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ORIGINAL PAPER

A system evaluation of NBA rookie contract execution efficiency with stacked Autoencoder and hybrid DEA

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Abstract
Most labor contract evaluations rely on performance evaluations by human resource management, which is time-consuming and costly. However, there has been little research into quantitative contract evaluations. This paper embedded a Stacked Autoencoder into a weighted two-stage data envelopment analysis model to evaluate NBA rookie seasonal contracts in an attempt to quantitatively assess contract execution efficiency. It was found that the model was able to effectively evaluate the NBA rookie contracts and provide guidance to the coach regarding their on-court performances. The NBA rookie contract execution analyses also found that performance and therefore contract fulfilment was possibly affected by time allocation problems. Finally, a dynamic and comprehensive contract evaluation system that has significant possible commercial value was constructed to assist the player, coach and manager make timely decisions, which may be a breakthrough in objective human resource management performance evaluation systems.

Keywords Contract execution efficiency · NBA · Stacked Autoencoder · Two-stage DEA

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1 Introduction

On June 23rd, 2016, Brandon Ingram from Duke University was drafted by the Los Angeles Lakers in the 1st round as the 2nd pick, and signed a multi-year contract with the Los Angeles Lakers worth 23.8 million dollars. However, how did the Lakers assess the worth of the contract?

The NBA draft is an annual event from which many great players have emerged such as Michael Jordan in the 1984 draft, Ray Allen and Kobe Bryant in the 1996 draft, and Lebron James, Carmelo Anthony, and Dwayne Wade in the 2003 draft. Regardless of potential, all players start out as rookies to allow them time to develop the comprehensive skills necessary to enhance the team play. As there are generally little experience difference between the rookie players, therefore, to assess their contract is appropriate in the same beginning level as a try in contract evaluation. Consequently, to assess the contract of Brandon Ingram can be transformed into a contract evaluation problem of rookie player.

Collected 2016 NBA rookie data and data from the following three regular seasons, this paper try to address the evaluation question by placing all the rookies in a hybrid data driven neural network and data envelope analysis (DEA) system to assess their contract execution so as to make a tool extension innovation in solving traditional human resource management problems.

However, post-contract evaluation mainly relies on the balanced score card (BSC) and key performance indicators (KPI), which are time-consuming and relies heavily on experience management (Bai and Sarkis 2014; Basso et al. 2018; Nara et al. 2019); so an effective and quantitative contract evaluation method is needed. DEA is therefore adopted as a substitute objective method in performance evaluations and contract extension evaluations (Yang et al. 2014; Volz 2016).

While, high dimensionality problem happened when too many basketball skill indexes were accumulated as input and output variables. However, previous solving method such as the super DEA method (Chaiwuttisak 2019) and a combination of principle component analysis (PCA) and DEA (Adler and Yazhemsky 2010; Poldaru and Roots 2014; Dong et al. 2016) were found not adapt to our system. As a result, a neural network dimension reduction method was embedded into a two-stage DEA model to solve the contract evaluation problem.

Contract evaluation could be more easily and more inexpensively conducted using a cumulative quantitative method, which could also form the basis for the development of a comprehensive contract management system that could be generalized to the entire sports industry. Further, as NBA rookies are considered new employees, from an enterprise management perspective, the contract evaluation system developed in this paper could be a valuable reference for formal contract offers after the completion of the rookie internship.

The remainder of this paper is organized as follows. Section 2 gives the literature review to explain step by step why a hybrid data envelope analysis and neural network method is proposed. From Sect. 3, how the proposed method is conducted can be seen vividly and specifically by the conceptual model and the computational model. Moreover, the important proposed concept of the contract execution efficiency, and the data preprocessing are also given here. Section 4 discusses the NBA rookie contract execution efficiencies from three years time dimension, and three stage dimensions (the 1st stage, the 2nd stage and the overall stage) in DEA. Section 6 concludes two main findings, gives further suggestions, and outlines future research directions.

2 Literature review

Being part of human resource management, contract management has been widely researched, especially in the areas of equity, sociality, and security (Gallagher et al. 2015; Wang et al. 2016; Akee et al. 2019). In many industries, and especially in project contract administration, contract management is closely associated with performance appraisal (Trinkūnienė et al. 2017; Berrios and McKinney 2017; Nan and Fei 2019). Two major performance evaluation methods are associated with employee contract evaluation; the balanced score card (BSC) (Sancho 2016; Modak et al. 2017) and key performance indicators (KPI) (Kucukaltan et al. 2016; Amzat 2017).

However, traditional human resource management performance evaluation has inevitable subjective bias. Jacob and Lefgren (2008) examined the identification of effective teachers by principals from a subjective performance evaluation perspective and found that while the principals were generally able to identify the most and the least effective teachers, they lacked the ability to distinguish the generally effective teachers. Traditional performance appraisal subjectivity has been widely examined. Ferris et al. (2008), for example, argued that performance evaluations needed to consider when political, social, cognitive, and emotional relationships were important components, and Golman and Bhatia (2012) argued that performance evaluations based on well-defined and clear criteria would be less subject to bias. Consequently, in an attempt to overcome subjective evaluations, many tools have been proposed to improve the BSC and KPI. For example, based on a BSC that included fuzzy multiple criteria decision making, Wu et al. (2009) performed an empirical banking performance evaluation and proved the effectiveness of the proposed framework. Basso et al. (2018) proposed a hybrid BSC and DEA model to evaluate museum performances, and based on neighborhood rough set theory, Bai and Sarkis (2014) proposed a two-stage approach to identify the KPIs for sustainable supply chains and then proved its effectiveness using DEA. Nara et al. (2019) identified 33 occupational health and safety KPIs, evaluated the individual competitiveness values for each enterprise in the Brazilian slaughterhouse industry, and then used a hybrid artificial neural network model to identify the most influential KPIs. Nevertheless, subjective bias is inevitable and objective data applications in performance evaluation are approaching to the utilization of data envelope analysis (DEA) method especially in sports industry.

DEA is a classic relative efficiency evaluation method, which has an advantage over multi criteria (or multi inputs and outputs) evaluations when there are multiple decision making units (DMU), and as the data-oriented objective statistical results are reliable, they can provide superior guidance on the evaluated objects than either the BSC or KPI. DEA has been found to be a very useful objective evaluation tool in the sports industry for both performance evaluation and contract extension evaluations. For example, DEA has been employed to assess team performance (Table 1) in basketball (Hofler and Payne 1997; Yang et al. 2014; Moreno and Lozano 2014), and baseball (Lewis 2014; Volz 2016) and club performance in the football industry (Villa and Lozano 2016; Chaiwuttisak 2019). DEA has also been employed to assess management performance, which is the primary concern of general team managers and coaches. For example, to assess NBA team efficiency, Yang et al. (2014) developed a two-stage DEA model with additive efficiency decomposition that considered the relationships between two stages, and Moreno and Lozano (2014) developed a network DEA approach that considered both first-team wages and bench-team wages.

Therefore, DEA has been found to be a viable objective evaluation method compared with traditional performance evaluation, and has also been used to assess the performance of individual tennis players (Landete et al. 2017; Chitnis and Vaidya 2014; Toloo 2013; Ruiz et al. 2013). However, much of the previous research has generally focused on determining the most efficient decision making unit, and has not specifically focused on team sports such as football, baseball, or basketball in which all team players are vital to the overall success. Even though there also have been some interesting individual player studies, the players' contracts have only ever been considered inputs that had a literal value. For example, Cooper et al. (2009) evaluated NBA player efficiency using weights that reflected the player's skill contributions to the game, but did not include how these contributed to overall team performance, and Chen and Johnson (2010) researched the dynamics of the performance space in major league baseball pitchers from 1871 to 2006 to assess the pitchers' growth properties and efficiency variations, but also did not include team assessments. In more recent studies, Oukil (2018) developed improved weighting schemes to fully rank 15 baseball players that included cross-efficiency and ordered weighted averaging operators. However, there has been no research that has included the manager effects or the internal and external team circumstances, all of which can affect organizational performance management. Therefore, to go some way to filling this research gap, this paper constructed a weighted two stage DEA model to evaluate NBA rookie player performances and contract executions that also considered internal partnerships and external rivals.

When there are too many input and output variables connected to the Decision Making Units (DMUs), the DEA data process can suffer from high dimensionality, and many DMUs may be identified as efficient (Adler and Golany 2002). Several methods have been developed to overcome this problem, such as the super DEA method (Chaiwuttisak 2019) and a combination of principle component analysis (PCA) and DEA (Adler and Yazhemsky 2010; Poldaru and Roots 2014; Dong et al. 2016), both of which were found to improve the discriminatory power of the models by removing some subordinate principle components; however, both resulted in severe information loss in our application. As a result, the well dimensionality reduction method of the Stacked Autoencoder (Bengio et al. 2006) which has perfect information maintain ability was tried to embed into the weighted two-stage model to evaluate the performance of an employee.

Table 1 Sports industry literature review

Evaluate focus	Sports	Paper purpose or conclusion	References
Teams	Basketball	Assess the potential of 27 teams in the NBA	Hofler and Payne (1997)
Teams	Baseball	Two-stage DEA model is better than standard DEA model	Sexton and Lewis (2003)
Teams	Basketball	Previous two-stage DEA model on sports industry; did not consider the relationship between the stages	Yang et al. (2014)
Teams	Baseball	A network DEA to improve single-stage DEA models	Lewis (2014)
Teams	Basketball	Network DEA approach performs better than the standard DEA	Moreno and Lozano (2014)
Teams	Football	Measuring the scoring efficiency of football teams in a match	Villa and Lozano (2016)
Clubs	Football	The relationship between business performance and sports performance	Galariotis et al. (2018)
Clubs	Football	Distinguish and rank efficient clubs	Chaiwuttisak (2019)
Players	Tennis	A mixed integer programming approach	Toloo (2013)
Players		Cross-efficiency evaluation	Ruiz et al. (2013)
Players		Traditional DEA model	Chitnis and Vaidya (2014)
Players		DEA model with a probability distribution	Landete et al. (2017)
Players	Basketball	DEA model with non-zero weights	Cooper et al. (2009)
Players	Baseball	Traditional DEA model	Chen and Johnson (2010)
Teams/managers	Baseball	Two applications of DEA model	Volz (2016)
Players	Baseball	A DEA cross-evaluation framework	Oukil (2018)

Therefore, to resolve the subjective bias problem in traditional performance evaluation and overcome the high dimensionality problems in traditional DEA methods, this paper introduces an artificial neural network into the DEA for performance evaluation, and overturns the traditional relationship between the contract and performance evaluation that views contract signing as the end result of the performance evaluation, as in this paper the performance evaluation can be equated to contract supervision. Therefore, this paper seeks to extend employee contract management by developing an ongoing performance evaluation system for contract evaluation that may inspire researchers to change their contract management perspectives.

3 Proposed method

3.1 Draft rule

The NBA draft, which is an annual event where all teams in the league choose their preferred players from a large pool of qualified players, was first held in 1947. In 1989, the NBA and the National Basketball Players Association agreed to hold only two rounds, which was far fewer than in previous years. The draft rules are as follows and as shown in Fig. 1. The initial fourteen picks in the first round are given to non-playoff teams, with the order being decided by lottery. After the first three are selected, the remaining picks are decided in the reverse order of the remaining teams, and the order of the 15th to the 30th picks is decided based on the order of the regular season playoff teams. In the second-round draft, the order is the reverse of the regular-season rankings for the 30 teams.

Data were obtained from advanced analysis data and the NBA Advanced Stats (2018), which are the official NBA statistics; therefore, the data were precise and without system errors. The 2016 NBA rookie data and data from the following three regular seasons (2016–2017, 2017–2018 and 2018–2019) were then extracted to evaluate the contract performances.

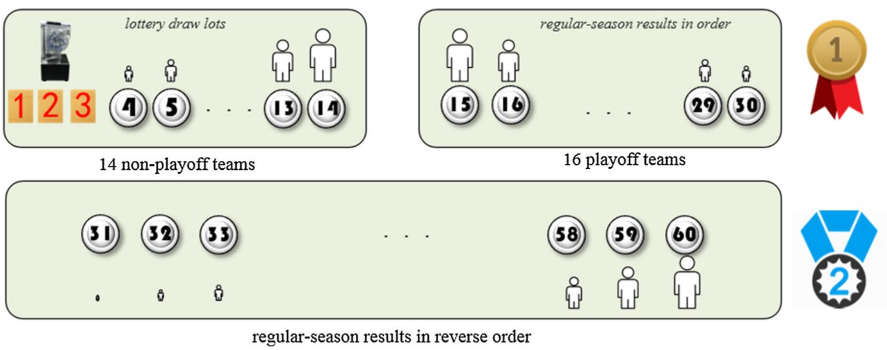


Fig. 1 NBA draft rule

3.2 Conceptual model

The rookie contract is a specific contract signed by first-round pick rookies to protect them from being waived in the first two seasons. In this paper, we evaluated all rookie (both the 1st round and the 2nd round rookies) contracts in the first three seasons. Contract management is divided into five processes; negotiation, signing, execution, supervision and evaluation (Berrios and McKinney 2017). A conceptual figure was designed in Fig. 2 to describe the evaluation process.

After the manager signs the rookie's contract (step 1), the coach executes and supervises the contract (step 2). Although first-round contracts are special as the first two years are guaranteed and the first year salary is fixed, all rookies share the common property of being newcomers who have no previous relationship with the other team members. Therefore, it is also necessary to evaluate both the internal circumstances, such as team partnerships, and the external circumstances, such as rival relationships. As a fixed effect is a key criterion for output-oriented DEA models, the rookie's skill, teamwork ability, relationship with the coach, and competitive strength are taken as the core factors that affect the coach's decision as to whether the rookie is on-court or left on the bench. Taking all these factors into consideration, a two stage DEA structure was built (as seen in step 4) to assess the efficiency of each rookie in each game; that is, the contract was evaluated from the

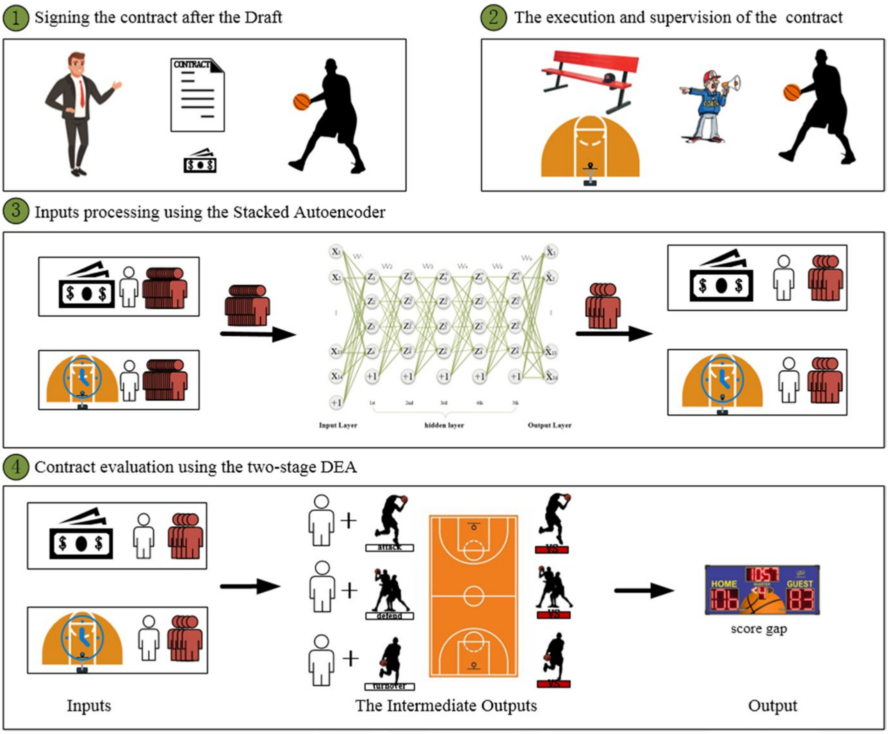


Fig. 2 The conceptual figure of the proposed method

mean efficiency over 82 games in one season, which is the normal contract evaluation cycle.

To maintain the homogeneity of the decision making units (DMU), the two-stage DEA was employed to first evaluate the NBA team efficiencies (step 4), in which the DMU was each team game. To assess the contributions of the rookies to the team, namely the contract value, a structure was built based around "the other 14 players and the rookie", which was then combined with a weight setting to transform the team's input and output into the rookie's input and output for the team. Details and the weight setting process are given in the following section.

The inputs were the contract values for each of the 15 players (15 players a team was assumed in this paper; five starters and ten substitutes) and the on-court times of each of the 15 players. Although all thirty teams had no less than fifteen players, for this analysis, the first fifteen players were selected based on the number of games they played throughout the season. The annual salary was determined from the season contract and was an important resource input for the player and the largest team input (Yang et al. 2014); this team input variable was also used in Volz (2016) and Oukil (2018). As the on-court time variable was based on the coaching tactics in each game, it was different for each game. This input has not been considered in previous sports industry evaluation research. The intermediate outputs were the skill indexes, which were classified into three types for the other 14 players and the rookie: *attack*, *defend*, *t&f* and *rookie_a*, *rookie_d*, *rookie_t&f* index (as shown in Fig. 3). In the second stage, the 15 players competed to win a game, and the skill indexes of the rival team were added, with the final output being the score gap rather than a win or a loss. As the rival data were associated with the home team data, the host team circumstances also needed to be considered (Villa and Lozano 2016). The score gap reflected the game outcome and the outcome degree; that is, a large loss, an overwhelming victory, or a close win. While the number of won and lost games were considered in Hofler and Payne (1997), Sexton and Lewis (2003) and Yang et al. (2014), the winning or losing margins were not considered.

Because the coach and manager are more focused on player performance than controlling costs, an output orientation was applied. Further, as the player also hopes to play well to produce greater output on their fixed contract, and as the on-court time allocated by the coach varies based on their specific tactics, a variable return to scale model was considered more practical. The undesirable outputs were therefore calculated with the inputs. As in many previous multi-stage DEA studies, it

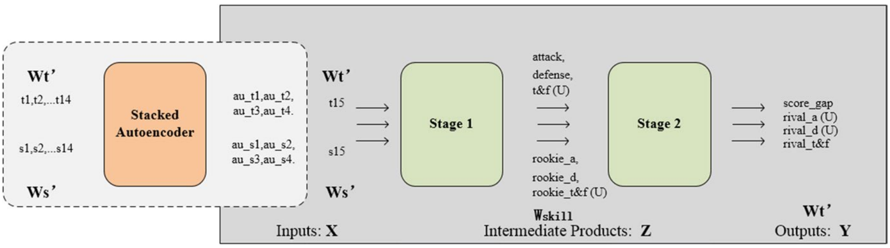


Fig. 3 Structure of the weighted two-stage model with stacked Autoencoder

was assumed that all stages were equally important (Zhou et al. 2018); therefore, the overall efficiency was calculated as an average of the efficiency of the first and second stages in this paper.

In the data calculation process, there was severe DEA discrimination in the first stage because there were 30 separate input variables. Therefore, to reduce the dimensions, a stacked Autoencoder feature extraction method was employed (as seen in step 3). The stacked Autoencoder, which has become a popular deep learning approach, was developed from the traditional Autoencoder (DeMers and Cottrell 1993). Basically, the stacked Autoencoder is a neural network that has multiple layers of sparse Autoencoders, in which the output of each layer is connected to the input of the successive layer. The deep network architecture of the stacked Autoencoder has a feature extraction advantage as there are minimum errors between the output data and the raw data (Saha et al. 2016; Zabalza et al. 2016; Chan et al. 2017; Zhou et al. 2017).

Similar to the Autoencoder, the stacked Autoencoder also has both encoder and decoder steps; however, the stacked Autoencoder has more hidden layers, as shown in step 3. In the encoder step the input data vector is mapped to a code vector that reflects the inputs, after which in the decoder step, the code vector is utilized to reconstruct the input vectors with minimum error (Jiang et al. 2017). The first step equation follows $z = \sigma(w_1 x + b_1)$, where x is the input data, z is the target compressed data, w_1 is the weight matrix and b_1 is the bias vector. $\sigma(\cdot)$ was the sigmoid function $\sigma(x) = \frac{1}{1+e^{-x}}$ in this paper, which is nonlinear activation function that can be replaced by a hyperbolic tangent function or a rectified linear unit (Feng and Duarte 2018).

The stacked Autoencoder was applied to the other 14 player contract value and time input variables (as shown in step 3), the learning rate was set at 0.001, and there were five hidden layers that were trained layer by layer unsupervised until the data were output. The next step was reconstruction, which required that the compressed data z be mapped to the output data, which was also considered original data. The reconstruction errors were minimized using a back-propagation algorithm to optimize the parameter values w and b.

3.3 The computational model

Having realized the conceptual figure for the proposed model, a computational model (Fig. 3) is given here to clarify the calculation process, in which it can be seen that the DMUs were transformed into each rookie game with a weight setting. Therefore, the inputs were the rookie's contract value and on-field time, the intermediate outputs were the rookie's skill indexes, and the outputs were the rookie's contribution toward the final score gap and the rival team's skill indexes.

In the Stacked Autoencoder process, the time input of the other 14 players $(t1, t2, \ldots, t14)$ multiplied with the rookie time wight w_t' were input into the model to reduce the dimensionality and four variables $(au\_t1, au\_t2, au\_t3, au\_t4)$ were output, which were the inputs for the first stage of the DEA model. The detail for the weight design is explained in the following section. Likewise, the salary input for the other 14 players ($s1, s2, \ldots, s14$) multiplied with the rookie salary weight w_s' were input into the model and four variables ($au\_s1, au\_s2, au\_s3, au\_s4$) output. Three types of weights; w_t', w_s' and w_{skill} (Fig. 3); were used to transform the team inputs and outputs into individual inputs and outputs. For example, in Eq. (1), w_t' was used as the time weight to transfer the team time input to the fifteenth player's (the rookie) time input t_{15}. It was assumed that there was no extra time and the game was fixed at 240 min for five players; that is, $5 \times 48 = 240$, or 5 players times 48 min a game. Therefore, by multiplying the fourteen players' and the rookie's time inputs by the time weight, the rookies time input was extracted.

$$\mathrm{w}_t' = \frac{t_{15}}{240} \tag{1}$$

As shown in Eq. (2), w_s' was the contract weight used to transfer the fifteen players' contract value inputs to the rookie's contract value input, for which s_{15} was the rookie's under-year contract value, and the denominator was the sum of the other fifteen players' within-year contract values regardless of the team's actual total payments. Therefore, the team input was transformed into the rookie's time and contract inputs using w_t' and w_s'.

$$\mathrm{w}_s' = \frac{s_{15}}{\sum_{i=1}^{15} s_i} \tag{2}$$

As shown in Eq. (3), a set of three weights; w_A, w_D and w_T; was used to transform the team's total skill index into a personal skill index.

$$w_{skill} = \left\{ w_A = \frac{Rookie\_A}{Attack\ Data+Rookie\_A}, \; w_D = \frac{Rookie\_D}{Defend\ Data+Rookie\_D}, \; w_{\mathrm{T}} = \frac{Rookie\_T}{Turnover+Rookie\_T} \right\} \tag{3}$$

A weight, w_t', was assigned to the *score_gap* and *rival_t&f* outputs in the second-stage. As all player efforts result from on-court time, the more time a player plays, the greater their contribution to the result; therefore, each output was multiplied by the weight w_t'.

In the first stage of the two-stage DEA model, $au\_t1, au\_t2, au\_t3, au\_t4$ were combined with $t15 * w_t'$ ($t15$ being the on-field time of the rookie) to become the on-field time inputs of the rookie; $au\_s1, au\_s2, au\_s3, au\_s4$: were combined with $s15 * w_s'$ ($s15$ being the rookie's salary) to become the rookie's salary inputs. As the variables of the other 14 players were processed with weighting, a double weighting for $au\_t1, au\_t2, au\_t3, au\_t4$ or $au\_s1, au\_s2, au\_s3, au\_s4$ was not needed.

The intermediate products Z included the skill indexes of the other 14 players multiplied by the rookie's skill weight, w_{skill}; namely, $attack * w_{skill}$, $defend * w_{skill}$, $t\&f * w_{skill}$. And the rookie's multiplied with their own skill weights, w_{skill}; namely $rookie\_a * w_{skill}$, $rookie\_d * w_{skill}$, $rookie\_t\&f * w_{skill}$. These 6 variables were the outputs in the first stage where $t\&f * w_{skill}$ and $rookie\_t\&f * w_{skill}$ were the undesirable outputs that were calculated as the inputs.

Three skill indexes (*attack*, *defend*, *t&f*) were constructed to reduce the variables, alleviate the discrimination, and allow for an evaluation of the comprehensive team contribution of the rookie. Cooper et al. (2009) classified the skill indexes into four; shooting, rebounding, ball handling and defense; and also agreed that this was important to reduce dimensionality. Yang et al. (2014) constructed a comprehensive variable PP (player performance) that included all skill indexes together to measure the efficiency of NBA teams. Taking these two references into consideration, we constructed our own indexes as shown in Eqs. (4), (5) and (6), with less weight being given to fouls to emphasize the other skill indexes that better reflected the rookie's personal skills and teamwork abilities.

$$attack = scores + 2 * assists + 2 * offensive\_rebound \tag{4}$$

$$defend = 2 * block + 2 * steal + 2 * defensive\_rebound \tag{5}$$

$$t\&f = 2 * turnover + foul \tag{6}$$

The team attack and defense data were associated with the team tactics, the team members' physical qualities, and the team members' teamwork. The attack data included total team scores, team assists, and offensive rebounds to reflect the team's scoring and teamwork abilities. The defense data included defensive rebounds, blocks, and steals to reflect the integrated team defensive strengths. There were also two undesirable skill indexes; turnover and personal fouls; however, as these were inevitable game outputs, they were combined into one category, with turnover allocated two points and a personal foul allocated one point. A rebound, a block, a steal, and a turnover were allocated two points to emphasize the importance of personal skills, an assist was allocated two points to underline the teamwork, and a personal foul was allocated one point to downgrade its importance as fouls are inevitable during a game and sometimes have strategic meanings.

The second stage was the operational stage and was related to the game outcomes. The intermediate products Z were the inputs to this stage; however, as team turnover was an undesirable variable in the first stage and did not contribute positively to the second stage outcome, it was not considered as an input to the second stage. The variables used for the calculation are shown in Table 2.

Table 2 Calculating variables

Stage	Input variables	Output variables
The 1st	au_t1, au_t2, au_t3, au_t4, au_s1, au_s2, au_s3, au_s4	$attack * w_{skill}$, $defend * w_{skill}$
	$t15 * w'_t$, $s15 * w'_s$, $t\&f * w_{skill}$, $rookie\_t\&f * w_{skill}$	$rookie\_a * w_{skill}$, $rookie\_d * w_{skill}$
The 2nd	$attack * w_{skill}$, $defend * w_{skill}$, $rookie\_a * w_{skill}$	$score\_gap * w'_t$, $rival\_t\&f * w'_t$
	$rookie\_d * w_{skill}$, $rival\_a * w'_t$, $rival\_d * w'_t$	

The rival data; $rival\_a$, $rival\_d$, and $rival\_t\&f$; were calculated using Eqs. (4)–(6), with the rival attack and rival defense data being the undesirable data inputs for the second stage. To accentuate the differences between the win and loss score margins, 100 points were artificially added to the positive score gaps. For example, on November 22nd, 2017, the host team Dallas Mavericks beat the Memphis Grizzlies by 95 to 94. As this margin was only one point, the score was adjusted to a 101 point difference to obviously differentiate it from a losing point margin. As negative score margins were not suitable for the DEA model, all data were processed using max-min normalization to avoid negative values. The second stage outputs were; score gap $score\_gap * w_t'$, rival attack data $rival\_a * w_t'$, rival defense data $rival\_d * w_t'$, rival turnover and foul $rival\_t\&f * w_t'$.

3.4 Contract execution efficiency

Contract execution efficiency (eA) is a user defined concept to evaluate the rookie's real value to the team. For each rookie, one efficiency value corresponded with one on-field game in our proposed two-stage DEA model, with the efficiency being marked 0 if they were absent from the game. Because contracts are normally evaluated season by season over all 82 games, the rookie's real value to the team is generally evaluated for the whole 82 games regardless of whether the rookie played for the full season or not. Ideally, players would be considered to have contributed their full value to the team if they had played all 82 games, and that the contract would have been executed effectively because of these on-field games. In reality, however, as few rookies play a full season, the contract execution efficiency is an average of the 82 game efficiency. Two key points affect contract execution efficiency: (1) play enough games in one season; (2) perform excellently enough to help the team win the game.

Different to contract execution efficiency, personal efficiency (evA) only considers the on-field games when evaluating a rookie's personal value, and was designed to assist in analyzing the maximum value of the contract execution efficiency. Personal efficiency is an average of the rookie's valid game efficiency, and reflects the rookie's potential maximum contract execution efficiency; that is, the actual contract execution efficiency approaches the personal efficiency of the on field games as the 82 games are completed in the season. For example, Brandon Ingram played 79 games in the 2016–2017 season; therefore, his personal efficiency was the mean efficiency of those 79 games, and the contract execution efficiency was the mean value over 82 games. Both personal efficiency and contract execution efficiency can be divided more specifically into 1st stage efficiency (or individual skill efficiency), 2nd stage efficiency (or teamwork efficiency), and overall efficiency, as discussed in the following.

3.5 Rookie selection and data accumulation

Valid rookie selection criteria were developed by the researchers and the basic information for the drafted (rookie) players is summarized in Table 3. Although there are

Table 3 Drafted players

Round	Player	Team	16/17/18	Round	Player	Team	16/17/18
1	Ben Simmons	76ers	3/1/1	31	Deyonta Davis	Grizzlies	1/1/4
2	Brandon Ingram	Lakers	1/1/1	32	Ivica Zubac	Lakers	1/1/1
3	Jaylen Brown	Celtics	1/1/1	33	Cheick Diallo	Clippers	4/1/1
4	Dragan Bender	Suns	1/1/1	34	Tyler Ulis	Suns	1/1/2
5	Kris Dunn	Timberwolves	1/1/1	35	Rade Zagorac	Celtics	2/2/2
6	Buddy Hield	Pelicans	1/1/1	36	Malcolm Brogdon	Bucks	1/1/1
7	Jamal Murray	Nuggets	1/1/1	37	Chinanu Onuaku	Rockets	4/4/1
8	Marquese Chriss	Suns	1/1/1	38	Patrick McCaw	Warriors	1/1/1
9	Jakob Poeltl	Raptors	1/1/1	39	David Michineau	Pelicans	2/2/2
10	Thon Maker	Bucks	1/1/1	40	Diamond Stone	Clippers	1/2/2
11	Domantas Sabonis	Thunder	1/1/1	41	Stephen Zimmerman	Magic	1/2/2
12	Taurean Prince	Hawks	1/1/1	42	Isaiah Whitehead	Nets	1/4/2
13	Georgios Papagiannis	Kings	1/1/2	43	Zhou Qi	Rockets	3/1/2
14	Denzel Valentine	Bulls	1/1/3	44	Isaia Cordinier	Hawks	2/2/2
15	Juancho Hernangomez	Nuggets	1/1/1	45	Demetrius Jackson	Celtics	1/4/4
16	Guerschon Yabusele	Celtics	3/1/1	46	AJ Hammons	Mavericks	4/2/2
17	Wade Baldwin IV	Grizzlies	1/1/4	47	Jake Layman	Blazers	1/1/1
18	Henry Ellenson	Pistons	1/1/4	48	Paul Zipser	Bulls	1/1/2
19	Malik Beasley	Nuggets	1/1/1	49	Michael Gbinije	Pistons	1/2/2
20	Caris LeVert	Nets	1/1/1	50	Georges Niang	Pacers	1/4/1
21	DeAndre' Bembry	Hawks	1/1/1	51	Ben Bentil	Celtics	4/2/2
22	Malachi Richardson	Hornets	4/1/4	52	Joel Bolomboy	Jazz	1/4/2
23	Ante Zizic	Celtics	3/1/1	53	Petr Cornelie	Nuggets	2/2/1
24	T Luwawu-Cabarrot	76ers	1/1/1	54	Kay Felder	Cavaliers	1/4/2
25	Brice Johnson	Clippers	1/4/1	55	Marcus Paige	Jazz	3/4/2
26	Furkan Korkmaz	76ers	3/1/1	56	Daniel Hamilton	Nuggets	3/4/2
27	Pascal Siakam	Raptors	1/1/1	57	Wang Zhelin	Grizzlies	2/2/2
28	Skal Labissiere	Kings	1/1/4	58	Abdel Nader	Celtics	3/1/1
29	Dejounte Murray	Spurs	1/1/3	59	Isaiah Cousins	Kings	2/2/2
30	Damian Jones	Warriors	4/4/1	60	Tyrone Wallace	Jazz	3/1/1

Label 1 in 16/17/18 means the selected rookie in the model; Labels 2,3 and 4 record the different reasons for discarding the rookie data; Label 2 means the rookie left the NBA; Label 3 means that the rookie was not eligible until the following season; Label 4 means that the rookie played very few games compared to their teammates generally 60 rookies in a draft, some may not satisfy the team requirements or may not be able to adapt and decide to leave; for example, in 2016, six rookies left, who are labelled 2 in Table 3. In some cases when a rookie is too young to join the NBA in the current year, contracts are not immediately validated, which means that the rookies are not eligible until the following season; for example, in 2016, there were nine such draftees, who are labelled 3 in Table 3. Finally, there were a further six players, labelled 4, who played very few games compared to their teammates. These three player types were discarded from the data and therefore, the actual contract execution values for 39 valid rookies were evaluated for the 2016–2017 season.

All teams were considered in the competitive environment even though six teams in the 2016–2017 season, and nine teams in the 2017–2018 and 2018–2019 seasons did not have any valid drafted players. As each of the 30 teams played 82 games, each rookie had 82 unique data sets regardless of whether they were on court. Therefore, in total there were 3690 data sets for the 2016–2017 season, 3936 data sets for the 2017–2018 season and 3444 data sets for the 2018–2019 season.

4 Discussion

4.1 Dimensionality reduction

To be able to assess single player rather than team efficiency, the team inputs needed to be decomposed into individual inputs; however, as a direct decomposition would cause the DEA model discrimination problems previously mentioned, the assessment would not be effective. Therefore, to reduce the discrimination problems, principal component analysis (PCA) was adopted at first, the cumulative proportion of variance for which is shown in Table 4.

The stacked Autoencoder can also be used for dimension reduction of the contract (salary) variables $s1, s2, \ldots, s14$ and time variables $t1, t2, \ldots, t14$ as it has high information conservation. Using the stacked Autoencoder to reduce the dimension reduction effect proved more effective, as shown in Table 5, which displays the mean square error (MSE) values recorded after using the stacked Autoencoder. The equation was as follows, $MSE = \frac{1}{N}\sum_{t=1}^{N} (\hat{X} - X)^2$, where $\hat{X}$ was the reconstructed value, X was the observed value, and N was the total number of test data. Apart from the rookie's contract and the time variables, there were fourteen contract variables and another fourteen time variables in each year. Even when these variables were reduced to one dimension, the MSE values were smaller than 0.03.

However, as the five dimensions still had too many variables, the data were reduced to four dimensions, which avoided any large structural information losses and meant that there would be less efficient DMUs identified. The Atacked Autoencoder was then applied to the 3690 data sets and the fourteen 2016–2017 season variables, for which the contract and time MSE recorded by the stacked Autoencoder were only 0.0021 and 0.0109; therefore, the stacked Autoencoder proved to be more effective than the PCA. For the 3936 data sets and fourteen 2017–2018 season player variables, the contract and time MSE were 0.0041 and 0.0124, and for the

Table 4 Cumulative proportion of variance for the PCA

Variables	Season	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12	PC13	PC14
t(14)	16–17	0.4531	0.5394	0.5972	0.6520	0.7003	0.7469	0.7902	0.8297	0.8661	0.8995	0.9304	0.9563	0.9791	1.0000
s(14)		0.9242	0.9647	0.9839	0.9918	0.9955	0.9972	0.9984	0.9990	0.9995	0.9998	0.9999	1.0000	1.0000	1.0000
t(14)	17–18	0.4349	0.5247	0.5882	0.6474	0.7043	0.7541	0.7953	0.8334	0.8692	0.9021	0.9312	0.9587	0.9841	1.0000
s(14)		0.9164	0.9608	0.9761	0.9895	0.9955	0.9979	0.9988	0.9992	0.9996	0.9998	0.9999	1.0000	1.0000	1.0000
t(14)	18–19	0.4397	0.5124	0.5802	0.6447	0.7037	0.7525	0.7959	0.8361	0.8748	0.9063	0.9340	0.9605	0.9843	1.0000
s(14)		0.7146	0.8476	0.9045	0.9455	0.9706	0.9838	0.9897	0.9934	0.9957	0.9975	0.9985	0.9993	0.9998	1.0000

Table 5 MSE values recorded after using the stacked autoencoder

Dimension to	2016–2017 Season		2017–2018 Season		2018–2019 Season	
	s(14)	t(14)	s(14)	t(14)	s(14)	t(14)
Dimension 8	0.0012	0.0048	0.0019	0.0057	0.0077	0.0081
Dimension 6	0.0011	0.0057	0.0018	0.0059	0.0118	0.0113
Dimension 4	0.0021	0.0109	0.0041	0.0124	0.0168	0.0119
Dimension 2	0.0080	0.0110	0.0066	0.0125	0.0233	0.0275
Dimension 1	0.0095	0.0202	0.0079	0.0127	0.0245	0.0281

3444 data sets and fourteen variables in the 2018–2019, the season and contract and time MSE were 0.0168 and 0.0119.

As a result, the Stacked Autoencoder was embedded into the two-stage DEA in the proposed model.

4.2 Efficiency summary

Two types of average efficiencies were calculated to evaluate the rookies' contract values.

(1) The average efficiencies of 82 average games; $e1$, $e2$ and eA (Tables 9, 10 and 11in the "Appendix"); which reflected the contract execution efficiencies in the 1st stage, 2nd stage and overall for all season games on the premise that the more games a player played in a season, the greater the benefit they created for the team, and the more effective the contract. eA, therefore, also represented the contract execution efficiency.

(2) The average efficiencies of valid games; $ev1$, $ev2$ and evA; which reflected the personal efficiency from the 1st stage, the 2nd stage and overall. evA, therefore, also represented the personal efficiency.

The two stage efficiencies and the overall efficiency in the three seasons were then comprehensively compared. Table 6 summarizes the mean values for the 21 rookies evaluated over the three seasons to allow for a comparison over time.

The increase in the mean salary reflected improving contract quality and improving rookie competencies. The mean salary, *m_salary*, increased season by season from 2.39 million dollars to 2.60 million dollars to 2.72 million dollars. Rookies

Table 6 Mean values over the three seasons

Season	m_salary	m_n_game	m_e1	m_e2	m_eA	m_ev1	m_ev2	m_evA
2016–2017	239.0	61.0	0.5827	0.4764	0.5297	0.7844	0.6318	0.7083
2017–2018	259.6	62.5	0.7220	0.4764	0.5995	0.9302	0.6227	0.7767
2018–2019	271.7	61.7	0.7318	0.4544	0.5931	0.9763	0.5949	0.7856

The units for *m_salary* were 10,000USD

whose salary decrease are generally eliminated under the fierce NBA competition; for example, Patrick McCaw, who had been selected as the 38th pick, had his salary cut in the 2018–2019 season from 1.31 million dollars to 0.79 million dollars.

The mean number of on-court games,*m_n_game*, increased from 61 to 62.5 at first, which reflected the rookie's adaptation and experience and the increase in the coach's trust; however, the following decrease to 61.7 could have been because of competition pressure and/or injury.

The first stage average efficiency, *m_e*1 and *m_ev*1 increased significantly from the 2016–2017 season to the 2017–2018 season. *m_ev1*, which was the personal efficiency in the 1st stage, improved from 0.7844 to 0.9302, which indicated the rookies' rapid growth in personal skills in the first two seasons. In the third season, the growth speed steadied; however, the second stage average efficiency, *m_e*2 and *m_ev*2 indicated a decreasing status, which consequently influenced *m_eA*, which also decreased slightly in the third season. This type of abnormal decrease is discussed more specifically later in this paper in reference to individual cases.

4.3 Individual skill efficiency (*e1*) and potential maximum skill efficiency (*ev1*) in the first stage

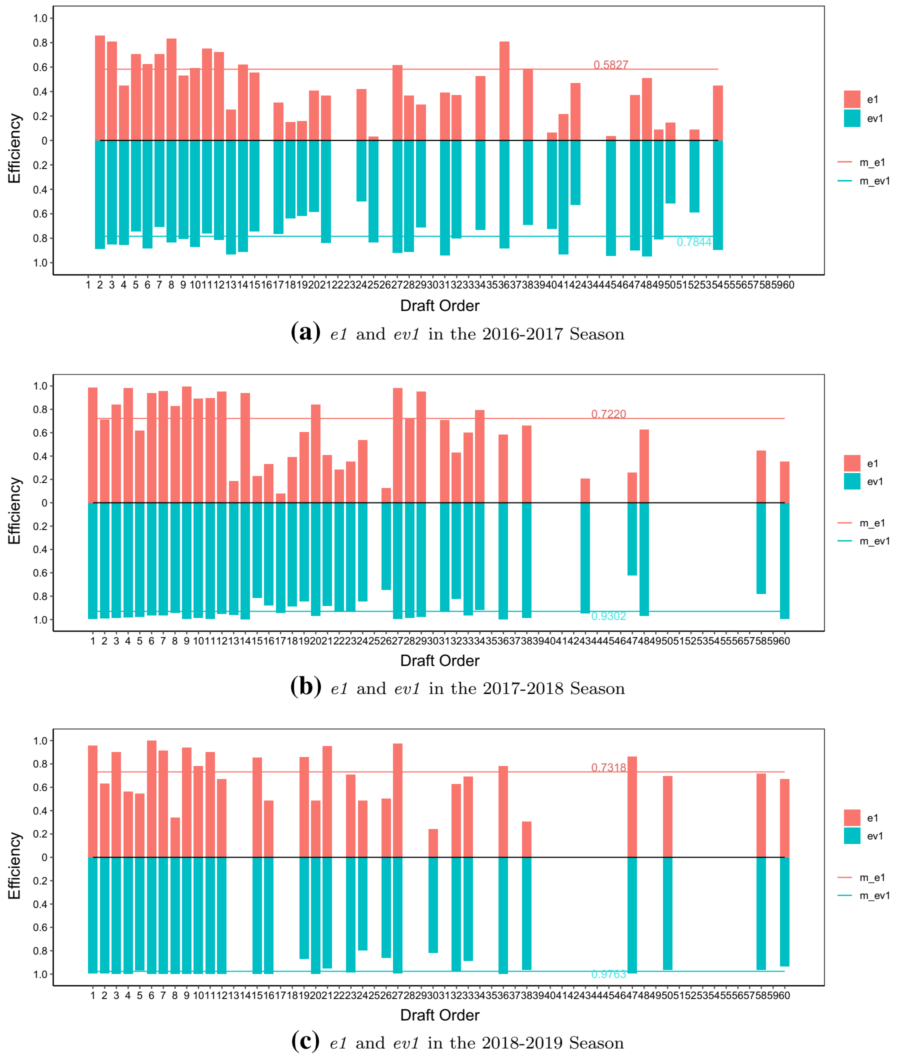
Figure 4 shows the contrasts between the rookies' first stage contract execution efficiency (the individual skill efficiency, *e1*), and the first stage personal efficiency (the potential maximum skill efficiency, *ev1*) for the 2016–2017 season, the 2017–2018 season, and the 2018–2019 season, the details for which are given below.

The more games a rookie played, the higher the contract execution efficiency. The first stage efficiency was the individual skill evaluation that indicated the degree to which the rookie transformed their on- court time and their contract value into the on-court skill indexes; that is, how the individual skills affected the contract execution. Therefore, the on-court time is a crucial input for rookies after they sign their contract. However, the on-court time is decided on by the coach, who is basically the contract process controller; therefore, to gain more on-court chances and ensure better contract execution, player and coach coordination is necessary.

Generally, a rookie gets more on-court chances because of their individual skills. For example, the Laker's rookie, Brandon Ingram, who was the 2nd pick, was found to be the best performer in the 2016–2017 season with an *e1* as high as 0.855, which indicated that because of his consistent on-court skills, the coach gave him 79 on-court opportunities at an average of 28.8 min each. As Brandon Ingram had effective contract execution, the manager was willing to renew his contract and increase his salary in the following season.

Ideally, contract execution efficiency should increase over time as the rookie develops their skills. Overall, the *ev*1 of all rookies improved across the latter three seasons, and the efficiency scores were very high, with 30 players having efficiencies higher than 0.9 in the 2017–2018 season, and 17 players having efficiencies approaching 1 in the 2018–2019 season.

Contracts are generally not renewed if rookie performances are not satisfactory in the first stage. As the coach's compensation is mainly based on the players on-court



(a) *e1* and *ev1* in the 2016-2017 Season

(b) *e1* and *ev1* in the 2017-2018 Season

(c) *e1* and *ev1* in the 2018-2019 Season

Fig. 4 Actual individual skill efficiency *e1* and potential maximum individual skill efficiency *ev1*

performances (Soebbing et al. 2016), and as the coach is the contract process controller and the manager is the results controller, the rookie needs to impress the coach enough to be given more on-court opportunities to be able to fully execute the contract. A large deviation between the *e1* and *ev1*, therefore, could also be seen to represent the coach's overall negative attitude towards the rookie player, which in turn affects the manager's decision to renew or not to renew the contract in the following season. For example, the Clippers player, Brice Johnson, who was the 25th pick in the first-round, had the lowest *e1* scores in the 2016–2017 season because he had only three games on-court; therefore, as his 1.27 million dollar annual contract was not sufficiently executed, he was later traded. Though he was protected by the rookie contract in the first two seasons, poor performances mean being assigned to the development league or being traded. Finally, on March 27th, 2018, he was waived by the Memphis Grizzlies and is now a free player.

Frequent trading also affects a rookie's performance. On February 1st, 2019, Timothy Luwawu was traded again by the Thunder to the Chicago Bulls. His contract execution efficiency was evaluated to assess how different teams relate to different internal team circumstances (Table 11 in the "Appendix"), and a comprehensive value calculated for both teams. Compared with Furkan Korkmaz, who was the 26th pick and played approximately the same number of games in the 3rd season, each efficiency value for Luwawu was lower. Though people tend to blame present circumstances for poor performances, frequent changes also appear to affect performance.

The $ev1$ is a reference value for the manager as it reflects the potential maximum individual skill efficiency of the rookie. There are two kinds of situation when $ev1$ is more valuable than $e1$ for managers, the first of which is player injury. For example, as Ivica Zubac from the Los Angeles Lakers, who was the 32nd pick, was injured during the 2016–2017 season, he only played 38 games; therefore, the possible $e1$ could be generalized because he had a high $ev1$ even though he only played a few games. From a financial perspective, injuries represent a loss to the team and a player could be traded after the contract protection period. However, considering player potential from a long term management perspective, the players should be taken care of to cultivate organizational commitment. The second case is when a player is not sufficiently utilized by the coach. For example, Skal Labissiere from the Kings, who was selected as the 28th pick, had a high $ev1$ at 0.911 and a growth potential 0.412 higher than Timothe Luwawu. However, Labissiere's $e1$ was only 0.366, 0.420 lower than Luwawu's because he only played 33 games. Therefore, the manager needs to remind the coach not to waste the human resources by limiting a rookie's playing opportunities as they had spent 1.19 million dollars on Labissiere's contract. Therefore, the coach's ethical leadership is vital for player organizational commitment (Constandt et al. 2018).

However, for rookies who seem to have low potential, the team manager needs to consult with the coach to downgrade the contract to avoid wasting the team's limited resources. For example, although the Nets' Isaiah Whitehead, the 42nd pick, played 73 games in 2016–2017 season, his $ev1$ was only 0.527; as a result, the coach reduced his on-court chances in the 2017–2018 season and the manager traded him at the end of this season. However, the decision could have been made earlier as the 2nd round rookies are not protected by the rookie contract and the contract decision making cycle is based on a short rookie growth cycle, which demonstrates the important role the coach plays in contract execution. Therefore, to differ the 2nd round rookies from the 1st round rookies, more strict contract evaluation cycles are needed. As the NBA is highly competitive, and the growth rookie cycle is very short, there is low team tolerance for slow growth especially in the 2nd round pick rookies; therefore, a team cannot spend too much time waiting for a player to grow and the rookie needs to be ready to demonstrate their abilities. However, if rookies do not demonstrate their potential, the team manager would select another recruit; therefore, when the $e1$ or $ev1$ is low, the manager and coach need to make timely human resource decisions.

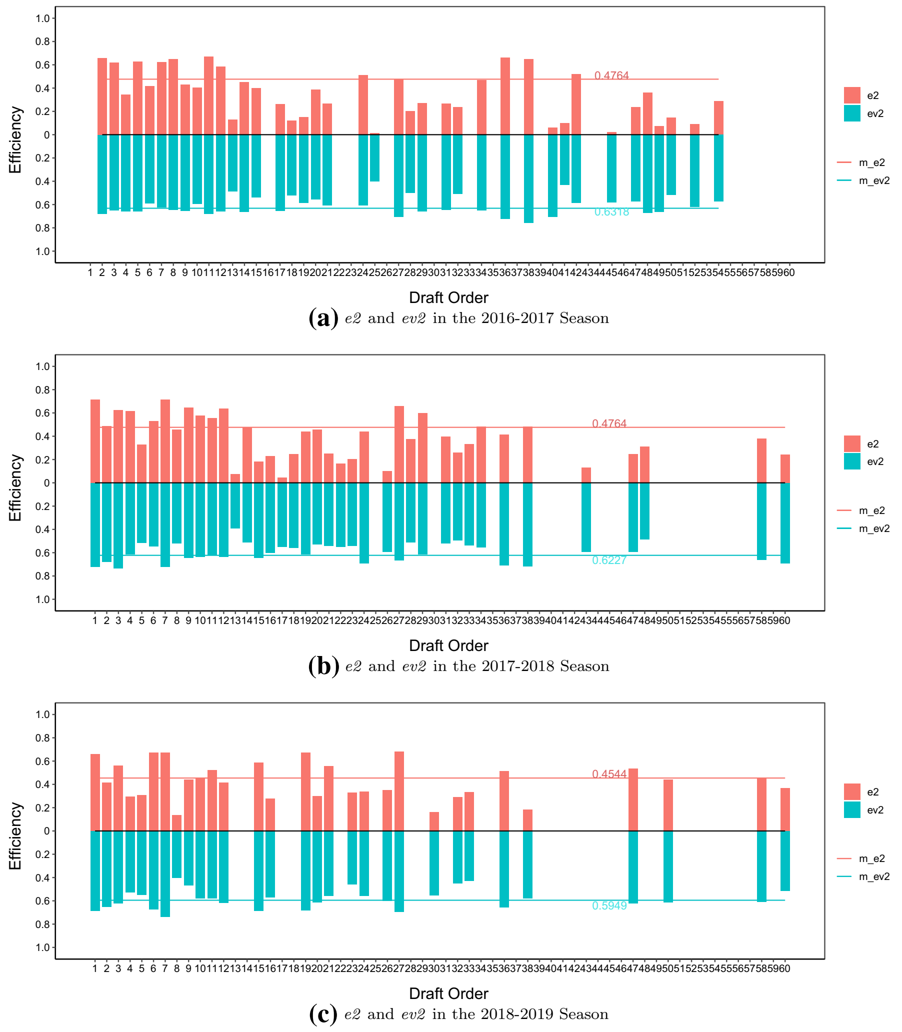
4.4 Personal teamwork efficiency (*e2*) and potential maximum personal teamwork efficiency (*ev2*) in the second stage

Individual skill efficiency is a contract execution efficiency determinant that can also be affected by internal and external circumstances such as different competitors or other uncontrollable factors (Yang et al. 2014). However, internally, individual skill efficiency is affected by teamwork quality, which is the key to winning. Therefore, the second stage efficiency is defined as personal teamwork efficiency, which reflects the rookies' teamwork ability to deal with the complex internal and external circumstances (Fig. 5).

The $e2$ is always lower than the $e1$ because of complex and generally uncontrollable circumstances. As can be seen, most rookie's $ev2s$ were lower than 0.8, with many lower than 0.7. High $ev2$ and $e2$ scores reflect high teamwork abilities and generally stable playing circumstances. In the 2016–2017 season, for example, Patrick McCaw from the Warriors, who was selected as the 38th pick, received the third highest $e2$ at 0.648, and would have had the highest $e2$ at 0.759 ($ev2$) if he had played the full season. As he played guard, his role was to organize attacks and assist his teammates to score. He had a high $e2$ and a relatively low $e1$ (0.688), and because his team won the League Championship in this season, he received the highest *ev2*; therefore, even though he had a low $e1$, McCaw's outstanding personal teamwork efficiency resulted in a contract renewal for the following season. Unfortunately, he didn't maintain his advantage, which was his core competence, and his contract was not executed effectively in the 3rd season. On January 7th, 2019, he was waived by the Cleveland Cavaliers.

A low *e2*, on the other hand, indicates that a rookie has been affected by circumstances, has low organizational integration, or relatively poor teamwork performances. Georgios Papagiannis from the Kings, who was the 13th pick, was unable to adapt to the circumstances in the 2016–2017 season, which was reflected in his low *e2* at 0.131 and low *ev2* at 0.487. As these were also low in the following 2017–2018 season, he was assigned to the development league 16 times and was released by the Kings as soon as his rookie contract expired. As a result, the importance of *e2* is not as obvious as *e1* because it can be affected by many factors; however, they are still closely connected.

As basketball relies on teamwork, if a player is unable to adapt to the circumstances or unable to cooperate well with his teammates, it can be quite difficult for a team to win a game and create greater team value. Therefore, rookies with low personal teamwork efficiencies need to improve their contract execution efficiency by strengthening their team-work, otherwise they may be traded, assigned to the development league or released. Many targeted efforts can be performed; for example, assists can help rookies integrate. In the 2017–2018 season, Ben Simmons from the 76ers, who was the 1st pick, was the most efficient teamwork player at 0.715, primarily because of the many assists he gave in each game, which made him a popular team leader. Inevitably, Ben Simmons was officially optioned to the 76ers for the 2018–2019 season; therefore, if a player is willing to be a leader or organizer, while he may sacrifice some individual points when assisting teammates, in the long run, the team may gain a greater overall score.



(a) *e2* and *ev2* in the 2016-2017 Season

(b) *e2* and *ev2* in the 2017-2018 Season

(c) *e2* and *ev2* in the 2018-2019 Season

Fig. 5 Actual personal teamwork efficiency *e2* and potential maximum personal teamwork efficiency *ev2*

As mentioned, the *e*2 and *ev*2 may not improve when circumstances change. As can be seen from Table 6, the *m_ev2*, the mean efficiency of *ev2*, was generally lower in the second season and was significantly lower in the third season. Yang et al. (2014) explained that second stage transfer efficiency could be influenced by many uncontrollable factors such as spectators, luck, and others; therefore, it is reasonable that the second stage mean efficiency can fall in the following season. However, as this study is focused on rookies who are new to the organization from a human resource perspective, these changes were assessed from an organizational socialization perspective.

Organizational socialization is a learning process whereby the rookies acquire the needed knowledge, skills, values, and norms to enable them to adapt to the team competition (Leidner et al. 2018; Bauer and Erdogan 2011). Therefore, at the beginning, as the rookies are adapting to the team, they tend to play more passive roles (Morrison 1993), such as actively assisting their more seasoned teammates. Over time, the rookies begin to play more proactive roles as they become more socialized (Morrison 1993). Organizational socialization can improve the rookies' self-efficacy, job satisfaction, and performances (Liao et al. 2017) and lead to better organizational commitment, which better integrates them into the organization and improves overall team performances (Allen and Shanock 2013). Therefore, having developed appropriate relationships in the 2nd season, the rookies gain the trust of the coach and are given more on-court opportunities, and may therefore try to challenge the original leadership structure to gain more on-court time. However, as the total time is fixed at 240 min for a team in each game, on-court time is such a scarce resource that the more time the rookie is on-court, the less playing time their teammates have, which is a zero sum game in the special game structure of the sports industry. The time resource allocation problem further increases the complexity of the internal partnership circumstances. As a result, more socialized rookies may prefer to demonstrate their personal skills and score more rather than just assist their teammates, which would improve their contract efficiency but could damage their on-court teammates benefit, which in turn reduces the overall teamwork efficiency and the average efficiency of the valid games, as is evidenced in Table 7. Twenty-one rookies played all three seasons, with 90.5% of them having an increasing *ev1* year on year; however, at the same time, 81.0% had reducing *ev2s*.

The significant *ev2* decreases in the third year could be because the rookies were being treated like normal players by the coach; that is, the rookie property gradually reduced in the first two seasons, but disappeared in the 3rd season, indicating the evolutionary process from a rookie contract to a formal contract. A rookie contract not only protects the rookies from being waived until after the first two seasons, but also provides hidden protections, such as being given more on-court chances when competing against a relatively weak team, or being assigned for training in the last section of a game when the team is going to either lock the win or suffer an absolute loss. However, these hidden protections tend to disappear toward the end of rookie contract, which means that they are faced with fiercer internal and external circumstances at which time more superior teamwork ability is needed. Therefore, many rookies may not have been able to adapt and consequently suffered a significant *ev2* decrease in the 2018–2019 season.

All in all, as the rookie performance in the 1st season may not fully reflect rookie value because of the hidden protections, the absolute efficiency value is not as important as the changing trends.

4.5 Contract execution efficiency (*eA*) and personal efficiency (*evA*)

The contract execution efficiency (*eA*), which is actually the overall stage efficiency, is a comprehensive evaluation of the rookie contract, as it considers both the rookie's individual skills (the 1st stage) and teamwork abilities (the 2nd stage) (Fig. 6). Personal efficiency (*evA*), which represents the potential maximum contract execution efficiency, is an added index to evaluate the contract performance.

Contract management generally cares more about the actual value than the potential value. In the 2016–2017 season, Diamond Stone from the Clippers, who was the

Table 7 ev1 and ev2 comparisons in three seasons

Order	Player	*ev1*			*ev2*		
		2016–2017	2017–2018	2018–2019	2016–2017	2017–2018	2018–2019
2	Brandon Ingram	0.887	0.990	0.994	*0.682*	*0.679*	*0.651*
3	Jaylen Brown	0.851	0.988	1.000	0.651	0.733	0.622
4	Dragan Bender	0.852	0.981	1.000	*0.659*	*0.615*	*0.526*
5	Kris Dunn	0.742	0.978	0.970	0.660	0.518	0.548
6	Buddy Hield	0.881	0.964	0.998	0.589	0.545	0.674
7	Jamal Murray	0.706	0.967	1.000	**0.624**	**0.722**	**0.737**
8	Marquese Chriss	0.834	0.943	1.000	*0.648*	*0.520*	*0.401*
9	Jakob Poeltl	0.804	0.997	1.000	*0.653*	*0.647*	*0.468*
10	Thon Maker	0.868	0.987	1.000	0.594	0.638	0.579
11	Domantas Sabonis	0.761	0.996	1.000	*0.679*	*0.621*	*0.579*
12	Taurean Prince	0.812	0.952	1.000	*0.658*	*0.636*	*0.615*
15	Juancho Hernangomez	0.745	0.817	1.000	**0.540**	**0.644**	**0.687**
19	Malik Beasley	0.618	0.846	0.869	**0.586**	**0.614**	**0.680**
20	Caris LeVert	0.583	0.971	1.000	0.557	0.527	0.613
21	DeAndre' Bembry	0.839	0.886	0.951	0.609	0.542	0.556
24	Timothe Luwawu	*0.499*	*0.845*	*0.796*	0.609	0.694	0.555
27	Pascal Siakam	0.920	0.996	0.996	0.705	0.667	0.696
32	Ivica Zubac	0.802	0.822	0.971	*0.509*	*0.494*	*0.449*
36	Malcolm Brogdon	0.882	0.998	1.000	*0.722*	*0.709*	*0.657*
38	Patrick McCaw	0.688	0.986	0.964	*0.759*	*0.717*	*0.580*
47	Jake Layman	*0.898*	*0.624*	*0.994*	**0.575**	**0.594**	**0.619**

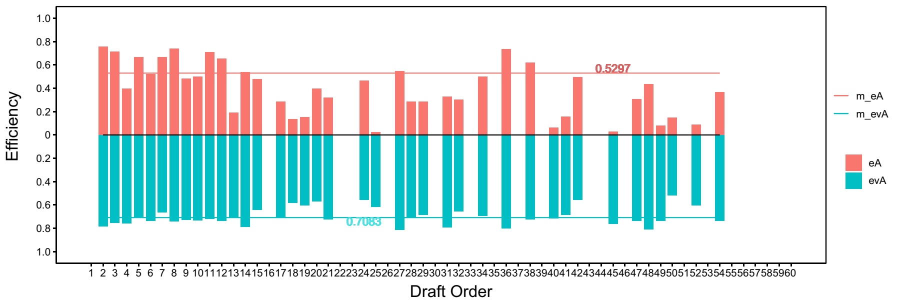
The italic values in *ev1* mean not consecutive increasing through three years

The italic values in *ev2* mean consecutive decreasing through three years

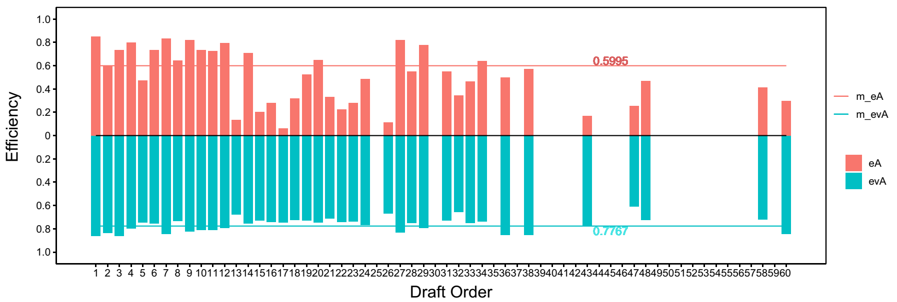
The bold values in *ev2* mean consecutive increasing through three years

40th pick, had a low contract execution efficiency because his contract was not sufficiently executed, primarily because he had poor performances and was therefore not trusted by the coach who did not give him enough chances to sufficiently execute his contract even though his contract was valued at 0.54 million dollars. As the coach's role is to develop tactics to win the game rather than to give all players equal playing time, he was unconcerned about Diamond Stone being devolved to the development league or being traded. Players under contract are in a passive role until they are able to effectively and efficiently execute their contracts, and only when this happens, do they have bargaining power when renewing their contracts.

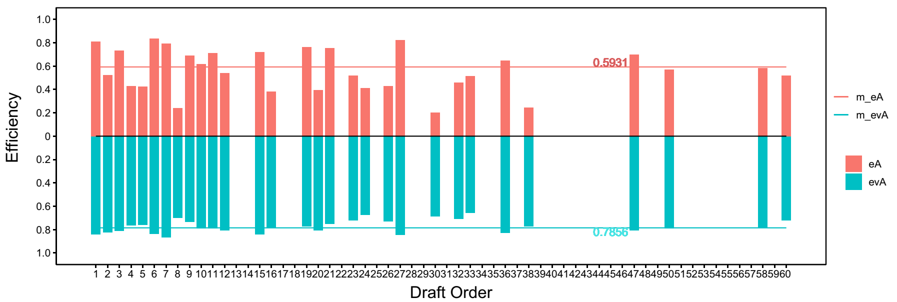
As contract management analysis accounts for both individual skills and teamwork abilities, poor performances in either category can lead to contract termination. However, the incentive mechanism for a well-executed contract seems to be



(a) eA and evA in 2016-2017 Season



(b) eA and evA in 2017-2018 Season



(c) eA and evA in 2018-2019 Season

Fig. 6 Actual contract execution efficiency eA and potential maximum contract execution efficiency evA

simple contract renewal. Pascal Siakam from the Raptors, who was the 27th pick, achieved high contract execution efficiency in both the 2017–2018 season and the 2018–2019 season, which resulted in both team option contracts being exercised on time. As his contract value was not high because of contract limitations, more welfare could have been offered; that is, the coach could give him more playing time to prove himself, or the manager could extend his contract, give him greater welfare benefits, and emphasize team culture to cultivate Siakam's organizational commitment. Therefore, more humanized management and an upgraded contract could be more suitable for players with excellent contract execution.

Effective and efficient contract execution is dependent on four main factors: (1) the manager signs the contract with the rookie and pays him an adequate annual salary; (2) the coach gives the rookie enough chances to play so as to create team value; (3) the rookie seeks to improve his skills to improve his on-court skill index; and (4) the rookie cooperates with his teammates well to maximize team efficiency and create maximum team value. To avoid being released, every NBA player and especially the rookies need to pay attention to these factors.

4.6 A dynamic evaluation system for rookie contract efficiency evaluations

In this section, a dynamic and comprehensive contract evaluation system is built based on the eA calculated using the proposed model (Table 8). Four quartile levels were set for the of *eA* value; *A*(0.75, 1.00], *B*(0.50, 0.75], *C*(0.25, 0.50] and *D*(0, 0.25]; and three finer levels were added to make the gap more obvious; for example, $A+(0.917,1], A(0.833,0.917], A-(0.750,0.833]$. As this system is intuitive, it is useful for the rookies, the coaches, and the managers as all the evaluated results are related to current career development.

While a final result is given for each season, the system is not limited by the fixed season cycle as is also able to can provide real-time evaluation results throughout the season as it is updated at the end of each game; therefore, because it is automatic and dynamic, the system has great practical value for both the team and the rookies.

(1) Most importantly, the system can provide information so that management can make accurate personnel decisions when contracts expire. Normally, managers make personnel changes at the end of a season by reviewing the past season and looking forward to the subsequent season. Therefore, this system can assist managers in deciding whether or not a rookie should be re-signed based on the assessment of each rookie's value to the team and their individual return on investment. For example, even though the evaluation results for Brandon Ingram showed a decreasing trend, his salary increased each season as he was judged to be a good player because his potential was very good, but was not seen as a valuable player because his contract execution efficiency passively decreased with each increase in salary. Over time, as he did not effectively or efficiently execute his contract, he was not worth his contract from a commercial perspective, which may have been the reason he was traded timely by the Los Angeles Lakers on July 6th, 2019.

The system is able to identify those rookies who are falling below the desired performance levels for both the coach and the team manager; however, it should be remembered that contract renewal also considers comprehensive factors, such as the players commercial value and team strategy. All rookies in level A, however, should be considered for contract renewal, but those in level D should be released.

(2) Real-time evaluation can be useful for some urgent personnel decisions. As there are sometimes chances to trade for a better player during a season, the system give a reference evaluation of the current players using only part of the season data. As the rookie growth cycle and personnel decisions are generally shorter than a complete season, managers can dynamically adjust the evaluation cycle of

Table 8 The dynamic recommendation system for the rookies

Order	Efficiency			Evaluation			Order	Efficiency			Evaluation		
	16–17	17–18	18–19	16–17	17–18	18–19		16–17	17–18	18–19	16–17	17–18	18–19
1	–	0.850	0.810	–	A	A–	31	0.329	0.551	–	C–	B–	–
2	0.756	0.601	0.522	A–	B	B–	32	0.304	0.345	0.460	C–	C	C+
3	0.714	0.735	0.732	B+	B+	B+	33	–	0.467	0.513	–	C+	B–
4	0.397	0.798	0.428	C	A–	C+	34	0.498	0.639	–	C+	B	–
5	0.667	0.475	0.426	B+	C+	C+	35	–	–	–	–	–	–
6	0.520	0.736	0.836	B–	B+	A	36	0.733	0.500	0.647	B+	B–	B
7	0.665	0.834	0.795	B	A	A–	37	–	–	–	–	–	–
8	0.741	0.643	0.239	B+	B	D+	38	0.618	0.571	0.245	B	B–	D+
9	0.480	0.822	0.689	C+	A–	B+	39	–	–	–	–	–	–
10	0.500	0.734	0.616	B–	B+	B	40	0.061	–	–	D–	–	–
11	0.711	0.728	0.712	B+	B+	B+	41	0.158	–	–	D	–	–
12	0.655	0.794	0.542	B	A–	B–	42	0.495	–	–	C+	–	–
13	0.191	0.133	–	D+	D	–	43	–	0.170	–	–	D+	–
14	0.537	0.710	–	B–	B+	–	44	–	–	–	–	–	–
15	0.478	0.205	0.720	C+	D+	B+	45	0.028	–	–	D–	–	–
16	–	0.280	0.383	–	C–	C	46	–	–	–	–	–	–
17	0.286	0.064	–	C–	D–	–	47	0.305	0.253	0.698	C–	C–	B+
18	0.135	0.318	–	D	C–	–	48	0.435	0.470	–	C+	C+	–
19	0.154	0.525	0.765	D	B–	A–	49	0.081	–	–	D–	–	–
20	0.397	0.649	0.393	C	B	C	50	0.146	–	0.569	D	–	B–
21	0.318	0.331	0.753	C–	C–	A–	51	–	–	–	–	–	–
22	–	0.226	–	–	D+	–	52	0.089	–	–	D	–	–
23	–	0.279	0.519	–	C–	B–	53	–	–	–	–	–	–

Table 8 (continued)

Order	Efficiency			Evaluation			Order	Efficiency			Evaluation		
	16–17	17–18	18–19	16–17	17–18	18–19		16–17	17–18	18–19	16–17	17–18	18–19
24	0.466	0.488	0.412	C+	C+	C	54	0.368	–	–	C	–	–
25	0.023	–	–	D–	–	–	55	–	–	–	–	–	–
26	–	0.115	0.428	–	D	C+	56	–	–	–	–	–	–
27	0.545	0.822	0.825	B–	A–	A–	57	–	–	–	–	–	–
28	0.284	0.549	–	C–	B–	–	58	–	0.413	0.585	–	C	B
29	0.284	0.776	–	C–	A–	–	59	–	–	–	–	–	–
30	–	–	0.201	–	–	D+	60	–	0.299	0.520	–	C–	B–

the system to reflect this shorter term, such as half a season or even a ten-game cycle, which allows them to quickly identify the current player statuses and make more reasoned, scientific human resource decisions, such as when to trade, when to provide a two-way contract, when to assign a player to the development league, and when to simply release a player (for example, rookies in level D).

(3) Coaches could use the system to explain why they are limiting a rookie's on-court playing time. There are many doubts and conflicts regarding on-court time allocation. A time interval allocation scheme can be written into the regulations based on the evaluation levels; that is, low level evaluations could be offered relatively shorter on-court time and higher level evaluations could be offered relatively longer on-court time. Rookies could also use the system to monitor their performances and assess whether they are in danger of contract downgrading, after which they could use the hybrid DEA model to assess their performances in terms of individual skills and teamwork.

5 Conclusion

With the aim of assessing NBA contract execution efficiencies, this paper first imbedded a Stacked Autoencoder into a weighted two-stage DEA model to evaluate NBA rookie contracts in 2016, from which there were two main findings.

On-court time, which is allocated by the coach, is a scarce resource for all the players. The game time, which is limited to 240 min per game, cannot be artificially increased and cannot be controlled by the players. As a result, the coach, who has the absolutely authority on-court and is the limited time resource allocator, becomes the determinant for any gap between actual player value and potential player value. Previous research, however, has paid little attention to the decisive function of the coach when evaluating team or player performances; therefore, this paper could inspire future research to evaluate these performances more comprehensively. This paper introduced an artificial neural network into the DEA as an innovative performance evaluation tool, which proved effective in solving the high dimensionality problems during data cleaning.

Both the proposed model and the proposed contract evaluation system have huge commercial value, and could also be generalized to the sports industry as a whole or even to human resource systems in other industry sectors. In future work, we plan to use ten year rookie data to assess the rookie interactions in different years and we also plan to develop a more comprehensive NBA player evaluation system.

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Appendix: Efficiency tables

See Tables 9, 10 and 11.

Table 9 Player efficiency in the 2016–2017 season

Round	Team	Player	Salary	n_game	*e1*	*e2*	*eA*	*ev1*	*ev2*	*evA*
2	Lakers	Brandon Ingram	528	79	0.855	0.657	0.756	0.887	0.682	0.785
3	Celtics	Jaylen Brown	474	78	0.809	0.619	0.714	0.851	0.651	0.751
4	Suns	Dragan Bender	428	43	0.447	0.346	0.397	0.852	0.659	0.756
5	Timberwolves	Kris Dunn	387	78	0.706	0.628	0.667	0.742	0.660	0.701
6	Pelicans	Buddy Hield	352	58	0.623	0.417	0.520	0.881	0.589	0.735
7	Nuggets	Jamal Murray	321	82	0.706	0.624	0.665	0.706	0.624	0.665
8	Suns	Marquese Chriss	294	82	0.834	0.648	0.741	0.834	0.648	0.741
9	Raptors	Jakob Poeltl	270	54	0.530	0.430	0.480	0.804	0.653	0.729
10	Bucks	Thon Maker	257	56	0.593	0.406	0.500	0.868	0.594	0.731
11	Thunder	Domantas Sabonis	244	81	0.751	0.671	0.711	0.761	0.679	0.720
12	Hawks	Taurean Prince	232	73	0.723	0.586	0.655	0.812	0.658	0.735
13	Kings	Georgios Papagiannis	220	22	0.250	0.131	0.191	0.933	0.487	0.710
14	Bulls	Denzel Valentine	209	56	0.621	0.452	0.537	0.909	0.662	0.786
15	Nuggets	Juancho Hernangomez	199	61	0.554	0.402	0.478	0.745	0.540	0.643
17	Grizzlies	Wade Baldwin IV	179	33	0.307	0.264	0.286	0.762	0.655	0.709
18	Pistons	Henry Ellenson	170	19	0.148	0.121	0.135	0.638	0.521	0.580
19	Nuggets	Malik Beasley	163	21	0.158	0.150	0.154	0.618	0.586	0.602
20	Nets	Caris LeVert	156	57	0.406	0.387	0.397	0.583	0.557	0.570
21	Hawks	DeAndre' Bembry	150	36	0.368	0.267	0.318	0.839	0.609	0.724
24	76ers	Timothe Luwawu	133	69	0.420	0.512	0.466	0.499	0.609	0.554
25	Clippers	Brice Johnson	127	3	0.030	0.015	0.023	0.832	0.401	0.617
27	Raptors	Pascal Siakam	120	55	0.617	0.473	0.545	0.920	0.705	0.813
28	Kings	Skal Labissiere	119	33	0.366	0.201	0.284	0.911	0.500	0.706
29	Spurs	Dejounte Murray	118	34	0.294	0.273	0.284	0.709	0.659	0.684

Table 9 (continued)

Round	Team	Player	Salary	n_game	*e1*	*e2*	*eA*	*ev1*	*ev2*	*evA*
31	Grizzlies	Deyonta Davis	137	34	0.390	0.267	0.329	0.941	0.644	0.793
32	Lakers	Ivica Zubac	103	38	0.372	0.236	0.304	0.802	0.509	0.656
34	Suns	Tyler Ulis	92	59	0.526	0.469	0.498	0.731	0.652	0.692
36	Bucks	Malcolm Brogdon	93	75	0.806	0.660	0.733	0.882	0.722	0.802
38	Warriors	Patrick McCaw	54	70	0.587	0.648	0.618	0.688	0.759	0.724
40	Clippers	Diamond Stone	54	7	0.062	0.060	0.061	0.721	0.705	0.713
41	Magic	Stephen Zimmerman	95	19	0.216	0.100	0.158	0.932	0.433	0.683
42	Nets	Isaiah Whitehead	107	73	0.469	0.521	0.495	0.527	0.585	0.556
45	Celtics	Demetrius Jackson	145	3	0.034	0.021	0.028	0.942	0.581	0.762
47	Blazers	Jake Layman	60	34	0.372	0.238	0.305	0.898	0.575	0.737
48	Bulls	Paul Zipser	75	44	0.509	0.360	0.435	0.949	0.671	0.810
49	Pistons	Michael Gbinije	65	9	0.089	0.073	0.081	0.807	0.665	0.736
50	Pacers	Georges Niang	65	23	0.144	0.147	0.146	0.515	0.517	0.516
52	Jazz	Joel Bolomboy	60	12	0.086	0.091	0.089	0.586	0.619	0.603
54	Cavaliers	Kay Felder	54	41	0.448	0.287	0.368	0.895	0.575	0.735

The *salary* units were 10,000USD

Table 10 Player efficiency in the 2017–2018 season

Round	Player	Team	Salary	n_game	*e1*	*e2*	*eA*	*ev1*	*ev2*	*evA*
1	Ben Simmons	76ers	617	81	0.985	0.715	0.850	0.997	0.724	0.861
2	Brandon Ingram	Lakers	552	59	0.713	0.489	0.601	0.990	0.679	0.835
3	Jaylen Brown	Celtics	496	70	0.843	0.626	0.735	0.988	0.733	0.861
4	Dragan Bender	Suns	447	82	0.981	0.615	0.798	0.981	0.615	0.798
5	Kris Dunn	Bulls	405	52	0.620	0.329	0.475	0.978	0.518	0.748
6	Buddy Hield	Kings	368	80	0.940	0.531	0.736	0.964	0.545	0.755
7	Jamal Murray	Nuggets	336	81	0.955	0.713	0.834	0.967	0.722	0.845
8	Marquese Chriss	Suns	307	72	0.828	0.457	0.643	0.943	0.520	0.732
9	Jakob Poeltl	Raptors	283	82	0.997	0.647	0.822	0.997	0.647	0.822
10	Thon Maker	Bucks	268	74	0.891	0.576	0.734	0.987	0.638	0.813
11	Domantas Sabonis	Pacers	255	74	0.899	0.556	0.728	0.996	0.621	0.809
12	Taurean Prince	Hawks	242	82	0.952	0.636	0.794	0.952	0.636	0.794
13	Georgios Papagiannis	Kings	230	16	0.188	0.077	0.133	0.962	0.393	0.678
14	Denzel Valentine	Bulls	219	77	0.939	0.480	0.710	1.000	0.511	0.756
15	Juancho Hernangomez	Nuggets	208	23	0.229	0.181	0.205	0.817	0.644	0.731
16	Guerschon Yabusele	Celtics	225	31	0.332	0.228	0.280	0.879	0.602	0.741
17	Wade Baldwin IV	Blazers	22	7	0.081	0.047	0.064	0.946	0.550	0.748
18	Henry Ellenson	Pistons	178	36	0.390	0.246	0.318	0.888	0.560	0.724
19	Malik Beasley	Nuggets	170	59	0.608	0.441	0.525	0.846	0.614	0.730
20	Caris LeVert	Nets	163	71	0.841	0.456	0.649	0.971	0.527	0.749
21	DeAndre' Bembry	Hawks	157	38	0.410	0.251	0.331	0.886	0.542	0.714
22	Malachi Richardson	Hornets	150	25	0.285	0.167	0.226	0.934	0.549	0.742
23	Ante Zizic	Celtics	165	31	0.353	0.204	0.279	0.934	0.540	0.737
24	Timothe Luwawu-Cabarrot	76ers	139	52	0.536	0.440	0.488	0.845	0.694	0.770

Table 10 (continued)

Round	Player	Team	Salary	n_game	*e1*	*e2*	*eA*	*ev1*	*ev2*	*evA*
26	Furkan Korkmaz	76ers	147	14	0.128	0.101	0.115	0.747	0.593	0.670
27	Pascal Siakam	Raptors	131	81	0.984	0.659	0.822	0.996	0.667	0.832
28	Skal Labissiere	Kings	131	60	0.723	0.375	0.549	0.988	0.513	0.751
29	Dejounte Murray	Spurs	131	80	0.953	0.599	0.776	0.977	0.614	0.796
31	Deyonta Davis	Grizzlies	131	62	0.707	0.395	0.551	0.935	0.522	0.729
32	Ivica Zubac	Lakers	131	43	0.431	0.259	0.345	0.822	0.494	0.658
33	Cheick Diallo	Clippers	131	51	0.600	0.334	0.467	0.964	0.537	0.751
34	Tyler Ulis	Suns	131	71	0.795	0.482	0.639	0.918	0.556	0.737
36	Malcolm Brogdon	Bucks	131	48	0.584	0.415	0.500	0.998	0.709	0.854
38	Patrick McCaw	Warriors	131	55	0.661	0.481	0.571	0.986	0.717	0.852
43	Zhou Qi	Rockets	82	18	0.209	0.131	0.170	0.950	0.595	0.773
47	Jake Layman	Blazers	131	34	0.259	0.246	0.253	0.624	0.594	0.609
48	Paul Zipser	Bulls	131	53	0.626	0.313	0.470	0.969	0.485	0.727
58	Abdel Nader	Celtics	117	47	0.447	0.378	0.413	0.780	0.660	0.720
60	Tyrone Wallace	Jazz	75	29	0.353	0.244	0.299	0.997	0.690	0.844

Table 11 Player efficiency in the 2018–2019 season

Round	Player	Team	Salary	n-game	*e1*	*e2*	*eA*	*ev1*	*ev2*	*evA*
1	Ben Simmons	76ers	643	79	0.959	0.661	0.810	0.995	0.686	0.841
2	Brandon Ingram	Lakers	576	52	0.631	0.413	0.522	0.994	0.651	0.823
3	Jaylen Brown	Celtics	517	74	0.902	0.562	0.732	1.000	0.622	0.811
4	Dragan Bender	Suns	466	46	0.561	0.295	0.428	1.000	0.526	0.763
5	Kris Dunn	Bulls	422	46	0.544	0.308	0.426	0.970	0.548	0.759
6	Buddy Hield	Kings	383	82	0.998	0.674	0.836	0.998	0.674	0.836
7	Jamal Murray	Nuggets	350	75	0.915	0.674	0.795	1.000	0.737	0.869
8	Marquese Chriss	Cavaliers	321	27	0.341	0.137	0.239	1.000	0.401	0.700
9	Jakob Poeltl	Spurs	295	77	0.939	0.439	0.689	1.000	0.468	0.734
10	Thon Maker	Pistons	280	29	0.390	0.231	0.311	1.000	0.592	0.796
10	Thon Maker	Bucks	280	35	0.427	0.245	0.336	1.000	0.575	0.787
10	Thon Maker	Pistons/Bucks	280	64	0.780	0.452	0.616	1.000	0.579	0.790
11	Domantas Sabonis	Pacers	266	74	0.902	0.522	0.712	1.000	0.579	0.789
12	Taurean Prince	Hawks	253	55	0.671	0.413	0.542	1.000	0.615	0.808
15	Juancho Hernangomez	Nuggets	217	70	0.854	0.586	0.720	1.000	0.687	0.843
16	Guerschon Yabusele	Celtics	267	41	0.488	0.278	0.383	1.000	0.569	0.785
19	Malik Beasley	Nuggets	177	81	0.858	0.672	0.765	0.869	0.680	0.775
20	Caris LeVert	Nets	170	40	0.488	0.299	0.393	1.000	0.613	0.806
21	DeAndre' Bembry	Hawks	163	82	0.951	0.556	0.753	0.951	0.556	0.753
23	Ante Zizic	Cavaliers	195	59	0.709	0.329	0.519	0.986	0.457	0.721
24	Timothe Luwawu-Cabarrot	Bulls	154	29	0.266	0.178	0.222	0.726	0.488	0.607
24	Timothe Luwawu-Cabarrot	Thunder	154	21	0.232	0.166	0.199	0.905	0.647	0.776
24	Timothe Luwawu-Cabarrot	Bulls/Thunder	154	50	0.485	0.338	0.412	0.796	0.555	0.675
26	Furkan Korkmaz	76ers	174	48	0.504	0.351	0.428	0.861	0.600	0.731

Table 11 (continued)

Round	Player	Team	Salary	n-game	*e1*	*e2*	*eA*	*ev1*	*ev2*	*evA*
27	Pascal Siakam	Raptors	154	80	0.972	0.679	0.825	0.996	0.696	0.846
30	Damian Jones	Warriors	154	24	0.240	0.162	0.201	0.820	0.554	0.687
32	Ivica Zubac	Lakers	154	33	0.418	0.176	0.297	0.979	0.413	0.696
32	Ivica Zubac	Clippers	154	26	0.329	0.172	0.251	0.964	0.504	0.734
32	Ivica Zubac	Lakers/Clippers	154	59	0.629	0.291	0.460	0.971	0.449	0.710
33	Cheick Diallo	Pelicans	154	64	0.692	0.334	0.513	0.886	0.428	0.657
36	Malcolm Brogdon	Bucks	154	64	0.780	0.513	0.647	1.000	0.657	0.829
38	Patrick McCaw	Raptors	79	26	0.306	0.184	0.245	0.964	0.580	0.772
47	Jake Layman	Blazers	154	71	0.861	0.536	0.698	0.994	0.619	0.807
50	Georges Niang	Jazz	151	59	0.695	0.442	0.569	0.966	0.614	0.790
58	Abdel Nader	Thunder	138	61	0.718	0.451	0.585	0.965	0.607	0.786
60	Tyrone Wallace	Clippers	135	62	0.671	0.369	0.520	0.933	0.513	0.723

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