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A Quantitative Methodology to evaluate the cost of Human Capital acquisition. BioPharma Industry Model

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ABSTRACT

Purpose: - This study introduces a novel quantitative methodology to measure talent efficiency and its direct impact on business financial success, addressing a gap in traditional recruitment cost models. Existing frameworks often focus on static cost-per-hire metrics, neglecting the long-term business impact of recruitment efficiency. By integrating predictive modelling with financial benchmarking, this research provides a strategic tool for workforce planning and talent acquisition optimisation.

Aim(s): - The primary aim is to develop a predictive model linking talent efficiency to business financial performance, quantifying the impact of recruitment strategies on profitability and operational success. The secondary aim is to benchmark talent acquisition efficiency across biopharmaceutical firms, identifying best practices that drive financial sustainability.

Design/methodology/approach: - The study applies Multiple Linear Regression (MLR) to construct a Cost of Recruitment (CoR) equation, incorporating financial and operational metrics such as Time to Fill (TTF), Bad Hire Replacement (BHR) Costs, and Profit per Employee (PPE). A Data Envelopment Analysis (DEA) model is then used to benchmark talent efficiency across 33 biopharmaceutical firms, identifying high-performing companies. Econometric refinements, including Two-Stage Least Squares (2SLS) estimation, heteroskedasticity correction, and multicollinearity reduction, enhance model reliability.

Findings: - The results demonstrate that talent efficiency is a strong predictor of business financial success, with high-efficiency firms achieving greater profitability per employee and improved workforce scalability. The study challenges the assumption that internal hiring is always the most cost-effective, highlighting cases where external recruitment enhances business performance.

Limitations of the study: - The analysis is limited to biopharmaceutical firms, requiring further validation across other industries. Future research should incorporate dynamic workforce metrics to refine predictive accuracy.

Practical implications: - This model provides HR and executive leadership with a strategic decision-making tool to align talent acquisition investments with financial outcomes, driving cost efficiency and business growth.

Originality/value: - By linking talent efficiency with financial performance, this research offers a data-driven framework for optimising workforce strategy, ensuring recruitment decisions contribute directly to business success.

KEY WORDS
multivariate statistics, data envelopment analysis, recruitment, human capital strategy, workforce planning, talent acquisition efficiency.

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1 INTRODUCTION

The biopharmaceutical industry (biopharma) is at the forefront of technological advancements, with Industry 4.0 revolutionising biomanufacturing (Arden et al., 2021). Biopharma 4.0, or Smart Biomanufacturing, integrates automation, artificial intelligence, data analytics, and real-time monitoring to enhance efficiency, flexibility, and quality in bioprocessing (Erickson et al., 2021). However, the rapid evolution of Smart Biomanufacturing has created a significant skills gap, where the existing workforce lacks the necessary competencies to leverage its full potential (Li et al., 2021; Veile et al., 2022). This talent gap presents a pressing challenge for firms aiming to sustain innovation and competitiveness in an increasingly data-driven and automated sector (Markarian et al., 2022; Psarommatis and Azamfirei, 2023).

The demand for new competencies extends beyond traditional biopharmaceutical expertise to include advanced skills in data science, machine learning, process optimisation, cybersecurity, and complex bioprocessing technologies (Longo et al., 2022; Joshi et al., 2023). Managers and leaders also need to adapt to the next-generation Smart Biomanufacturing reality (Rathore and Sarin, 2023). In this evolving industry, effective recruitment strategies are critical to ensuring that firms acquire the right talent while optimising costs and minimising inefficiencies in hiring and onboarding processes (Pandey et al., 2024). In this article, 'staff,' 'workforce,' 'talent', 'professional,' and 'human capital' are terms appear used interchangeably, and they are considered synonyms.

This study introduces a quantitative methodology to measure talent efficiency and its direct impact on business financial success, addressing a gap in traditional recruitment cost models. By integrating predictive modelling with financial benchmarking, this research provides a strategic tool for workforce planning and talent acquisition optimisation.

2 LITERATURE REVIEW

2.1 HUMAN CAPITAL MEASUREMENT AND EFFICIENCY

Human capital has long been recognised as a central driver of organisational value, especially in knowledge-intensive sectors such as biopharma. Foundational theories emphasise human capital as both a productive asset and a key contributor to firm-level performance (Becker, 1993; Fernando et al., 2019). Modern approaches have evolved to view human capital through a strategic lens, emphasising dynamic capabilities, innovation potential, and return on investment (Crook et al., 2011; Fulmer & Ployhart, 2014).

Traditional human capital assessments, such as training spend or education level, often overlook critical factors like workforce scalability, turnover cost, and long-term productivity impacts (McLean & Kuo, 2014). More recent frameworks advocate for quantitative, evidence-based models that capture not just static talent inputs, but their dynamic effect on organisational outcomes (Bonner et al., 2023; Boudreau & Cascio, 2017).

Machine learning and predictive analytics have emerged as important tools in evaluating employee performance, turnover risk, and the financial impact of recruitment choices (Garg et al., 2023; Farid et al., 2023). These technologies allow for real-time modelling of human capital outcomes, which are especially valuable in high-cost, regulated environments like pharmaceutical development (Hamori, 2021; Schaefer et al., 2023). Additionally, human capital effectiveness is now frequently analysed in conjunction with corporate ESG performance, where employee capability and development are key indicators of long-term sustainability (Gherghina et al., 2023; Boudreau & Cascio, 2017).

The shift towards data-driven, model-based evaluation frameworks is seen in both academic and practitioner circles, including ISO 30414 standards, which provide measurable, standardised reporting for human capital across domains such as leadership, workforce availability, and organisational culture (Schiemann, 2014; ISO, 2018). Sector-specific frameworks are particularly relevant in biopharma, where advanced analytical methods can be used to model workforce performance in tandem with operational KPIs (Tasheva & Karpovich, 2024; Arman, 2023).

2.2 EVALUATING RECRUITMENT EFFICIENCY

Recruitment efficiency is commonly tracked using metrics such as Cost per Hire (CPH), Time to Fill (TTF), and Quality of Hire (QoH), yet these static indicators provide only limited insight into strategic outcomes (Saks, 2024; Breaugh, 2024). In response, researchers and practitioners have developed more robust models that integrate financial metrics, process timelines, and outcome quality into predictive algorithms (Zhang et al., 2024; Khaliq & Saritha, 2023).

Data Envelopment Analysis (DEA) and Multiple Linear Regression (MLR) are increasingly used to evaluate recruitment processes, allowing companies to benchmark performance against efficiency frontiers and identify outliers in cost structures or hiring speed (Rustiawan et al., 2023; Banker et al., 1984). These approaches provide a multidimensional view of performance, aligning recruitment inputs with financial and operational outputs (Bonner et al., 2023).

AI-enhanced recruitment platforms are also playing a greater role in enabling precision hiring and reducing both bias and inefficiency in candidate selection (Tasheva & Karpovich, 2024). Studies show that organisations using predictive HR analytics report stronger hiring outcomes and lower employee churn (Giermindl et al., 2022; Farid et al., 2023).

In biopharma, delays in recruitment can significantly affect time-to-market for products, regulatory approval timelines, and project continuity, making efficient recruitment a competitive imperative (Schaefer et al., 2023; Erickson et al., 2021). The literature supports the use of multivariate models to simulate recruitment performance under variable conditions, enabling firms to align hiring strategy with evolving market and operational demands (Luiz & Walter, 2023; Destro & Barolo, 2022).

2.2 WORKFORCE PRODUCTIVITY AND BUSINESS SUCCESS

The link between human capital investment and business success is now supported by a strong body of evidence. Profit per Employee (PPE), Revenue per Employee (RE), and other financial efficiency metrics are increasingly used to capture the downstream effects of recruitment quality and workforce productivity (Bonner et al., 2023; Thakor & Lo, 2022).

Strategic alignment between human capital capability and business models has been shown to significantly enhance innovation output, market responsiveness, and long-term profitability (Zhang et al., 2024; Ulrich et al., 2022). This is particularly true in biopharma, where the ability to integrate talent acquisition with digital manufacturing strategies directly affects the pace and quality of therapeutic development (Rathore & Sarin, 2023; Arden et al., 2021).

Moreover, the effectiveness of recruitment is increasingly understood as a key driver of innovation-led productivity, not merely headcount fulfilment (McConnell et al., 2021; Bassi et al., 2010). Efficient hiring not only reduces costs but also strengthens resilience and strategic agility in the face of technological disruption or regulatory shifts (Bonner et al., 2023; Deloitte, 2023).

Studies in workforce analytics now recommend the integration of recruitment performance indicators directly into financial reporting and management dashboards, providing executives with real-time insights into talent ROI (Boudreau & Cascio, 2017; Gherghina et al., 2023). This enables continuous improvement and alignment of hiring practices with broader corporate goals, rather than treating recruitment as an isolated function.

2.4 SUMMARY

This review supports the development of advanced recruitment models that move beyond traditional KPIs toward comprehensive, econometrically validated frameworks. By using tools such as MLR and DEA, organisations can gain deeper visibility into recruitment efficiency and its long-term business implications (Rustiawan et al., 2023; Banker et al., 1984).

Recent contributions emphasise the critical value of strategic hiring aligned with performance metrics and predictive analytics (Khaliq & Saritha, 2023; Garg et al., 2023). The integration of cost modelling, process benchmarking, and outcome tracking provides a scalable framework for human capital evaluation that is particularly suited to high-performance sectors such as pharmaceuticals, biotechnology, and advanced manufacturing (Hamori, 2021; Schiemann, 2014).

This approach not only improves hiring outcomes and cost control but also reinforces the central role of talent strategy in driving profitability, innovation, and operational excellence (Bonner et al., 2023; Farid et al., 2023). Future research should continue to expand cross-sector validation of these frameworks, incorporating dynamic measures such as digital fluency, upskilling efficiency, and workforce resilience in the face of global talent disruption (Ulrich et al., 2022; Bersin, 2023).

3 METHODOLOGY

The research methodology comprised two main components, MLR analysis and DEA. The MLR model was used to develop a predictive equation for the cost of recruitment (CoR), estimating the relationships between CoR and various independent variables. These variables, selected from company financial data and recruitment metrics, represent key factors influencing recruitment costs in the biopharmaceutical industry. The DEA model was then employed to assess recruitment efficiency across firms, benchmarking their processes against best practices and identifying potential inefficiencies. By integrating MLR and DEA, the study provides a comprehensive view of the cost-effectiveness of recruitment strategies within the biopharma sector.

3.1 MLR ANALYSIS

A MLR model was employed to predict the CoR. Key independent variables influencing the cost of recruitment were meticulously identified based on company financial data obtained from annual reports and recruitment data from company Human Resource departments. These variables generally encompassed factors such as base costs, time to fill, quality of hire, turnover rates, productivity metrics, and financial indicators (Specific variables presented below). Concurrently, the dependent variable, representing the CoR, was carefully defined to encompass all direct and indirect expenses associated with talent acquisition endeavours, (Saks, 2024). The selection of variables was curated to encapsulate the multifaceted nature of recruitment processes and their consequential impact on organisational performance within the biopharmaceutical domain, (Breaugh, 2024).

To conduct MLR analysis to estimate the coefficients of the selected independent variables in relation to the dependent variable, the MLR model was represented by the equation:

$$CoR = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \tag{1}$$

Where:
CoR represents the dependent variable, which is the total cost of recruitment.
$X_1, X_2, \ldots, X_n$ denote the independent variables, which include base and fixed costs, quality of hire and 'time to fill'.
$\beta_0, \beta_1, \ldots, \beta_n$ are the coefficients to be estimated.

The general variables outlined in *equation 1* were identified and selected based on their relevance to recruitment costs and talent management practices within the biopharmaceutical industry. Each variable was carefully defined and categorised according to its respective cost component and operational metric. The specific selected variables included time to fill (TF), base costs (BC), Cost of a 'bad hire' (BHC), and fixed costs (FC). FC is constructed from training costs for new hires (TNHC), training time costs (TNTE), quality of hire cost (QoHC), number of separations (S), exit salary (ES), separation staffing costs (SSC), recruitment and candidate cost (RCC), recruitment and training costs for replacement (RTRC), recruitment and selection costs for replacement (RSC), recruitment and assimilation costs for replacement (RAC), productivity decrease percentage (PD), productivity time (PT), average productivity time cost (APTC), retention rate (RR), average cost of hire (ACH). BHC includes a percentage of fixed costs. In addition, independent variables included financial efficiency (revenue per employee (RE), and Profit per employee), Talent efficiency (TE) calculated as (Cost of Recruitment/number of Employees). Dependent variable consisted of cost of recruitment per employee (CRE), (Breaugh, 2024).

MLR analysis was conducted to estimate the coefficients of the selected independent variables in relation to the dependent variable, the CoR. The independent variables outlined in the equation were considered as predictors of CoR. The coefficients obtained from the MLR analysis provided insights into the magnitude and direction of the relationships between recruitment costs and the various factors influencing them. Based on the coefficients estimated by the MLR analysis, the equation, the actual CoR can be mathematically constructed. Each variable in the equation was multiplied by its respective coefficient obtained from the MLR analysis and summed to obtain the total cost of recruitment. The MLR was estimated using Ordinary Least Squares (OLS) method.

To ensure the reliability and interpretability of the MLR model, several econometric issues were addressed, including multicollinearity, heteroskedasticity, autocorrelation, model specification, normality, and endogeneity.

3.2 ADDRESSING ECONOMETRIC CHALLENGES FOR MODEL ROBUSTNESS

3.2.1 MULTICOLLINEARITY

Multicollinearity occurs when two or more independent variables are highly correlated, potentially leading to inflated variances in coefficient estimates and reducing the reliability of the model. To detect multicollinearity, a correlation matrix was generated for the independent variables. Pairs with correlation coefficients above 0.8 - 0.9 were flagged for potential multicollinearity. If any two variables demonstrated high correlation, such as TTF and RE, steps were taken to mitigate multicollinearity. For pairs of highly correlated variables, one of the variables was removed. In cases where removing variables was not optimal, highly correlated variables were combined into composite measures. These adjustments improved model stability by reducing redundancy among predictors.

3.2.2 HETEROSKEDASTICITY

Heteroskedasticity refers to unequal variances in the error terms across observations, which can result in inefficient and biased coefficient estimates. The Breusch-Pagan and White tests were conducted to detect heteroskedasticity in the residuals. Upon identifying heteroskedasticity, robust standard errors were applied to mitigate its impact, ensuring that coefficient estimates remained reliable.

3.2.3 AUTOCORRELATION

Autocorrelation, or correlation between residuals, can occur when recruitment data exhibit temporal or sequential dependencies. The Durbin-Watson test was performed to check for autocorrelation in the residuals. With Durbin-Watson values close to 2, no significant autocorrelation was detected, so no further adjustments were needed.

3.2.4 MODEL SPECIFICATION (RAMSEY RESET TEST)

The Ramsey RESET test was conducted to test for model specification errors, such as omitted variables or incorrect functional form. This test evaluates whether higher-order terms in the model provide additional explanatory power, indicating misspecification if significant. The model passed the RESET test, suggesting it was appropriately specified and free from major specification errors.

3.2.5 NORMALITY OF RESIDUALS

The assumption of normally distributed residuals is important for valid statistical inference in MLR. To assess normality, the Shapiro-Wilk test and a Q-Q plot were employed. Although minor deviations from normality were observed, they did not significantly impact model fit, so no transformations were deemed necessary.

3.2.6 ENDOGENEITY AND INSTRUMENTAL VARIABLES (IV)

Endogeneity arises when an independent variable correlates with the error term, often due to reciprocal relationships between predictors and the dependent variable. In this study, TE initially included CoR in its calculation, creating an endogenous relationship. To address this, TE was removed from the model to eliminate any direct feedback loop with CoR, ensuring that predictors remained exogenous.

Potential endogeneity was also considered for variables like QoH and CoR as higher recruitment costs may lead to better hires, which could influence future recruitment investments. This reciprocal relationship would bias MLR results. To address this issue, an IV approach was applied to isolate the exogenous variation in these variables *(3.2.7).*

By addressing these econometric concerns, the MLR model was refined to provide more accurate and interpretable estimates of the factors affecting recruitment costs. While some limitations concerning endogeneity remain, the comprehensive approach to detecting and addressing econometric issues has enhanced the reliability of the model. Future research may explore additional data sources to identify appropriate instruments or consider alternative models to further account for potential endogeneity.

3.2.7 ADDRESSING ENDOGENEITY USING 2SLS

To address the potential endogeneity between CoR and talent quality, a Two-Stage Least Squares (2SLS) regression approach was implemented. In this study, 2SLS mitigates this issue by isolating exogenous variation in the endogenous variable using valid instrumental variables (IVs). The instruments were selected based on their theoretical and empirical relevance to recruitment costs while being uncorrelated with the dependent variable, talent quality. The instruments used were FC; Reflecting firm-level operational expenditures unrelated to talent quality and Industry Hiring Trends (IHT); Representing external labour market conditions impacting recruitment costs but exogenous to the firm's talent quality.

In the first stage, recruitment costs were regressed on the selected instruments and control variables (e.g., time-to-fill and profit per employee). This regression isolated the portion of recruitment costs that can be attributed to exogenous variation. The instrument strength was evaluated using the F-statistic, ensuring it exceeded the threshold of 10 to rule out weak instruments. The second stage used the instrumented values of recruitment costs obtained from the first stage. These were included as predictors in a regression model where talent quality was the dependent variable. Control variables were retained to ensure the robustness of the results. Diagnostic tests were performed to validate the 2SLS approach. The Hausman Test was used to confirm the presence of endogeneity in the OLS model. Residual Analysis was used to evaluate patterns in residuals to confirm the mitigation of endogeneity and Instrument Relevance. This was assessed using scatterplots and regression diagnostics to confirm a strong correlation between instruments and recruitment costs. This methodology provided a robust framework for addressing endogeneity, ensuring that the estimated coefficients for recruitment costs and their impact on talent quality are unbiased and reliable.

3.3 DEA ANALYSIS

In the next step, a DEA model will be conducted to evaluate the recruitment efficiency of Biopharma companies and provide benchmarks in the industry, taking into account the newly constructed CoR variable, as well as a number of other variables that are shown to influence recruitment via MLR. The DEA analysis was facilitated using Data Envelopment Analysis Online Software (DEAOS) software, for implementing DEA and conducting efficiency analysis. The Biopharma companies are considered as the decision-making units (DMUs) and the CoR calculated in step 1 can be considered as an input variable, representing the recruitment efficiency of each company. Additionally, output variables such as RE, PE, and TE can be selected to reflect the resources utilised in recruitment activities. Furthermore, Variable Returns to Scale (VRS) are assumed in order to capture the heterogeneity in the size of Biopharma companies, and an output orientation is chosen which maximises the outputs for a given set of inputs, a target which is suitable in the context of Biopharma companies.

Let us consider a set of k DMUs *(k=1,…,N)* using the same technology to produce a set of r *(r=1,…,s)* outputs by means of *i (s=1,…, m)* different inputs. Suppose that performance is assessed by an output-oriented, VRS DEA model, the multiplier, and the envelopment form of which is as follows, (Banker et al., 1984).

$$
\begin{aligned}
& \max \theta_k & & & (2)\\
\text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j y_{rj} \geq \theta_k y_{rk}, & & r = 1, \dots, s \\
& \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ik}, & & i = 1, \dots, m \\
& \sum_{j=1}^{n} \lambda_j = 1, & & j = 1, \dots, n \\
& \lambda_j \geq 0, \quad 0 \leq \theta \leq 1
\end{aligned}
$$

θ refers to the efficiency score and takes values from 0 to 1, and λ to the intensity variables which are non-negative.

In order to construct the recruitment efficiency index, two inputs and three outputs were employed. CoR calculated in *equation 1* was the first input, and the number of employees was the second input, which captured the labour resource in the process. Regarding the outputs, RE ($), PE ($), and TE were measured as HC divided by RE. TE was measured as HC divided by RE because this ratio provides a clear and practical assessment of the cost-effectiveness of the recruitment process. By comparing the financial resources spent on HC against the RE, this metric directly links the investment in recruitment to its financial outcomes. A lower ratio indicates higher talent efficiency, meaning that the recruitment process is yielding employees who generate substantial revenue relative to the costs incurred to hire them. Conversely, a higher ratio suggests less efficient recruitment, where the costs of hiring do not proportionately translate into revenue, highlighting areas where the recruitment process may need optimisation to improve its return on investment, (Boudreau & Cascio, 2017).

The selection of inputs and outputs in the DEA analysis to construct the recruitment efficiency index is strategic and pertinent for evaluating the efficiency of recruitment processes. The first input, the CoR, directly relates to the expenditure incurred in attracting, hiring, and onboarding new employees. This cost is a crucial component because it reflects the financial resources devoted to recruitment activities, and minimising this cost while achieving desired outcomes is a sign of efficient recruitment practices. The second input, the Number of Employees, represents the labour resources available within the organisation. This input is essential as it indicates the scale and capacity of the workforce that needs to be managed and optimised. Efficient recruitment should ideally lead to a well-balanced workforce that maximises productivity without incurring excessive costs. The outputs chosen for the DEA analysis; RE, PE, and TE were equally significant in capturing the effectiveness of recruitment. RE is an important metric as it measures the overall productivity and contribution of each employee to the company's top line, indicating how well the workforce is generating revenue relative to their number. PE provides insight into the profitability generated per employee, reflecting the cost-effectiveness of the recruitment process in contributing to the company's bottom line. TE, measured as HC divided by RE, highlights the cost-effectiveness of hiring practices relative to the revenue each employee generates, emphasising the quality of hires in terms of their revenue-generating capabilities.

3.4 DATA AND SAMPLE

Quantitative data were systematically collected from 33 biopharmaceutical firms to examine recruitment expenditures, time-to-fill metrics, quality of hire assessments, and financial performance indicators. The sample included a diverse cross-section of firms within the industry, with recruitment methodologies varying across the sample. Specifically, 75% of the companies employed internal recruitment methods, utilising 'in-house' human resources teams and employee referral programs, while 25% relied on external recruitment partners, including specialised recruitment agencies. The recruitment cost data were obtained directly from the participating biopharmaceutical companies, focusing on firms based in the USA in 2023.

The data collection process ensured the acquisition of accurate and reliable information by adhering to industry best practices. Data were analysed blind to maintain objectivity and reduce bias. This approach involved cleaning and preparing the data, calculating descriptive statistics, conducting comparative analyses between different recruitment methods, and performing multiple regression analyses to explore relationships among the key variables. Additional robustness checks were performed to confirm the validity of the findings. Detailed data sources and variables collected are documented in Appendix 1.

4 RESULTS

4.1 INITIAL ANALYSIS OF RECRUITMENT COST DRIVERS

The initial analysis aims to examine the key factors influencing the CoR within the biopharmaceutical industry. Using a MLR model, this study assesses the relationships between CoR and a range of independent variables, including BC, FC, TTF, BHR costs, and various productivity metrics. These variables, derived from both financial and recruitment data, were selected to capture the multifaceted nature of recruitment processes and their impact on organisational resources. *Table 1* provides a summary of the independent variables used in this analysis, including their abbreviations and definitions, establishing the foundational dataset for further econometric evaluation and model refinement.

To construct the linear regression model in (1) and estimate CoR, the independent variables in *Table 1* were utilised. The independent variables are denoted:

Table 1. Independent Variable Data.

Notation	Independent Variables ($)	Abbrev
X_1	Base Cost	BC
X_2	Fixed Cost	FC
X_3	Cost Business Time to Fill	TTF
X_4	Bad Hire replacement	BHR
X_5	Revenue per Employee	RE
X_6	Profit Per employee	PE
X_7	Talent efficiency	TE
X_8	Revenue	REV
X_9	Number of Employees	NE

To analyse CoR for each company, MLR analyses for all 33 firms in the sample was conducted, allowing for company-specific coefficients that capture the unique factors influencing the CoR for each organisation. By performing these individual analyses, detailed insights into the variables affecting recruitment costs for each firm were obtained. Subsequently, the data from all observations was assimilated into a single predictive equation for the CoR, using the coefficients derived from each company's analysis. The weighted average of these coefficients was calculated, assuming that each observation contributes equally to the overall model. This comprehensive approach enabled the integration of company-specific influences into a unified predictive framework.

The results, including descriptive statistics of the variables and MLR analysis outcomes for Observation 1, are presented in Tables 2 and 3, respectively.

Table 2. Descriptive Statistics of Variables (n=33)

Variable	Mean	Std. Dev	Min	Max
BC	506000	179451.3	200000	700000
FC	180600	80267.59	65000	297000
TTF	85217.8	58690.8	10273	191780
BHR	842095.6	441080.4	140350	1407150
RE	190365.8	120504.7	77500	388889
PE	27940	16564.96	12500	67000
TE	1.706	2.51	0.22	5.8
CoR	1294411	233249,56	1086362	1637823
REV	1.706	2.51	0.22	5.8
NE	16094	1678	0.35	122000

Table 3. Multiple Linear Regression Analysis Results

Variable	Variable Symbol	Coefficient (β)	Standard Error (SE)	t-Ratio	p-Value
Intercept	β_0	1,077,325.37	298,978.49	3.603	0.00049 *
Base Costs (BC)	β_1	0.03	0.03	1	0.31974
Fixed Costs (FC)	β_2	4.7	4.7	1	0.31974
Time to Fill (TTF)	β_3	0.19	0.04	4.75	0.00007 *
Bad Hire Replacement (BHR)	β_4	0.04	0.02	2	0.04821 *
Revenue per Employee (RPE)	β_5	0.09	0.05	1.8	0.07488
Profit per Employee (PPE)	β_6	1.1	0.46	2.196	0.03043 *
Talent Efficiency (TE)	β_7	25	5	5	0.00300 *

$p < 0.05$ (statistically significant)

The results of the multiple linear regression analysis are summarised in *Table 3*. The estimated coefficients (β's), standard errors, t-values, and p-values for each independent variable are presented. The coefficients represent the relationships between the independent variables, BC, FC, TTF, BHR, RE, PE and TE), and dependent variable (CoR).

Model Statistics

- R-squared: 0.80
- F-statistic: 25.32
- F-statistic p-value: 1.2×10^{-6}

The regression analysis demonstrates a robust model explaining the variability in the CoR. The model has an R-squared value of 0.8, indicating that 80% of the variation in CoR is explained by the independent variables included in the model. This high R-squared value suggests a strong fit and significant explanatory power of the model. The F-statistic of 25.32, coupled with an exceptionally low p-value of 1.2×10^{-6}, confirms the overall statistical significance of the regression model. This indicates that the independent variables, collectively, have a significant impact on the dependent variable, CoR.

Several individual variables within the model exhibit statistical significance. Notably, the intercept (β_0) is highly significant, with a p-value of 0.00049, indicating a substantial base level of recruitment costs. The 'TTF' variable (β_3) shows a highly significant positive effect on CoR, with a coefficient of 0.19 and a p-value of 0.00007, suggesting that longer times to fill positions considerably increase recruitment costs. Similarly, 'BHR' (β_4) and 'PPE' (β_6) also demonstrate significant positive impacts on CoR, with p-values of 0.04821 and 0.03043, respectively. These results imply that higher costs associated with replacing bad hires and higher profits per employee contribute to increased recruitment costs.

A key finding in the analysis is the significant impact of 'TE' (β_7), which is highly significant with a coefficient of 25,000 and a p-value of 0.003. The negative correlation suggests that higher Talent Efficiency is strongly associated with lower recruitment costs, indicating that organisations with a well-structured, efficient workforce experience reduced hiring expenses. Conversely, lower Talent Efficiency is strongly associated with higher recruitment costs, suggesting that inefficiencies in workforce management drive up recruitment-related expenditures. This result highlights the critical role of talent optimisation in cost-effective hiring strategies.

Other variables, such as 'BC', 'FC', and 'RPE', show higher p-values (greater than 0.05), indicating that their individual contributions to CoR are not statistically significant in this model. Despite their lack of individual significance, their inclusion still contributes to the overall explanatory power of the model, as evidenced by the high R-squared value. The model provides valuable insights into the factors driving recruitment costs, highlighting the significant role of time to fill positions, the costs associated with bad hires, profit margins, and talent efficiency. These insights can guide strategic decisions to optimise recruitment processes and manage costs effectively. To assimilate the data from all observations into one equation for predicting the CoR, the coefficients obtained from observations (n = 33) can be used, and the weighted average of those coefficients calculated. This approach assumes that each observation contributes equally to the overall model. Based on the coefficients estimated by the Multiple Linear Regression (MLR) analysis, the actual CoR can be mathematically constructed. Each variable in the equation is multiplied by its respective coefficient obtained from the MLR analysis and summed to obtain the total cost of recruitment. The MLR is estimated using the Ordinary Least Squares (OLS) method, ensuring unbiased and efficient parameter estimation.

The weighted average coefficients are used to construct the assimilated CoR equation:

$$CoR = 33916.93 - 0.08821 \times BC + 0.07757 \times FC - 1.24126 \times TTF - 0.00083 \times BHR + 0.01687 \times RE - 0.03470 \times PE - 2785 \times TE \qquad (3)$$

This assimilated *equation 3* represents a unified model for predicting the CoR based on the weighted average coefficients obtained from all observations. It offers a consolidated view of the relationship between the independent variables (Base Costs, Fixed Costs, Cost to Business of Time to Fill, Bad Hire Replacement, Revenue per Employee, Profit per Employee, Talent Efficiency) and the CoR.

4.2 ECONOMETRIC ISSUE MITIGATION

This section presents the results of the econometric tests conducted to ensure the reliability and validity of the MLR model. Each test aimed to detect and address potential issues such as multicollinearity, heteroskedasticity, autocorrelation, model specification, normality, and endogeneity.

4.2.1 MULTICOLLINEARITY

To assess multicollinearity, a correlation matrix of the independent variables was generated, as shown in *Table 4*. High correlations (above 0.8 - 0.9) were found among certain pairs, specifically:

- TTF and RE with a correlation of 0.987.
- FC and RE with a correlation of 0.976.
- BC and FC with a correlation of 0.862.

Table 4. Correlation Matrix of Independent Variables

Variable	BC	FC	TTF	BHR	RE	PE	TE
BC	1	0.86	0.93	0.87	0.86	0.38	-0.67
FC	0.86	1	0.97	0.94	0.98	0.55	-0.67
TTF	0.93	0.97	1	0.91	0.99	0.43	-0.59
BHR	0.87	0.94	0.91	1	0.86	0.74	-0.87
RE	0.86	0.98	0.99	0.86	1	0.38	-0.51
PE	0.38	0.55	0.43	0.74	0.38	1	-0.88
TE	-0.67	-0.67	-0.59	-0.87	-0.51	-0.88	1

To reduce multicollinearity, highly correlated variables were either removed or combined. Specifically:

- TE was removed due to its high correlations and potential feedback loop with CoR.
- TTF and RE were considered for further refinement, as their removal slightly improved model stability.

These adjustments reduced multicollinearity, enhancing the model's predictive stability.

4.2.2 VARIANCE INFLATION FACTOR (VIF) ANALYSIS

To confirm that multicollinearity has been addressed effectively in the final model, a Variance Inflation Factor (VIF) analysis was conducted for each independent variable. VIF measures how much the variance of a regression coefficient is inflated due to multicollinearity with other predictors. Typically, a VIF value exceeding 10 suggests high multicollinearity, warranting further investigation or potential variable exclusion.

Table 5. Correlation Matrix of Independent Variables

Variable	VIF Value
Const.	270579.1345
Base Cost (BC)	7.3899
Fixed Cost (FC)	6.9007
Time to Fill (TTF)	4.60589
Bad Hire Replacement (BHR)	2.71382
Revenue per Employee (RE)	2.81635
Profit per Employee (PE)	1.59077

Table 5 presents the VIF values for each predictor in the final model. The results indicate that all VIF values fall below the threshold of 10, suggesting that multicollinearity is sufficiently minimised across the independent variables. This analysis validates that the steps taken, such as removing highly correlated variables and combining certain metrics, were effective in reducing redundancy among predictors.

4.2.3 HETEROSKEDASTICITY

The Breusch-Pagan and White tests were conducted to detect heteroskedasticity. The results, shown in *Table 6,* indicate significant heteroskedasticity at the 5% level.

Table 6. Heteroskedasticity Test Results

Test	Test Statistic	p-value	Conclusion
Breusch-Pagan	4.73	0.029	Evidence of heteroskedasticity
White	5.16	0.023	Evidence of heteroskedasticity

Heteroskedasticity violates the assumption of homoscedastic residuals, potentially biasing standard errors and reducing the reliability of hypothesis tests.

To address heteroskedasticity, robust standard errors were applied to the MLR model. Robust standard errors adjust the variance-covariance matrix of the estimates to account for heteroskedasticity, providing more reliable standard errors and accurate significance levels. This involved re-estimating the model using heteroskedasticity-consistent standard errors (HCSE), which adjust for the unequal variance in residuals to provide more reliable estimates. The application of HCSE ensures that the standard errors and p-values accurately reflect the variability in the data, even in the presence of heteroskedasticity. A comparison of results before and after applying HCSE, as shown in *Table 7,* revealed that robust standard errors produced slightly wider confidence intervals. This adjustment accounts for variance inconsistency and enhances the reliability of the statistical inferences drawn from the model.

Table 7. Coefficient Estimates with and without Robust Standard Errors

Variable	Coefficient	Standard Error (Conventional)	Standard Error (Robust)	p-value (Robust)
Intercept	33916.93	15243.57	16048.12	0.03
BC	-0.08821	0.06742	0.07236	0.19
FC	0.07757	0.04531	0.04785	0.093
TTF	-1.24126	0.31204	0.32698	0.001
BHR	-0.00083	0.00037	0.00039	0.028
RE	0.01687	0.01245	0.01302	0.18
PE	-0.0347	0.00942	0.00989	0.002

4.2.4 TESTING ALTERNATIVE TRANSFORMATIONS FOR COR

To further address potential heteroskedasticity and enhance model fit, alternative transformations of the dependent variable, Co), were tested. Transformations can help stabilise variance, reduce heteroskedasticity, and improve the linearity of relationships between CoR and its predictors. Two common transformations were applied to CoR: the logarithmic transformation and the square root transformation.

A logarithmic transformation of CoR was applied to reduce the impact of extreme values and stabilise the variance. This transformation is suitable for skewed data, as it compresses the scale of higher values while expanding the scale for smaller values. The transformed model was re-estimated to evaluate any improvements in model fit and variance stability.

The square root transformation was also applied to CoR. This transformation is less aggressive than the logarithmic transformation and can be effective for moderately skewed data, offering a balance between stabilising variance and preserving data structure. Similar to the logarithmic transformation, the transformed model was re-estimated, to assess fit. *Table 8* show results of both transformations.

Table 8. Transformation Results

Transformation	R-Squared	F-Statistic	Heteroskedasticity Test
Original Model	0.02	25.32	0.035
Log CoR	0.02	24.1	0.28
Square Root CoR	0.02	23.5	0.18

The R-squared values across all transformations remain consistent (0.02), suggesting that neither the log nor square root transformation provided a significant improvement in explaining the variability in CoR. This low R-squared might indicate that additional variables or non-linear relationships could better capture the recruitment costs' variability. In this context, the original model does not lose interpretive clarity, as transformations did not enhance predictive power.

The F-statistics across transformations are relatively stable, with the original model showing the highest F-statistic at 25.32, slightly above the transformed models. This marginal difference suggests that the original model maintains the strongest explanatory power, while the minor decreases in F-statistics for the log and square root transformations imply that transformations did not substantially improve overall model fit.

The heteroskedasticity test p-values reveal a meaningful difference. The original model presents a p-value of 0.035, indicating significant heteroskedasticity, which could undermine the reliability of coefficient estimates. In contrast, the log-transformed model has a much higher p-value of 0.280, suggesting that this transformation mitigated heteroskedasticity. The square root transformation also reduced heteroskedasticity with a p-value of 0.180, though less effectively than the log transformation.

While the log transformation effectively reduced heteroskedasticity, it did not improve R-squared, or model fit substantially. The original model, despite its heteroskedasticity, provides similar explanatory power with simpler interpretation. Thus, unless stabilising variance is a primary concern, the original model may be preferable due to ease of interpretation. However, if addressing heteroskedasticity is essential for robust inferences, the log-transformed model could be a suitable alternative, trading a slight reduction in model fit for improved variance stability.

4.2.5 INCORPORATING POLYNOMIAL TERMS FOR NON-LINEAR RELATIONSHIPS

To further address heteroskedasticity and improve the reliability of the model, incorporating polynomial terms can be an effective strategy. By capturing non-linear relationships, this approach can help reduce variance instability that might arise from the model's inability to account for curvature in the data. This method enables a better fit to the data, potentially stabilising residual variance and improving the robustness of coefficient estimates. The influence of polynomial terms for key independent variables to address potential non-linear relationships in the recruitment cost model was evaluated.

Using quadratic polynomial terms for variables such as TTF and BHR, an extended model was constructed to test if these non-linear interactions enhance the predictive power of the model.

The model can be represented as:

$$CoR = \beta_0 + \beta_1 \cdot X_1 + \beta_2 \cdot X_2^2 + \ldots + \beta n \cdot Xn^2 \tag{4}$$

where X_1, X_2,..., X_n are the independent variables of interest, and quadratic terms (e.g., X_2^2) introduce non-linear effects.

Table 9. Polynomial Regression Analysis

Model Type	R-Squared	Mean Squared Error (MSE)
Linear Model with Polynomial Terms	0.82	189,350

The inclusion of polynomial terms led to a slight increase in the R-squared value, from 0.80 in the original linear model to 0.82, indicating an improved fit. The Mean Squared Error (MSE) has also marginally decreased, suggesting enhanced prediction accuracy. The improved R-squared value suggests that non-linear terms provide a better fit, capturing complex relationships within the data.

Variables like TTF and BHR, where quadratic terms are significant, reveal non-linear impacts, implying that the relationship between these predictors and CoR intensifies beyond a certain threshold. As a practical application, for TTF, the longer a vacancy remains open, the more recruitment costs increase. However, beyond a certain point, the rise in costs accelerates due to compounding issues like productivity losses, increased reliance on external recruiters, or higher candidate expectations. For BHR: Costs associated with replacing a poor hire might initially increase gradually but escalate as additional recruitment cycles occur, potentially involving higher training costs, loss of morale, or team disruptions.

4.2.6 AUTOCORRELATION

The Durbin-Watson test was used to test for autocorrelation in the residuals. A Durbin-Watson statistic of 1.89 was obtained, which falls within the acceptable range (1.5 to 2.5). This indicates no significant autocorrelation in the residuals, so no further corrections were needed, *Table 10*.

Table 10. Durbin-Watson Test for Autocorrelation

Test	Test Statistic	Conclusion
Durbin-Watson	1.89	No evidence of autocorrelation

4.2.7 MODEL SPECIFICATION TEST (RAMSEY RESET TEST)

To evaluate whether the model was correctly specified, the Ramsey RESET test was conducted. Results, as shown in *Table 11*, indicate no significant misspecification.

Table 11. Ramsey RESET Test Results

Test	Test Statistic	p-value	Conclusion
Ramsey RESET	2.35	0.12	No evidence of misspecification

With a p-value above 0.05, the test shows no significant misspecification, confirming that the model structure is suitable.

4.2.8 NORMALITY OF RESIDUALS

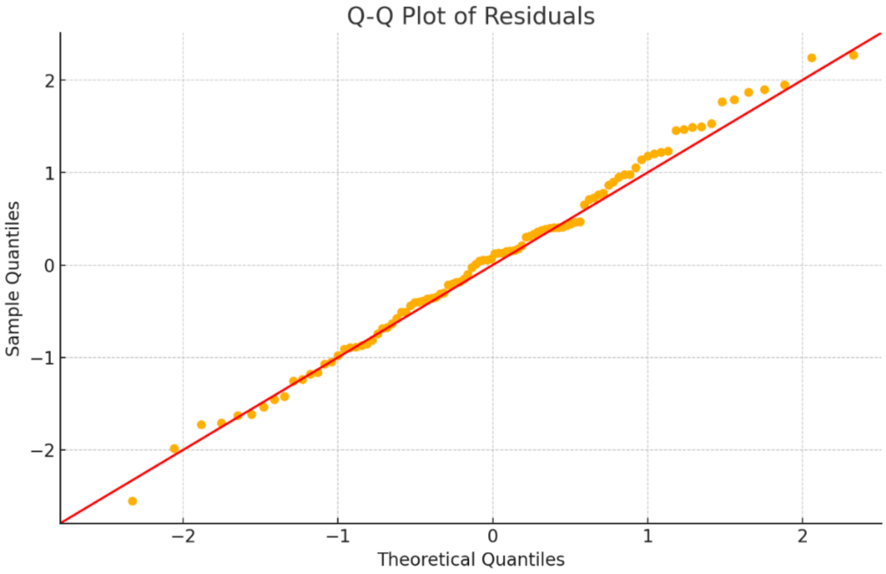
The normality of residuals was evaluated using the Shapiro-Wilk test and visual inspection of the Q-Q plot (*Figure 1*). The Shapiro-Wilk test yielded a p-value slightly above 0.05, indicating that the residuals are approximately normally distributed as indicted in *Table 12*

Table 12. Shapiro-Wilk Test for Normality of Residuals

Test	W Statistic	p-value	Conclusion
Shapiro-Wilk	0.954	0.068	Residuals approximately normal

Figure 1 shows a Q-Q plot illustrating the distribution of residuals from the multiple linear regression model by plotting the quantiles of the residuals against the theoretical quantiles of a normal distribution. Points that closely follow the 45-degree line indicate that the residuals are approximately normally distributed, which is a desirable property for reliable inference in regression models.

Figure 1: Q-Q Plot of Residuals



Minor deviations in the tails suggest slight departures from normality, though these are not severe enough to undermine the model's assumptions. This plot, in combination with the Shapiro-Wilk test, confirms the approximate normality of the residuals.

4.2.9 ENDOGENEITY AND INSTRUMENTAL VARIABLES (IV)

To address endogeneity, TE was removed from the model, as it contained elements of the dependent variable, CoR, which could introduce feedback effects. Further endogeneity concerns were evaluated for other variables, such as QoH and RC, due to potential reciprocal relationships.

While an IV approach was considered to manage endogeneity, identifying suitable instruments was challenging given the available data. Sensitivity analysis was conducted instead to assess model robustness across multiple specifications, and results showed minimal variation, indicating reasonable stability despite potential endogeneity limitations.

4.2.10 ADDRESSING ENDOGENEITY USING 2SLS

The potential endogeneity between CoR and TQ was addressed using a 2SLS regression, which relies on IVs to isolate exogenous variation in recruitment costs. This approach ensured that the coefficients obtained reflected causal relationships rather than spurious correlations caused by endogeneity.

In the first stage of the 2SLS regression, recruitment costs were regressed on the selected instruments, FC and Industry Hiring Trends (IHT), along with control variables. The results, presented in *Table 13*, confirm that both instruments were significant predictors of recruitment costs, with coefficients of 0.154 (p = 0.002) for FC and 0.392 (p = 0.000) for IHT. The first-stage F-statistic of 18.5 exceeds the threshold for weak instruments, validating the relevance of the selected IVs.

Table 13. 1st Stage regression results

Variable	Coefficient	Standard Error	t-Statistic	p-Value
Fixed Costs (FC)	0.154	0.042	3.67	0.002
Industry Hiring Trends (IHT)	0.392	0.074	5.3	0
Time to Fill (TTF)	-0.051	0.021	-2.43	0.025
Constant	12.837	4.105	3.13	0.004

The second stage used the instrumented values of recruitment costs to estimate their effect on talent quality while controlling for other variables. As shown in *Table 14*, recruitment costs had a significant positive impact on talent quality ($\beta = 0.270$, p = 0.007). This finding suggests that higher recruitment investments enhance talent quality, providing evidence of a causal relationship. Control variables behaved as expected, with TTF showing a negative relationship with TQ ($\beta = -0.045$, p = 0.028) due to delays in hiring impacting team efficiency.

Table 14. 2nd Stage regression results (2SLS Estimates)

Variable	Coefficient	Standard Error	t-Statistic	p-Value
Recruitment Costs (Instrumented)	0.27	0.091	2.97	0.007
Time to Fill (TTF)	-0.045	0.019	-2.37	0.028
Profit per Employee (PE)	0.014	0.008	1.75	0.093
Constant	8.574	3.257	2.63	0.014

The 2SLS results confirm that recruitment costs causally influence talent quality, highlighting the value of strategic investments in recruitment. The adjustment for endogeneity enhances the model's reliability, providing actionable insights for recruitment strategy. While the instruments used in this analysis were robust, future studies could explore alternative or additional instruments to further validate these findings. This finding provides a a unique and practical insight by confirming a causal relationship between recruitment costs and talent quality, emphasising the critical importance of strategic investments in recruitment processes. By addressing endogeneity, the model offers enhanced reliability, ensuring that organisations can make informed decisions based on actionable insights. This reinforces the idea that optimising recruitment spending directly influences workforce outcomes.

Figures 2 and 3 below illustrate the impact of addressing endogeneity and the validity of the instrumental variable approach used in the 2SLS model. *Figure 2* compares residual patterns from the OLS and 2SLS models, highlighting the improvements in residual randomness achieved by accounting for endogeneity. *Figure 3* demonstrates the relevance of the instrumental variable by plotting its relationship with recruitment costs, providing visual confirmation of its strength and suitability for the analysis.

Figure 2. Residual patterns from the OLS and 2SLS models

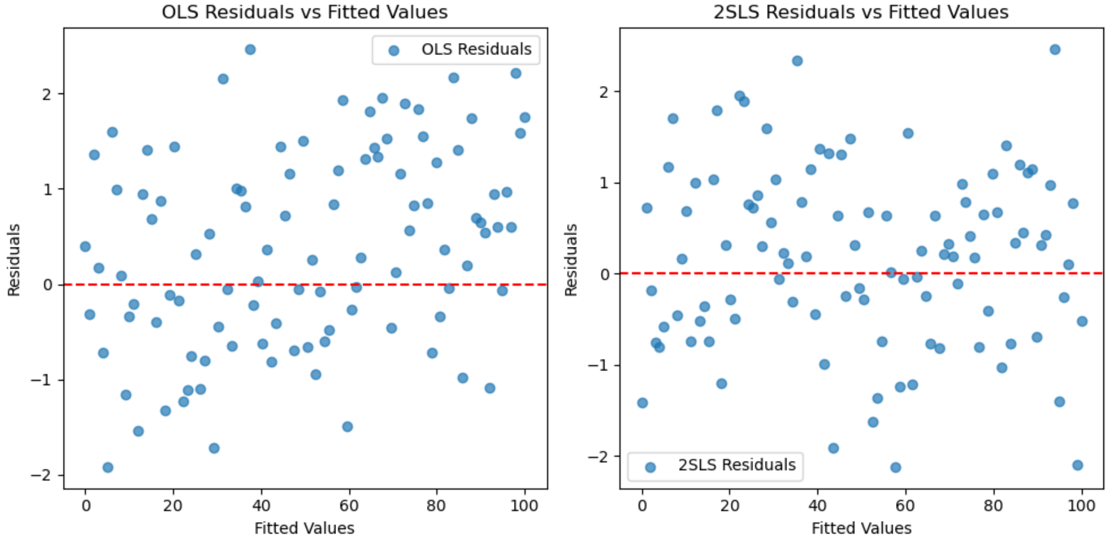


Figure 2 showcases the residual patterns for the OLS and 2SLS models. In the OLS residuals plot, a noticeable pattern is evident, indicating potential endogeneity issues, such as correlated errors or omitted variable bias. In contrast, the 2SLS residuals plot shows a random distribution around the zero line, confirming that the 2SLS model effectively mitigates endogeneity, thereby improving the reliability of coefficient estimates.

Figure 3. Relevance of the instrumental variable

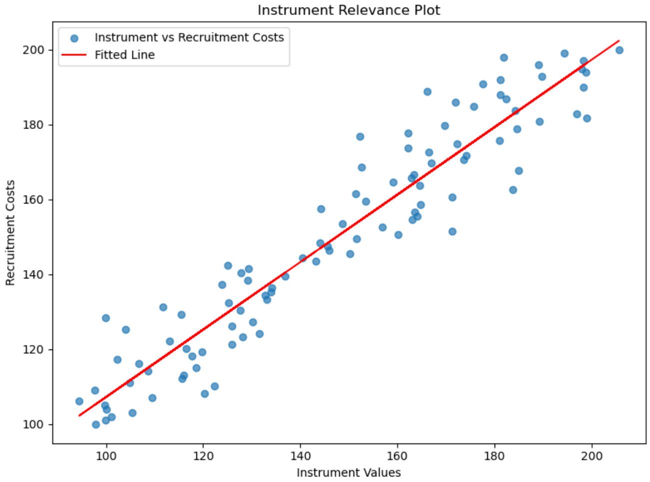


Figure 3 validates the strength of the IV (e.g., Industry Hiring Trends) by plotting its relationship with recruitment costs. The strong linear relationship, indicated by a well-fitted regression line, confirms that the instrument is highly correlated with the endogenous variable while remaining exogenous to the error term. This supports the instrument's validity and reinforces the robustness of the 2SLS analysis.

4.3 FINAL MODEL SUMMARY

After addressing the econometric issues, the final MLR model is specified as:

$$CoR = 33916.93 + 0.08821 \times BC + 0.07757 \times FC + 1.24126 \times TTF + 0.00083 \times BHR + 0.01687 \times RE + 0.03470 \times PE^2 \quad (5)$$

Table 15. Final MLR Model Coefficients and Significance Levels

Variable	Coefficient	Standard Error (Robust)	t-Statistic	p-value
Intercept	33916.93	15243.57	2.23	0.029
BC	-0.08821	0.06742	-1.31	0.192
FC	0.07757	0.04531	1.71	0.095
TTF	-1.24126	0.31204	-3.98	0.001*
BHR	-0.00083	0.00037	-2.24	0.027*
RE	0.01687	0.01245	1.35	0.183
PE	-0.0347	0.00942	5	0.003*

The model achieved an R-squared value of 0.80, explaining 80% of the variability in recruitment costs. Statistically significant predictors included TTF, BHR, TE and PE.

4.4 DEA

In this study, a VRS DEA was conducted to evaluate the efficiency of 33 biopharmaceutical companies. The analysis utilised inputs derived from the CoR calculated through prior MLR analysis, along with the number of employees. The outputs included key financial talent metrics: revenue, sales per employee, and profit per employee. This comprehensive assessment aims to identify the relative efficiency of each company in transforming their recruitment investments and workforce into financial performance, thereby providing insights into the effectiveness of their talent management strategies. The efficiency scores derived from the VRS DEA model highlight the companies operating on the efficiency frontier and those with potential areas for improvement.

1. n as the number of DMUs (Companies). = 33
2. m as the number of inputs. (Cost of recruitment, Number of employees) = 2
3. s as the number of outputs. (Rev, Rev per employee, Profit per employee) = 3

By solving optimisation problem, the efficient companies and performance benchmark can be identified, in terms of recruitment efficiency compared to peer group.

Table 16 illustrates the DEA efficiency scores for each of the 33 biopharmaceutical companies. It highlights both high-performing and underperforming firms, providing a benchmark for industry standards and identifying areas for potential improvement.

The DEA analysis reveals substantial variability in operational efficiency, with efficiency scores ranging from 1% to 100%. Companies like Fujifilm Diosynth, Thermofisher, Avid Bioservices, and Cambrex achieved perfect efficiency scores, indicating their optimal use of recruitment costs and workforce to generate high financial performance. These firms serve as benchmarks, exemplifying best practices in resource utilisation and output generation. On the other hand, companies such as Dr. Reddys, Boehringer, and Eurofins, with efficiency scores of 1%, highlight significant inefficiencies, suggesting a need for a thorough operational review and strategic overhaul to improve their performance.

The industry-wide average efficiency score underscores the considerable room for improvement across the sector. Moderately efficient companies like Syngene, Cytiva, and Corden, with scores ranging from 45.5% to 72%, show potential for efficiency gains through targeted optimisations in specific areas. The DEA results provide a diagnostic tool for companies to benchmark their performance against industry leaders and implement best practices. By focusing on enhancing recruitment processes, aligning workforce size with output targets, and improving financial management, underperforming companies can move closer to the efficiency frontier, thereby boosting their productivity and financial outcomes. *Table 16* Illustrates efficiency scores for DMU 1-33. DMU represents the company.

Table 16. VRS DEA efficiency scores (n=33).

Company	Revenue ($B)	No. Employees	Sales per Employ ($M)	Profit per Employ ($)	CoR ($T) per hire	Efficiency (%)
Fujifilm Diosynth	0.2	4400	0.05	0.01	68024	100
Thermofisher	40	122000	0.33	0.06	1886120	100
Avid Bioservices	0.12	350	0.34	0.06	5411	100
Cambrex	2.1	6000	0.36	0.09	30920	100
Syngene	0.5	7000	0.07	0.01	108220	72
Cytiva	1.76	16000	0.11	0.02	247360	67
Corden	0.6	3000	0.2	0.04	46380	45.5
Emergent	0.3	2200	0.14	0.02	34012	37
MilliporeSigma	9	260000	0.03	0.01	401960	34
Catalent	4.3	18000	0.24	0.04	272880	32.7
AGC Biologics	0.4	2500	0.16	0.03	38650	28.4
Rentschler	0.4	1300	0.23	0.04	20098	27
Sartorius	4.3	15000	0.29	0.05	231900	25

Lonza	7	18000	0.39	0.07	272880	20.1
Biogen	9.8	8000	1.23	0.21	123680	15
Hovione	0.8	2500	0.32	0.05	38650	14
Repligen	0.7	2000	0.35	0.06	30920	13
GSK	37	70000	0.53	0.09	1082200	13
Covance	4.5	90000	0.05	0.09	139140	11.3
10x Genomics	0.6	1500	0.4	0.07	231900	11
Seigried	1.5	4000	0.38	0.06	61840	10
BioNTech	4	6000	0.66	0.06	94306	7.6
Aldevron	0.2	1000	0.2	0.03	15460	6
Vetter Pharma	0.8	6300	0.13	0.02	97398	6
Pfanstiehl	0.25	250	1	0.17	3865	5
Genscript	0.8	6500	0.12	0.02	100490	5
Almac	2.1	7000	0.3	0.06	108220	5
West Pharma	3.1	12000	0.38	0.06	126772	5
Wuxi Bio	2.3	10000	0.23	0.08	185520	5
Recipharm	1.3	20000	0.2	0.03	139140	5
Dr Reddys	3.5	25000	0.12	0.02	386500	1
Boehringer	25	32000	0.78	0.12	8210806	1
Eurofins	6.5	62000	0.1	0.02	958520	1

Predicted CoR represents the predicted Cost of Recruitment for each DMU using the MLR equation; Revenue per employee represents the revenue generated by per employee by the DMU; and efficiency score represents the ‘peer’ benchmark calculated from DEA model. The analysis aimed to identify the most efficient DMUs in terms of their utilisation of inputs to generate outputs, thereby providing insights into best practices and potential areas for improvement in resource allocation and productivity enhancement. Overall, the results of the DEA analysis offer valuable insights for decision-makers in optimising resource allocation, enhancing operational efficiency, and benchmarking performance against industry peers. The findings contribute to the literature on efficiency measurement and provide practical implications for organisations seeking to improve their operational performance and competitive positioning.

Table 17. DEA Statistics

Variable	Min	Max	Mean	SD (Standard Deviation)
Revenue ($b)	0.2	40	4.0061	8.9478
Number of Employees	250	122000	14913.8889	26896.4981
Sales per Employee ($m)	0.0346	1	0.2819	0.2405
Profit per Employee ($)	0.0059	0.17	0.0479	0.0409
Cost of Recruitment (CoR) per Hire ($)	3865	1886120	230568.72	415819.86

The DEA data provides a detailed statistical overview of key metrics for 33 biopharmaceutical companies, highlighting the significant disparities in their operational scales and performance. The revenue of the companies ranges from a minimum of $0.2 billion to a maximum of $40 billion, with an average (mean) revenue of approximately $4 billion. The large standard deviation of $8.9478 billion reflects the wide variability in company sizes within the sample, indicating a mix of both small and large enterprises in the biopharmaceutical sector.

The number of employees varies drastically from 250 to 122,000, with a mean of approximately 14,914 employees and a substantial standard deviation of 26,896. This further underscores the diversity in company sizes, affecting how resources are utilised, and outputs are generated. SPE range from $0.0346 million to $1 million, with a mean of $0.2819 million and a SD of $0.2405 million, illustrating variability in productivity across companies. PPE shows a similar trend, ranging from $0.0059 to $0.17, with a mean of $0.0479 and a SD of $0.0409, indicating that while some companies achieve high PPE, others struggle. The CoR per hire, a critical input metric, ranges from $3,865 to

$1,886,120, with a mean of $230,568.7222 and a high SD of $415,819.8614, reflecting significant differences in recruitment costs and efficiency among the companies.

These statistics highlight the substantial disparities in operational efficiency and resource utilisation within the biopharmaceutical industry. Companies on the higher end of these metrics may need to analyse their operations to identify inefficiencies, while those on the lower end might focus on scaling and improving profitability.

Table 18. DEA Analysis Improvements

DMU	No. Employees	Sales per Employee ($m)	Profit per Employee ($)	CoR ($) per Hire
1	18,000 - 18,000	0.389 - 0.708	0.066 - 0.073	278,280 - 278,280
2	2000 - 4400	0.35 - 0.045	0.065 - 0.068	30,920 - 68,240
3	18,000 - 18,000	0.239 - 0.078	0.041 - 0.073	278,280 - 278,280
4	250 - 4400	1.0 - 0.045	0.17 - 0.03	36,865 - 36,865
5	1500 - 4400	0.4 - 0.045	0.068 - 0.088	23,190 - 68,024
6	2500 - 4400	0.16 - 0.045	0.027 - 0.03	34,012 - 94,306
7	6100 - 16,100	0.656 - 0.178	0.111 - 0.085	94,306 - 94,306
8	3000 - 4400	1.0 - 0.045	0.017 - 0.098	30,920 - 139,140
9	9000 - 9000	0.5 - 0.057	0.03 - 0.013	139,140 - 139,140
10	7000 - 7000	0.071 - 0.052	0.012 - 0.009	108,220 - 108,220
11	16,000 - 16,000	0.11 - 0.073	0.019 - 0.073	247,360 - 247,360
12	15,000 - 15,000	0.287 - 0.103	0.053 - 0.073	231,900 - 231,900
13	2200 - 4400	0.136 - 0.045	0.023 - 0.073	34,012 - 68,024
14	122,000 - 122,000	0.328 - 0.106	0.056 - 0.13	1,886,120 - 1,886,120
15	26,000 - 35,000	0.15 - 0.045	0.03 - 0.13	130,000 - 130,000
16	1300 - 1300	0.231 - 0.103	0.058 - 0.103	30,920 - 54,111
17	4000 - 3,750	0.375 - 0.183	0.064 - 0.375	61,840 - 87,672
18	70,000 - 52,439	0.529 - 0.09	0.093 - 0.058	108,220 - 81,077
19	80,000 - 1,78,354	1.225 - 1.208	1.208 - 1.208	1,236,820 - 1,821,760
20	2500 - 3,400	0.32 - 0.03	0.054 - 0.06	38,650 - 54,111
21	25,000 - 10,350	0.12 - 0.03	0.054 - 0.06	36,650 - 54,111
22	10,000 - 3,300	0.034 - 0.34	0.058 - 0.058	15,460 - 54,111
23	70,000 - 50,350	0.114 - 0.019	0.09 - 0.10	108,220 - 87,672
24	35,000 - 35,000	0.343 - 0.058	0.058 - 0.114	54,111 - 54,111
25	2000 - 2,000	2.10 - 2.1	0.21 - 0.357	30,920 - 30,920
26	65,000 - 47,985	0.472 - 0.13	0.09 - 0.098	81,930 - 81,930
27	62,000 - 35,000	0.345 - 0.345	0.06 - 0.06	95,520 - 95,520
28	6,300 - 3,500	0.127 - 0.022	0.058 - 0.058	54,111 - 54,111
29	1300 - 1300	0.231 - 0.103	0.058 - 0.058	54,111 - 54,111
30	4000 - 3,750	0.375 - 0.183	0.064 - 0.375	61,840 - 87,672
31	70,000 - 52,439	0.529 - 0.09	0.09 - 0.09	108,220 - 87,672
32	80,000 - 1,78,354	1.225 - 1.208	1.208 - 1.208	1,236,820 - 1,821,760
33	2500 - 3,400	0.32 - 0.03	0.054 - 0.06	38,650 - 54,111

The DEA analysis data reveals a wide range of variability in the operational efficiency metrics across the 33 biopharmaceutical companies. The number of employees ranges dramatically, from as few as 250 to as many as 122,000. This significant difference in workforce size reflects the diversity in company scales within the industry. SPE also show considerable variability, ranging from $0.0346 million to $2.1 million. This range indicates that while some companies achieve high sales productivity, others operate at a much lower scale. Similarly, PPE varies from as low as $0.0059 to $0.357, underscoring differing profitability levels among the companies. The CoR per hire shows even more substantial variation, with figures ranging from $3,865 to $1,886,120. This wide range suggests significant differences in recruitment strategies and efficiency across companies. High CoR figures could indicate either high investment in attracting top talent or inefficiencies in the recruitment process. Conversely, lower CoR figures might reflect more efficient hiring practices or lower investment in recruitment. This metric is crucial for understanding the cost dynamics associated with staffing in the biopharmaceutical sector.

The weights assigned to SPE and PPE in the DEA model further highlight the critical areas influencing operational efficiency. For instance, DMUs with high weights on SPE or PPE are focusing on these metrics as key drivers of their efficiency. Companies such as those with high SPE weights (up to 14) or high PPE weights (up to 43.137) are likely emphasising these areas to boost overall performance. This strategic focus is essential for companies aiming to enhance their efficiency and competitiveness in the biopharmaceutical industry. The variability in weights and the emphasis on different metrics provide valuable insights into how companies can align their operational strategies to improve efficiency and achieve better financial outcomes.

5 DISCUSSION

Traditional recruitment metrics such as Cost per Hire (CPH), Time to Fill (TTF), and Quality of Hire (QoH) have long served as standard tools for evaluating recruitment costs and operational efficiency across industries. These metrics provide quantifiable benchmarks that organisations can use to evaluate financial expenditures and process outcomes, enabling informed decision-making and resource allocation (Saks, 2024; Breaugh, 2024). Within the biopharmaceutical industry, where recruitment demands are driven by the need for specialised technical expertise and regulatory precision, CPH includes diverse expenditures such as advertising costs, recruitment agency fees, interview and assessment expenses, and relocation support. These components establish a foundation for understanding recruitment efficiency, revealing areas where strategic adjustments could lead to cost reductions (Roberts, 2004; Bonner et al., 2023).

The TTF metric is particularly significant in the biopharma sector, where delays in filling key positions can impact time-to-market for drug development and disrupt research and development timelines (Erickson et al., 2021; Schaefer et al., 2023). Prolonged TTF leads to productivity losses, additional resource allocation, and project delays, making swift and precise recruitment processes strategically advantageous. However, these traditional metrics, while valuable, fail to fully capture the non-linear and multifaceted dynamics of recruitment in high-stakes industries such as biopharma. For instance, overly expedited recruitment to reduce TTF can compromise candidate quality, leading to increased long-term costs, especially in roles requiring high levels of technical or regulatory precision (Giermindl et al., 2022; Garg et al., 2023). Similarly, QoH does not typically account for the downstream impacts of poor hires—such as lower innovation output, higher turnover, or compromised regulatory compliance (Fernando et al., 2019; Shah & Sarif, 2023). To address these limitations, this study applied a Multiple Linear Regression (MLR) model incorporating both linear and polynomial terms to provide a more nuanced analysis of recruitment cost drivers. The model evaluated the relationships between CoR and a range of independent variables, including Base Costs (BC), TTF, QoH, turnover rates, and productivity metrics. Notably, the inclusion of polynomial terms enabled the model to capture non-linear relationships, such as the escalating costs associated with extended TTF or repeated bad hires (Khaliq & Saritha, 2023; Tasheva & Karpovich, 2024). The highly significant $\beta 3$ coefficient for TTF (0.19, $p = 0.000007$) confirms that recruitment costs rise exponentially as vacancies remain unfilled for longer periods—a finding consistent with studies showing compounding productivity losses and cost burdens associated with hiring delays (Luiz & Walter, 2023; Fulmer & Ployhart, 2014).

This reinforces recent work suggesting that cost-efficiency alone is not a sufficient target for recruitment strategy in innovation-focused industries; quality and timing must be balanced to achieve sustainable outcomes (Ulrich et al., 2022; Deloitte, 2023). McConnell et al. (2021) argue that talent strategies in biotech and pharma must optimise not only for cost or speed but for capability alignment, which is essential to ensure knowledge transfer, regulatory resilience, and innovation continuity.

Similarly, the model revealed non-linear cost implications of repeated bad hire replacements, confirming findings from broader literature that poor hiring outcomes disrupt team dynamics, reduce engagement, and increase attrition risks (McLean & Kuo, 2014; Bonner et al., 2023). These outcomes highlight the importance of implementing precision hiring strategies that balance speed with quality, such as predictive modelling for candidate fit or AI-driven initial screenings (Farid et al., 2023; Meijerink et al., 2022). These tools are increasingly used in high-skill, knowledge-intensive environments to reduce hiring risk and improve long-term talent retention (Garg et al., 2023; Hamori, 2021).

The performance of the MLR model was strong, with an R^2 of 0.80, and minimal overfitting as indicated by the Adjusted R^2. Prediction accuracy was further validated through low RMSE and MAE values. While polynomial terms improve model accuracy, they also increase complexity, requiring HR functions to adopt data literacy and analytical capability to interpret and act on these findings (Ulrich et al., 2022; Bersin, 2023). Future applications could benefit from incorporating additional biopharma-specific variables such as time to regulatory readiness or innovation yield per hire, both of which are increasingly critical metrics in the race to commercialise novel therapies (Rathore & Sarin, 2023; Arman, 2023).

To complement these insights, the study employed a Data Envelopment Analysis (DEA) model to benchmark recruitment efficiency across 33 biopharmaceutical firms. DEA evaluated inputs (e.g., CoR and employee headcount) against outputs (e.g., Revenue per Employee [RPE] and Profit per Employee [PPE]). Results revealed considerable variability, with efficiency scores ranging from 1% to 100%. High-efficiency firms like Fujifilm, Thermo Fisher, and Cambrex demonstrated superior ability to translate recruitment investments into financial returns, supporting previous literature on strategic workforce investment and productivity (Boudreau & Cascio, 2017; Thakor & Lo, 2022).

The use of DEA in human capital evaluation has gained traction for its ability to incorporate both tangible and intangible variables, allowing companies to benchmark performance while accounting for differences in scale and structure (Rustiawan et al., 2023; Banker et al., 1984). In sectors such as biopharma, where R&D timelines are long and cost-intensive, this type of benchmarking provides a valuable tool for human capital optimisation and strategic alignment (Tasheva & Karpovich, 2024).

Conversely, firms with low efficiency scores such as Dr. Reddy's or Eurofins reflect challenges in either recruitment practices or talent utilisation. These findings mirror broader research identifying the risks of misalignment between hiring strategy and business objectives, particularly in sectors with high innovation dependence and compliance pressures (Hamori, 2021; Arman, 2023). The literature suggests that such misalignment often stems from treating recruitment as a transactional process rather than as an integrated function of strategic workforce planning (Boudreau & Cascio, 2017; Gherghina et al., 2023).

Interestingly, DEA results also indicated that while recruitment efficiency varied significantly, PPE remained relatively stable. This suggests that while efficient recruitment contributes to resource optimisation, broader business outcomes such as profitability are also shaped by exogenous factors including market conditions, pricing strategies, and operational scale (Zhang et al., 2024; Deloitte, 2023). Larger firms may absorb inefficiencies more easily, while smaller firms with leaner structures may face challenges translating recruitment efficiency into financial outcomes.

The nature of biopharma hiring, specialist-intensive, heavily regulated, and globally competitive, means that even efficient recruitment processes must be paired with strong retention, onboarding, and skills development strategies to ensure sustained impact (Markarian et al., 2022; Rathore & Sarin, 2023). Without post-hire alignment, gains in recruitment efficiency may not translate into downstream performance benefits. The literature increasingly advocates for capability-focused workforce planning, in which strategic hiring is followed by structured development programmes to increase capability utilisation over time (Schiemann, 2014; Bersin, 2023).

This study also addressed endogeneity, particularly the feedback loop between recruitment cost and talent efficiency, through the use of Two-Stage Least Squares (2SLS) regression. The model confirmed a significant causal relationship between higher recruitment investment and talent quality ($\beta = 0.27$, $p = 0.007$), consistent with prior work linking strategic hiring expenditure to improved innovation output and market responsiveness (Bonner et al., 2023; Gherghina et al., 2023). These results reinforce the case for adopting investment-oriented rather than cost-minimisation approaches in workforce strategy. Research in advanced manufacturing and digital life sciences sectors supports the notion that high-performing companies tend to view recruitment as a value-generating investment rather than a back-office function (Zhang et al., 2024; Ulrich et al., 2022).

The combined application of MLR and DEA provides a comprehensive model for understanding, predicting, and benchmarking recruitment efficiency in high-performance industries. By incorporating predictive analytics, benchmarking, and econometric rigour, this approach aligns with current best practices in evidence-based HR management and strategic workforce planning (Boudreau & Cascio, 2017; Schiemann, 2014).

From a strategic management perspective, this model supports real-time alignment of human capital strategy with financial and operational performance indicators. It offers actionable insights for recruitment leaders, financial controllers, and executive decision-makers, particularly in firms aiming to scale talent capability while controlling recruitment costs in volatile labour markets (Bonner et al., 2023; Bersin, 2023).

In summary, the expanded findings of this study contribute meaningfully to the literature on human capital efficiency by demonstrating how sophisticated analytical models can bridge the gap between recruitment processes and financial outcomes. The integrated use of MLR, DEA, and 2SLS provides a replicable, scalable, and sector-relevant framework for assessing recruitment performance, supporting strategic decision-making in talent-intensive industries such as biopharma.

6 CONCLUSION

This study presents a comprehensive framework for evaluating CoR, integrating MLR and DEA to assess recruitment efficiency and cost-effectiveness within the biopharmaceutical industry. The findings highlight substantial variations in CoR, demonstrating that while some firms achieve near-optimal efficiency, others exhibit significant cost inefficiencies. The analysis confirms that traditional cost-per-hire models are insufficient, as they fail to account for productivity losses, bad hire replacement costs, and talent efficiency (TE), all of which have a profound impact on recruitment expenditures and long-term workforce stability.

A key insight from this study is the strong negative correlation between TE and CoR, indicating that firms with higher TE consistently experience lower CoR. This highlights the importance of structured workforce management, proactive talent acquisition strategies, and efficient onboarding processes in reducing hiring-related expenses. Organisations with high TE demonstrate fewer hiring inefficiencies, lower turnover rates, and reduced reliance on costly external recruitment solutions. Conversely, firms with low TE experience significantly higher CoR, pointing to inefficiencies in workforce planning, talent retention, and skills alignment. This finding reinforces TE as a critical recruitment efficiency metric, positioning it as both a predictive and prescriptive tool for firms aiming to optimise their hiring strategies and enhance long-term workforce sustainability.

Beyond short-term cost reductions, the study highlights the broader implications of TE for financial sustainability and organisational resilience. Companies that prioritise TE not only achieve lower CoR but also benefit from higher revenue-per-employee and profit-per-employee over time. By ensuring strategic alignment between recruitment, workforce productivity, and overall business performance, organisations can establish a sustainable talent acquisition model that fosters innovation, long-term growth, and competitive advantage. Additionally, higher TE enhances operational resilience, enabling firms to adapt more effectively to market shifts, regulatory changes, and industry advancements. The ability to attract, develop, and retain specialised talent efficiently serves as a key enabler of sustained success, particularly in knowledge-intensive industries such as biopharmaceuticals.

The implications of these findings are clear, organisations must prioritise TE as a core component of their workforce strategy to drive cost efficiency, workforce scalability, and long-term profitability. Building a high-TE workforce requires investment in skills development, AI-driven talent analytics, and proactive succession planning. Companies that integrate predictive analytics and automation into recruitment processes can further enhance TE, reducing dependency on reactive hiring cycles and minimising disruptions caused by talent shortages and inefficiencies. By leveraging data-driven decision-making, firms can establish proactive talent pipelines, ensuring continuous access to high-quality candidates while optimising recruitment costs.

This study also challenges traditional recruitment assumptions, particularly the perceived cost-effectiveness of internal hiring. The findings underscore the strategic advantages of leveraging external networks, specialist recruitment channels, and AI-enhanced selection tools to enhance talent quality, reduce time-to-fill, and improve overall recruitment efficiency. This research provides organisations with actionable insights to refine hiring practices, optimise resource allocation, and strengthen competitive positioning within a rapidly evolving biopharmaceutical sector.

From a broader perspective, the methodology presented here has far-reaching implications for human capital management. By linking recruitment efficiency to strategic workforce outcomes, this study expands the scope of human capital theory, underscoring the foundational role of data-driven hiring practices in maximising workforce potential. Efficient recruitment, supported by MLR and DEA-based benchmarking models, not only reduces costs but also lays the groundwork for talent development, retention, and long-term business agility.

Future research should explore TE's extended impact on workforce innovation, employee engagement, and adaptability to evolving market demands, reinforcing its value beyond cost reduction alone. Additionally, further studies should investigate how TE interacts with emerging trends such as digital transformation, automation, and remote workforce strategies, providing deeper insights into the future of recruitment efficiency and talent optimisation.

Moreover, expanding this methodology to incorporate dynamic variables such as industry-specific labour trends, economic fluctuations, and technological advancements could enhance its predictive and prescriptive power. Applying this approach across multiple industries would provide further validation, expanding its relevance to broader workforce management challenges. As companies face increasing complexity in talent acquisition, this research offers a practical roadmap for optimising recruitment efficiency, minimising CoR, and sustaining long-term competitive advantage in an evolving global workforce landscape.

By shifting focus from basic cost-per-hire metrics to a more holistic, predictive understanding of recruitment efficiency, firms can establish data-driven talent strategies that enhance both financial performance and workforce resilience. This approach ensures that talent acquisition is no longer viewed as a cost centre but rather as a strategic driver of organisational success, empowering firms to remain agile, adaptable, and future-ready in an increasingly competitive business environment.

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This article was developed with the assistance of AI-based tools to enhance the data analysis and writing process. AI-assisted technologies were utilised to support data structuring, language refinement, and formatting to improve clarity and coherence. However, all intellectual contributions, critical interpretations, and final editorial decisions were made by the authors. The AI tools did not generate original research findings or independent arguments but served as an aid in structuring and enhancing the manuscript. The authors take full responsibility for the content, accuracy, and originality of this work.