 4-3 defense. This difference, as well as other offensive and defensive strategies, are not accounted for within HEART. However, the methodology does provide a framework in which players from any playing position can be evaluated from a team-contribution standpoint. Although the quality of forecast should improve as the quality of information also improves, being able to forecast the contribution values for any player regardless of playing position allows decision-makers to develop hiring strategies for evaluating and selecting players in the offseason. This is vital given the timing of when the NFL Draft and free agency hiring periods occur within the offseason. Hiring managers must consider which players might add the most value to their teams, which is not an easy decision to make considering each team's draft order, or other considerations such as trades that can occur between draft slotting or perhaps other trades related to players on a team's active roster. Each and every decision that takes place have both short term and long term considerations and any hiring mistake will have its repercussions in terms of a team's on-the-field performance, as well as other financial considerations.

HEART Conclusions

In terms of the "usefulness," experts rated "assessing the risk of injuries" and "financial contracts" as the two lowest-rated decision-making categories. In terms of these categories, the hypothesis tests revealed that the results were "somewhat useful" based on the mean tests, and from "somewhat useful" to "useful" based on the median tests. In terms of financial contracts, this result was not necessarily surprising, since free agency contracts are complicated by the "supply and demand" of the players that are available during the offseason. From a rookie standpoint, salaries are based on where a player was selected in the NFL Draft. In terms of "assessing the risk of injuries," the contributions' values from the HEART methodology will not reflect injuries if players do not miss a substantial number of games due to injuries. However, on several occasions, survey respondents left favorable feedback in terms of HEART's ability to limit or identify potential areas of risk when making football-hiring decisions. Five of the eight remaining decision-making categories were classified as "useful" or "very useful." These decision-making categories included "which playing positions should be targeted," "which players should be targeted," "draft selection trades," "overall decisions for the NFL Draft," and "overall decisions for NFL free agency."

In summary, several contributions were made to the field based on the research conducted. For example, football's Pythagorean Theorem winning percentage model was developed. The development of the expected and theoretical contribution values provides a way in which players of the same or different playing positions could be compared in order to determine who will contribute more to a team's future winning percentage. The development of the performance-aging curves provides a way in which a player's physical characteristics at any age can be used as an input attribute for a predictive model. Finally, a methodology has been developed that will help NFL hiring managers identify potential areas of risk which support decisions related to player and draft pick selection trades, as well as hiring decisions in the NFL Draft and free agency signing periods. In terms of future work, the authors hope to explore data mining methods that could provide additional insights to hiring managers. For example, it would be useful for player evaluators and hiring managers to know which inputs are more important to a team's winning percentage. To better understand how inputs contribute towards a team's performance, sophisticated sensitivity analysis methods could be employed (Oztekin, Delen, & Turkyilmaz, 2013; Sevim, Oztekin, Bali, Gumus, & Guresen, 2014; Oztekin & Riaz Khan, 2014; Oztekin, Kizilaslan, Freund, & Iseri, 2016).

References

Abrams, W., Barnes, J. C., & Clement, A. (2008). Relationship of Selected pre-NBA Career Variables to NBA Players' Career Longevity. *The Sport Journal, 11*(2).

Al-Shboul, R., Syed, T., Memon, J., & Khan, F. (2017). Automated Player Selection for a Sports Team using Competitive Neural Networks. *International Journal of Advanced Computer Science and Applications, 8*(8), 1-4.

Barron, D., Ball, G., Robins, M., & Sunderland, C. (2018). Artificial Neural Networks and Player Recruitment in Professional Soccer. *PLoS ONE, 13*(10). doi:https://doi.org/10.1371/journal.pone.0205818

Beyer, K., Fukuda, D., Redd, M., Stout, J., & Hoffman, J. (2016). Player Selection Bias in National Football League Draftees. *The Journal of Strength & Conditioning Research, 30*(11), 2965-2971.

Birnbaum, P. (2019). *A Guide To Sabermetric Research*. Retrieved February 11, 2019, from https://sabr.org/sabermetrics

CBS Sports. (2016). *19 of the biggest NFL Draft busts ever*. Retrieved from http://www.cbssports.com/nfl/photos/biggest-draft-busts-ever

Chien, C., & Chen, L. (2007). Using Rough Set Theory to Recruit and Retain High-Potential Talents for Semiconductor Manufacturing. *IEEE Transactions on Semiconductor Manufacturing, 20*(4), 528-541.

Chien, C., & Chen, L. (2008). Data Mining to Improve Personnel Selection and Enhance Human Capital: A Case Study in the High-technology Industry. *Expert Systems with Applications, 34*, 280-290.

Clark, T., & Jones, M. (2007). Achieving Competitive Advantage in a High Turnover, Dynamic Market. *International Conference of the System Dynamics Society*, (pp. 1-15). Boston, Massachusetts, USA.

Clason, D., & Dormody, T. (1994). Analyzing Data Measured by Individual Likert-Type Items. *Journal of Agricultural Education, 35*(4), 31-35.

Clemente, F., & Martins, F. (2017). Network Structure of UEFA Champions League Teams: Association with Classical Notational Variables and Variance Between Different Levels of Success. *International Journal of Computer Science in Sport, 16*(1), 39-50.

Coates, D. (2002). The Economic Impact of Postseason Play in Professional Sports. *Journal of Sports Economics, 3*(3), 291-299.

Demir, E. (2014). A Decision Support Tool for Predicting Patients at Risk of Readmission: A Comparison of Classification Trees, Logistic Regression, Generalized Additive Models,and Multivariate Adaptive Regression Splines. *Decision Sciences, 45*(5), 849-880.

Deshpande, S., & Jenson, S. (2016). Estimating an NBA player's Impact on His Team's Chances of Winning. *Journal of Quantitative Analysis in Sports, 12*, 51-72.

Ebben, W., & Blackard, D. (2001). Strength and Conditioning Practices of National Football League Strength and Conditioning Coaches. *Journal of Strength and Conditioning Research, 15*(1), 48–58.

ESPN. (2004, Apr. 25). *NFL Draft-pick Value Chart*. Retrieved Dec 28, 2009, from ESPN Insider: http://sports.espn.go.com/espn/print?id=2410670&type=story

Football's Future. (2007). *2007 NFL Free Agents*. Retrieved Mar. 13, 2009, from http://www.footballsfuture.com/2007/nfl/freeagents.html

Forbes. (2018). *NFL Team Valuations*. Retrieved from https://www.forbes.com/nfl-valuations/list/#tab:overall

Fry, M., Lundberg, A., & Ohlmann, J. (2007). A Player Selection Heuristic for a Sports League Draft. *Journal of Quantitative Analysis in Sports, 3*(2), 1-35.

Gavião, L., Sant'Anna, A., Lima, G., & Garcia, P. (2019). Evaluation of Soccer Players Under the Moneyball Concept. *Journal of Sports Sciences*, 1-21.

Goldstein, G., & Hersen, M. (1984). *Handbook of Psychological Assessment.* New York: Pergamon Press.

Hartman, M. (2011). Competitive Performance Compared to Combine Performance as a Valid Predictor of NFL Draft Status. *Journal of Strength & Conditioning Research, 25*.

Hendricks, W., DeBrock, L., & Koenker, R. (2003). Uncertainty, Hiring, and Subsequent Performance: The NFL Draft. *Journal of Labor Economics, 21*(4), 857-886.

Hilbert, D. (1902). Mathematical Problems. *Bulletin of the American Mathematical Society, 8*, 437-479.

Hsu, P., Galsanbadam, S., Yang, Y., & Yang, C. (2018). Evaluating Machine Learning Varieties for NBA Players' Winning Contribution. *International Conference on System Science and Engineering (ICSSE)*, (pp. 1-6). New Taipei.

Hvattum, L. M. (2019). A Comprehensive Review of Plus-Minus Ratings for Evaluating Individual Players in Team Sports. *International Journal of Computer Science in Sport, 18*(1), 1-23.

James, B. (1979). *The Bill James Abstract.* self-published.

James, B. (1985). *The Bill James Historical Baseball Abstract.* Villard.

Jamieson, S. (2004). Likert Scales: How to (Ab)use Them. *Medical Education, 38*, 1212-1218.

Larsen, A., & Fenn, A. (2006). The Impact of Free Agency and the Salary Cap on Competitive Balance in the National Football League. *Journal of Sports Economics, 7*(4), 374-390.

Lewin, D. (2007). *2007 Quarterbacks Draft Preview*. Retrieved from Football Outsiders: http://www.footballoutsiders.com/nfl-draft/2007/2007-quarterbacks-draft-preview

Lubke, G., & Muthen, B. (2004). Applying Multigroup Confirmatory Factor Models for Continuous Outcomes to Likert Scale Data Complicates Meaningful Group Comparisons. *Structural Equation Modeling, 514-534*, 11.

Macey, N. (2005, Jan. 19). *How Much Should Rookie Quarterbacks Play?* Retrieved Nov. 20, 2009, from Football Outsiders: http://www.footballoutsiders.com/stat-analysis/2005/how-much-should-rookie-quarterbacks-play

Massey, C., & Thaler, R. (2005). *Overconfidence vs. Market Efficiency in the National Football League.* Working Paper W11270, National Bureau of Economic Research (NBER).

Mirabile, M. (2007). The NFL Rookie Cap: An Empirical Analysis of One of the NFL's Most Closely Guarded Secrets. *The Sport Journal, 10*(3), 1-8.

Moy, D. (2006). *Regression Planes to Improve the Pythagorean Percentage: A regression model using common baseball statistics to project offensive and defensive efficiency.* MS Thesis, University of California Berkeley, Statistics, Berkeley, CA.

Mulholland, J., & Jensen, S. T. (2014). Predicting the Draft and Career Success of Tight Ends in the National Football League. *Journal of Quantitative Analysis in Sports, 10*, 381-396.

Nagarajan, R., & Li, L. (2017). Optimizing NBA Player Selection Strategies Based on Salary and Statistics Analysis. *IEEE 15th Intl Conf on Dependable, Autonomic and Secure Computing, 15th Intl Conf on Pervasive Intelligence and Computing, 3rd Intl Conf on Big Data Intelligence and Computing and Cyber Science and Technology Congress(DASC/PiCom/DataCom/CyberSciTech)*, (pp. 1076-1083). Orlando, FL.

Newman, D., & Sin, H. (2009). How do Missing Data Bias Estimates of Within-group Agreements? Sensitivity of SDwg, CVwg, rwg(j), rWG(j)*, and ICC to Systematic Nonresponse. *Organizational Research Methods, 12*(1), 113-147.

Ng, F., Rouse, P., & Harrison, J. (2016). Classifying Revenue Management: A Taxonomy to Assess Business Practice. *Decision Sciences*, 1-34.

Oztekin, A., & Riaz Khan, M. (2014). A Business-Analytic Approach to Identify Critical Factors in Quantitative Disciplines. *Journal of Computer Information Systems, 54*, 60-70.

Oztekin, A., Delen, D., & Turkyilmaz, A. Z. (2013). A Machine Learning-based Usability Evaluation Method for eLearning Systems. *Decision Support Systems, 56*, 63-73.

Oztekin, A., Kizilaslan, R., Freund, S., & Iseri, A. (2016). A Data Analytic Approach to Forecasting Daily Stock Returns in an Emerging Market an Emerging Market. *European Journal of Operational Research,, 253*(3), 697-710.

Pantuso, G. (2017). The Football Team Composition Problem: A Stocastic Programming Approach. *Journal of Quantitative Analysis in Sports, 13*, 113-129.

Perl, J., & Memmert, D. (2017). A Pilot Study on Offensive Success in Soccer Based on Space and Ball Control – Key Performance Indicators and Key to Understand Game Dynamics. *International Journal of Computer Science in Sport, 16*(1), 65-75.

Peterson, K., & Evans, L. (2019). Decision Support System for Mitigating Athletic Injuries. *International Journal of Computer Science in Sport, 18*(1), 45-63.

Pitts, J. D., & Evans, B. (2018). Evidence on the Importance of Cognitive Ability Tests for NFL Quarterbacks: What are the Relationships Among Wonderlic Scores, Draft Position and NFL Performance Outcomes? *Applied Economics, 50*, 2957-2966.

Pitts, J., & Evans, B. (2018). Drafting for Success: How Good Are NFL Teams at Identifying Future Productivity at Offensive-Skill Positions in the Draft? *The American Economist, 64*(1), 102-122.

Pro-Football Reference. (2009). Retrieved from Coaches, Records, and Coaching Totals: http://www.pro-football-reference.com/coaches/

Robbins, D. (2011). Positional Physical Characteristics of Players Drafted Into the National Football League. *J Strength Cond Res, 25*(10), 2661-2667.

Rothstein, M., & Goffin, R. (2006). The Use of Personality Measures in Personnel Selection: What does current research support? *Human Resource Management Review, 15*, 155-180.

Saikia, H., Bhattacharjee, D., & Radhkrishnan, U. (2016). A New Model for Player Selection in Cricket. *International Journal of Performance Analysis in Sport, 16*(1), 373-388.

Schatz, A. (2004). *Method to Our Madness*. Retrieved Nov. 20, 2009, from Football Outsiders: http://www.footballoutsiders.com/info/methods

Schatz, A. (2005). Football's Hilbert Problems. *Journal of Quantitative Analysis in Sports, 1* (1), 1-8.

Scheffer, J. (2002). Dealing with Missing Data. *Research Letters in the Information and Mathematical Sciences, 3*, 153-160.

Schuckers, M. (2011). An Alternative to the NFL Draft Pick Value Chart Based upon Player Performance. *Journal of Quantitative Analysis in Sports, 7*(2), 1-14.

Sevim, C., Oztekin, A., Bali, O., Gumus, S., & Guresen, E. (2014). Developing an Early Warning System to Predict Currency Crises. *European Journal of Operational Research, 237*(3), 1095-1104.

Shadabi, F., Sharma, D., & Cox, R. (2006). Learning from Ensembles: Using Artificial Neural Network Ensemble for Medical Outcomes Prediction. *Innovations in Information Technology*, 1-5.

Sisson, D., & Stocker, H. (1981). Analyzing and Interpreting Likert-type survey data. *The Delta Pi Epsilon Journal, 31*(2), 81-85.

STATS Inc. (2007). Retrieved from http://www.stats.com

Stern, H. (1998). American Football. In J. Bennett, *Statistics in Sport* (pp. 3-23). London: Arnold Applications of Statistics.

Strohmeier, S., & Piazza, F. (2013). Domain Driven Data Mining in Human Resource Management: A Review of Current Research. *Expert Systems with Applications, 40*, 2410-2420.

Thieme, J., Song, M., & Calantone, R. (2000). Artificial Neural Network Decision Support Systems for New Product Development Project Selection. *Journal of Marketing Research, 37*(4), 499-507.

Uzochukwu, O., & Enyindah, P. (2015). A Machine Learning Application for Football Players' Selection. *International Journal of Engineering Research & Technology, 4*(10), 459-465.

Whiting, S., & Maynes, T. (2016). Selecting Team Players: Considering the Impact of Contextual Performance and Workplace Deviance on Selection Decisions in the National Football. *Journal of Applied Psychology, 101*(4), 484-497.

Wolfson, J., Addona, V., & Schmicker, R. (2011). The Quarterback Prediction Problem: Forecasting the Performance of College Quarterbacks Selected in the NFL Draft. *Journal of Quantitative Analysis in Sports, 7*(3), 1-22.

Yaldo, L., & Shamir, L. (2017). Computational Estimation of Football Player Wages. *International Journal of Computer Science in Sport, 16*(1), 18-38.

Young, W., Weckman, G., & Holland, W. (2009). A Survey of Methodologies for the Treatment of Missing Values within Datasets: Limitations and Benefits. *Theoretical Issues in Ergonomics Science*.

Appendix

Performance-Aging Curve Results: 10-Yard Dash

T*able 9. Performance-Aging Curve* Results for the 10-Yard Dash for DE & DT

Parameter	Estimate	Standard Error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	0.993317	0.004212	235.8344	0.000000	0.984047	1.002587
f_2	0.003265	0.002842	1.1488	0.274994	-0.002990	0.009520
f_3	0.000170	0.000230	0.7408	0.474307	-0.000335	0.000676

Table *10*. Performance-Aging Curve Results for the 10-Yard Dash for K & P

Parameter	Estimate	Standard Error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	1.002812	0.002770	362.0765	0.000000	0.997052	1.008572
f_2	-0.000361	0.001094	-0.3301	0.744626	-0.002636	0.001914
f_3	0.000112	0.000054	2.0855	0.049407	0.000000	0.000224

Table *11*. Performance-Aging Curve Results for the 10-Yard Dash for OLB & MLB

Parameter	Estimate	Standard Error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	0.997016	0.001769	563.4973	0.000000	0.993194	1.000838
f_2	0.004954	0.001078	4.5958	0.000502	0.002625	0.007283
f_3	-0.000016	0.000112	-0.1438	0.887836	-0.000257	0.000225

Table *12*. Performance-Aging Curve Results for the 10-Yard Dash for OT, OG, & C

Parameter	Estimate	Standard Error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	1.002880	0.001049	955.7688	0.000000	1.000675	1.005084
f_2	0.002682	0.000488	5.4958	0.000032	0.001657	0.003707
f_3	-0.000072	0.000028	-2.5613	0.019629	-0.000132	-0.000013

Table *13*. Performance-Aging Curve Results for the 10-Yard Dash for QB

Parameter	Estimate	Standard Error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	0.991190	0.002486	398.6891	0.000000	0.985890	0.996489
f_2	0.003019	0.001424	2.1205	0.051043	-0.000016	0.006054
f_3	0.000267	0.000122	2.1950	0.044317	0.000008	0.000526

Table *14*. Performance-Aging Curve Results for the 10-Yard Dash for RB, FB, & TE

Parameter	Estimate	Standard Error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	1.038613	0.008213	126.4585	0.000000	1.020536	1.056689
f_2	0.021168	0.005777	3.6643	0.003726	0.008453	0.033882
f_3	-0.001015	0.000658	-1.5421	0.151317	-0.002463	0.000434

Table *15*. Performance-Aging Curve Results for the 10-Yard Dash for SS & FS

Parameter	Estimate	Standard	t-value	p-level	Lo. Conf.	Up. Conf.

		Error			Limit	Limit
f_1	1.012404	0.000627	1613.762	0.000000	1.011067	1.013741
f_2	0.001505	0.000338	4.456	0.000462	0.000785	0.002225
f_3	-0.000030	0.000026	-1.156	0.265871	-0.000085	0.000025

Table *16*. Performance-Aging Curve Results for the 10-Yard Dash for WR & CB

Parameter	**Estimate**	**Standard Error**	**t-value**	**p-level**	**Lo. Conf. Limit**	**Up. Conf. Limit**
f_1	1.004906	0.001601	627.8675	0.000000	1.001418	1.008393
f_2	-0.001065	0.001034	-1.0300	0.323338	-0.003317	0.001188
f_3	0.000338	0.000094	3.5855	0.003744	0.000133	0.000544

Performance-Aging Curve Results: 20-Yard Dash

Table *17*. Performance-Aging Curve Results for the 20-Yard Dash for DE & DT

Parameter	**Estimate**	**Standard error**	**t-value**	**p-level**	**Lo. Conf. Limit**	**Up. Conf. Limit**
f_1	1.002230	0.003639	275.4420	0.000000	0.994553	1.009907
f_2	-0.003281	0.003173	-1.0343	0.315499	-0.009975	0.003412
f_3	0.001032	0.000216	4.7676	0.000179	0.000575	0.001489

Table *18*. Performance-Aging Curve Results for the 20-Yard Dash for K & P

Parameter	***Estimate***	***Standard error***	***t-value***	***p-level***	***Lo. Conf. Limit***	***Up. Conf. Limit***
f_1	*1.021358*	*0.004002*	*255.2219*	*0.000000*	*1.013036*	*1.029680*
f_2	*0.000727*	*0.002571*	*0.2826*	*0.780238*	*-0.004620*	*0.006073*
f_3	*0.000088*	*0.000124*	*0.7093*	*0.485917*	*-0.000170*	*0.000346*

Table *19*. Performance-Aging Curve Results for the 20-Yard Dash for OLB & MLB

Parameter	***Estimate***	***Standard error***	***t-value***	***p-level***	***Lo. Conf. Limit***	***Up. Conf. Limit***
f_1	*1.004599*	*0.000920*	*1092.473*	*0.000000*	*1.002650*	*1.006548*
f_2	*0.003696*	*0.000781*	*4.734*	*0.000225*	*0.002041*	*0.005351*
f_3	*-0.000022*	*0.000056*	*-0.392*	*0.700331*	*-0.000141*	*0.000097*

Table *20*. Performance-Aging Curve Results for the 20-Yard Dash for OT, OG, & C

Parameter	***Estimate***	***Standard error***	***t-value***	***p-level***	***Lo. Conf. Limit***	***Up. Conf. Limit***
f_1	*0.991635*	*0.001100*	*901.4193*	*0.000000*	*0.989303*	*0.993967*
f_2	*-0.000621*	*0.000847*	*-0.7330*	*0.474148*	*-0.002418*	*0.001175*
f_3	*0.000158*	*0.000047*	*3.3711*	*0.003891*	*0.000059*	*0.000257*

Table *21*. Performance-Aging Curve Results for the 20-Yard Dash for QB

Parameter	***Estimate***	***Standard error***	***t-value***	***p-level***	***Lo. Conf. Limit***	***Up. Conf. Limit***
f_1	*0.995524*	*0.001487*	*669.3533*	*0.000000*	*0.992411*	*0.998637*
f_2	*0.007936*	*0.001076*	*7.3754*	*0.000001*	*0.005684*	*0.010188*
f_3	*-0.000157*	*0.000062*	*-2.5244*	*0.020649*	*-0.000288*	*-0.000027*

Table *22*. Performance-Aging Curve Results for the 20-Yard Dash for RB, FB, & TE

Parameter	*Estimate*	*Standard error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*0.995880*	*0.002011*	*495.1871*	*0.000000*	*0.991593*	*1.000167*
f_2	*0.007269*	*0.001875*	*3.8760*	*0.001493*	*0.003272*	*0.011266*
f_3	*0.000059*	*0.000151*	*0.3930*	*0.699879*	*-0.000262*	*0.000380*

Table *23*. Performance-Aging Curve Results for the 20-Yard Dash for SS & FS

Parameter	Estimate	Standard error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	1.007127	0.000858	1173.838	0.000000	1.005298	1.008956
f_2	0.002074	0.000773	2.682	0.017062	0.000426	0.003723
f_3	0.000068	0.000059	1.138	0.272906	-0.000059	0.000194

Table *24*. Performance-Aging Curve Results for the 20-Yard Dash for WR & CB

Parameter	Estimate	Standard error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	1.009300	0.001956	516.0221	0.000000	1.005191	1.013410
f_2	-0.000575	0.001429	-0.4027	0.691929	-0.003577	0.002426
f_3	0.000103	0.000088	1.1731	0.256037	-0.000081	0.000287

Performance-Aging Curve Results: 40-Yard Dash

Table 25. Performance-Aging Curve Results for the 40-Yard Dash for DE & DT

Parameter	Estimate	Standard error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	1.000439	0.001517	659.5735	0.000000	0.997252	1.003625
f_2	-0.019025	0.014580	-1.3049	0.208364	-0.049655	0.011606
f_3	0.004090	0.001117	3.6621	0.001783	0.001744	0.006437

Table 26. Performance-Aging Curve Results for the 40-Yard Dash for K & P

Parameter	Estimate	Standard error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	1.000601	0.003164	316.2668	0.000000	0.994021	1.007180
f_2	-0.010662	0.003614	-2.9505	0.007637	-0.018177	-0.003147
f_3	0.001152	0.000177	6.4901	0.000002	0.000783	0.001521

Table 27. Performance-Aging Curve Results for the 40-Yard Dash for OLB & MLB

Parameter	*Estimate*	*Standard error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*1.002767*	*0.000901*	*1112.473*	*0.000000*	*1.000856*	*1.004678*
f_2	*0.006774*	*0.001307*	*5.182*	*0.000091*	*0.004003*	*0.009546*
f_3	*-0.000135*	*0.000095*	*-1.422*	*0.174153*	*-0.000337*	*0.000066*

Table 28. Performance-Aging Curve Results for the 40-Yard Dash for OT, OG, & C

Parameter	Estimate	Standard error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	0.990656	0.001653	599.2155	0.000000	0.987168	0.994144
f_2	-0.017127	0.002243	-7.6364	0.000001	-0.021859	-0.012395

f_3	0.001134	0.000129	8.8195	0.000000	0.000863	0.001405

Table 29. Performance-Aging Curve Results for the 40-Yard Dash for QB

Parameter	Estimate	Standard error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	0.998664	0.001667	599.0908	0.000000	0.995161	1.002166
f_2	0.004482	0.002327	1.9264	0.069996	-0.000406	0.009370
f_3	0.000381	0.000152	2.4980	0.022400	0.000061	0.000701

Table 30. Performance-Aging Curve Results for the 40-Yard Dash for RB, FB, & TE

Parameter	Estimate	Standard error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	1.01	0.01	184.64	0.00	1.00	1.02
f_2	-0.05	0.01	-6.22	0.00	-0.07	-0.04
f_3	0.01	0.00	9.55	0.00	0.01	0.01

Table 31. Performance-Aging Curve Results for the 40-Yard Dash for SS & FS

Parameter	Estimate	Standard error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	1.003931	0.000833	1204.863	0.000000	1.002155	1.005707
f_2	0.001953	0.001281	1.524	0.148229	-0.000778	0.004683
f_3	0.000073	0.000099	0.732	0.475483	-0.000139	0.000284

Table 32. Performance-Aging Curve Results for the 40-Yard Dash for WR & CB

Parameter	Estimate	Standard error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	1.004095	0.000767	1309.334	0.000000	1.002484	1.005706
f_2	-0.001307	0.000952	-1.373	0.186717	-0.003307	0.000693
f_3	0.000164	0.000058	2.803	0.011767	0.000041	0.000286

Performance-Aging Curve Results: Bench Press

Table 33. Performance-Aging Curve Results for the Bench Press for DE & DT

Parameters	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*0.999182*	*0.006152*	*162.4256*	*0.000000*	*0.986203*	*1.012161*
f_2	*0.058950*	*0.048546*	*1.2143*	*0.241230*	*-0.043474*	*0.161374*
f_3	*-0.006846*	*0.003295*	*-2.0777*	*0.053208*	*-0.013798*	*0.000106*

Table 34. Performance-Aging Curve Results for the Bench Press for K & P

Parameters	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*0.561425*	*0.007114*	*78.91765*	*0.000000*	*0.546586*	*0.576265*
f_2	*-0.055925*	*0.039127*	*-1.42930*	*0.168354*	*-0.137543*	*0.025694*
f_3	*-0.002869*	*0.002065*	*-1.38921*	*0.180043*	*-0.007176*	*0.001439*

Table 35. Performance-Aging Curve Results for the Bench Press for OLB & MLB

Parameters	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*

f_1	*0.952340*	*0.005326*	*178.8024*	*0.000000*	*0.941049*	*0.963631*
f_2	*0.027328*	*0.038588*	*0.7082*	*0.489017*	*-0.054476*	*0.109131*
f_3	*-0.004512*	*0.002808*	*-1.6067*	*0.127669*	*-0.010465*	*0.001441*

Table 36. Performance-Aging Curve Results for the Bench Press for OT, OG, & C

Parameters	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*1.008957*	*0.004515*	*223.4586*	*0.000000*	*0.999333*	*1.018581*
f_2	*-0.182520*	*0.030237*	*-6.0363*	*0.000023*	*-0.246969*	*-0.118071*
f_3	*0.006356*	*0.001634*	*3.8907*	*0.001449*	*0.002874*	*0.009837*

Table 37. Performance-Aging Curve Results for the Bench Press for QB

Parameters	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*0.774145*	*0.010161*	*76.19007*	*0.000000*	*0.752798*	*0.795491*
f_2	*0.056911*	*0.057777*	*0.98502*	*0.337671*	*-0.064473*	*0.178296*
f_3	*-0.012441*	*0.003239*	*-3.84152*	*0.001196*	*-0.019245*	*-0.005637*

Table *38*. Performance-Aging Curve Results for the Bench Press for RB, FB, & TE

Parameters	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*1.001629*	*0.020437*	*49.01159*	*0.000000*	*0.957796*	*1.045461*
f_2	*0.294117*	*0.150209*	*1.95805*	*0.070458*	*-0.028049*	*0.616283*
f_3	*-0.020807*	*0.011074*	*-1.87885*	*0.081246*	*-0.044558*	*0.002945*

Table *39*. Performance-Aging Curve Results for the Bench Press for SS & FS

Parameters	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*1.100648*	*0.005913*	*186.1414*	*0.000000*	*1.088045*	*1.113251*
f_2	*-0.010394*	*0.033262*	*-0.3125*	*0.758972*	*-0.081291*	*0.060503*
f_3	*-0.000780*	*0.002569*	*-0.3035*	*0.765667*	*-0.006256*	*0.004697*

Table *40*. Performance-Aging Curve Results for the Bench Press for WR & CB

Parameters	Estimate	Standard Error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	1.050613	0.008585	122.3762	0.000000	1.032577	1.068650
f_2	0.041506	0.036088	1.1501	0.265136	-0.034312	0.117324
f_3	-0.005437	0.002245	-2.4222	0.026205	-0.010152	-0.000721

Performance-Aging Curve Results: Cone Drill

Table *41*. Performance-Aging Curve Results for the Cone for DE & DT

Parameters	Estimate	Standard Error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	1.006532	0.002941	342.2828	0.000000	1.000328	1.012737
f_2	-0.002717	0.006676	-0.4070	0.689069	-0.016802	0.011367
f_3	0.002141	0.000453	4.7293	0.000194	0.001186	0.003096

Table *42*. Performance-Aging Curve Results for the Cone for K & P

Parameters	Estimate	Standard Error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	1.016611	0.003590	283.1825	0.000000	1.009146	1.024077
f_2	-0.009333	0.005902	-1.5813	0.128761	-0.021606	0.002941
f_3	0.000829	0.000286	2.9035	0.008497	0.000235	0.001423

Table *43*. Performance-Aging Curve Results for the Cone for OLB & MLB

Parameters	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*0.999129*	*0.000491*	*2033.788*	*0.000000*	*0.998076*	*1.000183*
f_2	*0.007433*	*0.001265*	*5.876*	*0.000040*	*0.004720*	*0.010147*
f_3	*0.000042*	*0.000110*	*0.380*	*0.709759*	*-0.000195*	*0.000279*

Table *44*. Performance-Aging Curve Results for the Cone for OT, OG, & C

Parameters	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*1.004132*	*0.001386*	*724.7031*	*0.000000*	*1.001209*	*1.007055*
f_2	*0.003695*	*0.002808*	*1.3157*	*0.205731*	*-0.002230*	*0.009620*
f_3	*0.000275*	*0.000160*	*1.7228*	*0.103062*	*-0.000062*	*0.000612*

Table *45*. Performance-Aging Curve Results for the Cone for QB

Parameters	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*0.999912*	*0.001559*	*641.5138*	*0.000000*	*0.996624*	*1.003201*
f_2	*0.022728*	*0.003307*	*6.8719*	*0.000003*	*0.015750*	*0.029707*
f_3	*-0.000617*	*0.000224*	*-2.7504*	*0.013655*	*-0.001090*	*-0.000144*

Table *46*. Performance-Aging Curve Results for the Cone for RB, FB, & TE

Parameters	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*0.989457*	*0.001285*	*769.9453*	*0.000000*	*0.986701*	*0.992213*
f_2	*0.017630*	*0.003329*	*5.2961*	*0.000113*	*0.010490*	*0.024770*
f_3	*0.000146*	*0.000291*	*0.5038*	*0.622250*	*-0.000477*	*0.000770*

Table *47*. Performance-Aging Curve Results for the Cone for SS & FS

Parameters	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*1.006360*	*0.000114*	*8836.836*	*0.000000*	*1.006116*	*1.006604*
f_2	*0.000551*	*0.000287*	*1.920*	*0.075523*	*-0.000065*	*0.001167*
f_3	*0.000013*	*0.000024*	*0.524*	*0.608410*	*-0.000039*	*0.000065*

Table *48*. Performance-Aging Curve Results for the Cone for WR & CB

Parameters	Estimate	Standard Error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	1.008548	0.000087	11591.32	0.000000	1.008365	1.008731
f_2	-0.000275	0.000168	-1.64	0.118290	-0.000627	0.000077
f_3	0.000035	0.000010	3.40	0.003160	0.000013	0.000056

Performance-Aging Curve Results: Horizontal Jump

Table *49*. Performance-Aging Curve Results for the Horizontal Jump for DE & DT

Parameter	Estimate	Standard Error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	0.992815	0.004575	217.0309	0.000000	0.983164	1.002467
f_2	0.173558	0.155002	1.1197	0.278407	-0.153468	0.500584
f_3	-0.052683	0.010513	-5.0114	0.000107	-0.074863	-0.030503

Table *50*. Performance-Aging Curve Results for the Horizontal Jump for K & P

Parameter	Estimate	Standard Error	t-value	p-level	Lo. Conf. Limit	Up. Conf. Limit
f_1	0.992815	0.004575	217.0309	0.000000	0.983164	1.002467
f_2	0.173558	0.155002	1.1197	0.278407	-0.153468	0.500584
f_3	-0.052683	0.010513	-5.0114	0.000107	-0.074863	-0.030503

Table *51*. Performance-Aging Curve Results for the Horizontal Jump for OLB & MLB

Parameter	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*0.993258*	*0.001866*	*532.4155*	*0.000000*	*0.989282*	*0.997235*
f_2	*-0.248541*	*0.082515*	*-3.0121*	*0.008754*	*-0.424417*	*-0.072666*
f_3	*0.007830*	*0.007252*	*1.0798*	*0.297305*	*-0.007627*	*0.023287*

Table *52*. Performance-Aging Curve Results for the Horizontal Jump for OT, OG, & C

Parameter	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*0.995975*	*0.003732*	*266.8399*	*0.000000*	*0.988133*	*1.003817*
f_2	*0.120469*	*0.098454*	*1.2236*	*0.236879*	*-0.086376*	*0.327314*
f_3	*-0.018164*	*0.005665*	*-3.2066*	*0.004891*	*-0.030065*	*-0.006263*

Table *53*. Performance-Aging Curve Results for the Horizontal Jump for QB

Parameter	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*1.017852*	*0.003341*	*304.6868*	*0.000000*	*1.010883*	*1.024820*
f_2	*-0.776416*	*0.098967*	*-7.8452*	*0.000000*	*-0.982857*	*-0.569974*
f_3	*0.021630*	*0.005794*	*3.7330*	*0.001312*	*0.009543*	*0.033717*

Table *54*. Performance-Aging Curve Results for the Horizontal Jump for RB, FB, & TE

Parameter	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*1.021198*	*0.003089*	*330.6271*	*0.000000*	*1.014650*	*1.027745*
f_2	*-0.451332*	*0.127317*	*-3.5449*	*0.002695*	*-0.721233*	*-0.181432*
f_3	*-0.006336*	*0.010152*	*-0.6242*	*0.541326*	*-0.027856*	*0.015184*

Table *55*. Performance-Aging Curve Results for the Horizontal Jump for SS & FS

Parameter	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*0.989716*	*0.004720*	*209.7040*	*0.000000*	*0.979711*	*0.999721*
f_2	*-0.148080*	*0.204235*	*-0.7250*	*0.478893*	*-0.581039*	*0.284878*

f_3	*-0.001030*	*0.015836*	*-0.0650*	*0.948943*	*-0.034600*	*0.032540*

Table *56*. Performance-Aging Curve Results for the Horizontal Jump for WR & CB

Parameter	**Estimate**	**Standard Error**	**t-value**	**p-level**	**Lo. Conf. Limit**	**Up. Conf. Limit**
f_1	1.000019	0.000971	1029.525	0.000000	0.997960	1.002078
f_2	0.014913	0.033358	0.447	0.660818	-0.055803	0.085630
f_3	-0.008519	0.002106	-4.045	0.000940	-0.012984	-0.004054

Performance-Aging Curve Results: Shuttle Drill

Table 57. Performance-Aging Curve Results for the Shuttle for DE & DT

Parameters	**Estimate**	**Standard Error**	**t-value**	**p-level**	**Lo. Conf. Limit**	**Up. Conf. Limit**
f_1	0.992051	0.003297	300.9160	0.000000	0.985096	0.999007
f_2	-0.004490	0.004478	-1.0026	0.330102	-0.013938	0.004958
f_3	0.001465	0.000305	4.8042	0.000165	0.000822	0.002109

Table 58. Performance-Aging Curve Results for the Shuttle for K & P

Parameters	**Estimate**	**Standard Error**	**t-value**	**p-level**	**Lo. Conf. Limit**	**Up. Conf. Limit**
f_1	1.064939	0.002819	377.7352	0.000000	1.059076	1.070802
f_2	-0.004170	0.002747	-1.5179	0.143945	-0.009883	0.001543
f_3	0.000432	0.000133	3.2475	0.003853	0.000155	0.000708

Table 59. Performance-Aging Curve Results for the Shuttle for OLB & MLB

Parameters	***Estimate***	***Standard Error***	***t-value***	***p-level***	***Lo. Conf. Limit***	***Up. Conf. Limit***
f_1	*1.012562*	*0.003030*	*334.1748*	*0.000000*	*1.006139*	*1.018985*
f_2	*0.023255*	*0.003974*	*5.8514*	*0.000025*	*0.014830*	*0.031679*
f_3	*0.000224*	*0.000283*	*0.7910*	*0.440508*	*-0.000377*	*0.000825*

Table 60. Performance-Aging Curve Results for the Shuttle for OT, OG, & C

Parameters	***Estimate***	***Standard Error***	***t-value***	***p-level***	***Lo. Conf. Limit***	***Up. Conf. Limit***
f_1	*0.986270*	*0.002117*	*465.8953*	*0.000000*	*0.981823*	*0.990718*
f_2	*0.002460*	*0.002534*	*0.9707*	*0.344570*	*-0.002864*	*0.007784*
f_3	*0.000159*	*0.000145*	*1.0927*	*0.288951*	*-0.000147*	*0.000465*

Table 61. Performance-Aging Curve Results for the Shuttle for QB

Parameters	***Estimate***	***Standard Error***	***t-value***	***p-level***	***Lo. Conf. Limit***	***Up. Conf. Limit***
f_1	*1.029668*	*0.000211*	*4870.705*	*0.000000*	*1.029224*	*1.030112*
f_2	*0.007510*	*0.001934*	*3.883*	*0.001089*	*0.003447*	*0.011574*
f_3	*0.000022*	*0.000147*	*0.148*	*0.883779*	*-0.000286*	*0.000330*

Table 62. Performance-Aging Curve Results for the Shuttle for RB, FB, & TE

Parameters	***Estimate***	***Standard Error***	***t-value***	***p-level***	***Lo. Conf. Limit***	***Up. Conf. Limit***

f_1	*0.989280*	*0.002946*	*335.7729*	*0.000000*	*0.983000*	*0.995560*
f_2	*0.010483*	*0.004271*	*2.4542*	*0.026818*	*0.001379*	*0.019588*
f_3	*0.000396*	*0.000341*	*1.1593*	*0.264443*	*-0.000332*	*0.001123*

Table 63. Performance-Aging Curve Results for the Shuttle for SS & FS

Parameters	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*1.009783*	*0.000688*	*1468.111*	*0.000000*	*1.008297*	*1.011269*
f_2	*0.004167*	*0.001026*	*4.060*	*0.001352*	*0.001949*	*0.006384*
f_3	*-0.000115*	*0.000086*	*-1.334*	*0.205205*	*-0.000302*	*0.000071*

Table 64. Performance-Aging Curve Results for the Shuttle for WR & CB

Parameters	**Estimate**	**Standard Error**	**t-value**	**p-level**	**Lo. Conf. Limit**	**Up. Conf. Limit**
f_1	0.999052	0.001663	600.7092	0.000000	0.995558	1.002546
f_2	-0.006430	0.001905	-3.3753	0.003371	-0.010432	-0.002428
f_3	0.000617	0.000117	5.2571	0.000053	0.000370	0.000864

Performance-Aging Curve Results: Vertical Jump

Table 65. Performance-Aging Curve Results for the Vertical Jump for DE & DT

Parameters	**Estimate**	**Standard Error**	**t-value**	**p-level**	**Lo. Conf. Limit**	**Up. Conf. Limit**
f_1	1.008495	0.003360	300.1892	0.000000	1.001407	1.015583
f_2	0.005264	0.033483	0.1572	0.876920	-0.065378	0.075906
f_3	-0.009087	0.002282	-3.9819	0.000964	-0.013902	-0.004272

Table 66. Performance-Aging Curve Results for the Vertical Jump for K & P

Parameters	**Estimate**	**Standard Error**	**t-value**	**p-level**	**Lo. Conf. Limit**	**Up. Conf. Limit**
f_1	0.928834	0.006095	152.3891	0.000000	0.916158	0.941509
f_2	-0.178443	0.045128	-3.9542	0.000725	-0.272292	-0.084595
f_3	0.004947	0.002190	2.2591	0.034638	0.000393	0.009501

Table 67. Performance-Aging Curve Results for the Vertical Jump for OLB & MLB

Parameters	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*0.987306*	*0.001143*	*863.9663*	*0.000000*	*0.984884*	*0.989729*
f_2	*-0.075118*	*0.012526*	*-5.9970*	*0.000019*	*-0.101671*	*-0.048564*
f_3	*0.003215*	*0.000897*	*3.5849*	*0.002477*	*0.001314*	*0.005116*

Table 68. Performance-Aging Curve Results for the Vertical Jump for OT, OG, & C

Parameters	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*1.021158*	*0.004342*	*235.1636*	*0.000000*	*1.012035*	*1.030281*
f_2	*0.023528*	*0.032970*	*0.7136*	*0.484618*	*-0.045739*	*0.092794*
f_3	*-0.005261*	*0.001897*	*-2.7729*	*0.012544*	*-0.009246*	*-0.001275*

Table 69. Performance-Aging Curve Results for the Vertical Jump for QB

Parameters	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*1.032702*	*0.005365*	*192.4961*	*0.000000*	*1.021474*	*1.043931*
f_2	*-0.366911*	*0.044666*	*-8.2146*	*0.000000*	*-0.460397*	*-0.273425*
f_3	*0.013631*	*0.002598*	*5.2465*	*0.000046*	*0.008193*	*0.019069*

Table *70*. Performance-Aging Curve Results for the Vertical Jump for RB, FB, & TE

Parameters	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*1.026992*	*0.003009*	*341.3169*	*0.000000*	*1.020539*	*1.033446*
f_2	*-0.151899*	*0.037554*	*-4.0448*	*0.001206*	*-0.232446*	*-0.071353*
f_3	*-0.002062*	*0.003211*	*-0.6421*	*0.531156*	*-0.008948*	*0.004825*

Table *71*. Performance-Aging Curve Results for the Vertical Jump for SS & FS

Parameters	*Estimate*	*Standard Error*	*t-value*	*p-level*	*Lo. Conf. Limit*	*Up. Conf. Limit*
f_1	*0.966173*	*0.001594*	*606.2117*	*0.000000*	*0.962776*	*0.969570*
f_2	*0.011859*	*0.020367*	*0.5822*	*0.569051*	*-0.031553*	*0.055270*
f_3	*-0.004182*	*0.001566*	*-2.6700*	*0.017479*	*-0.007520*	*-0.000843*

Table *72*. Performance-Aging Curve Results for the Vertical Jump for WR & CB

Parameters	**Estimate**	**Standard Error**	**t-value**	**p-level**	**Lo. Conf. Limit**	**Up. Conf. Limit**
f_1	0.991951	0.002197	451.5470	0.000000	0.987336	0.996566
f_2	-0.022708	0.022735	-0.9988	0.331111	-0.070472	0.025055
f_3	-0.000996	0.001395	-0.7142	0.484273	-0.003928	0.001935

On-the-Field Input Attributions

Table 73. Attributes for Offensive and Defensive Positions

Statistic	**Description**
Year	Integer. the year of the NCAA or NFL season
Team	Text. team name from NCAA or NFL
League	Binary. NCAA (0) or NFL (1)
Age	Integer. age of player
Cumulative Games Started	Integer. total number of games started in the NCAA or NFL
Cumulative Games Played	Integer. total number of games played in the NCAA or NFL
Games Started	Integer. number of games started in a season
Games Played	Integer. number of games played in a season
Height	Integer. height of player measured in inches
Weight	Integer. weight of player measured in pounds

Table 74. Attributes for Offensive Positions

Statistic	**Description**
Pass Attempts	Integer. number of pass attempts thrown by a player
Pass Completions	Integer. number of pass completions thrown by a player
Pass Yards	Integer. number of passing yards thrown by a player
Pass #Games with 250+ yards	Integer. number of games in a season with 250 or more yards
Pass #Games with 200+ yards	Integer. number of games in a season with 200 or more yards

Pass #Games with 150+ yards	Integer. number of games in a season with 150 or more yards
Pass Interceptions	Integer. number of passes intercepted in a season
Pass Touchdowns	Integer. number of touch downs thrown per season
Pass Sacked	Integer. number of times sacked in a season
Pass Yards After Catch	Integer. number of passing yards recorded after the catch
Pass Yards to Catch (Yards in Air)	Integer. number of yards thrown in the air until catch
Rush Attempts	Integer. number of rushing attempts per season
Rush Yards	Integer. number of rushing yards per season
Rush Touchdowns	Integer. number of rushing touchdowns per season
Rush Yards Lost Caught Behind LOS	Integer. number of negative yards per season
Rush Yards after Contact Block	Integer. number of rushing yards after first contact per season
Rush Yards before Contact	Integer. number of rushing yards before contact per season
Rush #50 yards games	Integer. number of games in a season with 50 or more rushing yards
Rush #100 yards games	Integer. number of games in a season with 100 or more rushing yards
Rush #150 yards games	Integer. number of games in a season with 150 or more rushing yards
Rush #Fumbles	Integer. number of rushing fumbles per season
Rec. Receptions	Integer. number of receptions per season
Rec. Yards	Integer. number of receiving yards per season
Rec. Touchdowns	Integer. number of receiving touchdowns per season
Rec. Yards after Catch	Integer. number of receiving yards after the catch per season
Rec #games with 150+ yards	Integer. number of games in a season with 150 or more receiving yards
Rec #games with 100+ yards	Integer. number of games in a season with 100 or more receiving yards
Rec #games with 50+ yards	Integer. number of games in a season with 50 or more receiving yards
Rec targets	Integer. number or receiving targets per season
Block #Sacks Allowed	Integer. number of sacks given up per season
Block #Number of Penalties	Integer. number of penalties received per season
Block #Penalty Yards	Integer. number of penalty yards given up per season

Table *75*. Attributes for Defensive Positions

Statistic	Description
Def. #Tackles	Integer. number of tackles per season
Def. #Assisted Tackles	Integer. number of assisted tackles per season
Def. #Sacks	Integer. number of sacks per season
Def. #Stuffs	Integer. number of tackles behind the line of scrimmage per season
Def. #QB Knock downs	Integer. number of times a defensive player knocked a quarterback down per season
Def. #Interceptions	Integer. number of interceptions per season

Table *76*. Attributes for Special Teams

Statistic	Description
Punt #Punts	Integer. number of punts punted per season
Punt Yardage	Integer. number of yards punted per season
Punt #Touchbacks	Integer. number of punts that landed in the end zone per season

Punt #Punts inside the 20	Integer. number of punts the landed inside the 20-yard line per season
Kick #Field Goals Made 0-35 Yards	Integer. number of field goals made between 0 to 35 yards per season
Kick #Field Goals Attempted 0-35 Yards	Integer. number of field goals attempted between 0 to 35 yards per season
Kick #Field Goals Made 35+ Yards	Integer. number of field goals made beyond 35 yards per season
Kick #Field Goals Attempted 35+ Yards	Integer. number of field goals attempted beyond 35 yards per season
Punt Ret. #Punt Returns	Integer. number of returned from a punt per season
Punt Ret. Yardage	Integer. number of yards returned from a punt per season
Punt Ret. #Touchdowns	Integer. number of touchdowns scored from punts per season
Kick Ret. #Kickoff Returns	Integer. number of times a kickoff was returned per season
Kick Ret. Yardage	Integer. number of kick return yards per season
Kick Ret. Touchdowns	Integer. number of kick return touchdowns per season

Table *77*. Attributes for the Team

Position	Description
Year	Integer. the year of the NCAA or NFL season
Team Name	Text. team name from NCAA or NFL
#Wins	Integer. number of wins per season
#Losses	Integer. number of losses per season
Team Points Scored	Integer. number of points scored per season
Opponent Points Scored	Integer. number of points given up per season

Rules for Player Allocation

Table *78*. Rules for Player Allocation

Position	Statistic #1	Statistic #2	Statistic #3	Statistic #4	Statistic #5
QB1 & QB2	Games Started	Games Played	Pass Attempts	Pass Completions	Pass Yards
RB1 & RB2	Games Started	Games Played	Rush Attempts	Rush Attempts	Rush Yards
TE1 & TE2	Games Started	Games Played	Rec. Receptions	Rec. Yards	Rec. Touchdowns
WR1 & WR2	Games Started	Games Played	Rec. Receptions	Rec. Yards	Rec. Touchdowns
Ce1:	Games Started	Games Played	Cumulative Games Started	Cumulative Games Played	Block #Number of Penalties
OT1 & OT2	Games Started	Games Played	Cumulative Games Started	Cumulative Games Played	Block #Number of Penalties
OG1 & OG2	Games Started	Games Played	Cumulative Games Started	Cumulative Games Played	Block #Number of Penalties
DE1 & DE2	Games Started	Games Played	Def. #Tackles	Def. #Assisted Tackles	Def. #QB Knock downs
DT1	Games Started	Games Played	Def. #Tackles	Def. #Assisted Tackles	Def. #QB Knock downs
LB1, LB2,	Games	Games	Def. #Tackles	Def. #Assisted	Def. #QB

& LB3	Started	Played		Tackles	Knock downs
CB1 & CB2	Games Started	Games Played	Def. #Tackles	Def. #Assisted Tackles	Def. #Interceptions
Sa1 & Sa2	Games Started	Games Played	Def. #Tackles	Def. #Assisted Tackles	Def. #Interceptions
Ki1:	Games Started	Games Played	Kick #Field Goals Attempted 0-35 Yards	Kick #Field Goals Attempted 35+ Yards	Kick #Field Goals Made 0-35 Yards
Pu1:	Games Started	Games Played	Punt #Punts	Punt Yardage	Punt #Touchbacks
PR1:	Games Started	Games Played	Punt Ret. #Punt Returns	Punt Ret. Yardage	Punt Ret. #Touchdowns
KR1:	Games Started	Games Played	Kick Ret. #Kickoff Returns	Kick Ret. Yardage	Kick Ret. Touchdowns
Co:	Games Started	Games Played	Games	Wins	Losses

ANN Models A, B, and C

Table *791*. ANN Model Summary

HEART Model	HL#1 Nodes	HL#2 Nodes	HL#1 Neuron Type	HL#2 Neuron Type	Output Neuron Type	Learning Algorithm	ANN Architecture	Testing Performance (R^2)	Training Performance (R^2)
A	15	5	Sig	Sig	Sig	CG	MLP	68.2%	67.3%
B	14	5	Sig	Sig	Sig	CG	MLP	75.8%	68.5%
C	16	5	Sig	Sig	Sig	CG	MLP	74.4%	68.6%

Table *802*. Goodness-of-fit Summary for ANN A

Partition	MAE	Min |Error|	Max |Error|	R^2	Win% ±	Game ±
Training	0.010	0.001	0.252	0.682	0.248	3.974
Validation	0.003	0.000	0.221	0.617	0.108	1.736
Testing	0.013	0.003	0.321	0.673	0.212	3.389

Table *813*. Goodness-of-fit Summary for ANN B

Partition	MAE	Min |Error|	Max |Error|	R^2	Win% ±	Game ±
Training	0.008	0.005	0.217	0.871	0.217	3.475
Validation	0.002	0.000	0.242	0.707	0.217	3.476
Testing	0.002	0.000	0.242	0.685	0.217	3.476

Table *824*. Goodness-of-fit Summary for ANN C

Partition	MAE	Min |Error|	Max |Error|	R^2	Win% ±	Game ±
Training	0.042	0.001	0.235	0.743	0.172	2.755

Validation	0.072	0.004	0.21	0.725	0.167	2.676
Testing	0.072	0.004	0.20	0.686	0.144	2.306

Additional Open-Ended Responses

Table *835*. Open-Ended Comments

Player Evaluations for the 2007 NFL Draft and Free Agent Class
"ANY additional information is always welcomed."
"There are always players that are overlooked that can help improve team performance. Now, managers have a method to find them. They may not necessarily start, but they may be called on as backup or even to play special teams. "
"The model is extremely useful because it provides additional information that can be used to reduce the risk associated with selecting players in the Draft. This model interprets tangible attributes associated with the players, which can be used in addition to 'intangible' evaluations. The collection of evaluations can ultimately give evaluators a better sense of how players will perform in the NFL from multiple standpoints (i.e. on-the-field and off-the-field)."
"In terms of player contracts, I don't think the model would be very useful. A large part of rookie salaries are based on when a player was selected and his position relative to what other players were paid in previous years. So if a player is ultimately selected, his salary is somewhat already known."
"From my viewpoint, the results are extremely useful because it would assist with making decisions based on whether it would be advantageous for juniors in college to enter the NFL Draft"
"The model seems to have correctly identified some of the true elite talent in the 2007 Draft. This information is extremely useful because teams often miss out on drafting these players even though they were in the position to take them."
"The information would have been useful since you were able to pin point some of the top players at the top of the list that ended up not being drafted as high as you had them rated. Not only would that improve a team's personnel but also you would save them money because of draft slotting. Team could use this information to trade down into the Draft in order to grab a player that was not highly rated on other team's board."
"The ranking of players based on Theoretical Value appears to do an excellent job ranking the truly elite players, but beyond that, it fails. Numerous highly ranked players (e.g. Mike Doss, Justin Harrell, Chad Brown) are either currently out of football or have been so ineffective they have barely seen the field. In theory, the Expected Wins number would give a team a truer gauge as to who to select, but many of those rankings appear off as well. For example, Leon Hall and Marcus McCauley each rate higher than Darrelle Revis. Because of this, I'm not quite sure what to make of an attempt to balance the Theoretical vs. the Expected values. In some cases, each one appears to be a better gauge. While it is easily to look back and determine which one would work in certain cases, I'm not sure one would have been able to do that at the present time."
"I feel the RB and LB contribution values are very rich with info. Both the RB and LB values are useful in terms of comparing Free agent production verses Drafted player numbers. For example, to know that Expected Value of Nate Clements was -0.07 and Lavar Arrington's value was -0.13 is very useful. Nate's numbers in 2007 indicate he was overpriced with respect to his HEART ratings, which must reflect his loss of speed due to aging. This information would have saved the Niners big

free agent money since Clements had a poor return and there were other CBs available in the draft. As for Arrington, he had a bad history of injuries with the Skins and I think he was really overpaid with respect to his win contribution. Ultimately, I think productive LBs and RBs can be found in later rounds, which the HEART values seemed to agree with. The values also agree with my belief that teams over pay for older players."

"In my opinion, the information provided in the table would have been useful because it shows that several players' Theoretical value ended up far-exceeding their expected value, which would allow decision maker to assess and manage risk."

"Gives a quantitative value for each player, which helps determine risk/reward."

"The Team-Specific results show that the Bengals needed a CB during the 2007 off season, which I agreed with the team's decision in the draft. Based on the Team-Specific ratings generated by the model, the team could prioritize a list of players that were scouted. I also found the information to be useful because the model found more value in the Draft class for this position than in the Free Agency."

I see this information as being useful in regards to the impact of a player's history of injury. For example, if the Expected Value is dramatically lower than the Theoretical value, then it is likely due to an injury, which would require a team to investigate the player more. Likewise, if you believe a player is worth taking a risk on but his Theoretical Value is still low, it might suggest that the risk really isn't worthwhile. Overall, I think the tool would be useful because it could provide information that could be considered along with other information when making decisions."

"I think that the model could have been useful in assessing the risk of a player's pre-existing injuries. For example, it was widely known that Justin Harrell had a pre-existing injury coming out of college. Without the Expected value, this model could have influenced a team to take this player higher in the draft because they would have believed he would have been able to make a big impact. However, the model seemed to identify the risk involved with taking this player because there was a large difference between his Expected and Theoretical values, which ultimately might have persuaded a team to select someone else with less risk."

"An issue with only viewing 35 players is that there is a lack of inclusion of all positions. For my evaluation of the Cleveland Browns, I would have been interested in seeing a wider range of positions. The Browns selected Joe Thomas in the 1st round who by all accounts has fully lived up to expectations and is one of the top linemen in the game. The fact that he and all other offensive tackles are left out of this list is curious."

"The model represents a statistical perspective of the best player available based on ability and position availability. The Cleveland Browns selected Joe Thomas with the #3 overall pick in the 2007 draft and by comparing his impact to this model, one could say that the model did not properly assess the Browns needs or Joe Thomas' ability. However, when considering that possibility, one must also realize that the model is not designed to be the only tool used in draft and free agent analysis."

"I think this tool would very useful in deciding between alternative decisions. For example, would it have been better if the Browns acquired Adrian Peterson in the first round and then added a mid-round right tackle to bookend with Kevin Schaffer? Or would it have been better to add Joe Thomas at left tackle in the first round and then add a mid-round running back? This method seems to be a good way of comparing alternative strategies when dealing with draft picks."

"As with other struggling teams, a true position of need did not emerge. I think this actually reflects the state of the Browns franchise in which the team had several 'holes' to fill in the 2007 offseason. In contrast, the model suggested certain playing positions that could help a team improve for some of the more successful teams in the league, which is useful. With that being said, it is difficult to say how useful this information would have been to the teams prior to the offseason."

"it is an interesting forecast tool which provides insight to player's value"

In my opinion, I don't know if the information provided would have affected my personal decisions heading into the draft or free agency. I have a very 'Bill Parcels' view on the draft; if you see player and you think your team can use what that player can do, so you get that player"

"In my opinion the information would be only useful in certain circumstances only. Teams are always looking for an edge but I doubt that this model would significantly affect these decisions. I would have to see more results over a longer period of time."

"It is interesting to see that the number one player for the Colts that the model identified was a safety. This could be due to their current safety issues with Sanders. In browsing other team-specific results, it seems that the contribution values are much lower for the Colts than others, which may indicate that the model knew that the Colts were going to be good in the 2007 season. It also seemed like the Colts had more Free Agents as higher targets than other teams. It also seemed a bit odd that the model thought the Colts needed a tight end. However, it does seem that there was much difference in the top-35 player values, which may go back to the model knowing that there wasn't much room for improvement."

"From a total decision-making standpoint, I have mixed feelings about the usefulness of the model. In one sense, I do not think the best player for the Cowboys was identified. The model indicated that running back would be a great addition, which is confusing because Barber came off of a Pro Bowl season in the previous year. In the following year, the team's roster was basically the same and ironically Dallas did go ahead and selected 2 running backs (one in 1st and one in the 4th round). It seems the team and its decision makers agreed with the results of the model. Maybe the model result was based on the fact that Julius Jones was aging and his production was declining, maybe the model misinterpreted the emerging talent of Marion Barber, or maybe the model reflected the recent trend of teams utilizing a two backs?"

"I think that the model could be useful involving trades, because it shows the number of players at each position that are perceived to be the top of the class. This would give you an idea of where you need to trade to get one of those players at that position"

"It is very useful to have a quantitative scale that you can use to compare players across various playing positions. It also seems to be very useful in formulating strategies of when a team might take a player. The model seems useful because it correctly identified this team's weakness during the offseason."

"It's useful in ordering the players by position. It puts numbers on punters vs. offensive linemen, for example, but I'm not sure I would be ready to use that number as the decision-making tool."

"The model seems to do a good job in picking out the elite players from this Draft, which is amazing considering the difficulty in assessing players across different playing positions. It was also fooled on some of the players that experts thought were highly valued but later turned out as 'busts.' However, it seems that decision makers could use the Expected and Theoretical values as

additional insight to potentially avoided these decisions or at least identify when a risky decision is being made, which is very useful."

"It is very difficult to use any sort of mathematical model for the draft because the college and pro game are two totally different things. Draft analysis is 99 percent based on film study and personal evaluations, and 1 percent based on numbers. Regarding free agency, it is hard to incorporate math into the scheme factor. Teams run different types of schemes, which makes number translations a very uneven process."

"It is very difficult to use any sort of mathematical model for the draft because the college and pro game are two totally different things. Draft analysis is 99 percent based on film study and personal evaluations, and 1 percent based on numbers."

"Out of the top-35 players listed, many of the players were defensive ends. As we know, the Falcons selected a defensive end with the 8th pick in the 2007 draft, which was a decision I supported. It is interesting that the model seemed to think there was a high level of variance between players of this position, which wasn't necessarily the case before the draft. Years later, it is interesting to know that most highly sought ends are now currently struggling in the league, which would have made the information provided by the model useful. However, it would be interesting to know if the model takes defensive scheme (i.e. 4-3 vs 3-4 defensive ends) into account when formulating the contribution values."

"I think it is difficult to say how useful this model would have been prior to the draft or free agency signing period in 2007. There are a lot of "Busts" that are listed in the top-35. I realize that it is not a decision-making tool, but some of those players had character circumstances that affected their draft status, which to my knowledge the model does not incorporate."