Holistic Performance Evaluation using Income per Employee and Salary Metrics

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Abstract

Background: Business performance analysis is a growing field in which traditional metrics, such as total income and profit margins, are increasingly complemented by insights into the impact of employee investments on company success. **Objectives:** This paper introduces a different approach to corporate evaluation that combines traditional metrics with the proposed Income per Employee Index (IPEI) and Income per Salary Index (IPSI), highlighting the strategic value of human capital. The proposed measures build on existing measures and offer a simple way to assess employee output as an indicator of operational efficiency. **Methods/Approach:** We hypothesize that integrating IPEI and IPSI with traditional financial metrics provides a more detailed understanding of human capital utilization in relation to a company's operational effectiveness. To achieve this, a combination of methods is used: from exploratory data analysis for initial insights to clustering and classification to identify patterns and assess the role of the proposed metrics in predicting gross profit. **Results:** The derived metrics' discriminative and evaluative properties yielded several clusters of observed companies. Additionally, these metrics demonstrated reasonable accuracy in predicting gross profit categories. Based on these results and IPEI and IPSI characteristics, we propose ways to interpret them. **Conclusions:** The research contributes to understanding operational efficiency and human resource strategies, broadening the scope of interdisciplinary research and practical business applications.

Keywords: operational efficiency; income per employee metric; income per salary metric; exploratory data analysis; clustering; classification

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Introduction

In contemporary business research, given the complexity of the modern business environment, the quest to understand the dimensions of business success extends beyond traditional metrics such as total revenue, profit margins, and export volume. This leads to a move towards more detailed analysis, including a wide range of metrics that encompass a company's financial and operational stability. A combination of established metrics (such as revenue, profit, and profit margins) and new, refined measures (such as return on investment (ROI), operating costs, and customer acquisition costs) is needed to provide adequate assessments of a company's performance. The diverse collection of existing metrics includes earnings before interest, taxes, depreciation, and amortization (EBITDA), cash flow, and market share, among others, highlighting the versatility of today's corporate performance assessment (Bragg, 2012; Choiriyah et al., 2020). However, recent trends highlight the implications of thoroughly examining how employee-related investments affect overall business success.

According to Chadwick (2010), different varieties of HRM system synergy enable researchers to better understand and estimate the impact of HRM systems on organizational performance. Delery and Gupta (2016) support the idea that HRM practices enhance organizational effectiveness, provide evidence that HRM practices can enhance each other's effectiveness, and underscore the value of theory-driven methodological approaches. The authors found that HRM systems comprising practices that ensure selective staffing, performance-based pay, and enhanced employee opportunities through participation in decision-making result in higher levels of organizational effectiveness. Delery and Roumpi (2017) argue that higher firm performance is achieved through an appropriate HRM system for the firm's particular strategic context. While investigating the relationship between corporate social responsibility and financial performance, Barauskaite and Streimikiene (2021) highlight the perspectives on methodological developments in corporate valuation and the increasing recognition of non-traditional measures of success and development. Furthermore, Garcia-Bernardo and Janský (2024) point out that financial strategies can obscure the value created by companies and their employees.

Another difficulty with financial measures is that they can provide a picture of a corporation's current situation but not an indication of its future (Alzyadat et al., 2015). Similarly, Bryan (2007) advocates using profit per employee as a performance metric, emphasizing human capital as a key asset in wealth creation and proposing a new approach to measuring corporate value that focuses on talent rather than capital. The results of Ahmić and Čizmić (2021, p. 215) highlight the importance of talented managers for a company's overall success and the difficulties in retaining them. A growing body of research contributes to understanding the relationship between quality of work life, organizational commitment, downsizing strategies, as well as algorithmic management and their effects on revenue per employee and overall financial performance (Yadav et al., 2019; Yan & Sloan, 2016; Yu & Park, 2006; Zhang et al., 2022, etc.).

There is also a particular focus on digital transformation, which aims to increase efficiency, improve data management, and enable better decision-making; this includes not only the adoption of new technologies but also the strategic alignment of human resources practices with organizational goals, solving potential obstacles and ensuring the establishment of key performance indicators (KPI) to measure success during the transformation process (Ziebell, 2019). As Barišić et al. (2021) pointed out, using digital tools alone has positive aspects; it optimizes work processes and enables faster, more efficient achievement of organizational goals. Numerous national and multinational strategies aim to enhance educational systems by leveraging ICT to acquire skills, competencies, and knowledge more effectively, thereby adding value for future generations (Mihajlović et al., 2023).

A new paradigm is emerging that places employees' well-being and efficiency at the centre of business progress. Evidence indicates that most employers implement procedures and measures to manage workers' health and create healthy workplaces to meet legal requirements, respond to employee requests, enhance company image/reputation, and improve productivity. (Jain et al., 2018) found that human resource management practices can improve employees' well-being in the workplace and further enhance their work performance. Studies consistently show that employee health and well-being are correlated with production efficiency (Tamers et al., 2019). Another study found that workers who scored high on its well-being measure were 20 percent more productive than those who scored low. This relationship highlights the importance of well-being for maintaining an involved and efficient workforce (Alnizari, 2024). This change confirms that people drive the company's achievements. Recognizing employees as a critical asset, this article introduces a complementary approach to assessing corporate performance that combines traditional financial metrics with indices that highlight the importance of employee-related investments. Investigating indicators such as revenue per employee and revenue per salary, we emphasize their role in measuring operational efficiency, defined here as optimizing resource use to maximize results. We also examine how human capital correlates with improved financial performance.

This paper explores the integration of traditional financial metrics with new measures: the Income per Employee Index (IPEI) and the Income per Salary Index (IPSI). These measures emphasize the strategic value of human capital and provide a simple method to assess employee output and operational efficiency. The goal was to integrate financial and non-financial metrics to enable a more comprehensive assessment of the organization in the future. The motivation for the proposal was to provide new insights into the value of HRM for organisational success. Nowadays, management needs to ensure the organisation not only lowers costs and differentiates, but also creates new value and strives to achieve outcomes that improve the business's competitive strategy. An employee's personal factors and an individual's perception and value system can be meaningful systems for development. The study uses exploratory data analysis, clustering, and classification to validate that combining IPEI and IPSI with traditional metrics offers a nuanced understanding of company performance, particularly in human capital utilization. Results show distinct company clusters and reasonable accuracy in predicting gross profit, enhancing insights into operational efficiency and human resource strategies.

This research offers a holistic view of corporate performance by integrating employee-centric measures with traditional indicators of business success. The underlying idea is that substantial investment in the workforce could lead to improved company performance, as measured by conventional financial metrics and proposed employee importance indices. This approach recognizes employees as a key asset and examines how their well-being and development contribute to the broader business goal of prosperity. Singh and Gautam (2023) theorized that firms choose to devote more resources to improving employee well-being because individuals, especially managers, believe in the "happy-productive worker hypothesis", which asserts that happier employees will be more productive than those who are not. However, the market circumstances of the lack of employees pose new challenges, so Moric et al. (2021) 's findings offer a valuable suggestion: firm managers should be aware that temporary workers can be a valuable source of innovation; however, they can also hamper other aspects of the firm's performance. Therefore, managers should be cautious when hiring temporary workers and find the "best balance" between permanent and temporary workers. The findings of Idowu (2017) demonstrate significant positive results when the organization uses performance assessment as a motivation tool, and the impact of training and development on employees' performance and productivity is also notable (Sal & Raja, 2016).

For management and company executives, analyzing labor cost efficiency relative to profitability supports strategic planning, such as hiring and investment decisions. It serves as a measure of management's efficiency in using human capital, and this kind of analysis supports hiring, pay, and benefits decisions, aligning labor costs with company revenues and market conditions while offering insight into workforce productivity and return on human capital investment.

Financial analysts and investors use these metrics as indicators of a company's operational efficiency and financial health. They influence investment decisions and enable comparative analysis of companies within industries to identify those that convert labor costs more efficiently into revenue. Industry analysts and economists exploit the data to examine labor productivity and efficiency trends across sectors, informing broader economic analysis and policy debates about employment practices and wage policies. For employees and unions, these metrics provide a basis for wage negotiations and insights into a company's financial stability and growth prospects, influencing perceptions of job security. For all stakeholders, these measures offer unique perspectives on company performance, highlighting the importance of integrating them with other financial and operational indicators for a holistic view of company health and performance.

Investigating how investments in human capital affect corporate success represents a relevant turning point in research. This study's focus on integrating employee-centric measures with established financial metrics addresses a gap in the literature. It offers fresh insights into the symbiotic relationship between workforce well-being and financial performance. After establishing traditional benchmarks for assessing corporate performance, it becomes apparent that part of the puzzle, as Barauskaite and Streimikiene (2021) eloquently put it, lies in understanding the role of human capital. This realization leads us to focus on employee-focused measures and emphasize the strategic value of investing in the workforce. Based on a review of existing metrics, we propose two variants, IPEI and IPSI, and further demonstrate how they can illuminate employee contributions to a company's operational effectiveness and financial performance.

By detailing the role of income per employee and income per wage indices in assessing operational efficiency and linking them to financial results, this research contributes to the theoretical and empirical understanding of corporate performance evaluation. Not only is it consistent with contemporary moves toward more inclusive and holistic approaches to business success, but it also sets the stage for future research in operations management. So, the other parts of the paper – Methods, Results, and Proposed Use of Metrics – deepen the research question. The *Methods* systematize existing indicators related to employee productivity and contribution to organizational success, primarily financial. It further explains the new measures, the Income Per Employee Index (IPEI) and the Income Per Wage Index (IPSI), which can be used to track the strategic value of human capital and provide a simple method for assessing employee performance and operational efficiency. The *Results* present evaluation metrics and the application of human resource strategies, monitored through IPEI and IPSI, which ultimately show that the metrics exhibit a noticeable yet complex relationship with profit creation. Bearing in mind that many other factors affect profitability, the fact that IPEI and IPSI alone achieve an average classification accuracy of 80% further supports the view that these measures capture relevant aspects of operational efficiency. Finally, the implications for research and practice are discussed. Proposal for the use of metrics and its interpretation based on the results of the analysis IPEI and IPSI, as given in the *Proposed use of metrics*. The interpretation of the IPEI/IPSI matrix is focused on combining revenue and profit levels, providing a comprehensive framework for evaluating a company's performance from a human capital efficiency perspective.

Theoretical background

In this part, we systematize existing indicators related to employee productivity, compensation, and overall contribution to organizational success. This lays the groundwork for further exploration of employee-centric metrics and their impact on corporate performance. The following table provides an overview of various metrics, each offering specific insights into the impact of human capital on financial performance.

Table 1
Systematization of existing metrics of organizational success related to employee

Metrics	Meaning	Source
Profit per Employee	Efficiency measures show how much revenue each employee generates.	(Bryan, 2007) (Choudhary, 2014) (Mattsson, 2019)
Profit per R&D professional	Determines the profitability of the R&D function.	(Bragg, 2012)
Operating Profit per Employee	Looks at operating profit concerning employee count.	(Azim et al., 2015) (Moric et al., 2021)
Revenue per Employee	Revenue is divided by full labor cost.	(Bragg, 2012) (Robinson, 2020)
Benefit Costs per Employee	Benefit costs (insurance, taxes, and other benefits) divided by employee number.	(Bragg, 2012)
Payroll Transaction Cost per Employee	The cost of processing a payroll cycle through a payroll supplier is divided by the number of employees.	(Bragg, 2012)
Unit Output per Employee Hour	Aggregate output divided by total hours worked in production is a productivity measure.	(Bragg, 2012)
Net Income per Employee **EBITDA per Employee Cost**	Net income generated per employee. Earnings before interest, taxes, depreciation, and amortization divided by the number of employees.	(Choudhary, 2014) (Robinson, 2020) (Situm, 2014)

Labor Cost as Percentage of Revenue	Shows labor cost concerning total revenue. A similar version is the Salary Expense-to-Revenue Ratio, which accounts only for salary expenses as labor costs.	(Hilliard, n.d.)
Employee Sales vs. Cost Ratio	Sales revenue is divided by total employee cost.	(K. Johnston, 2019)
Human Capital ROI	Return on investment in human capital.	(Becker et al., 2012) (Flamholtz & Randle, 2011) (Brazen, 2004)
Training per Employee	Hours of training per employee. In the other version, it is the training cost divided by the number of employees.	(Kapsalis, 1997) (Mosier, 1990) (Mincer, 1962)
Employee Productivity	Output per employee over a specific period.	(Bragg, 2012) (Burke & Hsieh, 2006) (Candradewi et al., 2014) (Feng et al., 2022)
Operating Expense per Employee	Total operating expenses are divided by the number of employees.	(Carswell, 2017) (Ni et al., 2021)
Cost of Resources per hour	Entails analyzing operational tasks based on activity breakdown to occupancy and event schedules, estimating the time for each, determining the cost of resources, and then assigning these costs to services or outputs to set fees based on regular and temporary worker expenses.	(Novita Sari & Nengzih, 2023)
Compensation as a Percentage of Operating Expenses	Total compensation relative to overall operating expenses.	(Mohanram et al., 2020) (Palladino, 2021)
Benefits as a Percentage of Salary	Total benefits expense divided by total salary expense.	(A. C. Johnston, 2020)
Labor Efficiency Variance	Difference between actual and expected labor costs.	(Weinberger et al., 2023)
Employee Turnover Cost	Costs associated with replacing an employee.	(Tracey & Hinkin, 2008)
Workplace Outcome Suite (WOS) work presenteeism ratings	A self-reported scale that translates into the percentage of time worked that was productive/unproductive	(Attridge, 2020)
Value Added per Employee	The value added by the company is divided by the number of employees.	(Usman & Makhdum, 2021)
Employee Satisfaction's Impact on Profit Margins	Linking employee satisfaction scores to company profitability.	(Harter et al., 2002)
Talented Managers' impact on complete Company Success.	Linking talent managers to company success.	(Ahmić & Čizmić,2021)

Source: Authors' work

Fundamental indicators that help organizations standardize the efficiency and effectiveness of their staff in contributing to the company's financial performance include revenue per employee, return on human capital, and employee productivity ratio. Revenue per employee is calculated by dividing the company's total revenue by the number of employees, providing an average revenue per employee and serving as a direct indicator of employee productivity and operational efficiency. Return on human capital (ROHC) is the value a company creates per unit of investment in its workforce, typically measured by dividing net income or profit by total employee costs (including wages, benefits, and other employee-related costs). ROHC provides insight into how effectively a company uses its available human capital to generate profits.

The employee productivity ratio is another widely used metric that quantifies the output (products or services) per employee over a specific time frame. It is a broad metric that can vary considerably across industries due to differences in the definition of "output." In a financial context, this could be approximated as profit per employee. Since not all the required data to assess employee contribution may be readily available, we propose additional measures. The first one relates to income per employee, with the difference that we use total income, which is usually a publicly available metric defined as the income per employee index:

$$IPEI = \frac{total\ income}{number\ of\ employees} \qquad (1)$$

IPEI is directly linked to revenue per employee because it is essentially a distinct way of expressing revenue per employee that emphasizes total income. Total income is all income generated by the company's activities before any expenses are deducted. Therefore, IPEI can be seen as a form of revenue per employee, which offers a perspective on the efficiency with which a company employs its people resources to generate total income.

Like revenue per employee, IPEI can be beneficial to firm management in strategic planning, as it measures and enhances operational efficiency. A higher IPEI will mean that the company is effectively using its human resources to generate revenue. A lower IPEI may signal the need for process improvement, technology integration, or workforce training programs to increase productivity. In addition, this indicator can help organizations compare their performance with other companies in the same industry. Likewise, investors and analysts may use IPEI as part of a broader evaluation of an organization's operational efficiency and expansion prospects. For example, a consistently high IPEI may be perceived as an indication of a company's effective allocation of human resources and its overall operational health, so reinforcing the perception of a good investment.

Given that revenue per employee is a more common measure, we compared it with the calculated IPEI values. Their relationship is non-linear, so we calculated Spearman's correlation coefficient, which is statistically significant and indicates a moderately strong, positive relationship (ρ = 0.57). This is an initial recognition that IPEI is a valid metric for identifying patterns or fluctuations in revenue per employee, even when these relationships are not straightforward or linear. The positive correlation indicates that the other measure tends to grow as the first measure increases. Therefore, as evidenced by its moderate positive correlation with a more commonly used statistic, IPEI can provide supplementary insights into a company's operational efficiency with respect to its employees by improving business analytics.

Human Capital ROI is typically calculated by dividing the company's net income by its total employee costs (including salaries, benefits, and other related expenses). The objective of this metric is to quantify the financial return generated by investments in human capital. It offers valuable insights into a corporation's efficiency in converting its investment in personnel into earnings. The second measure we propose fits within the scope of Human Capital ROI, and can be seen as a refinement of that measure by using total (and not net) income and employee costs related to salaries, which can be defined as income per salary index:

$$IPSI = \frac{total\ income}{average\ monthly\ salary \cdot number\ of\ employees \cdot 12} \qquad (2)$$

The proposed metric, IPSI, has the potential to improve the assessment of a company's efficiency in earning income from employee salary expenditures. It offers a direct view of the relationship between salaries paid and income generated, providing a nuanced view of the financial impact of salary expenditure. In sectors where human capital is a substantial operating expense, such as service industries, IPSI can be particularly beneficial. This metric can support understanding of the balance between the income employees contribute and their compensation, guiding decisions on employee development, hiring, and wage adjustments. In addition, this measure is intuitively understandable to employees, as it establishes a relationship between the amount they receive and the company's total income.

Human capital ROI focuses on the total return on investment in human capital, measuring the net outcome of all employee-related costs. The IPSI, on the other hand, concentrates on the relationship between salaries and income, providing a more detailed but limited perspective on the role of salary expenses in the production of income. So, IPSI is an excellent tool for a more targeted study of compensation strategies, as it provides precise insights into the productivity of salary expenditures. In contrast, human capital ROI provides a general assessment of the profitability and effectiveness of a company's workforce investment.

The relevance of the proposed Income Per Salary Index (IPSI) is that it can be calculated from readily available data, a significant advantage for its application, especially compared to metrics like Human Capital ROI, which may require more detailed, sometimes confidential, information about employee benefits and related expenses. Relying on publicly available data, such as total revenue and average wages, to calculate the IPSI means it can be applied more widely, including by outside analysts, investors, and researchers who may not have access to detailed internal financial records. This makes the IPSI a valuable tool for assessing a company's external efficiency in generating revenue relative to wage costs. In addition, the simplicity of the IPSI calculation makes it accessible to a broader audience, including smaller investors or companies that may not have the resources for detailed financial analysis. This accessibility enables widespread market analysis by simplifying complex assessments of company performance. Additionally, the transparency of financial reporting and analysis is facilitated by the computation of IPSI using publicly available data. In this manner, organizations that disclose their IPSI would offer a transparent and uncomplicated indicator.

IPEI and IPSI serve as links between a company's financial performance and its human resource management approaches. This perspective offers accessible and relevant insights across multiple fields, including labor economics, strategic management, and organizational behavior, fostering interdisciplinary academic research. The simplicity, accessibility, and interdisciplinary nature of these indicators can facilitate empirical studies that compare organizational performance with industry norms, thereby introducing an additional dimension to the analysis of operational success and competitive dynamics.

In academic research and education, similar indices are already being used to evaluate various human resource management tactics and to investigate the relationship between employee investment and revenue generation. Therefore, we propose:

- H_1: The integration of the Income per Employee Index (IPEI) and Income per Salary Index (IPSI) with traditional financial metrics provides a more nuanced understanding of a company's operational efficiency and financial performance, particularly regarding the utilization of human capital.

The next step is to empirically test this assertion to gain a more comprehensive understanding of the significance of employee-centric measures in evaluating company performance. The subsequent section outlines the analytical tools and data-gathering processes used to examine the relationship between conventional financial indicators and our proposed indices, the IPEI and IPSI.

Methods

Data collection

The data was retrieved from a business magazine that summarized the leading indicators for the 1000 best companies in Croatia (Lidermedia, 2024). This shows the ease with which the data needed for this analysis can be gathered. The data was accessed and retrieved on February 14, 2024. Of these 1,000 companies, 20 reported having zero employees or an average net employee salary of 0. These companies were removed from further analysis.

To gain a deeper insight into companies' performances, we calculated two key metrics: the income per employee index (IPEI) and the income per salary index (IPSI). We calculate these HRM-focused measures as suggested in the previous section.

We begin by conducting an exploratory analysis to gain a fundamental understanding of the data set. After that, we turn to correlation analysis to discern the strength, direction, and shape of the relationship between these variables, which will guide further analysis.

All analyses are conducted using JASP version 0.16.4, a statistical software package chosen for its robust features that facilitate both basic and advanced statistical procedures, and for its suitability to the complexity of our dataset. We use this methodological approach, from exploratory analysis to classification models, to provide a multi-layered understanding of the dataset and comprehensive insights into the results, grounding interpretations and subsequent recommendations empirically.

Exploratory analysis, which provides initial insights into the data and its patterns, will guide a more in-depth examination. In the next section, we present descriptive statistics and visualizations that begin to reveal the complex interrelationships between financial performance and employee investment.

Exploratory data analysis

The table shows descriptive statistics indicators for the financial and operational metrics of the observed companies. The standard deviation is expressed across several variables, including total revenues for 2022, gross profit/loss, exports, and imports. This indicates marked variability among companies, i.e., it describes a diverse set of entities ranging from small to very large in terms of profit, profitability, and international trade activity. However, it should be noted that all observations refer to the most successful companies in the Republic of Croatia. Pronounced skewness and kurtosis for almost all variables indicate that the data distributions are far from a normal, symmetric distribution. There is a long right tail, particularly noticeable for financial data, where a small number of companies have very high values compared to others.

Table 2
Descriptive statistics

	Mode	Median	Mean	Std. Dev.	Skewness	Kurtosis	Min	Max
IPEI	*0.09	0.27	2.21	16.07	20.86	524.94	0.02	430.26
IPSI	1.90×10^{-6}	2.05×10^{-5}	3.24×10^{-4}	2.80×10^{-3}	15.3	258.82	1.90×10^{-6}	0.06
Total income 2022	25.3	36.73	92.04	261.94	11.9	178.51	19.57	4653.33
Income change	0.09	0.19	0.35	0.71	5.69	42.46	-0.69	7.79
Gross profit	0.87	2	4.83	34.17	-9.86	308.35	-778.88	397.9
Change profit	0	0.11	0.42	1.61	1.03	8.62	-7.26	9.18
Profit/Income	0.03	0.04	0.06	0.27	-20.44	554.91	-7.26	0.93
Export	0	3.46	24.56	128.39	16.91	336.72	0	2989.59
Import	0	1.77	20.08	114.03	24.78	699.92	0	3296.21
Number employees	1	161	362.67	744.51	6.67	61.62	1	9786
Average net salary	1001	1084.5	1276.8	895.25	3.41	23.45	2	11424

Note: * More than one mode exists; only the first is reported
Source: Authors' work

The average revenue is significantly higher than the median, indicating that a few companies have higher revenues, which pull the average towards higher values. The maximum reported revenue of 4653.33 million euros further supports this claim.
A positive average change in income suggests that, on average, businesses experienced growth. The pronounced asymmetry in the average change in income indicates that few firms experienced significant growth. Gross profit/loss is the amount a company earns after deducting the costs associated with creating and selling its products or the costs associated with providing its services. The minimum gross profit/loss is negative, indicating

that some companies had significant losses, while the maximum indicates the high profitability of others. Negative asymmetry suggests that losses are less frequent, although they can be significant. Negative values of the asymmetry of the profit-to-income ratio indicate a distribution with minor deviations, with most observations at higher values.

Both exports and imports exhibit high asymmetry and kurtosis, indicating that most companies have a concentration of exports and imports around lower values. The number of employees shows strong positive asymmetry, with most companies having a small number, while a few have a large number. Positive skewness and high kurtosis are also present in average net salaries, implying that most companies offer lower average wages, with a few exceptions offering very high wages.

The income per employee (IPEI) and income per salary (IPSI) indices exhibit pronounced right skewness and high kurtosis, indicating that while most companies achieve lower values of these indices, a few outliers achieve very high efficiency or productivity in generating profit per employee or per unit of salary.

The wide range of IPEI and IPSI values suggests significant differences in how companies manage human resources to generate revenue. This confirms the stated need to emphasize the importance of analyzing operational efficiency and managing labor costs. Understanding the factors that contribute to high skewness and kurtosis – especially in measures of income generation, profitability, and efficiency – could shape targeted human resource management strategies.

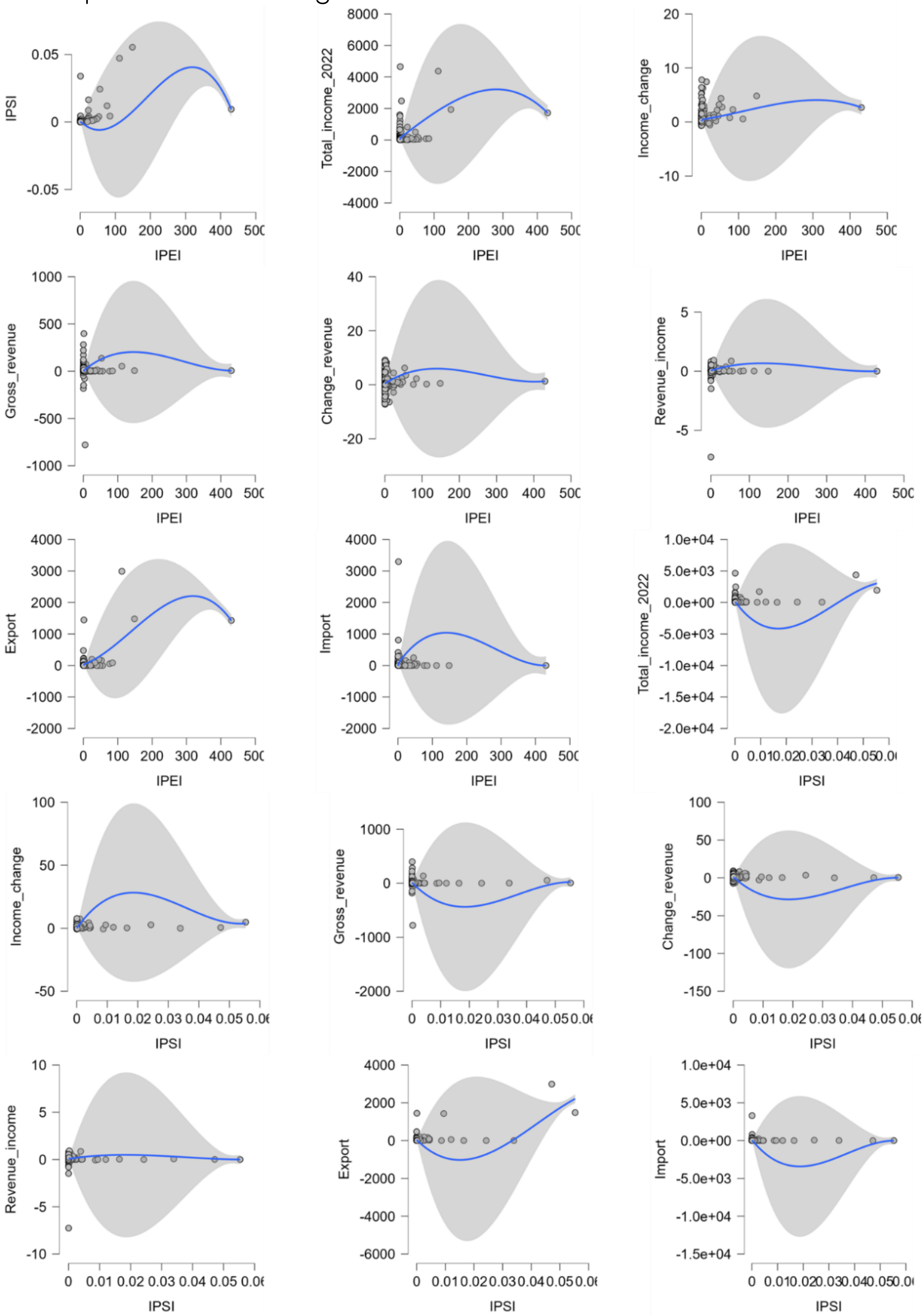
Scatter plots (Figure 1) show the relationship between pairs of variables denoted at the axes, where the blue line represents a smoothed regression line that indicates a general pattern between them. The shaded area around the regression line represents the confidence interval for the predictions. In many cases, the line is relatively flat (constant) around zero, and the shaded area is vast, suggesting a weak or nonexistent relationship between the variables.

Figure 1 also allows observation of non-linear relationships between specific pairs of variables. This is particularly evident in the non-linear relationships with positive slopes, such as between income per employee (IPEI) and exports and imports, and between income per worker (IPSI) and exports. That means traditional linear models cannot capture the underlying patterns and complexities in the data.

Given the first insights, we consider neighborhood-based clustering methods for further analysis. These methods are suitable for discovering structures in data that do not follow a linear relationship while allowing the data set to be segmented into meaningful clusters based on its natural grouping. Neighborhood-based clustering methods aim to identify local neighborhoods for each observation, thereby allowing data to be grouped by similarities that conventional clustering techniques might overlook, especially in the presence of nonlinear relationships.

Thus, in the observed con-text, this approach will enable the identification and classification of companies into clusters based on similarities in operational efficiency and financial results and, therefore, enable a conclusion on the claim that the integration of the Income per employee index (IPEI) and the Income per salary index (IPSI) with the traditional financial metrics provide a more thorough understanding of a company's operational efficiency, especially in terms of human capital management.

Figure 1
Scatterplots with smooth regression line



Source: Authors' work

Therefore, we apply the K-Nearest Neighbors (KNN) classification algorithm to predict a four-level ordinal gross profit or loss scale. This scale is defined by recoding the gross profit or loss variable into four categories: losses are coded as 1, profits up to 5 million euros as 2, up to 10 million euros as 3, and profits exceeding 10 million euros as 4. This classification approach using an ordinal variable allows us to model gradations of financial performance in the data set as we classify companies. In addition, KNN classification can predict a company's financial success based on investment in employees, providing evidence that the income per employee index (IPEI) and the income per wage index (IPSI) are predictors of a company's financial performance. This modeling approach seeks to deepen the understanding of how employee-focused measures translate to business success. The distinctions that the classification can identify provide valuable insights to companies seeking to optimize their workforce investments.

Neighborhood-based clustering

Neighborhood-based clustering is a family of clustering algorithms that focuses on the local neighborhoods of points to determine intrinsic groupings within the data. Unlike centroid-based clustering methods such as k-means, which aim to minimize variance within clusters, neighborhood-based methods define clusters based on the density of data points within a region or the distance to the nearest neighbors (James et al., 2013). This method does not require a specific data distribution, which makes it suitable for our data set, which contains asymmetrically distributed observations and non-linear relationships among variables.

Using this approach, companies can be grouped by similar financial characteristics or operational results, enabling the identification of subsets within a dataset. The clusters formed in this way will be further analyzed in order to identify specific characteristics and provide the basis for segment differentiation and the strategic decisions that result from it.

An additional advantage of neighborhood-based clustering is its ability to detect clusters of arbitrary shapes and sizes, which makes it particularly suitable for analyzing complex data sets where the relationships between variables are non-linear, and the distributions of the observed variables are asymmetric. This method is particularly suitable for datasets with high variability and outliers, as it is more robust in identifying the underlying data structure.

The objective is to ensure that clusters are meaningfully and clearly defined. So, when selecting results to present, we will choose a model with a higher silhouette score, which measures how well each object is separated from other clusters. In doing so, we take into account that this could lead to a compromise regarding the information criterion (Schwarz, 1978), because the silhouette score may favor a larger number of clusters (this often results in better separation), while the information criteria will be lower in favor of a smaller number of clusters due to its tendency towards simpler models. The silhouette score is based on the actual distances between data points, which better reflects the data's natural structure and enables a meaningful, clear definition of clusters. In addition, this method does not assume a specific data distribution, which is useful when the cluster structure is not necessarily spherical or when we expect more complex cluster shapes.

We expect the clusters to reveal groups of companies with similar business profiles that may not be apparent without this analysis. Identifying clusters of companies that share similar operational efficiency characteristics in human resource management can also inform strategic decisions, such as investment, expansion, or resource allocation. Furthermore, by analyzing the cluster characteristics based on the calculated cluster parameters, it is possible to identify groups of highly efficient or profitable companies. These companies can serve as examples of good practice and provide insight into the HRM strategies associated with their success in the data set.

K-Nearest Neighbors classification

To dissect the link between employee investment and business success, we chose neighborhood-based clustering and K-nearest neighbors (KNN) classification because of their ability to uncover patterns in the complex, nonlinear relationships in this data set.

KNN classifies data points with similar attributes into similar categories (James et al., 2013). This method enables the prediction of gross profit or loss, recorded as an ordinal variable, using income per employee (IPEI) and income per wage (IPSI) as predictors.

Gross profit or loss can be affected by a multitude of factors beyond the scope of the IPEI and IPSI alone, so we do not expect the KNN model to provide perfect predictions. Instead, our goal is to investigate the extent to which these predictors can provide reasonable estimates of the financial outcome categories, which can then serve as a preliminary indicator of the effectiveness of HRM strategies in contributing to a firm's business success.

For example, an assessment of the strength of the IPEI-IPSI relationship with gross profit or loss could inform preliminary risk assessment and decision-making. Identifying patterns among nearest neighbors that might indicate a firm's operational efficiency would provide a quick reference for categorizing firms based on the proximity of their financial profiles. Therefore, we expect this analysis to provide insight into how operational efficiency, as measured by IPEI and IPSI, relates to financial results and to identify areas where operational changes could affect financial performance.

By integrating the KNN classification into the research methodology, we follow a data-driven approach. The KNN classification model enables us to identify patterns in operational efficiency and its relationship with financial results by grouping companies based on their proximity to others with similar IPEI and IPSI values, providing insights into effective human capital management. In this way, we can assess the extent to which these indicators of operational efficiency predict financial success —that is, determine whether there is evidence supporting the hypothesis that human capital management, as expressed through IPEI and IPSI, affects business success. This approach and results provide a simple, interpretable classification system that can be easily transferred and applied in a business context.

Results

The findings from the exploratory analysis pave the way for a comprehensive examination of the results. Here, we interpret the findings from our neighborhood-based clustering and K-Nearest Neighbors classification, shedding light on the nuanced impacts of employee-centric measures on corporate performance.

Neighborhood-Based Clustering

Ten clusters were identified from a total of 980 observations, with an R^2 value of 0.84. The model's moderately high R^2 value implies that it captures a large portion of the variance in the data set (Table 3). Model fit was optimized based on the Akaike Information Criterion (AIC), with a reported value of 1040.68, while the Bayesian Information Criterion (BIC) was 1333.93, indicating model complexity. The model's medium complexity is indicated by its AIC and BIC values, as well as the use of six predictors. This suggests that the model achieves a satisfactory balance between accuracy and interpretability.

Since the silhouette score ranges from -1 to 1, an average of 0.64 indicates strong cluster cohesion and separation. This means that the data within the clusters are relatively close to each other, and the clusters are sufficiently separated from other clusters.

Table 3

Clustering Model

Clusters	N	R^2	AIC	BIC	Silhouette
10	980	0.84	1040.68	1333.93	0.66

Note: The model is optimized with respect to the *AIC* value.

The distribution of cluster sizes is uneven, with Cluster 4 containing the majority (853) of observations, while Clusters 6 and 9 contain one observation each (Table 4).

Table 4

Cluster Information

Cluster	1	2	3	4	5	6	7	8	9	10
Size	10	3	86	853	3	1	3	14	1	6
Explained proportion within-cluster heterogeneity	0.08	0.03	0.10	0.09	0.59	0.00	9.91×10^{-3}	0.05	0.00	0.05
Within the sum of squares	71.10	25.67	93.75	83.74	546.99	0.00	9.12	46.66	0.00	43.65
Silhouette score	0.10	0.33	0.02	0.75	0.09	0.00	0.34	0.18	0.00	0.14
Center Total_income_2022	1.31	-0.19	0.63	-0.18	9.86	9.10	0.72	0.02	17.41	3.99
Center Gross_profit	4.13	-0.10	0.40	-0.06	0.49	-22.94	-4.13	-0.06	11.50	0.34
Center Export	0.64	-0.19	0.28	-0.11	15.13	-0.19	-0.16	0.23	11.07	0.12
Center Import	0.33	0.02	0.40	-0.10	-0.18	-0.18	-0.17	0.07	28.73	2.84
Center IPEI	0.21	1.53	-0.10	-0.09	14.19	0.18	-0.05	2.34	-0.04	0.13
Center IPSI	0.03	8.77	-0.10	-0.09	13.21	-0.02	-0.08	1.10	-0.09	0.03

Source: Authors' work

The explained heterogeneity ratios within the cluster and within the sum-of-squares values indicate pronounced variability in cluster coherence. Cluster 5 stands out with a high internal sum of squares (546.99) and a well-explained proportion of within-cluster heterogeneity (0.59), suggesting that the cluster is diverse despite containing only three observations. This means that the observations within cluster 5 are highly diverse, contributing to a large sum of squared differences, in contrast to smaller clusters such as 1 and 2, which show less within-cluster heterogeneity.

Additionally, individual cluster silhouette scores vary, with Cluster 4 (the largest) achieving the highest (0.75). Such a high score indicates strong cluster cohesion and separation. In contrast, clusters 6 and 9 each have one observation and a silhouette score of 0.00, suggesting that the data are on the boundary between the two clusters, i.e., not clearly associated with either cluster. These companies are located at the border or in the transition between clusters, serving as outliers.

The maximum diameter (28.72) suggests that some clusters, such as Cluster 5, are relatively spread out (Table 5). A minimum separation (0.07) is slight and indicates potential overlap or lack of clear distinction between specific clusters, which aligns with the previously noted issues in Clusters 6 and 9 (Table 5).

A value of 0.43 for Pearson's γ suggests a moderate correlation between the clustered variables. These variables are somewhat related, but not highly interdependent.
The low value of Dunn's index (2.55×10^{-3}) further emphasizes the proximity between some clusters, supporting earlier insights into potential overlap or weak boundaries between them. This is already suggested by the silhouette scores, particularly the poor scores of Clusters 6 and 9. An entropy value of 0.54 indicates a moderate level of disorder or diversity within clusters. The Calinski-Harabasz Index (also known as the Variance Ratio Criterion) of 579.85 suggests a reasonable level of cluster validity, indicating that the clusters are well-defined and sufficiently separated.

Table 5
Evaluation Metrics

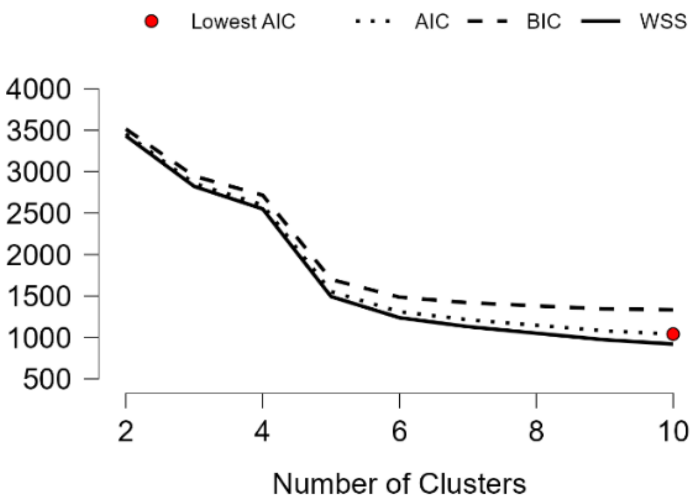
Parameter	Value
Maximum diameter	28.72
Minimum separation	0.07
Pearson's γ	0.43
Dunn index	2.55×10^{-3}
Entropy	0.54
Calinski-Harabasz index	579.85

Note: All metrics are based on the Euclidean distance

The analysis suggests a complex structure within the dataset, with significant variance in cluster sizes and characteristics. The presence of large and tiny clusters indicates a wide range of company profiles. Based on the lowest BIC, the clustering yielded 10 clusters (also the maximum allowed in this analysis). The lines in Figure 2 represent two information criteria, AIC and BIC, used to evaluate the model fit. Both criteria consider the model's log-likelihood and penalize the number of parameters to prevent overfitting. Typically, lower values are better, and the "elbow" or the point where the rate of decrease sharply changes (or "bends") can suggest a good balance between model fit and complexity. The WSS line shows the within-cluster sum of squares, a measure of cluster compactness. It is calculated as the sum of the squared differences within each cluster.

Again, a lower number is better, indicating that the observations are closer to their cluster centroids. The optimal number of clusters is often at the elbow of this line, where adding more clusters does not significantly improve cluster compactness. Based on this plot, the "elbow" is the point after which diminishing returns are observed in the reduction of AIC, BIC, or WSS. This means that increasing the number of clusters beyond this point probably does not provide a better fit to the data that would justify the additional complexity (i.e., additional clusters).

Figure 2
Elbow Method Plot



Source: Authors' work

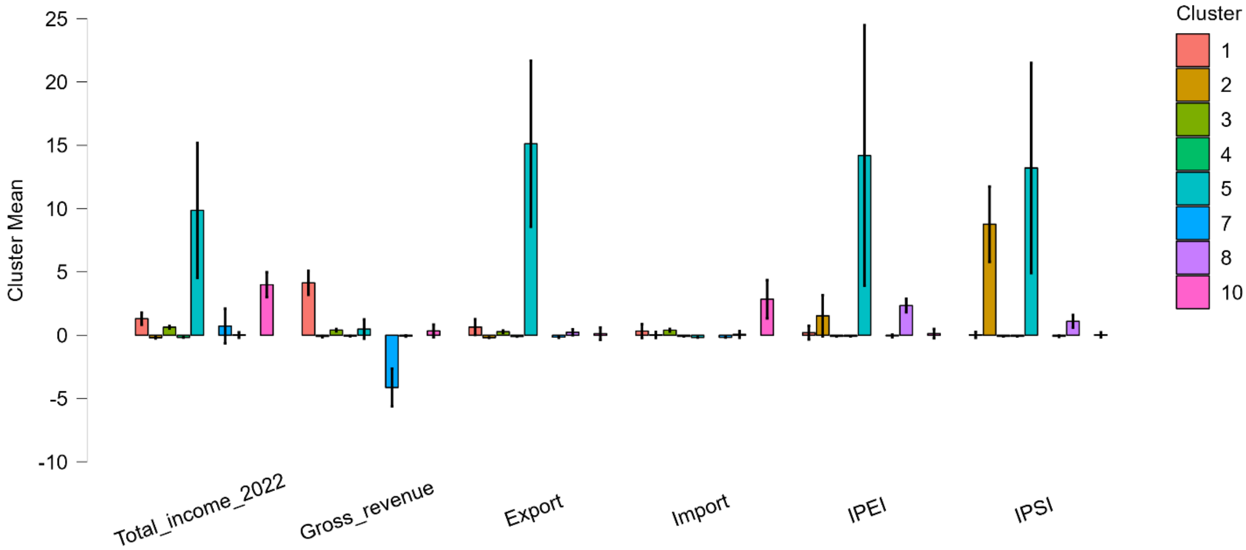
However, the reduction to 5 clusters yields a smaller, capped R-squared and higher BIC and AIC. Moreover, the result is one large cluster with 932 companies, one cluster with 43 companies, one with three companies, and two clusters with only one company each. Therefore, this diminishes the possible insights into additional variations among the companies. In addition, it is important to note that the parallel analysis without IPEI and IPSI achieved minimal AIC at 8 clusters. The largest cluster in that instance has 859 companies; one has 95, followed by clusters of size 11, 10, and 2, and three clusters with just one company.

In Figure 3, the colors indicate the 10 clusters identified by the analysis. Total revenue for 2022 is expressed in millions of euros and varies by cluster. In particular, clusters 5 and 9 show higher average total revenues, with cluster 5 showing the highest average value and the highest variance.

Gross profit also varies, with most clusters showing low average values, indicating they hover around the break-even point. However, cluster 1 has a significantly higher average gross profit, which indicates higher profitability within this cluster. Cluster 7, on the other hand, groups companies that incurred losses.

Regarding exports and imports, cluster 5 stands out with the highest average values, indicating that it comprises companies with pronounced international operations. Regarding IPEI, cluster 5 has the highest average, indicating the highest income per employee. IPSI is also most pronounced in cluster 5, followed by cluster 2. A high average IPSI indicates that companies in these clusters generate more revenue per unit of wage cost than those in other clusters.

Figure 3
Clusters' features



Source: Authors' work

The graph (Figure 3) shows a visual comparison of the clusters based on the measured indicators. It is complemented by Figure 4, which shows a scatter plot of company positions across different clusters (each represented by a different color). The following combines insights from Figures 3 and 4.

Group 1 shows minimal variability across most metrics, except for total revenue, which also has a higher mean, indicating a relatively homogeneous group in financial performance, except for profitability. With low variability in most metrics except total income, companies in this cluster could be in mature industries with consistent results. At the same time, income variability suggests that companies across sectors and sizes may exhibit some variance in total revenue despite similar operational efficiency.

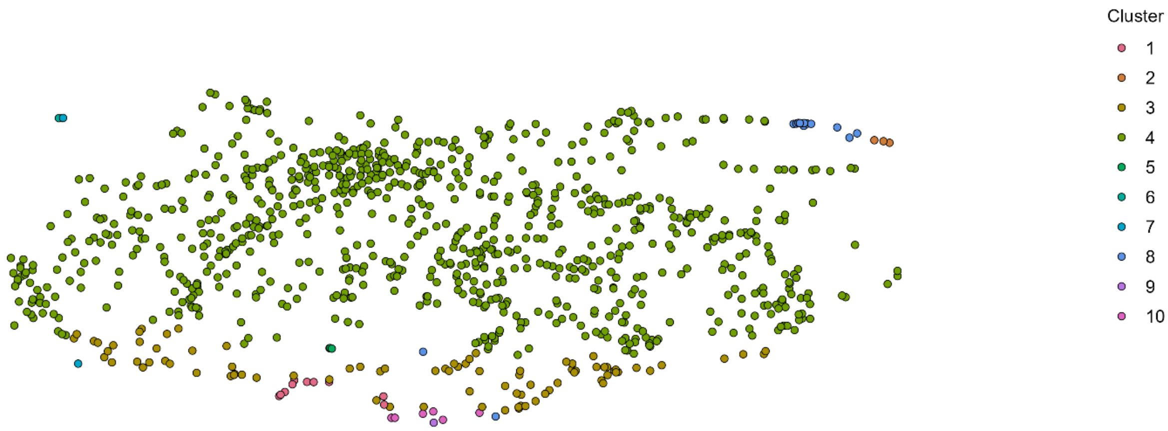
Cluster 2 shows low variability across most financial metrics, but higher variability for IPEI and IPSI. The low variability in financial metrics, but higher in IPSI, suggests that these firms may be in sectors where salary costs are a significant revenue generator, such as service-oriented industries where human capital is a primary asset.

Clusters 3 and 4 are not visible in most metrics, suggesting their small means and low variability. Cluster 5 shows high mean values and pronounced variability for total income, exports, IPEI, and IPSI. Exhibiting high mean values and high variability in total revenue, exports, IPEI, and IPSI, firms in this cluster are likely to perform well, with significant international operations, such as large multinational corporations with global market reach.
Cluster 7 appears to exhibit high gross loss variability, possibly indicating a diverse set of firms in terms of profitability. High variability in gross loss may indicate companies operating in volatile markets or in industries such as start-ups, investment companies, technology, or natural resources, where profitability may fluctuate significantly with market demand, investment cycles, or resource availability.

Cluster 8 has relatively small means and slight variation in financial results, but slightly higher means for IPEI and IPSI, suggesting higher returns from its employees, especially compared to clusters 1, 3, 4, 7, and 10. Companies in this cluster could be highly specialized, generating good income per employee and per wage unit. This could be indicative of industries such as consulting, technology, or other professional services where output per employee is high.

Cluster 10 shows higher mean values for total revenue and imports, suggesting that it may include firms engaged in some form of retailing or wholesaling within supply chains that rely heavily on imported goods. A significant investment in employees could reflect sectors that prioritize employee development and retention as a strategy to maintain competitive advantage.

Figure 4
t-SNE Cluster Plot



Source: Authors' work

Even before identifying the companies in small clusters (Table 6), it was possible to make an educated guess about the prominent characteristics. However, identification of the companies and related details enables confirmation. Table 6 presents the average metrics for each of the smaller clusters, while Table 7 represents the companies in each cluster and the sectors they belong to.

Table 6
Average metrics for each small cluster

Cluster averages/ clusters	1	2	5	6	7	8	9	10
Total income 2022	435.3	42.34	1827.07	2474.41	280.84	96.65	4653.33	1137.37
Income change	0.71	1	3.745	0.79	-0.2	1.06	0.56	0.5
Gross profit	146.12	1.39	5.79	-778.88	-136.16	2.67	397.9	16.42
Gross profit order	8.8	2	3	1	1	2.14	9	4
Profit income	0.41	0.03	0	-0.31	-2.95	0.06	0.08	0.015
Export	107.21	0.57	1455	0	4.53	54.22	1445.59	40.285
Import	57.59	22.03	0	0	0.56	27.72	3296.21	344.26
Number employees	2155	20	8.5	482	163.33	2.57	3005	2710.17

Average net salary	1511.3	105	2006	1579	2059.67	1511.43	1659	1032.83
IPEI	5.51	26.87	289.48	5.13	1.41	39.87	1.55	4.3
IPSI	0.00041	0.02488	0.03239	0.00027	0.00009	0.00342	0.00008	0.0004

Source: Authors' work

Table 7
Identified companies in small clusters

Companies	Sectors
Valamar Riviera d.d., Pliva Hrvatska d.o.o., OTP Banka d.d., Erste & Steiermärkische Bank d.d., Privredna Banka Zagreb d.d., Hrvatski Telekom d.d., Super Sport d.o.o., Tankerska Plovidba d.d., Zagrebačka Banka d.d., OMS-Upravljanje d.o.o.	Hotels and restaurants, Pharmaceuticals, Financial intermediation – banks, Telecommunications and postal services, Radio and television, culture, recreation, and entertainment, Transport - water transport, Oil and oil derivatives
ITX Hrvatska d.o.o., Auro Domus Bullion Market d.o.o., Vodoskok d.d.	Trade – retail, Trade - wholesale - other
MVM Ceenergy Croatia d.o.o., MET Croatia Energy Trade d.o.o., Prvo plinarsko društvo d.o.o.	Energy sector
Hrvatska Elektroprivreda d.d.	Energy sector
Fortenova Grupa d.d., Brodograđevna Industrija Split d.d., HEP Elektra d.o.o.	Management and business consulting, Shipbuilding and production of motor vehicles and parts, Energy sector
Continental Dynamics d.o.o., Delta Oil International d.o.o., Tetragram Projekt d.o.o., Axpo Trgovina d.o.o., Manta d.o.o., Rio Projekti d.o.o., Solex d.o.o., Gen-I Hrvatska d.o.o., Po.Tak d.o.o., Star Chemicals d.o.o., Quantum Crest d.o.o., MKM Yachts d.o.o., Fata S.P.A. - Podružnica, MVM Partner d.o.o.	Energy sector, Oil and oil derivatives, Financial intermediation – other, Real estate, Trade - wholesale – other, Computer and data services, Shipbuilding and production of motor vehicles and parts, Architecture, design, and engineering
INA d.d.	Oil and oil derivatives
Konzum Plus d.o.o., Lidl Hrvatska d.o.o., K.D., HEP Proizvodnja d.o.o., Medika d.d., Petrol d.o.o., Spar Hrvatska d.o.o.	Trade – retail, Trade - wholesale – other, Oil and oil derivatives, Energy sector

Source: Authors' work

Cluster 1 includes large organizations in telecommunications, pharmaceuticals, and banking. Companies in this cluster have stable financial metrics and consistent performance. Greater variability in total revenue suggests a broader range of operating scales, reflecting a mix of market leaders and smaller firms within these sectors. The telecommunications and pharmaceutical sectors often involve substantial capital investment and research, which can also lead to income variability. A significant number of employees and a moderate IPEI (with a cluster average of EUR 5.51 million in revenue per employee) indicate a stable profit per employee, in line with the extensive operations typical of these industries.

The average net salary is relatively high, which is characteristic of industries that require specialized skills and must offer competitive compensation to retain employees. However, their primary return does not come from investing in employees, as IPSI is relatively low (with a cluster average of 410 euros of revenue per euro of net employee salary; IPSI is multiplied by a million for ease of interpretation). This means that higher average wages are more likely a strategy to retain highly skilled workers (Cecere, 2017).

Cluster 2 includes companies from the trade sector—both retail and wholesale. These companies show minimal variability in financial metrics and more pronounced variation in IPSI. The variation in IPSI might reflect different strategies in salary expenditure relative to profit, which could be influenced by differing business models or operational efficiencies within the trade sector. A high average IPEI (26.87 million euros of income per employee) indicates that these companies' income depends heavily on the number of employees. The average IPSI is the second highest (24880 euros of income per euro of employee net salary), suggesting that companies should be aware of the importance of investing in their employees. However, the average net salary is surprisingly low, suggesting that employees may have other contracts or are compensated through provisions not reflected in the salary.

Cluster 5 is represented by business entities from the energy sector and is characterized by high total revenues and extremely high IPEI (289.48 million euros in revenue per employee), indicating that they efficiently generate profits per employee. This efficiency can also result from capital-intensive, technology-driven operations in the energy industry, where production can be substantial relative to the number of employees. This reflects the energy industry's high productivity and capital efficiency. The highest IPSI cluster average (32,390 euros of revenue per euro of net salary of employees) in this cluster may indicate that, although salary costs are also high, the return on those costs is high, a characteristic of industries that require highly specialized, well-paid labor.

Cluster 6, represented only by the outlier - Hrvatska elektroprivreda d.d., stands out for its extremely high total revenue of 2474.41 million euros. However, the negative gross profit (loss) of -778.88 million euros indicates business difficulties. Given this, due to state intervention, HEP was obliged to stabilize energy prices by subsidizing energy costs during periods of high volatility, resulting in significant financial burdens that contributed to realized losses. Both exports and imports are equal to zero, so the company's operations are focused on the domestic market. With 482 employees and an average net salary of €1,579, IPEI has a relatively low revenue of €5.13 million per employee, suggesting that, despite the smaller workforce, profit per employee is lower than expected given the total income. The very low IPSI of 270 euros of revenue per euro of net employee wages further indicates that the company's wage costs are not being translated into commensurate total revenue, which could reflect the effects of losses on financial efficiency.

Cluster 7 includes companies in management and business consulting, shipbuilding, and energy, making it a very diverse sector. This cluster brings together companies with potential financial difficulties (negative gross profit, i.e., loss), which may be associated with industries experiencing a downturn or high demand variability. This also reflects the high-risk nature of these high-paying sectors, where profitability can be significantly affected by market fluctuations, project cycles, and operating leverage. Since average net salaries are relatively high, the lower IPEI (1.41 million euros of income per employee) and the low IPSI (90 euros of income per euro of net employee salary) suggest that these companies may be struggling to generate profits efficiently relative to the number of employees and salary costs. Nevertheless, a low IPSI, combined with the sectors involved, may also reflect an employee compensation strategy aimed at retaining a highly skilled and specialized workforce.

Cluster 8 shows relatively modest financial indicators, with an IPEI of 39.87 and an IPSI of 0.00342, reflecting efficient revenue generation per employee and per salary compared to most other clusters. The small size of companies in this cluster (with an average of 2.57 employees) may contribute to their relatively high efficiency, especially for companies engaged in specialized services such as trading in energy and oil derivatives. Of course, this results in modest total revenue compared to most other clusters. Nevertheless, by focusing on high-margin services with lower operational complexity, these companies achieve better results with smaller, cheaper workforces. In addition, these companies operate in specialized and high-demand sectors and tend to have higher profit margins, contributing to solid performance even with limited personnel. This can also be seen in the IPSI of 3,420 euros in revenue per one euro of salary cost, indicating that these companies keep labor costs relatively low compared to the revenue they generate. This efficient cost management, combined with the ability to operate with fewer employees, helps maintain profitability even when overall revenue is modest.

A single entity, INA d.d., represents cluster 9 and exhibits the highest total income across all clusters at 4653.33 million euros, coupled with an income change of 0.56. This indicates a stable or improving financial situation. The gross profit is also the highest at 397.9 million euros, with an order of 9, suggesting robust profitability. The export of INA d.d. is very high at 1445.59 million euros, and the import figure is the largest among all clusters at 3296.21 million euros, which implies that the company is heavily involved in international trade. The large scale of imports relative to exports may indicate that it is a net importer due to its operations in the oil and derivatives sector, which often require the importation of raw materials. The IPEI at 1.55 million euros of income per employee is modest compared to the total income. This may be due to the large number of employees (3005), resulting in lower profit per employee than in some other clusters. The IPSI is the lowest among all clusters at 80 euros per euro of employee net salary, suggesting that, despite high overall profitability, the return on salary expenses is comparatively low, potentially due to the higher average net salary of 1659 and the large workforce required in this sector.

Cluster 10 includes companies from the retail, wholesale, and energy sectors, which show a higher average total revenue. IPEI is moderately high (4.3 million euros of revenue per employee). However, a lower IPSI (400 euros of revenue per euro of net employee salary) may indicate that these companies have higher wage costs overall, which makes sense in sectors with larger employee bases and lower margins per employee, such as retail.

However, it is worth noting that, in the analysis, predominantly state-owned companies subject to state interventions in end-user price regulation were singled out as "outliers". The fact that these companies are classified as outliers in the clustering analysis indicates a disruption of market dynamics. These interventions distort market behavior, ultimately leading to financial results that significantly deviate from expectations based on income level, placing them in extreme categories. Similarly, it can be argued that the state plays a specific role in Cluster 5. The common characteristic of companies in that cluster is exposure to state intervention, either through financial restructuring (Fortenova), state subsidies (Brodograđevna Industrija Split), or regulated prices (HEP Elektra), which, for better or worse, led them to deviate from expected market outcomes. However, the fact that these companies are grouped (and not identified as outliers) may mean that government intervention affects their core business operations differently, or with a less direct impact, than on the outliers.

When combined with qualitative data on identified companies and sectors, Table 5's metrics reflect each cluster's profit generation, profitability, and operational efficiency, thereby revealing the specific dynamics that affect cluster economic performance.

IPEI measures imply that employees play an important role in income generation, especially in areas that value efficiency and competence. A high IPEI suggests that organizations produce much income per employee. This is particularly evident in cluster 5, where the capital-intensive, technology-enabled operations of the energy sector enable significant profits with a relatively small workforce.

IPEI and IPSI measure how well organizations turn HR investments into earnings. The IPEI measures income per employee, indicating operational efficiency and productivity, while the IPSI measures salary cost-to-income, indicating the efficacy of the compensation strategy. Clusters 2 and 5 have strong IPEIs and IPSIs, indicating that these companies are efficient in their operations and in generating high returns from human resource investment.

IPSI scores across clusters reveal company compensation practices, with higher IPSI values indicating higher returns on human capital. For example, in Cluster 5, it may be interpreted as companies investing heavily in highly skilled, well-paid labor while still earning good returns.

K-Nearest Neighbors Classification

The K-Nearest Neighbors (KNN) classification algorithm was employed to predict the dependent variable, the gross profit, categorized into four classes (1, 2, 3, 4) based on profit levels, with the predictors IPEI and IPSI. Table 7 outlines the configuration and performance of a K-Nearest Neighbors (KNN) classifier. Using a triweight scheme that gives more weight to nearby neighbors and less to those farther away, this model predicts new data points based on the five most proximate cases in the training set. Proximity is determined by Manhattan distance.

The classification model was trained on 627 observations, and its hyperparameters were fine-tuned on a separate validation set of 157 observations. The model's predictive ability was evaluated on a test set of 196 observations, yielding an accuracy of 41 percent on both the validation and test sets. During testing, the model's hyperparameters were adjusted to optimize accuracy on the validation set. Although the obtained accuracy is low, it is important to consider that only two variables, IPEI and IPSI, were used as predictors. The model's accuracy would certainly improve by including more predictors, especially financial indicators. Nevertheless, the objective was to assess the extent to which the two proposed metrics possess the discriminating and evaluation features to yield a meaningful prediction.

Table 7
K-Nearest Neighbors Classification

Nearest neighbors	Weights	Distance	n(Train)	n(Validation)	n(Test)	Validation Accuracy	Test Accuracy
9	Tri-weight	Manhattan	732	52	196	0.59	0.59

Note: The model is optimized with respect to the accuracy of the validation set
Source: Authors' work

The confusion matrix shows the number of observations correctly and incorrectly predicted by the model in the four categories (Table 8). For category 1 (loss), only 1 out of 20 cases was correctly identified, while 19 were misclassified as category 2. This indicates a high misclassification rate for losses. Category 2, which represents a positive gross profit level up to EUR 5 million, has a better classification, with 106 correctly identified cases out of 128. However, there are still misclassifications into adjacent categories (5 were misclassified as category 1, 12 as category 3, and 5 as category 4). Category 3 (5-10 million euros of gross profit) and category 4 (more than 10 million euros of gross profit) - the highest levels of profit - show a low proportion of correct classifications (4 out of 20 for class 3 and 5 out of 28 for class 4), which indicates that the model struggles to identify the highest profit categories accurately.

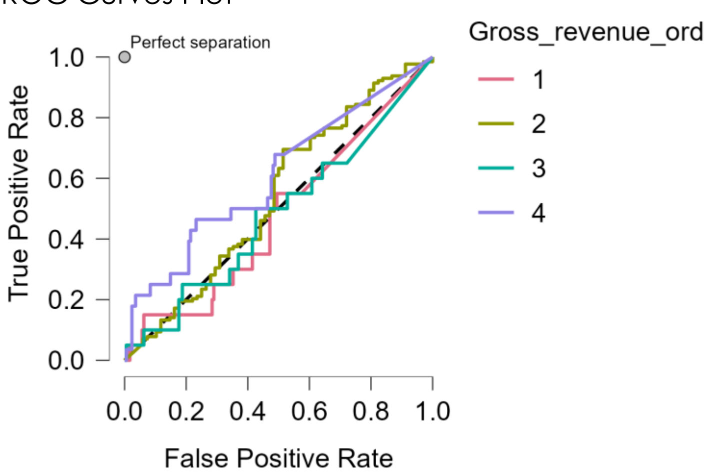
Table 8
Confusion Matrix

Observed	Predicted			
	1	2	3	4
1	1	19	0	0
2	5	106	12	5
3	0	15	4	1
4	0	18	5	5

Source: Authors' work

A receiver operating characteristic (ROC) curve is a graphical representation of a classification model's ability to distinguish between classes (Figure 5). The ROC curve plots the actual positive rate (recall, also known as sensitivity) versus the false positive rate (one minus specificity) at different threshold settings. Each row corresponds to one of the ordinal classes of gross profit (from 1 to 4). The upper-left corner is where the actual positive rate is high, and the false positive rate is low. The deviation of the curve toward the left corner for class 4 suggests that there is a better trade-off between sensitivity and specificity for this class.

Figure 5
ROC Curves Plot



Source: Authors' work

This implies that the model is better able to distinguish between firms in class 4 and those outside it, compared to the other classes. The second best is class 2, while classes 1 and 3 are worse, which is also reflected in the area under the curve and the values in Table 8. In general, if we wanted to use this model solely for gross profit classification, we would need to add additional predictors. Since that is not the goal of this analysis, we will continue to examine the model metrics to conclude the extent to which IPEI and IPSI may serve as predictors.

Accuracy in Table 9 shows the proportion of total correct predictions. The average accuracy is 0.80, meaning that 80% of the model's predictions are correct. However, accuracy varies significantly across classes, suggesting uneven model predictions. The reason might be the uneven distribution of observations across the classes and the overall small number of observations. Class 2 also stands out with the highest precision (0.67), recall (0.83), and F1 score (0.74). Recall, or actual positive rate, reflects the proportion of true positives that are correctly identified. At the same time, the F1 score combines precision and recall into a single metric, which is particularly useful when classification success is uneven across classes. The Matthews correlation coefficient (MCC) values are low across all classes, with weak correlation between observed and predicted classifications. The area under the curve (AUC) represents the model's ability to distinguish classes and indicates modest discrimination, with class 4 having the highest AUC of 0.61.

Table 9
Evaluation metrics

Metrics	1	2	3	4	Average / Total
Support	20	128	20	28	196
Accuracy	0.88	0.62	0.83	0.85	0.80
Precision (Positive Predictive Value)	0.17	0.67	0.19	0.45	0.54
Recall (True Positive Rate)	0.05	0.83	0.20	0.18	0.59
False Positive Rate	0.03	0.76	0.10	0.04	0.23
False Discovery Rate	0.83	0.33	0.81	0.55	0.63
F1 Score	0.08	0.74	0.20	0.26	0.55
Matthews Correlation Coefficient	0.04	0.08	0.10	0.22	0.11
Area Under Curve (AUC)	0.48	0.54	0.48	0.61	0.53
Negative Predictive Value	0.90	0.42	0.91	0.88	0.78
True Negative Rate	0.97	0.24	0.90	0.96	0.77
False Negative Rate	0.95	0.17	0.80	0.82	0.69
False Omission Rate	0.10	0.58	0.09	0.12	0.22
Threat Score	0.03	0.84	0.08	0.14	0.27
Statistical Parity	0.03	0.81	0.11	0.06	1.00

Source: Authors' work

The KNN model shows decent overall accuracy given the predictors used, but struggles to balance precision and recall across profit classes, especially in correctly identifying the lowest- and highest-profit companies. Since IPEI and IPSI are the only predictors, the model is expected to achieve only moderate predictive performance. Since a certain level of prediction was still achieved, this speaks in favor of the fact that these indices contain valuable information. However, the model does not include other important factors, such as investment, production costs, innovation, or market dynamics, all of which significantly affect gross profit. In other words, although IPEI and IPSI contain valuable information for profit classification, additional predictors or model adjustments are needed to improve model performance.

The employment of human resource strategies, as reflected in IPEI and IPSI, has a notable yet complex relationship with profit generation, suggesting that these factors alone do not fully capture the nuances of profit categorization without considering other operational or market variables. Nevertheless, given that many other factors also affect profit, the fact that IPEI and IPSI alone achieve an average classification accuracy of 80% is further evidence that these measures capture relevant aspects of operational efficiency.

Proposed use of metrics

Based on the analysis of the IPEI and IPSI indices and their characteristics derived from the calculation method, we suggest ways to interpret them (Table 10).

Understanding the relationship between the Income Per Employee Index (IPEI) and the Income Per Wage Index (IPSI) across different income and gross profit levels provides an additional lens for assessing the performance of human resources management in relation to business results. For example, the highest IPEI in the dataset is EUR 430.26 million per employee, and the lowest is EUR 19,354.68 per employee. The highest IPSI in the data set is EUR 55319.65 per euro of employee salary, and the lowest is EUR 1.9 per euro of employee salary. Various combinations of these indicators are possible, and their dynamics are explained below.

When both the IPEI and IPSI are high, the firm typically exhibits exceptionally effective use of human capital. This scenario is, of course, most favorable when income levels are high, indicating that the company is not only productive but also successful in translating that productivity into significant financial returns. In this context, the profit dimension adds another layer of insight. High gross profit with high IPEI and IPSI indicates a combination of market success and cost efficiency or even a monopoly. In addition to these situations, this result can also occur if the company operates in a capital-intensive industry, where significant revenues are primarily derived from investments in assets such as machinery, equipment, infrastructure, or technology.

Such companies tend to have fewer employees than companies in labor-intensive industries, leading to higher IPEI values. In such situations, the IPEI should be interpreted cautiously, while the IPSI will continue to reflect the company's compensation policy and measures to retain highly competent employees.

At moderate revenue levels, high performance, as measured by the IPEI and IPSI, suggests that the company is doing well but may be subject to market constraints or strategic choices that limit its revenue potential. This emphasizes and expands on the strategic role of human capital in achieving financial performance (Becker et al., 2012). A low-profit scenario, although rare, could highlight a company in a growth phase, investing all or almost all income in a small number of highly skilled employees.

Cases where IPEI and IPSI are moderate suggest balanced, although not exceptional, operations and human capital management. Rather than relying solely on operational excellence, companies in this category likely generate substantial revenue by leveraging their scale and diverse business lines. A stable state is characterized by moderate income with minimal fluctuations, suggesting that enterprises maintain the status quo without advancing the efficiency threshold. Low income in this field of the matrix indicates that operational and strategic inefficiencies constrain the company's capacity to improve its financial performance. It shows a clear association between operational and salary management efficiency levels and low gross profit, highlighting potential areas for improvement.

Table 10
Proposed metrics interpretation

	Low IPEI	Moderate IPEI	High IPEI
Low IPSI	o Companies facing challenges in operational efficiency and salary expense management o Significant issues in human capital utilization and financial management o Comprehensive operational and strategic reviews are necessary	o Average productivity per employee with poor returns on salary expenses o Misalignment between salary levels and productivity o Need for a review of compensation strategies or productivity enhancement measures	o Companies are generating high income per employee, but are not seeing proportional returns from their salary expenses o Overcompensation or inefficiencies in salary allocation
Moderate IPSI	o Low operational efficiency with moderate salary expense returns o Struggling with both productivity and managing salary costs effectively o Require strategic changes to improve operational performance	o An average operational and salary efficiency o Adequate performance with a potential for improvement, both in terms of productivity and salary expense management	o Efficiency in generating income per employee, but having a moderate return on salary expenses o While overall productivity is high, there might be room for improvement in how salary expenses are managed to motivate employees and maximize income
High IPSI	o Unusual combination; might indicate a mistake in calculation or collected data o Otherwise, this might occur in companies with low investment in employees, leading to strong returns on salaries but overall low productivity	o A balanced approach to employee productivity, with an opportunity for further improvement of operational processes o Effective management of salary expenses	o A highly efficient utilization of human resources with a strong return on salary investments o Maximizing workforce productivity and salary efficiency, leading to high operational efficiency and profitability o High-margin industries or companies with a competitive advantage in operational processes

Source: Authors' work

On the other hand, high gross profit may indicate a volume-driven approach where sales are high but do not necessarily reflect operational efficiency.

Low IPEI and IPSI values generally signal fundamental inefficiency in managing human capital and salary expenses. High income in this context would be unusual and may refer to income derived from activities outside the core operating sphere, such as the sale of assets. Alternatively, low IPEI and IPSI values, paired with high gross profit, may reflect a business model that relies on high-volume, low-margin operations. However, more commonly, moderate or low gross profits occur alongside low IPEI and IPSI, highlighting inefficiencies that hinder translating operational efforts into financial success. This reflects the assumption that profit-shifting practices can increase the complexity of financial strategies and their impact on apparent operational efficiency (Garcia-Bernardo & Janský, 2024).

The interpretation of the IPEI/IPSI matrix, in combination with income and profit levels, provides a more comprehensive framework for assessing company performance from a human capital efficiency perspective. In this way, additional insights into the efficiency of the use of human capital, the efficiency of salary expenditures, and how these factors are related to the broader financial achievements of the company, in accordance with Harter et al. (2002) and Yadav et al. (2019), with the possibility of additional examination and metric expansion to the relationship between employee satisfaction, engagement, quality of work life and business results, this framework can also serve practical purposes and help management identify strategic priorities, from improving operational efficiency to optimizing workforce investment, to align operational practices and financial results harmoniously.

Conclusion

In this paper, we introduced two measures: IPEI (income index per employee) and IPSI (income index per salary). These measures can be used to track the strategic value of human capital and to provide a simple method for assessing employee performance and operational efficiency. After demonstrating the ease of obtaining data and calculating the index, we continued with data-driven research to determine the added value of analyzing the role of human capital management in business success. We explored the broader implications of integrating IPEI and IPSI with traditional financial measures, paving the way for future research and practical applications in corporate performance assessment. The metrics have a noticeable but complex relationship with profit creation. The IPEI and IPSI alone have an average classification accuracy of 80%, indicating that these measures capture relevant aspects of operational efficiency. The IPEI and IPSI are valuable tools for a more detailed analysis of corporate performance, particularly regarding workforce utilization. Finally, we propose using metrics from the IPEI/IPSI matrix, combined with income and profit levels, to provide organizations with a framework for evaluating the company's performance from the perspective of human capital efficiency.

As we know in theory different factors predict business success, it is necessary to include already known metrics of organizational success related to employee such as Human Capital ROI (Becker et al., 2012; Flamholtz & Randle, 2011; Fitz-Enz, 2000), Turnover cost of employees (Tracey & Hinkin, 2008) or others that also illuminate the intricate relationship between income and human resource investment through mostly financial parameters. Forward, the paper emphasizes their value in enriching traditional business analysis and using these indices as a link between operational efficiency and human resources strategies.

The research contributes to understanding these intricate relationships by applying an interdisciplinary approach and connecting them to practical business applications. In the broader context of recognizing the importance of human capital in generating income, IPEI and IPSI provide an additional benchmarking tool to inform strategic corporate decision-making, guide policy formulation, and complement investor analysis. Although these indices should be interpreted in conjunction with other financial and operational metrics, their integration into business analysis underscores the importance of employees to the company's financial success.

The IPEI is a direct measure of employee productivity, providing insight into how effectively a company uses its workforce to generate revenue. A higher IPEI indicates better productivity or a business model that requires fewer employees to generate significant revenue.

The IPSI shows how effectively a company converts wage costs into revenue, indicating the return on investment in human capital. This measure provides insight into the balance between employee compensation and the value they bring to the company. For example, a higher IPSI may mean a high return on wage costs and is likely to occur in firms with highly skilled or efficient employees. IPEI and IPSI can also serve as tools for self-assessing situations in which operational enhancements in human capital management can significantly impact financial performance. For instance, a low IPEI may necessitate a process audit, the investigation of automation alternatives, or the implementation of education initiatives to enhance employee productivity.

Additionally, these measurements can assist in strategic planning by highlighting the impact of changes in employee numbers or salary levels on income. For example, if expanding the workforce would not significantly reduce IPEI, this indicates operational scalability. However, if the IPSI values are low, it may indicate that the organization should reassess its compensation practices to ensure that they are consistent with industry standards and effectively inspire people to improve their performance. These indices also enable organizations to compare their performance with that of their competitors. They may be especially appropriate for comparing organizations that seek similarly skilled employees.

Companies that retain highly skilled employees are more likely to have high IPEI and IPSI scores, indicating they have implemented effective HR strategies. The scientific benefits of employing IPEI and IPSI for firm evaluation are multifaceted, contributing to our understanding of human resource management, business analysis, and operations research. These metrics provide a quantifiable measure of a company's revenue generation from its human capital, offering a precise method to assess operational efficiency. They enrich the toolbox for financial performance analysis by providing new insights that standard financial metrics may not capture, particularly regarding workforce efficiency.

The displayed metrics, or their application, are not limited to business analytics; IPEI and IPSI serve as "bridges" connecting financial performance with human resource strategies. This multidimensional approach is necessary for multidisciplinary research, as it contributes to knowledge in labor economics, strategic management, and organizational behavior. For instance, they enable empirical research to benchmark performance and establish industry standards, thus incorporating a new dimension into competitive analysis. In academia, these measures could help assess a range of human resource strategies and investigate the relationship between revenue generation and investments in employees.

Furthermore, the methodological enhancement of predictive analytics can be achieved by applying it to predictive modeling. These applications have further potential to expand the bounds of methodological approach by incorporating human capital characteristics. A broader understanding of the relationship between revenue and employee investment might inform policy decisions affecting labor markets and company governance. Also, these indicators provide alternative criteria for analyzing a firm's profitability and growth potential, thereby improving the assessment of company value and investment risk. Additionally, IPEI and IPSI provide a concrete advantage to company decision-making by identifying potential operational improvements. They also encourage deeper investigation into the causal relationships between financial outcomes and employee-related issues, which may lead to the development of new theories or models in financial and operational management.

In essence, IPEI and IPSI are not independent indicators of company success, which is also a limiting factor; their ability to illuminate aspects of operational effectiveness related to human resources adds valuable insights to both academic study and practical application in business performance analysis. They encourage a deeper understanding of the contribution of labor factors to a firm's ability to generate income.

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