Acadlore Transactions on Applied Mathematics and Statistics
https://www.acadlore.com/journals/ATAMS

Evaluating the Employment Efficiency of IT Candidates Using Data Envelopment Analysis

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Received: 04-12-2023 **Revised:** 05-16-2023 **Accepted:** 05-30-2023

Citation: A. Mrdak and T. Nanuševski, "Evaluating the employment efficiency of IT candidates using data envelopment analysis," *Acadlore Trans. Appl Math. Stat.*, vol. 1, no. 1, pp. 10–21, 2023. https://doi.org/10.56578/atams010102.

Abstract: This study aims to identify efficient Information Technology (IT) candidates for a specific position and highlight areas for improvement using Data Envelopment Analysis (DEA). By streamlining the selection process and reducing costs, the findings can assist companies in making better-informed hiring decisions. Additionally, the results provide candidates with valuable feedback on areas for development, increasing their chances of securing employment in their desired company. The DEA model offers a unique advantage in this context by generating reference units for each candidate, enabling precise determination of the necessary changes in inputs or outputs for achieving efficiency. The Charnes, Cooper, and Rhodes (CCR) model served as the baseline, with parallel comparisons drawn against the Banker, Charnes, and Cooper (BCC) and categorical models to identify the most effective approach. The findings reveal the efficient candidates based on the assessed criteria, demonstrating that less experienced candidates can be evaluated as efficient compared to their more experienced counterparts. The hypothesis that the BCC model, with its more flexible efficiency frontier, results in poorer candidate differentiation was confirmed. This study highlights the value of adopting the DEA method in evaluating the employment efficiency of IT candidates, offering practical implications for both hiring organizations and job-seekers.

Keywords: Data envelopment analysis; Human resources; Information technology; CCR model; BCC model

1 Introduction

The field of human resources has garnered increasing significance in recent years, becoming a vital aspect of the successful operation of any organizational system. Employees within a company not only influence its functioning, generate new business ideas, and maintain organizational culture but also play a pivotal role in attaining a competitive advantage in the market.

Selecting candidates for specific positions is a complex process that requires human resources departments to evaluate which applicants can best fulfill the company's requirements, contribute to creating new value, and participate in maximizing the effectiveness and efficiency of operations. Candidate selection involves choosing applicants who are estimated to best meet job requirements and achieve the best results among those who have applied for a vacant position [1].

Equally important is the motivation and willingness of employees to learn and improve their skills through work and effort. This is where the quality of an organizational system is exhibited, as lasting success and the achievement of long-term goals necessitate both company satisfaction with its personnel and a sense of belonging and loyalty among employees. By accomplishing company goals, employees can also achieve their personal objectives.

The selection process is a complex activity with several objectives [2]. It aims to select candidates who will provide maximum positive effects for the company and themselves through their knowledge, skills, work attitude, and motivation, while minimizing errors in candidate selection to the lowest possible level. The selection procedure varies depending on factors such as the size of the organization, type of job, number of applicants, number of vacant positions, expertise of those responsible for selection, and other relevant factors.

1.1 Candidate Selection

Process of management of human resources includes six steps: planning, recruitment, selection, performance assessment, compensation and maintenance [3]. In this study, DEA method has been used for supporting process of decision making in selection candidates, and based on that the phases of the selection process are listed below [4]:

• analysis of submitted applications and supporting documents and selection of candidates who meet the requirements.

• conducting preliminary interviews with candidates.

• testing of candidates.

• conducting diagnostic interviews with candidates.

• verification of references provided by candidates during the job application process.

• making a job offer to the candidate with the terms of their employment.

Each selection process begins with candidates applying for a job opening, where the candidate provides basic information about themselves, as well as a resume, motivational letter, and cover letter to the company they are applying to. After that, the Human Resources department selects candidates from the submitted applications and proceeds to conduct preliminary interviews. During these interviews, HR staff have the opportunity to get to know the candidate better in terms of their behavior, motivation, and communication skills. Next, the candidates undergo testing, including logical reasoning tests, knowledge tests, motivation tests, personality tests, and intelligence tests. These tests assess the candidate's ability to solve specific problems, their behavior in specific work situations, their beliefs and cultural fit, personality type, as well as their level of logical reasoning. This information is crucial for making business decisions and adapting to the organizational culture of the company where the candidate may potentially be employed. Subsequently, a diagnostic interview takes place, where the candidate has a discussion with a subject-matter expert in the field they may potentially work in. This interview allows for feedback on the test results and potentially further verification of the candidate's technical knowledge.

Finally, the employer checks the references provided by the candidate when submitting their resume, including former employers and organizations where the candidate was involved in activities or projects that contributed to the functioning of the respective organization. Ultimately, it is the employer's decision to determine whether a candidate is suitable for the given position and they are responsible for informing the candidate of the outcome.

Unfortunately, it is common practice for companies to refrain from providing feedback to rejected candidates. This is a detrimental approach as it denies candidates the opportunity to understand their shortcomings and make improvements. Consequently, candidates are left without valuable information on areas they should focus on in order to better align themselves with specific job requirements.

Having in mind that the candidate selection process for employment is complex and partially subjective, many authors have been developing methods for achieving uniformity in this process for decades. The methods for candidate selection can be divided into two groups [5]:

• conventional methods

• unconventional methods

Conventional methods includes job application, submission of candidate's resume, recommendations, interviews, testing, and probationary work. The most commonly used and popular method among them is the interview.

The aim of conducting an interview is to assess the candidate's ability to successfully perform the job through various behavioral, situational, and organizational knowledge-related questions. The types of interviews, based on the questions and the manner of conducting them, are as follows [6]:

• structured interviews: In structured interviews, predefined questions are asked to the candidate in a specific order.

• semi-structured interviews: In semi-structured interviews, some questions are predetermined, while the interviewer has the flexibility to ask additional questions based on the candidate's responses.

• unstructured interviews: Unstructured interviews involve the interviewer asking questions randomly, depending on the candidate's answers.

By using structured interviews, the interviewer maintains a consistent approach and can compare responses across candidates more easily. On the other hand, unstructured interviews allow for more flexibility but may result in variations in the assessment process. Semi-structured interviews strike a balance between the two approaches, combining predetermined questions with the opportunity for additional inquiries.

This study seeks to assess the efficiency of candidates applying for a specific job position in the IT industry, which can inform decisions regarding hiring. Considering the complexity of candidate selection in the hiring process and the challenges faced by human resources departments in selecting suitable candidates due to large numbers of applicants for a single position, this research aims to simplify the selection process and provide decision-making support to human resources departments through the use of software.

In addition to offering decision-making support to human resources departments, this study aims to identify areas of improvement for candidates who have not been evaluated as efficient, ultimately helping them become more efficient.

2 Methodology

DEA is a non-parametric technique that considers multiple criteria to generate a relative efficiency index for each observed Decision Making Unit (DMU) [7]. The assessment of efficiency is based on input and output values and is inherently relative, as it depends on the number of units in the observed set, data structure, and range of input and output values. Each unit employs the same types of inputs and transforms them into the same types of outputs [8].

Prior to conducting the analysis, inputs and outputs for the units in the observed set are selected, and the lower bounds of the weight coefficients are determined. Fundamental DEA models are constructed under the assumption that weight coefficients represent the importance of each input and output for a specific DMU, with the goal of maximizing its efficiency. Subsequently, for each DMU, the possibility of producing the given output with lower input levels is analyzed (if feasible, inputs can be reduced), or conversely, the potential for achieving higher output levels with the given inputs is explored (if feasible, outputs can be increased). This process forms the efficiency frontier, a "envelope" representing the maximum output that each DMU can produce using the existing inputs.

Two conditions must be satisfied for a unit to be considered efficient [9]:

- It must be possible to increase any output without increasing any input or decreasing any other output.
- It must be possible to decrease any input without decreasing any output or increasing any other input.

2.1 Concept and Evaluation of Efficiency

Efficiency (derived from Latin "success") is a fundamental performance measure in contemporary business and can be defined as the ability of an organizational unit to achieve its objectives with minimal input and maximal results [10]. In organizations that employ a single input (such as costs, resources, labor, or space) and a single output (such as profit, revenue, or productivity), efficiency is calculated using the formula defined in Eq. (1).

$$Efficiency = \frac{\text{output}}{\text{input}} \tag{1}$$

The challenge of determining efficiency arises in organizations utilizing multiple diverse inputs to generate multiple diverse outputs (financial, technical, technological) [11]. Diverse inputs and outputs, expressed in different measurement units, necessitate scaling to accurately assess efficiency. Merely summing the quantities of inputs and outputs might lead to incorrect efficiency assessments. In such cases, efficiency is calculated using the formula defined in Eq. (2).

$$Efficiency = \frac{\text{weighted sum of output}}{\text{weighted sum of input}} \tag{2}$$

The weighted sum of outputs or inputs can be defined as the sum of the quantity of a specific output or input multiplied by its corresponding weight coefficient. In the context of candidate selection, consider the evaluation of language skills, specifically foreign language proficiency and programming language proficiency. If the company deems programming language proficiency to be a more important criterion, a higher weight coefficient would be assigned to the input/output related to programming language skills compared to the input/output related to foreign language skills.

2.2 DEA Models and Orientations

DEA models can be formulated differently depending on the problem being addressed using this methodology. Each model can be input-oriented or output-oriented [12].

- Input-oriented DEA models aim to minimize inputs while producing outputs, enabling inefficient decision-making units (DMUs) to become efficient by reducing their inputs;
- Output-oriented DEA models, conversely, aim to maximize outputs given a certain level of inputs. In this case, inefficient DMUs become efficient by increasing their outputs;
- Non-oriented DEA models also exist, considering the possibility of simultaneously decreasing inputs and increasing outputs for an inefficient DMU to become efficient. The orientation determines the direction of projecting the inefficient DMU onto the efficiency frontier.

In terms of the relationship between input and output changes, DEA models can be classified as follows [13]:

- Constant Returns to Scale (CCR) models;
- Variable Returns to Scale (BCC) models.

2.3 The General Form of the DEA Model Used in the Research

The general form of the model used in the research, the output-oriented CCR model [14], is defined by the expressions of Eqns. (3)-(6).

$$\min e_j = \frac{\sum_{i=1}^{s} b_i x_{ij}}{\sum_{r=1}^{t} a_r y_{rj}} \tag{3}$$

with constrains:

$$\frac{\sum_{i=1}^{s} b_i x_{ij}}{\sum_{r=1}^{t} a_r y_{rj}} \leq 1 \quad j = 1, \ldots, n \tag{4}$$

$$a_r \geq 0 \quad r = 1, \ldots, t \tag{5}$$

$$b_i \geq 0 \quad i = 1, \ldots, s, \tag{6}$$

in which:

- a_r the weight assigned to the r^{th} output (r=1,. . . ,t);
- b_i the weight assigned to the i^{th} input (i=1,. . . ,s);
- y_{ri} the value of the r^{th} output for the j^{th} DMU unit;
- x_{ij} the value of the i^{th} input for the j^{th} DMU unit;
- e_j relative efficiency calculated for the j^{th} DMU unit.

Since the BCC model with variable return to scale was also employed for comparison with the results of the basic CCR model, the equations of Eqns. (7)-(11) constitute the defined formulation of this model [15].

$$\min e_j = \sum_{i=1}^{s} b_i x_{ij} + a^* \tag{7}$$

with constrains:

$$\sum_{r=1}^{t} a_r y_{rj} = 1 \tag{8}$$

$$\sum_{i=1}^{s} b_i x_{ij} - \sum_{r=1}^{t} a_r y_{rj} + a^* \geq 0 \quad j = 1, \ldots, n \tag{9}$$

$$a_r \geq \varepsilon \quad r = 1, \ldots, t \tag{10}$$

$$b_i \geq \varepsilon \quad i = 1, \ldots, s, \tag{11}$$

in which:

- a_r the weight assigned to the r$^{\text{th}}$ output $(r = 1, \ldots, t)$;
- b_i the weight assigned to the i$^{\text{th}}$ input $(i = 1, \ldots, s)$;
- y_{rj} the value of the r$^{\text{th}}$ output for the j^{th} DMU unit;
- x_{ij} the value of the im$^{\text{th}}_{\text{in}}$ input for the j^{th}_{m} DMU unit;
- e_j relative efficiency calculated for the j^{th} DMU unit;
- a^* an additional variable that corrects returns to scale.

2.4 Advantages and Disadvantages of the DEA Method

Advantages of the DEA method, as mentioned in the literature [16], include:

• No requirement for price information;

• No assumption of complete efficiency of all entities;

• No assumptions regarding profit maximization or cost minimization;

• Allows decomposition of the total factor productivity index into technological change and changes in technical efficiency;

• Provides more information with a small number of assumptions.

Disadvantages of the DEA method, as stated in the literature [16], include:

• The need for data on a large number of entities; measurement errors can influence the position and shape of the efficiency frontier;

• Exclusion of essential inputs or outputs can result in biased results;

• Assumption of independence among inputs, outputs, and individual entities;

• When a small number of entities are considered, all decision-making units may be evaluated as efficient;

• The obtained measure of efficiency is only relative to the most successful entities in the sample.

3 Results

3.1 Implementation of the DEA Method

The DEA method was implemented following the six stages defined by Emrouznejad and Witte in the Cooper's unified process for non-parametric projects, also known as the Cooper framework [17]. These stages include defining concepts and goals, data structuring, model selection, performance comparison, evaluation, and results and application. Each stage is interconnected and influences the others.

3.1.1 Research criteria

The efficiency of employment candidates was determined based on several attributes and their respective levels, as shown in Figure 1. The most important attributes for candidates selection in IT industry obtained by MACBETH method. MACBETH (Measuring attractiveness through a categorical-based evaluation technique) is MCDA technique for reducing the number of observed criteria and determining their relative weights [18].

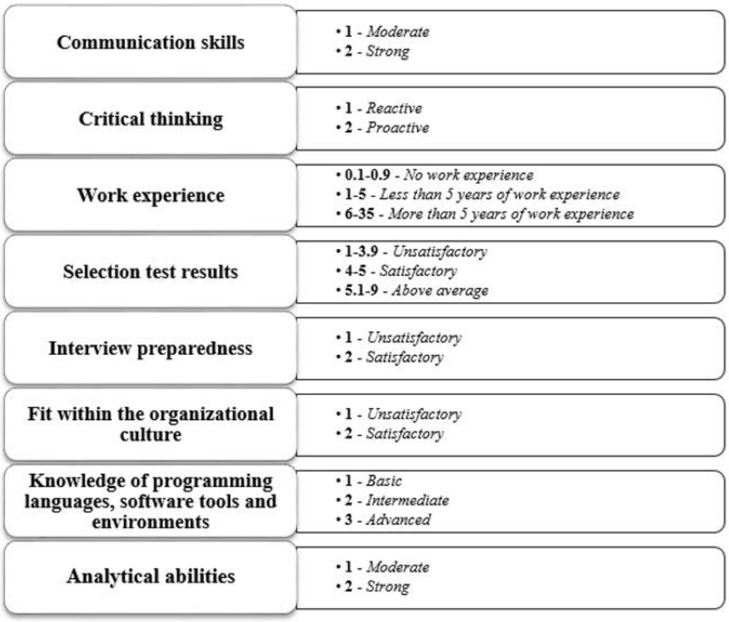

Figure 1. Attributes and attribute levels

Work experience and test results were considered as indicators of the candidates' previous achievements. The candidates' preparedness for interviews was assessed through their behavior, attire, gestures, manners, and responses to questions posed by the selection committee. The candidates' fit within the organizational culture was evaluated in terms of their willingness to embrace the company's values, dress code, communication systems, and hierarchy. Communication skills, critical thinking, knowledge of programming languages, software tools and environments, and analytical abilities were also included as criteria for evaluating the candidates.

3.1.2 Selection of DMUs and models

A total of 24 candidates were selected as decision-making units (DMUs) using software. The number of DMUs was set to be significantly higher than the number of criteria to ensure the DEA method produced realistic results. Work experience was chosen as an input for the output-oriented model, as it cannot be influenced during the selection process and exhibits a wider range of values than the other criteria. All other criteria were treated as outputs in the DEA method.

The CCR (Charnes, Cooper, and Rhodes) model was selected due to its ability to define the efficiency frontier more strictly, allowing for better differentiation among candidates [19]. The CCR model is preferable in this case, as it can rank candidates more effectively than the BCC (Banker, Charnes, and Cooper) or categorical models, which would consider most candidates as top-ranked due to the narrow value ranges of the criteria.

3.2 Analysis of the Obtained Results

Descriptive statistics were initially calculated for each attribute, including the maximum, minimum, mean, and standard deviation. These statistics, presented in Table 1, reveal that the work experience criterion exhibits the widest range of values, while the criteria of communication skills, analytical abilities, critical thinking, and fit within the organizational structure demonstrate the narrowest range of values.

Table 1. Descriptive statistics

	Work experience	Communication skills	Critical thinking	Test results	Interview preparedness	Fit whiting the org. culture	Knowledge of programming languages etc.	Analytical abilities
Max	17	2	2	8.2	2	2	3	2
Min	1	1	1	1	1	1	1	1
Mean	10.208	1.667	1.375	4.029	1.583	1.458	1.917	1.625
SD	4.062	0.471	0.484	1.821	0.493	0.5	0.640	0.484

It is very important to consider the correlation between inputs and outputs, where high correlation between two inputs or two outputs should be eliminated to reduce the dimensionality of the problem. Correlation represents the statistical relationship between certain attributes, and the level of statistical relationship is expressed by the degree of correlation [20]. Correlations between inputs and outputs were assessed, and it was determined that no high correlations existed between two outputs or two inputs, thus all attributes were included in the analysis. Figure 2 presents the rank for each candidate. The results indicate that only one candidate (DMU 12) is efficient. This candidate has only one year of work experience, significantly less than the other candidates, but achieves high values for the other criteria given the level of input, i.e., work experience. Although a candidate with ten years of work experience would be expected to have high output values, the candidate who achieves similar output values with fewer inputs is considered more efficient.

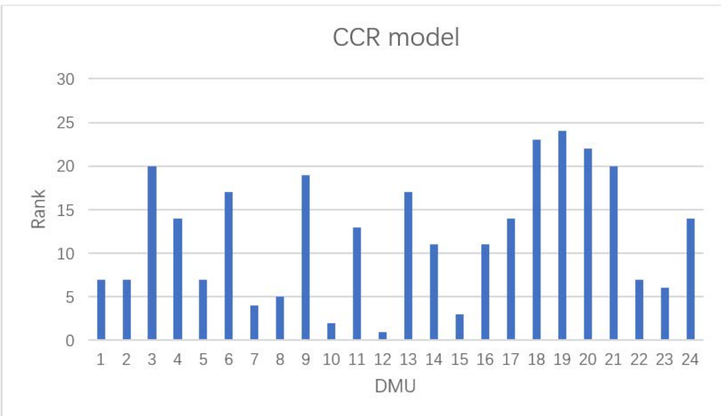

Figure 2. Rank of DMU obtained CCR model

In the context of the selection process, this suggests that candidates with little or no work experience can advance equally, or even surpass, their more experienced counterparts. This is a significant advantage for freshly educated individuals who may not have had the opportunity to gain work experience prior to their first employment due to academic and learning commitments. It is observed that the top candidate possesses strong analytical abilities, but the DEA method does not prioritize it as the most critical criterion for this candidate. Instead, the test results criterion, which has a higher mathematical value, is prioritized, although semantically, this might not be accurate. This highlights the issue of categorical values for the criteria.

The second-ranked unit, DMU 10, has slightly more work experience than the top-ranked candidate but also demonstrates higher values for the other output criteria. Although the DEA method ranks the candidate this way, it is suggested that DMU 10 should be considered first due to their significantly higher output values. As such, with only two years more work experience compared to the top-ranked candidate, DMU 10 should not be viewed as inferior. Table 2 displays the values of work experience, communication skills, critical thinking, and test results for each candidate, multiplied by their corresponding weight coefficients.

Table 2. Criterion values multiplied by criterion weights

DMU	Rank	$v(1)^*$ Work experience	$u(1)^\star$ Communication skills	$u(2)^\star$ Critical thinking	$u(3)^\star$ Test results
1	7	4.5	0	0	0
2	7	4.5	0	0	0
3	20	6	0	0	0
4	14	5	0	0	0
5	7	4.5	0	0	0
6	17	5.5	1	0	0
7	4	2.121212121	0	0	1
8	5	3	1	0	0
9	19	5.666666667	0	0	0
10	2	1.333333333	0	0	1
11	13	4.780487805	0	0	1
12	1	1	0	0	1
13	17	5.5	1	0	0
14	11	4.666666667	0	0	0
15	3	2	1	0	0
16	11	4.666666667	0	0	0
17	14	5	0	0	0
18	23	7.5	1	0	0
19	24	11.03030303	0	0	1
20	22	7	0	0	0
21	20	6	0	1	0
22	7	4.5	1	0	0
23	6	4	0	0	1
24	14	5	0	0	0

From Table 2, both the top-ranked candidate (DMU 12) and the second-ranked candidate (DMU 10) have the same value for the weight coefficient multiplied by the test results criterion, despite DMU 10 having a much higher test results value. However, DMU 10 has a higher weight coefficient for work experience, which serves as an input in this case, compared to the top-ranked candidate. Since the weight sum of inputs is part of the denominator in the nonlinear model's objective function, DMU 10's efficiency will be lower due to division by a larger number. Given the DEA method's flexibility in assigning weights to criteria based on priority, introducing weight constraints is recommended to prevent disparate rankings of semantically equal candidates.

Table 2 also shows that the DEA method assigned a weight coefficient of zero for the analytical abilities and critical thinking criteria for most DMUs, suggesting that these criteria were not considered differentiating factors for any candidate. In this case, weight constraints should be introduced to prevent selecting a candidate solely based on one criterion in which they significantly outperform other DMUs but have a weight coefficient of zero for most criteria.

The DEA method evaluates DMU 19 as the least efficient candidate, which is reasonable considering this candidate has 13 years of work experience but only scores 1 for most competencies, except for interview preparedness. This indicates that despite extensive work experience, this candidate has not managed to enhance their competencies, making them inefficient. Notably, DMUs with decision-making positions, assigned a value of 9 or 10 for work experience, share the seventh position in efficiency rankings.

Lastly, a brief review of projections and the possibility of improving inputs or reducing outputs to make a unit efficient is necessary. As an output-oriented approach was used, projections related to criteria defined as outputs should be examined.

The results show that projections for any of the output criteria are excessively high. For instance, candidate 24 needs to increase their communication skills by 1200%, reaching a value of 13. However, such projections are unrealistic within the context of candidate selection and the defined scales for the communication skills criterion, where the maximum value is 2. This issue of low value ranges for criteria can be resolved by defining ranges using different scales or employing a categorical model.

For the second-ranked candidate, it is reasonable to increase the test results value to 8.4, as this value exists on the scale. Conversely, increasing the value of the critical thinking criterion to 3 is illogical, as there is no defined value on the scale for that criterion. When using a categorical model, caution is essential since it is more flexible than the CCR model and could potentially result in most candidates being ranked in the first position. In such cases, additional constraints for weight coefficients should be introduced, preferably using the super-efficiency principle. However, the advantage of the categorical model lies in its ability to respect possible values for projections, which is crucial for interpreting how certain inefficient units can become efficient. Unrealistic projections cannot be used for this purpose. Table 3 presents the projections for the communication skills criterion, and the previously mentioned considerations apply to the criteria not shown in the table as well.

Table 3. Projections for the criterion of communication skills

		Communication kills		
DMU	**Rank**	**Current value**	**Benchmark**	**% wise**
1	7	1	9	800
2	7	2	9	350
3	20	1	12	1100
4	14	2	10	400
5	7	2	9	350
6	17	2	11	450
7	4	1	5	400
8	5	2	6	200
9	19	2	17	750
10	2	2	3	50
11	13	1	14	1300
12	1	1	1	0
13	17	2	11	450
14	11	2	14	600
15	3	2	4	100
16	11	2	14	600
17	14	2	10	400
18	23	2	15	650
19	24	1	13	1200
20	22	1	14	1300
21	20	1	12	1100
22	7	2	9	350
23	6	2	8	300
24	14	2	15	650

3.3 Comparative Analysis of CCR Model with BCC and Categorical Model

In this section, the results obtained using the BCC and categorical DEA models is summarized, which have certain advantages and disadvantages compared to the basic CCR model. As mentioned, the CCR model provided a clear distinction among candidates, but the obtained projections do not provide much information on what inefficient candidates should improve, as the values defined in the projections are outside the range defined by the criteria scales.

Based on the output-oriented categorical model results, it can be concluded that all DMU units are assessed as efficient, confirming the fact that the categorical DEA model yields a "more flexible efficiency frontier." According to the given rankings, all candidates should be hired. Therefore, the selection process in this case would boil down to the person responsible for candidate selection manually comparing candidates and assessing their efficiency for the job.

However, each DMU unit has a different reference unit, whereas in the CCR model, only DMU 12 was evaluated as the sole efficient unit. The projections in the categorical model are more realistic, as they do not exhibit increases in certain attribute values that are beyond the defined scales for criteria. In this case, the projections provide valuable insights even about falsely efficient units, i.e., those with projections greater than zero but an efficiency score equal to one. Based on this information, the personnel responsible for candidate selection can make a somewhat accurate decision.

Table 4. Projections for DMU units obtained by the categorical model

DMU	Communication skills		Critical thinking		Test results	
	Projection	% wise	Projection	% wise	Projection	% wise
1	2	100.00%	15.454 .545	54.55%	54.818 .182	149.17%
2	2	0.00%	1	0.00%	1	0.00%
3	2	100.00%	1.6	60.00%	5.4	0.00%
4	2	0.00%	2	0.00%	3.04	16.92%
5	2	0.00%	2	0.00%	2.6	0.00%
6	2	0.00%	2	0.00%	4.5	0.00%
7	1	0.00%	1	0.00%	6.6	0.00%
8	2	0.00%	12.727 .273	27.27%	58.909 .091	90.03%
9	2	0.00%	2	100.00%	4.8	71.43%
10	2	0.00%	1	0.00%	6.3	0.00%
11	1	0.00%	1	0.00%	8.2	0.00%
12	1	0.00%	1	0.00%	2.8	0.00%
13	2	0.00%	2	0.00%	4.2	0.00%
14	2	0.00%	2	0.00%	4.8	0.00%
15	2	0.00%	2	0.00%	2.5	0.00%
16	2	0.00%	1	0.00%	7.6	0.00%
17	2	0.00%	16.363 .636	63.64%	53.454 .545	37.06%
18	2	0.00%	2	0.00%	4.8	14.29%
19	2	100.00%	19.090 .909	90.91%	49.363 .636	49.59%
20	2	100.00%	2	100.00%	4.8	92.00%
21	2	100.00%	2	0.00%	4.34	66.92%
22	2	0.00%	2	0.00%	5.2	0.00%
23	2	0.00%	14.545 .455	45.45%	56.181 .818	0.32%
24	2	0.00%	1	0.00%	7.6	245.45%

Given that all units have been assigned a rank of 1 in this model, indicating that they are efficient, there are still certain projections that suggest some units are falsely efficient. Table 4 presents the projections for the communication skills, critical thinking and test results criteria. Based on that, DMU units 5, 6, and 7 are considered efficient because they have projections equal to zero for every criterion. However, for example, DMU 8 can be considered inefficient since it has projections for critical thinking and test results. In order for this unit to become efficient, the critical thinking projection would need to increase to 1.27, or approximately 27%. However, since the critical thinking scale consists of integer values ranging from 1 to 3, this increase does not make sense, and it can be concluded that DMU 8 is still efficient for this criterion, and the critical thinking value of 1 should be maintained.

Regarding the criterion of test results, the mentioned decision-making unit has a projection of 90.03%, indicating that the test results would need to increase by 5.89 to become efficient, suggesting that this DMU unit is falsely efficient. Similar considerations apply to all other units that have projections for some criteria. Truly efficient units are considered those with projections equal to zero for every criterion.

The variable returns to scale model, the BCC model, logically makes more sense to use, as increasing the input (in this case, work experience) does not lead to a proportional increase in the output attributes in the context of candidate selection. The same input data as the previous two models were used, and the orientation is also output-oriented, aiming to increase the output for a given level of input. The results obtained using the BCC model are presented in Figure 3.

It can be observed that the BCC model does not make as clear a distinction as the CCR model, which is why the research primarily focused on using the constant returns to scale model. In this case, most DMU units are ranked in first place, while DMU 3 occupies the second-to-last position. Similar to the application of the CCR model, DMU 19 is determined to be the least efficient unit in the observed set. The BCC model provides a slightly clearer distinction among candidates compared to the categorical model.

The projections obtained from this model are not ideal as the values exceed the values defined by the scales for the criteria, but they are significantly better compared to the CCR model. However, it can be determined that only DMU 12 is efficient, as it has projections equal to zero for every criterion, while the rest represent falsely efficient units.

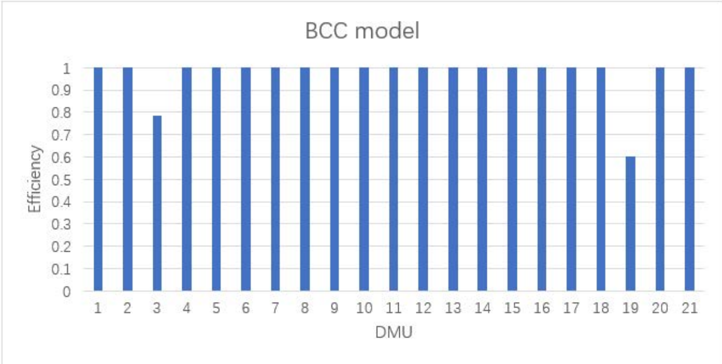

Figure 3. Results obtained using the BCC model

Through comparative analysis, it can be concluded that the CCR model provides the most concise results, which do not require detailed analysis and interpretation by an expert compared to the other two models. The CCR model assigns different ranks to each candidate, which is beneficial for decision-makers and recruiters as it eliminates the need for manual comparisons among candidates. However, this does not exclude the need for decision-makers to review the results generated by the method and use their experience to determine the validity of the results.

Although the categorical and BCC models may not provide an immediate clear distinction among candidates, a more detailed analysis of projections can identify falsely efficient units and determine the most suitable candidate for employment.

Based on all the previous interpretations, it can be concluded that a skilled analyst can utilize all three models if they are well aware of their strengths and weaknesses. Therefore, it is ideal to solve multiple models for any given set of input data, compare their results, and make informed business decisions accordingly.

4 Discussion

This section presents examples of applying DEA in the candidate selection process for specific job positions. The objective of reviewing various studies is to confirm the hypothesis that DEA is a flexible approach that can be applied to evaluate the efficiency of different business entities and systems. Most business systems monitor their operations using various parameters such as efficiency, effectiveness, and productivity. Often, current parameter values are compared to previous values to identify areas that need improvement to restore or enhance operational efficiency. However, the DEA method offers the opportunity for both internal and external comparisons, with a greater emphasis on external comparisons. This means that the business system itself should be compared to other systems in the market to identify potential areas for improvement.

In a study conducted by Johnson and Zhu in 2003 at WPI University, DEA was used for selecting the best candidate for a faculty position. The following criteria were utilized: research work, teaching performance, prior experience, and recommendations [9]. It is common for each member of the selection committee to have their own opinions or preferences towards certain candidates based on performance measures. Additionally, some candidates may emphasize their research work, while others may highlight their teaching abilities. During the process of reconciling conflicting opinions, it is highly likely that certain performance measures may be overlooked. Consequently, the assessment can be incomplete with respect to all selected performance measures [8].

Therefore, the assumption of mutual independence between inputs, outputs, and decision-making units is crucial in the DEA method. All the mentioned criteria must be taken into consideration, and a clear distinction must be made among the candidates in order to separate those who can confidently meet all the company's requirements. Furthermore, sample decision-making units (candidates) must be defined for each inefficient candidate, aiming to identify ways for improvement and thereby increasing the possibility of employment.

In a study conducted by Martinovic and Savic [8], Conjoint analysis was primarily used to determine the preferences of employees in the human resources sector regarding the skills and qualities that a candidate should possess to be selected for a specific job position. Subsequently, the study employed Data Envelopment Analysis (DEA) to select the most efficient candidate from the pool of observed candidates who applied for a particular position, and to assess what improvements are needed for inefficient candidates to become efficient.

In the study, three groups participated as respondents: decision-makers in the hiring process, students, and professors. Conjoint analysis determined that the most important criterion in the selection process was the completion of studies, followed by work experience. The least important criteria were rated as communication skills, teamwork, and language proficiency, with language proficiency being the least significant. For evaluating the efficiency of candidates in the hiring process, the study used three attributes as outputs: completed studies, work experience, and interview score, while the input was defined as fictional. Eighteen decision-making units were observed. Based on the results obtained in this study, it was concluded that companies commonly strive to select candidates with work experience to shorten the training process and enable the newly hired employee to start working immediately. However, a candidate who achieves a high score in the interview, indicating their readiness and interest in giving their maximum effort in the company, and who also has a high score for their completed studies, will be assessed as efficient and therefore has a great chance of being employed.

The combination of DEA (Data Envelopment Analysis) and Conjoint analysis facilitates the candidate selection process, both for the individuals conducting the selection and for the candidates themselves. HR professionals no longer need to independently compare the attribute values of candidates; they simply need to interpret the results provided by the DEA method and make a decision regarding which candidate to hire. On the other hand, the results of the Conjoint analysis are utilized to communicate to the candidates the techniques for skill enhancement and the preferred qualities of the decision-makers in the hiring process, thus highlighting the attributes they should possess to be ideal for the vacant position.

Moreover, to simplify the analysis, the numerous criteria used in the Conjoint analysis in this study were condensed into three. The issue of categorical criteria was addressed through quantification to enable the application of Data Envelopment Analysis.

5 Conclusions

Based on the previous discussion, it can be concluded that work experience is not the most important criterion in the selection process. Therefore, candidates with limited work experience can still be evaluated as efficient. On the other hand, a challenge arises when applying the DEA method to criteria with small ranges, specifically when they are defined on an ordinal scale.

For such criteria scales, the use of a categorical model is necessary. To retain the advantages of the CCR (Constant Returns to Scale) model, a constant yield to scale must be chosen. Semantically, this contradicts the meaning of a constant yield to scale because, for these criteria in the context of the selection process, the increase in inputs does not lead to a proportionate increase in outputs. This suggests that a variable yield to scale, or in the general case, the BCC (Variable Returns to Scale) model, should be used in future research and applications.

In conclusion, the application of DEA in the candidate selection process can be a valuable tool for HR professionals and decision-makers. It not only allows a comprehensive assessment of each candidate based on multiple criteria but also provides a quantitative framework for identifying areas of improvement for candidates who are deemed inefficient. Combining DEA with other analytical methods, such as Conjoint analysis, can further enhance the decision-making process by considering the preferences of stakeholders involved in the hiring process.

While the presented studies provide clear evidence of the usefulness of DEA in the candidate selection process, it is essential to recognize that DEA is not a one-size-fits-all solution. Decision-makers should carefully consider the specific context and requirements of each job position when applying DEA or any other analytical method. Moreover, continuous advancements in the field of data analysis and artificial intelligence are likely to provide new tools and techniques that can further improve the efficiency and effectiveness of the candidate selection process.

In the future, it would be valuable to test DEA's effectiveness in various industries and job positions and to explore its potential integration with other decision-making tools and techniques. Additionally, researchers should investigate the potential challenges and limitations of applying DEA in candidate selection, such as the impact of small sample sizes, the appropriate choice of input and output variables, and the treatment of categorical criteria. By addressing these issues and incorporating new advances in data analysis, DEA can become an even more valuable tool for improving the candidate selection process.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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