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# Evaluating the Efficiency of Human Capital at Small and Medium Enterprises in the Manufacturing Sector Using the DEA-Weight Russell Directional Distance Model

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**Abstract:** The present research aims to analyze the efficiency of human capital in relation to sales in each of the subsectors of economic activity within Mexican small- and medium-sized enterprises in the manufacturing industry. To accomplish this, a panel data set covering the years 2009–2020 is utilized. The inputs used are investment in training, salary, and days worked, with sales as the output. Initially, due to the high variability (cv > 1) of both the inputs and the output, the information is divided into three groups by quartiles: Group 1 < 25%, Group 2 = 25–75%, and Group 3 > 75%. As a first step in the analysis, a hypothesis test identifies a significant increase in sales for those subsectors that reported investing in training compared with those that did not. As a result, for the efficiency analysis, SMEs that report not investing in training are removed from the sample. Subsequently, to confirm the statistical explanation of the inputs for the output, a regression analysis is performed. With an input-oriented DEA model, it is found that most subsectors exhibit high overall and pure efficiency ($\geq$0.75) as well as increasing returns to scale. Interestingly, the research introduces a novel approach by proposing subgroups within SMEs, providing a more precise analysis. The findings of this study emphasize the fundamental role of human capital as a key driver of economic growth and innovation within the manufacturing sector. This research also highlights variations in efficiency among different subsectors, underscoring the need for tailored strategies for each. These results offer practical guidance for companies seeking to optimize their operations and contribute to the economic development of a developing country. In conclusion, this paper contributes both theoretically and practically to understanding the interaction between human capital and financial indicators. The results underscore the importance of investing in workforce development, ultimately promoting economic growth, improving productivity, and advancing social progress.

**Keywords:** SMEs; manufacturing economic sector; human capital; wages; data envelopment analysis; training investment



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## 1. Introduction

Due to globalization, companies must have the ability to face constant changes in terms of innovation and knowledge generation (Mejía de León et al. 2014). Human capital (HC) is one of the main factors that leads an organization to have sustainable competitive advantages. This is because HC is composed of individuals who contribute their intellectual wealth, experience, and motivation to help the organization achieve its most relevant goals and objectives (Kirberg 2016).

Research on HC has been approached from different perspectives—economic, administrative, and psychological—as well as levels: individual, firm, and country (Ployhart and Moliterno 2011). HC has been defined as the set of knowledge in education, job training, and experience that provides the abilities and skills for an individual to be economically productive (Becker 1993; Cardona-Acevedo et al. 2007; Konara and Wei 2019; Schultz 1961).

It is known that HC is an essential element for the competitiveness and economic growth of companies. Investing in HC generates an increase in skills, which results, among other things, in an increase in the organization's sales (Nielsen et al. 2010; Pasban and Nojedeh 2016; Sahinidis and Bouris 2008).

A company has two types of assets—tangible and intangible—with the economic value of the company being the sum of both (Kaplan and Norton 2002). Tangible assets are represented by physical and financial capital, while intangibles are represented by intellectual capital: structural, relational, and human, with the latter being the main element (Bayraktaroglu et al. 2019; González et al. 2017). Knowledge is the most precious and valued strategic resource, as if the organization understands and promotes it, then it will have the ability to respond quickly to inherent changes in the market and therefore increase the probability of survival (Bueno et al. 2001).

In Mexico, there are a total of 6,373,169 companies employing 36,038,272 people. Of these, 312,286 (4.9%) are small- and medium-sized enterprises (11–250 employees) with a total workforce of 11,063,750 (30.7%). Their life expectancy is 7.8 years, and only 20% of them manage to surpass 10 years. This, among other characteristics, is a response to the lack of investment in HC, since only 28.8%—3,186,360—of all SMEs invest in their HC, a condition that is going to have a direct impact on the organization's financial performance in the short and medium term and thus on its life expectancy (INEGI 2019).

In a developing country like Mexico, manufacturing activity is considered the main driving force of economic growth (Fernández Xicoténcatl et al. 2013; Bautista and Peralta 2017). It contributes 32% of the country's value added and makes significant contributions to job creation (Abraham et al. 2017). It is also one of the main pillars of the economy, representing around 18% of the country's gross domestic product (GDP) (Statista Research Department 2022). According to the North American Industry Classification System (NAICS), the manufacturing sector is composed of 21 subsectors grouped into 3 main categories: basic, transformative, and manufacturing, with a total of 86 branches, 179 sub-branches, and 292 activity classes (Instituto Nacional de Estadística y Geografía 2018).

While numerous studies have examined the impact of HC investments on sales from various perspectives, few have reported this impact at the level of economic activity subsectors, and even fewer have utilized a data envelopment analysis (DEA) model to investigate the relationship between investing in HC and sales. Thus, the aim of this research is to analyze the efficiency of human capital (training, wages, and days worked) in relation to sales in each of the subsectors of economic activity within Mexican small- and medium-sized enterprises in the manufacturing industry. In this paper, the DEA CCR input-oriented model is applied to calculate the technical efficiency (TE) (Charnes et al. 1978), and the DEA BCC input-oriented model (Banker et al. 1984) is applied to calculate the pure technical efficiency (PTE) to evaluate the efficiency of sales in relation to HC per economic activity subsector. Therefore, our study explores how this relationship can potentially confer a competitive advantage to each economic activity subsector.

## 2. Literature Review

### 2.1. Human Capital

Research on HC began in the late 1950s and early 1960s with Mincer, Schultz, and Becker (Becker 1962; Mincer 1958; Schultz 1961). Based on their work, the definition of HC consists of four main dimensions: education, training, experience, and health. However, as research progressed over time, different elements needed to be considered to provide a comprehensive definition of HC. Brooking and Motta (1996) concluded that knowledge, creativity, and competencies should be considered. Dzinkowski (2000) agreed with what Brooking and Motta reported regarding knowledge and competencies, adding skills to the definition. Lufungula and Borromeo (2019) and Pasban and Nojedeh (2016) described HC as the combination of employees' skills, training, and attitude. On the other hand, Hamadamin and Atan (2019) as well as Mihardjo et al. (2021) recognized attitude, motivation, and commitment as important elements in the definition of HC. Likewise, Lenihan et al. (2019) identified education, professional knowledge, personal experiences, and creativity as components to consider. Akdere and Egan (2020) considered employee capacity as a transcendental aspect of HC. Aman-Ullah et al. (2022) identified ability, knowledge, and capacity as fundamental attributes. Recently, it was determined that HC should be approached in a multidimensional way, and it consists of two transcendental factors, cognitive and noncognitive, each with various dimensions (Zhang et al. 2023). For better understanding, Figure 1 shows a general overview. Although much remains to be accomplished to unify the definition of HC, largely due to the inherent heterogeneity among each worker, it is important to generate indicators that allow for a comprehensive measurement of HC.

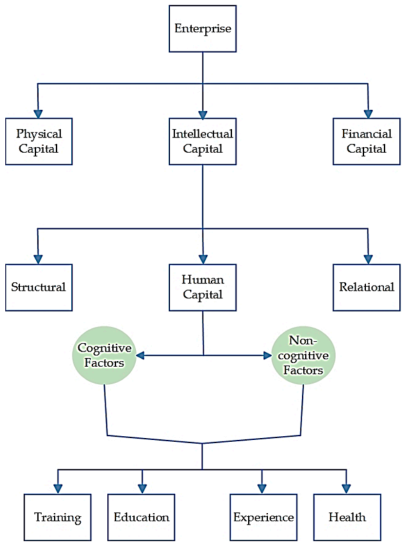


**Figure 1.** Overview of human capital.

Human capital is the most valuable intangible resource in any organization, regardless of its size (micro, small, or large). Its role is crucial in an organization's performance, particularly in today's fast-growing global economy, where companies of all sizes and industries require intellectual capital with a wide range of skills to ensure sustainability and competitiveness. Hence, investing in employees' skills generates a competitive advantage in the industry and, therefore, has a positive impact on the organization's financial performance indicators (Aman-Ullah et al. 2022; Muda and Rahman 2016). Sales are one of the primary financial performance indicators for companies (Bissoondoyal-Bheenick et al. 2023; Ernst et al. 2010; Keszey and Biemans 2016; Khan and Quaddus 2018), and HC is the primary element that can increase or decrease this indicator (Sitzmann and Weinhardt 2019).

In recent decades, several studies have focused on the impact of investment in HC on different populations, classified by company size or the economic sector to which they belong (Khan and Quaddus 2018).

### 2.2. HC in Small and Medium Enterprises

Small and medium enterprises (SMEs) play a critical role in the growth of the global economy. They act as catalysts for any country's economy, either in developed or, with much greater reason, developing countries such as Mexico. The flexibility in terms of opportunities, the ability to respond quickly to changes in demand, the speed of adaptation with respect to competitiveness in the market, and the generation of employment are some of the examples of why SMEs are of utmost importance (Erdin and Ozkaya 2020).

In some studies carried out in small- and medium-sized manufacturing enterprises in different countries such as Mexico, Peru, Chile, Colombia, and Japan, a significant increase in sales was identified in those that created improvement programs for their HC compared with those that did not (Gamage and Sadoi 2013; Acevedo and Tan 2011). In

Italy, a positive and significant impact on the productivity of organizations of different sizes and sectors was observed when investing in HC (Colombo and Stanca 2014). In Vietnam, small- and medium-sized enterprises are divided into two groups: (1) household business and (2) formal enterprises. Statistical evidence allows one to conclude that there is a significant effect from investment in HC in household businesses but not for formal enterprises (Duy and Oanh 2015). In small- and medium-sized enterprises in the southeastern region of Europe, it was found that investment in HC has a positive effect on organizational performance (Prouska et al. 2016).

In Malaysia, Yahya et al. (2012) conducted a study on SMEs in the country and, like Prouska, found a positive and significant effect on organizational performance when investing in HC. In Chinese manufacturing SMEs, the importance of salaries and training for HC has been analyzed, and they were identified as significant factors in increasing organizational financial performance (Liu and Lu 2016). Onkelinx et al. (2016) recognizes that both salary and training are fundamental elements of HC, in which investment is necessary to increase productivity. Zhao et al. (2018) demonstrates that the salary of HC is a determining factor for optimal individual performance. In a study conducted with panel data from 99 different countries, it was concluded that investment in HC by any size of company is crucial for productivity growth (Almeida and Aterido 2015). In a group of 40,000 small- and medium-sized manufacturing companies in Mexico, it was found that investment in training produces a significant increase in organizational sales (Rosales-Córdova and Llanos 2021).

Due to the lack of information identified in the literature review regarding investment in HC and its impact on financial organizational performance by the manufacturing subsector, the present study formulates the following hypothesis for investigation:

**H1.** *In each subsector of economic activity, SMEs that invest in training have significantly higher sales than SMEs that do not invest in training.*

**H2.** *In each subsector of economic activity, wages, training, and days worked are human capital variables that significantly explain sales.*

**H3.** *The SMEs in the three main subsectors—food, transportation, and chemical—in the Mexican manufacturing industry exhibit pure efficiency* $\geq$ *0.75.*

**H4.** *At least 50% of all the manufacturing subsectors exhibit an overall and pure efficiency* $\geq$ *0.75.*

This study provides valuable insights into the relationship between investment in HC and organizational financial performance, highlighting the importance of training and other key factors. The findings of this research are in the interest of policymakers, business leaders, and academics seeking to enhance the productivity and success of SMEs in different economic sectors.

### *2.3. Data Envelopment Analysis Method in Human Capital*

The application of data envelopment analysis (DEA) methodology in studying HC or human resource management (HRM) at the company level has been explored in various papers. However, only a limited number of studies have considered the incorporation of macroeconomic variables. Thus, the aim of this paper is to develop a DEA CCR input-oriented model and a DEA BCC input-oriented model to analyze the efficiency of HC at the macroeconomic level. The proposed models aim to incorporate human resource indicators as operational tools to reflect the strategic aspects of HC, as suggested by Olexová (2011). Additionally, both models consider quantitative indicators of human resource-controlling systems.

Cook et al. (2000) developed a DEA model to determine cost targets by identifying efficient bank branches. Their model incorporates a service input measure, represented by personal counts, and a sale output measure, represented by transaction types.

Monika and Mariana (2015) designed a DEA model to determine qualitative indicators for analyzing the productivity and efficiency of human resources in IT companies. Their model includes HC indicators such as remuneration and employee benefits, working conditions, managerial approach, work motivation, job satisfaction, and productivity.

Zhang and Shi (2019) developed a DEA model to evaluate educational performance, with a focus on the optimal allocation of social resources. Their model incorporated financial inputs (scientific and technical funds), educational expenses, material inputs (hardware, classrooms, etc.), and HC inputs (teachers, students, managers, etc.). They employed the principal components method to reduce the dimensions of the inputs and outputs.

Two studies incorporated macroeconomic variables. The first was written by Zhang et al. (2020), who developed a DEA model to investigate the technical efficiency, pure technical efficiency, and scale efficiency of maternal and child health hospitals in China at the district and country levels. Their study analyzed the utilization of government funds. They categorized the factors influencing hospital productivity into external factors (macroeconomic variables) and internal factors. The external factors include the catchment area, economic status, population, health insurance, distance, occupancy rate, and location (urban or rural). The internal factors comprise income, educational status, hospital staff, average length of stay, and hospital scale. The input variables in their study were the number of open beds, nurses, doctors, hospital area, devices, total expenditure, and health workers, while the output variables were total revenue, patient discharges, outpatient visits, health examinations, income from medical services, bed occupancy, and average inpatient days. The second was written by Kalapouti et al. (2020), who researched the problem of innovation efficiency using macroeconomic variables. Their analysis incorporated R&D expenditure and HC as input variables, whilst the output variables were the number of patent applications, degree of diversity of innovative activity, regional employment level, and regional development level.

In summary, the existing literature has primarily focused on applying DEA models to study HC at the company level. However, there is a gap in the research for considering macroeconomic variables. This article aims to fill this gap by developing two DEA models to analyze human capital efficiency by subsector of economic activity in small- and medium-sized manufacturing enterprises (i.e., at the macroeconomic level). However, this model can also be applied at the microeconomic level, whether to analyze a single company, a department, or multiple companies within a single subsector.

## 3. Methodology

This study investigates efficiency and productivity growth in the relationship between investing in HC and sales in small and medium enterprises (SMEs). To accomplish this, the DEA methodology is used to develop two productivity and efficiency models.

DEA models are linear programming mathematical formulations that empirically measure the efficiency of multiple entities called DMUs (Martín-Gamboa and Iribarren 2021). DEA models convert multiple inputs and outputs of a DMU into a scalar measure of operational efficiency (SE) relative to the DMUs in a set (Kumar and Gulati 2008). An SE can be calculated as the division between the overall technical efficiency (OTE) and pure technical efficiency (PTE), and DEA models calculate the OTE of a DMU while assuming constant returns to scale (CRS) and the PTE of a DMU while assuming variable returns to scale (VRS). The OTE is the technical efficiency calculated in the unchanged scale returns using the CCR DEA model, and the PTE is the relative efficiency calculated from the BCC model under a variable return-to-scale assumption which lacks the scale effects. A DMU produces optimally when the OTE is equal to the PTE because no efficiency gain occurs if the scale of production is changed. Finally, DEA models can measure the TE of a DMU from an input orientation or from an output orientation. Input-oriented TE aims to minimize inputs to produce the same level of outputs. On the contrary, output-oriented TE aims to maximize the outputs for a given set of input quantities (Kumar and Gulati 2008).

Since SMEs control investments in HC, and they do not have control over sales, in this paper, a DEA CCR input-oriented model is developed to calculate the OTE (Charnes et al. 1978), and a DEA BCC input-oriented model is designed to calculate the PTE (Banker et al. 1984) with the aim of measuring sales efficiency in the HC investments within SMEs. This is new in studies on HC in general and therefore an important contribution to current research on HRM.

### 3.1. CCR Input-Oriented Model

The CCR input-oriented model is a CRS DEA model that calculates the OTE for a DMU as the maximization of the ratio between the weighted sum of the outputs and the weighted sum of the inputs (Marjanović et al. 2018). The dual CCR input-oriented model is as follows:

$$\min OTE_0 = \theta_0 - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^-\right) \quad (1)$$

ST

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta_0 x_{i0} \quad i = 1, 2, \ldots, m \quad (2)$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{r0} \quad r = 1, 2, \ldots, s \quad (3)$$

$$s_i^-, s_r^+ \geq 0 \quad (4)$$

$$\lambda_j \geq 0 \quad j = 1, 2, \ldots, n \quad (5)$$

where $x_{ij}$ is the amount of input $i$ used by DMU $j$ ($DMU_j$), $x_{io}$ is the amount of input $i$ used by $DMU_0$, which is the DMU under analysis, $y_{rj}$ is the amount of output $r$ produced by $DMU_j$, $x_{ro}$ is the amount of output $r$ produced by $DMU_0$, $\lambda_j$ is the optimization variable that measures the relationship importance between $DMU_j$ and $DMU_0$, $\theta_o^*$ is the optimal OTE for $DMU_0$, and $s_i^-$ and $s_r^+$ are the slack variables that show by how much the inputs can be decreased ($\hat{x}_{i0} = \theta_0^* x_{i0} - s_i^{-*}$) and the outputs can be increased ($\hat{y}_{r0} = y_{r0} - s_r^{-*}$) to make $DMU_0$ efficient.

### 3.2. BCC Input-Oriented Model

The BCC input-oriented model is a VRS DEA model that calculates the PTE for a DMU as the maximization of the ratio between the weighted sum of the outputs and the weighted sum of the inputs, but this model eliminates the scale part from the analysis (Marjanović et al. 2018). The additional constraint $\sum_{j=1}^{n} \lambda_j = 1$ must be added to the CCR input-oriented model to calculate the efficiency of $DMU_0$ with VRS (Chen et al. 2015). Thus, the dual BCC input-oriented model is as follows:

$$\min PTE_0 = \theta_0 - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^-\right) \quad (6)$$

ST

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta_0 x_{i0} \qquad i = 1, 2, \ldots, m \quad (7)$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{r0} \qquad r = 1, 2, \ldots, s \quad (8)$$

$$s_i^-, s_r^+ \geq 0 \quad (9)$$

$$\lambda_j \geq 0 \qquad j = 1, 2, \ldots, n \quad (10)$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{11}$$

Finally, as has been mentioned, $SE_0 = OTE_0/PTE_0$. Normally, the $OTE_0$ calculated with the CCR input-oriented model will not surpass, $PTE_0$ calculated with the BCC input-oriented model for $\mathrm{DMU}_0$.

## 4. Case Study

In this section, we focus our attention on a study case that analyzes the efficiency of small and medium enterprises (SMEs) in Mexico. To accomplish this, we analyze HC (training, wages, and working days) efficiency in relation to sales within each economic activity subsector (EAS) of the Mexican manufacturing industry.

The data used in this case study were collected from the Instituto Nacional de Estadística y Geografía (INEGI). This is an autonomous institute responsible for regulating, coordinating, registering, and disseminating information in Mexico in terms of population, territory, resources, and the economy. The instrument used to collect the database that covers the years 2009–2020 (Instituto Nacional de Estadística y Geografía 2009–2020) was the annual survey of the manufacturing industry (Instituto Nacional de Estadística Geografía e Informática 2020). The observation units were the small- and medium-sized companies of the Mexican manufacturing industry. According to the Diario Oficial de la Federacion (DOF), published daily by the government of Mexico, SMEs are stratified by the number of workers that make them up, with a range from 11 to 250 employees (Diario Oficial de la Federación 2019). In accordance with the regulations established by the INEGI in the procedure for the implementation of the Annual Survey of the Manufacturing Industry, as well as for the acquisition of data from the microdata laboratory, this ensured the ethical use of information as well as its replicability and acquisition.

The input variables were (1) training investment, meaning payments made by a company for the training of its workers, including payments to internal and external instructors, training materials, and payments to educational institutions, also known as scholarships, (2) wages, meaning all payments and contributions, normal and extraordinary, in money and kind before any tax deduction to remunerate the work of the personnel dependent on the company name in the form of wages and salaries, social benefits, and profits distributed to the personnel, whether this payment is calculated on the basis of a working day or by the amount of work performed, (3) days, meaning the number of days dedicated directly to activities related to the production process of the establishment, and the output variable (4) sales, meaning revenues obtained for the production of goods and services.

The steps for building the database were as follows:

Step 1. Observation units or companies that had between 11 and 250 full-time employees were classified as small- and medium-sized companies.

Step 2. All observation units or companies that reported zero wages and sales were removed from the sample.

Step 3. All variables (input and output) were segmented by quartiles to control the high variability inherent with the data. Therefore, the data were categorized into three groups: Group 1, the first quartile (<25%), Group 2, the second and third quartile (25–75%), and Group 3, the fourth quartile (>75%). In this paper, only the data of Group 1 and Group 2 are analyzed.

Step 4. In each group, based on a hypothesis test, significantly higher sales were identified in the SMEs that reported investing in training compared with those that did not. Consequently, to analyze the efficiency, only the companies that reported investing in training were considered.

Step 5. To confirm the statistical explanation of training investment, wages and days worked a regression analysis were employed.

Once the database was refined, the 21 economic subsectors comprising the manufacturing industry were analyzed by DEA models.

Table 1 shows the results of the hypothesis tests.

**Table 1.** Hypothesis test of average sales per year: training investment/yes vs. training investment/no.

| EAS | Group 1 | | | | | Group 2 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Training/Yes | | Training/No | | t-Student for Independent Samples | Training/Yes | | Training/No | | t-Student for Independent Samples |
| | N | Average Sales per Year (millions) | N | Average Sales per Year (millions) | | N | Average Sales per Year (millions) | N | Average Sales per Year (millions) | |
| 311 | 656 | 16,080 | 829 | 4578 | $t_{(1483)} = 42.34$ * | 1329 | 87,743 | 1658 | 26,764 | $t_{(2985)} = 47.23$ * |
| 312 | 120 | 12,332 | 145 | 3794 | $t_{(263)} = 16.21$ * | 249 | 70,258 | 293 | 24,633 | $t_{(540)} = 19.07$ * |
| 313 | 148 | 16,426 | 220 | 5795 | $t_{(366)} = 19.59$ * | 307 | 67,797 | 440 | 31,027 | $t_{(745)} = 21.42$ * |
| 314 | 64 | 13,561 | 115 | 4324 | $t_{(177)} = 14.68$ * | 135 | 49,373 | 231 | 24,848 | $t_{(364)} = 15.93$ * |
| 315 | 159 | 9322 | 330 | 4163 | $t_{(487)} = 17.83$ * | 298 | 39,969 | 661 | 21,131 | $t_{(957)} = 20.93$ * |
| 316 | 100 | 10,625 | 238 | 4016 | $t_{(336)} = 17.83$ * | 208 | 46,242 | 481 | 18,244 | $t_{(687)} = 25.65$ * |
| 321 | 64 | 13,862 | 140 | 4048 | $t_{(144)} = 9.91$ * | 138 | 56,869 | 283 | 18,211 | $t_{(419)} = 27.84$ * |
| 322 | 82 | 35,166 | 80 | 5243 | $t_{(160)} = 18.81$ * | 168 | 162,434 | 163 | 41,127 | $t_{(299)} = 19.48$ * |
| 323 | 70 | 17,906 | 73 | 5627 | $t_{(141)} = 12.92$ * | 146 | 79,081 | 147 | 31,979 | $t_{(291)} = 13$ * |
| 324 | 11 | 20,322 | 18 | 3462 | $t_{(27)} = 4.23$ * | 23 | 291,330 | 36 | 34,131 | $t_{(57)} = 7.94$ * |
| 325 | 187 | 35,742 | 121 | 6723 | $t_{(306)} = 17.26$ * | 381 | 266,957 | 243 | 98,079 | $t_{(622)} = 17.39$ * |
| 326 | 265 | 17,617 | 255 | 5533 | $t_{(518)} = 20.96$ * | 589 | 85,977 | 511 | 40,028 | $t_{(1098)} = 24.21$ * |
| 327 | 158 | 13,852 | 220 | 4177 | $t_{(376)} = 27.71$ * | 325 | 69,512 | 441 | 27,612 | $t_{(764)} = 26.03$ * |
| 331 | 84 | 21,617 | 62 | 4193 | $t_{(144)} = 13.68$ * | 175 | 127,124 | 124 | 23,629 | $t_{(293)} = 14.19$ * |
| 332 | 286 | 15,613 | 256 | 4959 | $t_{(540)} = 21.16$ * | 579 | 83,655 | 514 | 29,667 | $t_{(1091)} = 27.20$ * |
| 333 | 173 | 19,272 | 134 | 5361 | $t_{(305)} = 19.08$ * | 357 | 84,628 | 271 | 22,585 | $t_{(626)} = 24.14$ * |
| 334 | 77 | 14,238 | 77 | 3984 | $t_{(152)} = 12.74$ * | 159 | 46,336 | 155 | 23,259 | $t_{(312)} = 15.87$ * |
| 335 | 95 | 12,916 | 77 | 4770 | $t_{(170)} = 10.26$ * | 194 | 62,423 | 155 | 29,945 | $t_{(347)} = 11.66$ * |
| 336 | 144 | 14,118 | 104 | 4606 | $t_{(246)} = 14.60$ * | 298 | 81,460 | 209 | 28,742 | $t_{(505)} = 17.78$ * |
| 337 | 97 | 13,941 | 140 | 5499 | $t_{(235)} = 13.39$ * | 199 | 45,660 | 280 | 23,867 | $t_{(477)} = 18.22$ * |
| 339 | 129 | 10,055 | 151 | 4335 | $t_{(278)} = 14.31$ * | 264 | 41,225 | 305 | 20,021 | $t_{(567)} = 20.83$ * |

* $p < 0.05$.

Tables 2 and 3 show the data of Group 1 and Group 2, respectively.

**Table 2.** Group 1 input and output variables.

| CCR | Group 1 | | | | | Group 2 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| EAS | N | Average Investment in Training per Year (MXN) | Average Payroll (millions of MXN) | Average Working Days | Average Sales per Year (millions of MXN) | N | Average Investment in Training per Year (MXN) | Average Payroll (millions of MXN) | Average Working Days | Average Sales per Year (millions of MXN) |
| 311 | 656 | 4408 | 2347 | 109 | 16,080 | 1329 | 37,258 | 8830 | 94 | 87,743 |
| 312 | 120 | 3284 | 2283 | 187 | 12,332 | 249 | 29,575 | 7091 | 75 | 70,258 |
| 313 | 148 | 4485 | 2485 | 130 | 16,426 | 307 | 24,961 | 7125 | 72 | 67,797 |
| 314 | 64 | 3581 | 2664 | 239 | 13,561 | 135 | 18,823 | 5138 | 52 | 49,373 |
| 315 | 159 | 2506 | 1610 | 117 | 9322 | 298 | 17,849 | 3953 | 43 | 39,969 |
| 316 | 100 | 2912 | 1551 | 72 | 10,625 | 208 | 15,184 | 5006 | 49 | 46,242 |
| 321 | 64 | 3800 | 2024 | 94 | 13,862 | 138 | 17,517 | 6247 | 60 | 56,869 |
| 322 | 82 | 9640 | 5134 | 237 | 35,166 | 168 | 63,178 | 16,805 | 173 | 162,434 |
| 323 | 70 | 4909 | 2614 | 121 | 17,906 | 146 | 25,490 | 8598 | 83 | 79,081 |
| 324 | 11 | 5492 | 3360 | 222 | 20,322 | 23 | 89,739 | 32,004 | 305 | 291,330 |
| 325 | 187 | 9798 | 5218 | 241 | 35,742 | 381 | 133,479 | 25,272 | 290 | 266,957 |

**Table 2.** *Cont.*

| CCR | | Group 1 | | | | Group 2 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **EAS** | **N** | **Average Investment in Training per Year (MXN)** | **Average Payroll (millions of MXN)** | **Average Working Days** | **Average Sales per Year (millions of MXN)** | **N** | **Average Investment in Training per Year (MXN)** | **Average Payroll (millions of MXN)** | **Average Working Days** | **Average Sales per Year (millions of MXN)** |
| 326 | 265 | 4799 | 2723 | 152 | 17,617 | 589 | 32,897 | 8938 | 91 | 85,977 |
| 327 | 158 | 3699 | 2515 | 200 | 13,852 | 325 | 27,424 | 7161 | 74 | 69,512 |
| 331 | 84 | 5926 | 3156 | 146 | 21,617 | 175 | 58,008 | 12,474 | 137 | 127,124 |
| 332 | 286 | 4280 | 2279 | 105 | 15,613 | 579 | 33,420 | 8585 | 89 | 83,655 |
| 333 | 173 | 5283 | 2813 | 130 | 19,272 | 357 | 41,427 | 8082 | 92 | 84,628 |
| 334 | 77 | 3883 | 2179 | 118 | 14,238 | 159 | 14,273 | 5090 | 49 | 46,336 |
| 335 | 95 | 3528 | 1949 | 101 | 12,916 | 194 | 22,337 | 6612 | 66 | 62,423 |
| 336 | 144 | 3836 | 2233 | 132 | 14,118 | 298 | 34,616 | 8195 | 87 | 81,460 |
| 337 | 97 | 3775 | 2269 | 144 | 13,941 | 199 | 19,913 | 4553 | 49 | 45,660 |
| 339 | 129 | 3592 | 1468 | 124 | 10,055 | 264 | 15,107 | 4338 | 44 | 41,225 |

**Table 3.** Group 2 input and output variables.

| BCC | N | Group 1 | | | | Group 2 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **EAS** | **N** | **Average Investment in Training per Year (MXN)** | **Average Payroll (millions of MXN)** | **Average Working Days** | **Average Sales per Year (millions of MXN)** | **N** | **Average Investment in Training per Year (MXN)** | **Average Payroll (millions of MXN)** | **Average Working Days** | **Average Sales per Year (millions of MXN)** |
| 311 | 656 | 5250 | 2772 | 228 | 16,080 | 1329 | 44,901 | 9476 | 268 | 87,743 |
| 312 | 120 | 3998 | 2511 | 228 | 12,332 | 249 | 42,124 | 10,718 | 265 | 70,258 |
| 313 | 148 | 4906 | 2718 | 236 | 16,426 | 307 | 34,156 | 7790 | 266 | 67,797 |
| 314 | 64 | 3581 | 2664 | 239 | 13,561 | 135 | 31,706 | 8685 | 262 | 49,373 |
| 315 | 159 | 3195 | 2053 | 228 | 9322 | 298 | 23,102 | 5116 | 262 | 39,969 |
| 316 | 100 | 4400 | 2302 | 215 | 10,625 | 208 | 29,337 | 7833 | 262 | 46,242 |
| 321 | 64 | 4290 | 2076 | 240 | 13,862 | 138 | 20,468 | 8990 | 280 | 56,869 |
| 322 | 82 | 9674 | 5151 | 241 | 35,166 | 168 | 85,480 | 17,908 | 276 | 162,434 |
| 323 | 70 | 5965 | 3147 | 223 | 17,906 | 146 | 46,696 | 11,693 | 266 | 79,081 |
| 324 | 11 | 5811 | 3437 | 235 | 20,322 | 23 | 89,739 | 32,004 | 305 | 291,330 |
| 325 | 187 | 9798 | 5218 | 241 | 35,742 | 381 | 133,479 | 25,272 | 290 | 266,957 |
| 326 | 265 | 5903 | 3114 | 222 | 17,617 | 589 | 54,818 | 15,539 | 266 | 85,977 |
| 327 | 158 | 4266 | 2689 | 230 | 13,852 | 325 | 39,913 | 9398 | 265 | 69,512 |
| 331 | 84 | 6762 | 3578 | 227 | 21,617 | 175 | 72,580 | 17,670 | 271 | 127,124 |
| 332 | 286 | 5472 | 2881 | 220 | 15,613 | 579 | 55,906 | 16,837 | 265 | 83,655 |
| 333 | 173 | 6258 | 3306 | 224 | 19,272 | 357 | 56,611 | 17,081 | 265 | 84,628 |
| 334 | 77 | 5177 | 2721 | 219 | 14,238 | 159 | 49,400 | 21,421 | 258 | 46,336 |
| 335 | 95 | 4892 | 2568 | 218 | 12,916 | 194 | 48,506 | 16,936 | 262 | 62,423 |
| 336 | 144 | 5151 | 2707 | 219 | 14,118 | 298 | 58,459 | 19,098 | 264 | 81,460 |
| 337 | 97 | 4980 | 2689 | 221 | 13,941 | 199 | 32,271 | 9964 | 261 | 45,660 |
| 339 | 129 | 6672 | 2726 | 231 | 10,055 | 264 | 33,885 | 11,802 | 260 | 42,580 |

### *4.1. Statistical Results*

The average employee range identified in each quartile group was as follows: Group 1 = [11–50], Group 2 = [51–150], and Group 3 = [151–250]. As mentioned in the steps for building the database, this segmentation was performed with the intention of controlling the inherent high variability of the studied variables. However, despite these efforts, the coefficient of variation for Group 3 remained high (>1), and therefore, it has been excluded from further analysis.

Table 1 presents the hypothesis tests conducted for each economic activity subsector in the two groups. In all cases, a statistically significant difference was observed in the sales of SMEs that reported investing in training compared with those that did not. Consequently, to analyze the efficiency of each subsector, only the SMEs that reported investment in training are considered.

Through multiple regression analysis, it was identified in both groups that the three utilized HC variables had a significant effect on sales.

$$\text{Group 1: S} = -35{,}443 + 500\ \text{TI} + 3.31\ \text{S} + 153\ \text{W}$$

where the following definitions apply:

| | | |
|---|---|---|
| S | = mean sales | ($) |
| TI | = mean training investment | ($) |
| S | = mean salary | ($) |
| W | = mean days worked | (days) |

$$F\ (20, 21) = 10.14,\ p < 0.001$$

$$\text{Group 2: S} = -438{,}253 + 747\ \text{TI} + 4.90\ \text{S} + 1446\ \text{W}$$

$$F\ (20, 21) = 21.04,\ p < 0.001$$

*4.2. DEA Results*

The size of the sample was confirmed because it fulfilled the validation rule n $\geq$ max {m $\times$ s; 3 (m + s)} (Cooper et al. 2007).

Figure 2 shows the OTE calculations for each EAS of the SMEs in Group 1 and Group 2. The OTE is the technical efficiency calculated in the unchanged scale returns using the CCR DEA model. According to the DEA efficiency distribution, 95.24% of the DEA OTE distribution was over 0.5 in Group 1, and 71.43% of the DEA OTE distribution was over 0.5 in Group 2. This means that the SMEs were more OTE efficient in Group 1 than in Group 2. In general, the higher the OTE, the better an SME makes full and reasonable use of its HC investments to make its sales efficiency higher. Hence, SMEs with low OTE must improve the allocation and use of HC investments to make their sales efficiency higher.

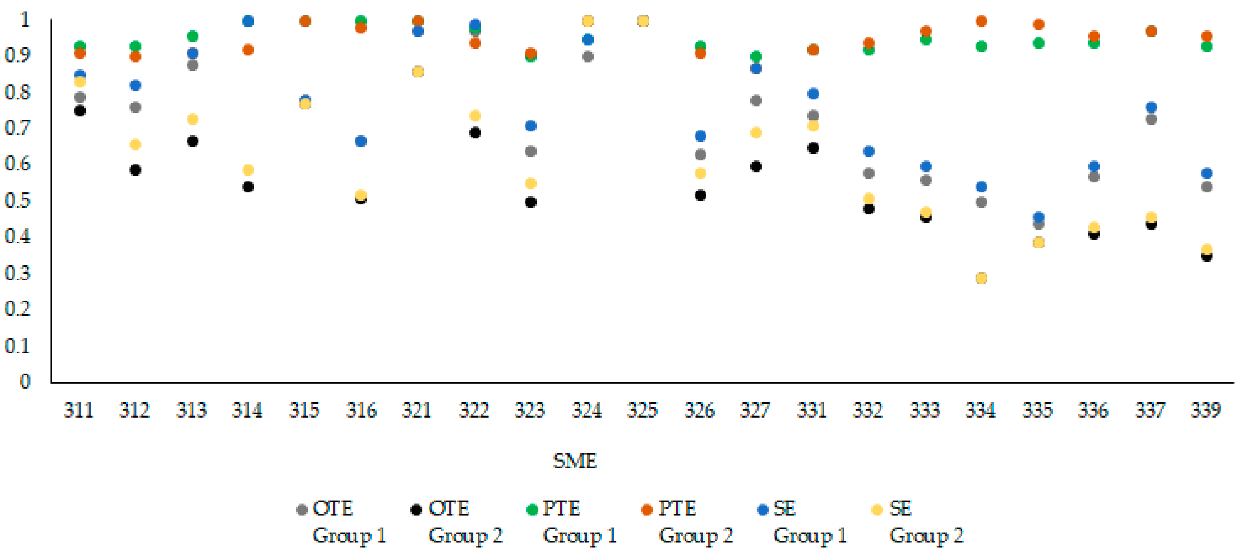


**Figure 2.** SMEs' overall technical efficiency, pure technical efficiency, and scale efficiency.

In Figure 2, SME 314 and SME 325 are the OTE effective DMUs of Group 1, and SME 324 and SME 325 are the OTE effective DMUs of Group 2, and they account for 9.52% of the total DMUs. The results indicate that these SMEs did not have excessive inputs and insufficient output because their HC investments in relation to their sales were in the optimal state, which means that these SMEs defined the efficiency frontier, and thus they defined the best practice. Because of that, they were the reference set for inefficient SMEs. Therefore, SME 314 and SME 325 in Group 1 and SME 324 and SME 325 in Group 2 reasonably allocated their HC investments, and they did not waste HC investments because these were in balance with their sales. Contrary to this, the OTE scores among the inefficient SMEs ranged from 43.70% to 97.00% in Group 1, and the OTE scores among the inefficient SMEs ranged from 28.89% to 86.00% in Group 2. SME 335 was the most non-DEA effective DMU of Group 1, and SME 334 was the most non-DEA effective DMU of Group 2. The non-DEA effective DMUs were all the SMEs with OTE < 1. These SMEs had excessive HC investments and insufficient sales, which means their HC investments in relation to their sales were not in the optimal state, and they accounted for 90.48% of the total DMUs. Strategically speaking, 19 out of 21 SMEs must improve their OTE while improving the use of HC investments.

Figure 2 also shows the PTE and SE calculations for each subsector of the SMEs in Group 1 and Group 2. The PTE is the relative efficiency calculated from the BCC model under the variable return-to-scale (VRS) assumption while lacking the scale effects. The PTE scores indicate that all inefficiencies resulted from managerial underperformance in managing HC investments. The results indicate that SME 314, SME 315, SME 316, SME 321, and SME 325 in Group 1 and SME 315, SME 321, SME 324, SME 325, and SME 334 in Group 2 acquired the status of local efficiency because their PTEs were equal to one. In addition, SME 314 and SME 325 in Group 1 and SME 324 and SME 325 in Group 2 acquired the status of being globally efficient because their efficiencies were on the efficient frontier under constant return-to-scale (CRS) assumptions (Table 4). The PTE was equal to one in SME 315, SME 316, and SME 321 in Group 1 and SME 315, SME 321, and SME 334 in Group 2, and therefore, these SMEs were efficient under the VRS assumption because their efficiencies were on the efficient frontier under the VRS assumption, but they were inefficient under the CRS assumption, making it possible to conclude that their overall technical inefficiency (OTIE = $1 - $ OTE) was not caused by poor HC investment utilization; rather, this was caused by the operations of SMEs with inappropriate scale sizes. In both groups, the remaining 16 SMEs achieved a PTE < 1. Out of these 16 SMEs, only in Group 1 did SME 322 have a PTE score lower than the SE score, which indicates that SME 322 had an inefficient utilization of HC investments, and this was mainly due to the inefficient management of HC investments. All the other SMEs failed to operate at the most productive scale size (scale inefficiency), which means they must reorganize the utilization of their HC investments to achieve optimal sales because the inappropriate size of their HC investments appears to be a cause of their technical inefficiency. Consequently, one objective of the SMEs is to operate at their most productive scales.

In Figure 2, the ability of each SME to choose the optimum size of their HC investment resources is indicated by the SE score, and in Table 4, the returns to scale analyses indicate that only SMEs 314 and 325 in Group 1 and SMEs 324 and 325 in Group 2 operated at CRS, which means these SMEs chose the optimum size for their HC investments. Contrary to this, in both groups, the other 19 SMEs experienced increasing returns to scale (IRS), and thus they operated at suboptimal scale sizes.

**Table 4.** SMEs' returns to scale.

| EAS | Group 1 | Group 2 | EAS | Group 1 | Group 2 | EAS | Group 1 | Group 2 |
|---|---|---|---|---|---|---|---|---|
| 311 | IRS | IRS | 322 | IRS | IRS | 332 | IRS | IRS |
| 312 | IRS | IRS | 323 | IRS | IRS | 333 | IRS | IRS |
| 313 | IRS | IRS | 324 | IRS | CRS | 334 | IRS | IRS |
| 314 | CRS | IRS | 325 | CRS | CRS | 335 | IRS | IRS |
| 315 | IRS | IRS | 326 | IRS | IRS | 336 | IRS | IRS |
| 316 | IRS | IRS | 327 | IRS | IRS | 337 | IRS | IRS |
| 321 | IRS | IRS | 331 | IRS | IRS | 339 | IRS | IRS |

We calculated the values of the OTE-inefficient SMEs for Group 1 and Group 2, and we classified them as follows: Marginally Inefficient, Above Average, Below Average, and Most Inefficient (Table 5). SMEs with OTE scores above the values of the third quartile (Q3 = 0.79 in Group 1 and Q3 = 0.66 in Group 2) but less than one were classified as

Marginally Inefficient. These SMEs were operating at high levels of efficiency, but they need to improve the utilization of HC investment resources a little more to become globally efficient. SMEs with OTE scores above the values of the second quartile (Q2 = 0.73 in Group 1 and Q2 = 0.52 in Group 2) but below the values of the third quartile (Q3 = 0.79 in Group 1 and Q3 = 0.66 in Group 2) were classified as Above Average. These SMEs were operating over the average, and they need to improve the utilization of HC investment resources more to become globally efficient. SMEs with OTE scores above the values of the first quartile (Q1 = 0.57 in Group 1 and Q1 = 0.45 in Group 2) but under the values of the second quartile (Q2 = 0.73 in Group 1 and Q2 = 0.52 in Group 2) were classified as Below Average. These SMEs were operating under the average, and they need to improve the utilization of HC investment resources much more to become globally efficient. Finally, SME's with OTE scores below the values of the first quartile (Q1 = 0.57 in Group 1 and Q1 = 0.45 in Group 2) were classified as Marginally Inefficient. These SMEs were the worst performers, and they need to improve much more in the utilization of HC investment resources to become globally efficient.

**Table 5.** Classification cluster of inefficient subsectors of SMEs with CCR-IO model.

| **Marginally Inefficient** | **Above Average** | **Below Average** | **Most Inefficient** | **Marginally Inefficient** | **Above Average** | **Below Average** | **Most Inefficient** |
|---|---|---|---|---|---|---|---|
| **Group 1** | **Group 1** | **Group 1** | **Group 1** | **Group 2** | **Group 2** | **Group 2** | **Group 2** |
| 311 | 312 | 316 | 333 | 311 | 312 | 316 | 334 |
| 313 | 315 | 323 | 334 | 313 | 314 | 323 | 335 |
| 321 | 327 | 326 | 335 | 315 | 326 | 332 | 336 |
| 322 | 331 | 332 | 336 | 321 | 327 | 333 | 337 |
| 324 | 337 | | 339 | 322 | 331 | | 339 |

In Figure 2, the SMEs with OTE = 1 had slacks equal to zero in the CCR DEA model, and the SMEs with PTE = 1 had slacks equal to zero in the BCC DEA model. This is because they were at the optimal solution of the CCR DEA model and BCC DEA model, respectively. All the inefficient SMEs had slack values different from zero. Slack values are highly important because they provide vital information concerning HC investment resources, or inputs, and average sales, or outputs, where an inefficient SME needs to improve its performance to attain OTE = 1 in the CCR DEA model and PTE = 1 in the BCC DEA model. This means that slacks are the proportional reduction in HC investments resources and the proportional increment in average sales that SMEs need to become globally efficient (OTE = 1) or locally efficient (PTE = 1). In this paper, slack values are the HC investment excesses that each SME must decrease to become efficient, since we are applying input-oriented models.

Table 6 adjusts the HC investment resources, or inputs, and the average sales, or output, to make each SME globally efficient, and Table 7 adjusts the HC investment resources, or inputs, and the average sales, or output, to make each SME locally efficient. As can be noticed, it is easier to become locally efficient than globally efficient because HC investment resources require decreasing more to become globally efficient than locally efficient.

Specifically, for Group 1, Figure 3 shows that the inefficient SMEs must reduce their average investment in training per year by 19.29%, their average payroll per year by 15.77%, and their average working days by 38.17% to produce the same average sales per year to be globally efficient, in comparison with being locally efficient. In Group 2, Figure 3 shows that the inefficient SMEs must reduce their average investment in training per year by 37.34%, their average payroll per year by 39.69%, and their average working days by 71.16% to produce the same average sales per year to be globally efficient, in comparison with being locally efficient. The average working days is the HC investment that must be reduced the most (Figure 3).

**Table 6.** Inputs and outputs to make each subsector SME globally efficient with CCR-IO model.

| EAS | Group 1 | | | | | Group 2 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | N | Average Investment in Training per Year (MXN) | Average Payroll (millions of MXN) | Average Working Days | Average Sales per Year (millions of MXN) | N | Average Investment in Training per Year (MXN) | Average Payroll (millions of MXN) | Average Working Days | Average Sales per Year (millions of MXN) |
| 311 | 656 | 4408 | 2347 | 109 | 16,080 | 1329 | 37,258 | 8830 | 94 | 87,743 |
| 312 | 120 | 3284 | 2283 | 187 | 12,332 | 249 | 29,575 | 7091 | 75 | 70,258 |
| 313 | 148 | 4485 | 2485 | 130 | 16,426 | 307 | 24,961 | 7125 | 72 | 67,797 |
| 314 | 64 | 3581 | 2664 | 239 | 13,561 | 135 | 18,823 | 5138 | 52 | 49,373 |
| 315 | 159 | 2506 | 1610 | 117 | 9322 | 298 | 17,849 | 3953 | 43 | 39,969 |
| 316 | 100 | 2912 | 1551 | 72 | 10,625 | 208 | 15,184 | 5006 | 49 | 46,242 |
| 321 | 64 | 3800 | 2024 | 94 | 13,862 | 138 | 17,517 | 6247 | 60 | 56,869 |
| 322 | 82 | 9640 | 5134 | 237 | 35,166 | 168 | 63,178 | 16,805 | 173 | 162,434 |
| 323 | 70 | 4909 | 2614 | 121 | 17,906 | 146 | 25,490 | 8598 | 83 | 79,081 |
| 324 | 11 | 5492 | 3360 | 222 | 20,322 | 23 | 89,739 | 32,004 | 305 | 291,330 |
| 325 | 187 | 9798 | 5218 | 241 | 35,742 | 381 | 133,479 | 25,272 | 290 | 266,957 |
| 326 | 265 | 4799 | 2723 | 152 | 17,617 | 589 | 32,897 | 8938 | 91 | 85,977 |
| 327 | 158 | 3699 | 2515 | 200 | 13,852 | 325 | 27,424 | 7161 | 74 | 69,512 |
| 331 | 84 | 5926 | 3156 | 146 | 21,617 | 175 | 58,008 | 12,474 | 137 | 127,124 |
| 332 | 286 | 4280 | 2279 | 105 | 15,613 | 579 | 33,420 | 8585 | 89 | 83,655 |
| 333 | 173 | 5283 | 2813 | 130 | 19,272 | 357 | 41,427 | 8082 | 92 | 84,628 |
| 334 | 77 | 3883 | 2179 | 118 | 14,238 | 159 | 14,273 | 5090 | 49 | 46,336 |
| 335 | 95 | 3528 | 1949 | 101 | 12,916 | 194 | 22,337 | 6612 | 66 | 62,423 |
| 336 | 144 | 3836 | 2233 | 132 | 14,118 | 298 | 34,616 | 8195 | 87 | 81,460 |
| 337 | 97 | 3775 | 2269 | 144 | 13,941 | 199 | 19,913 | 4553 | 49 | 45,660 |
| 339 | 129 | 3592 | 1468 | 124 | 10,055 | 264 | 15,107 | 4338 | 44 | 41,225 |

**Table 7.** Inputs and outputs to make each subsector SME technically efficient with BCC-IO model.

| EAS | Group 1 | | | | | Group 2 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | N | Average Investment in Training per Year (MXN) | Average Payroll (millions of MXN) | Average Working Days | Average Sales per Year (millions of MXN) | N | Average Investment in Training per Year (MXN) | Average Payroll (millions of MXN) | Average Working Days | Average Sales per Year (millions of MXN) |
| 311 | 656 | 5250 | 2772 | 228 | 16,080 | 1329 | 44,901 | 9476 | 268 | 87,743 |
| 312 | 120 | 3998 | 2511 | 228 | 12,332 | 249 | 42,124 | 10,718 | 265 | 70,258 |
| 313 | 148 | 4906 | 2718 | 236 | 16,426 | 307 | 34,156 | 7790 | 266 | 67,797 |
| 314 | 64 | 3581 | 2664 | 239 | 13,561 | 135 | 31,706 | 8685 | 262 | 49,373 |
| 315 | 159 | 3195 | 2053 | 228 | 9322 | 298 | 23,102 | 5116 | 262 | 39,969 |
| 316 | 100 | 4400 | 2302 | 215 | 10,625 | 208 | 29,337 | 7833 | 262 | 46,242 |
| 321 | 64 | 4290 | 2076 | 240 | 13,862 | 138 | 20,468 | 8990 | 280 | 56,869 |
| 322 | 82 | 9674 | 5151 | 241 | 35,166 | 168 | 85,480 | 17,908 | 276 | 162,434 |
| 323 | 70 | 5965 | 3147 | 223 | 17,906 | 146 | 46,696 | 11,693 | 266 | 79,081 |
| 324 | 11 | 5811 | 3437 | 235 | 20,322 | 23 | 89,739 | 32,004 | 305 | 291,330 |
| 325 | 187 | 9798 | 5218 | 241 | 35,742 | 381 | 133,479 | 25,272 | 290 | 266,957 |
| 326 | 265 | 5903 | 3114 | 222 | 17,617 | 589 | 54,818 | 15,539 | 266 | 85,977 |
| 327 | 158 | 4266 | 2689 | 230 | 13,852 | 325 | 39,913 | 9398 | 265 | 69,512 |
| 331 | 84 | 6762 | 3578 | 227 | 21,617 | 175 | 72,580 | 17,670 | 271 | 127,124 |
| 332 | 286 | 5472 | 2881 | 220 | 15,613 | 579 | 55,906 | 16,837 | 265 | 83,655 |
| 333 | 173 | 6258 | 3306 | 224 | 19,272 | 357 | 56,611 | 17,081 | 265 | 84,628 |
| 334 | 77 | 5177 | 2721 | 219 | 14,238 | 159 | 49,400 | 21,421 | 258 | 46,336 |
| 335 | 95 | 4892 | 2568 | 218 | 12,916 | 194 | 48,506 | 16,936 | 262 | 62,423 |
| 336 | 144 | 5151 | 2707 | 219 | 14,118 | 298 | 58,459 | 19,098 | 264 | 81,460 |
| 337 | 97 | 4980 | 2689 | 221 | 13,941 | 199 | 32,271 | 9964 | 261 | 45,660 |
| 339 | 129 | 6672 | 2726 | 231 | 10,055 | 264 | 33,885 | 11,802 | 260 | 41,225 |

Figure 4 shows the average reduction per HC investment resource that SMEs need to achieve to become globally efficient per classification cluster to produce the same average sales per year. In Group 1, the SMEs classified as Marginally Inefficient must reduce the average investment in HC per year by 15.46%, the average payroll per year by 16.55%, and the average working days by 35.40%. The SMEs classified as Above Average must reduce the average investment in HC per year by 26.37%, the average payroll per year by

25.18%, and the average working days by 34.37%. The SMEs classified as Below Average must reduce the average investment in HC per year by 40.80%, the average payroll per year by 36.93%, and the average working days by 52.62%. Finally, the SMEs classified as Most Inefficient must reduce the average investment in HC per year by 52.98%, the average payroll per year by 48.78%, and the average working days by 53.05%.

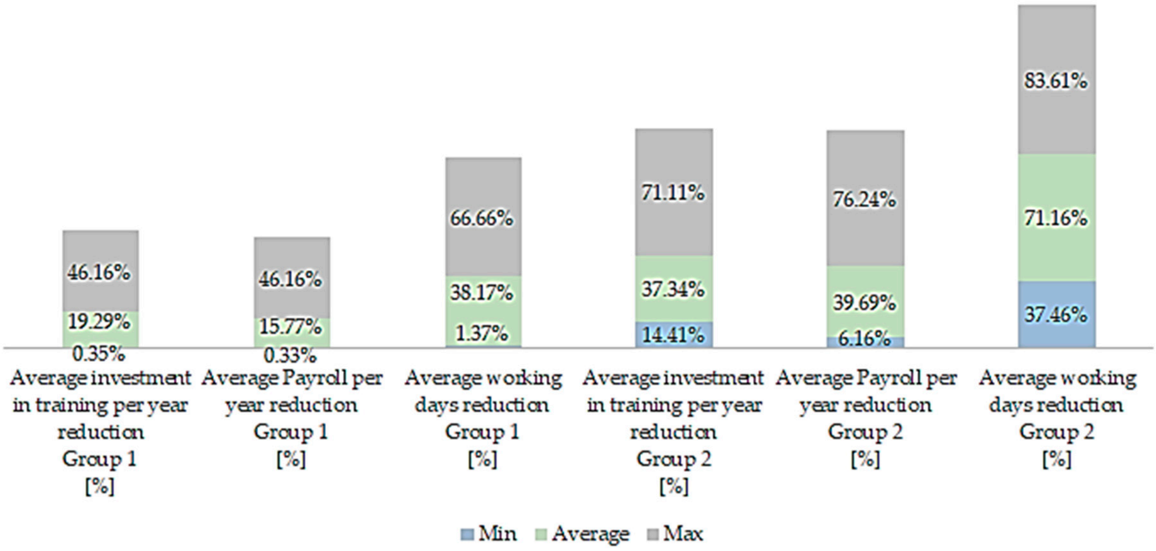


**Figure 3.** Percent of HC investment resource reduction to become globally efficient from being locally efficient per group.

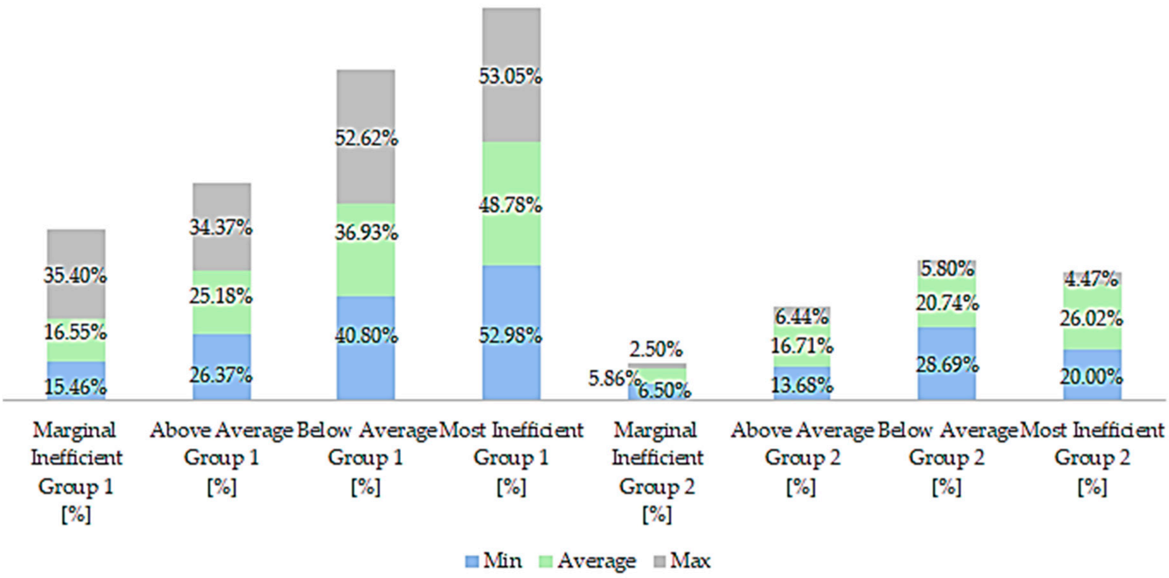


**Figure 4.** Average percentage of reduction per HC investment resource per classification cluster.

## 5. Discussion

The average number of employees in each of the subsectors fell within the range of 11–50 for Group 1, 51–150 for Group 2, and 151–250 for Group 3. Employee segmentation based on quartiles enabled the derivation of statistics with reduced variability.

Based on the results, it is evident that the interval established to define an SME was quite broad, since the behavior and needs vary depending on the number of employees. To give an example, if a company has 20 employees compared with 240 employees, both are considered SMEs. Additionally, the inherent variability represented by the human capital further underscores this point. Therefore, as was carried out in the current research, it is deemed necessary to generate subgroups. This condition enables a clearer analysis of individual responses to various stimuli.

While the variability of inputs and outputs was successfully managed for Group 1 and Group 2, the same cannot be said for Group 3. This situation prompts the need for an independent analysis of that dataset.

On one hand, the results in Table 1 demonstrate a statistically significant increase in sales observed within each of the economic activity subsectors for the SMEs that invested in training. This finding confirms the initial hypothesis regarding the effect of training investment. These results are in line with those reported by Aman-Ullah et al. (2022), Duy and Oanh (2015), Liu and Lu (2016), Prouska et al. (2016), and Yahya et al. (2012).

It is important to highlight that, on average, in both groups as well as across all subsectors, for every 10 companies that invest in training, 9 do not. This situation underscores the lack of awareness in a developing country like Mexico about the positive benefits of training for both social and economic growth. This is the reason why research such as the present study undoubtedly contributes to the country's development.

On the other hand, the second hypothesis was confirmed by identifying that training investment, days worked, and wages are variables that have a significant effect on sales. These findings are in line with those of Liu and Lu (2016), Parra Penagos and Fonseca (2015), Rosales-Córdova and Llanos (2021), and Sitzmann and Weinhardt (2019).

While various research using parametric or non-parametric models—such as DEA—has been conducted in the Mexican manufacturing industry to measure efficiency, whether by sector or subsector (Tavares Luna and Llamas 2018; Olvera Rebolledo and Suárez 2023; Santibañez et al. 2015; Rojas and Gómez 2018; Rojas et al. 2016), there are few works in which their input variables are exclusively based on human capital and are carried out particularly for SMEs.

In a developing country with a slowly growing economy (Aroche Reyes 2023), the proper allocation of resources to achieve organizational efficiency is crucial. The subsectors that play a pivotal role in contributing to the PIB (representing 64% of the total contribution of the manufacturing industries to the country's PIB) and in generating employment, listed in order of importance, are the following: the food industry (311), manufacturing of transport equipment (336), chemical industry (325), basic metal industries (331), beverage and tobacco industry (312), manufacturing of petroleum and coal products (324), and textile product manufacturing (314). Among these, the food industry, chemical industry, beverage and tobacco industry, petroleum and coal products, as well as textile product manufacturing sectors proved to be highly efficient—pure and overall—indicating optimal human capital management. This suggests that when SMEs are composed of 11–50 employees or 51–150 employees, to achieve maximum efficiency, there should be an average of 27.13 and 97.68 employees, respectively.

For Mexico, the fact that four of its manufacturing subsectors exhibit high efficiency—pure and overall—undoubtedly contributes to economic and social advancement (Almonte et al. 2021).

As observed in Table 5, the manufacturing of computers, communication, measurement, and other electronic equipment, components, and accessories (334), manufacturing of electrical apparatus and equipment for generating electrical energy (335), and manufacturing of transport equipment (336) were subsectors with low overall efficiency in both quartile groups. However, their pure efficiency is high and exhibits increasing returns. This can be interpreted in two ways: (1) with the current investment in human capital, sales should be higher, and (2) the same level of sales reported in these subsectors could be achieved with a lower investment in human capital. Given the input-oriented model, the latter interpretation is of interest in the present research.

Between these three mentioned subsectors, they contribute to 32.95% of the total PIB of the manufacturing industries. The most significant subsector in the country is the manufacturing of transport equipment. It is worth noting that the average percentage decrease required in the present group of subsectors in terms of training investment, salary, and working days was 32.22%, 38.98%, and 6.33%, respectively. This translates to an average of 25 employees for Group 1 and 98 employees for Group 2 being required to achieve 100% pure efficiency for these subsectors when taking into consideration subsectors 335 and 336, since subsector 334 already exhibited ideal pure efficiency. This confirms the third hypothesis for the food and chemical industries. Regarding the transport industry, only its overall efficiency was not what was expected.

It is important to highlight that each manufacturing subsector has its relevance—varying in degree—in terms of job creation and contribution to the PIB. Global efficiency is neither better nor worse than pure efficiency, as it depends on the specific type of efficiency being sought after, as well as the growth stage in which each SME finds itself.

Here, 47.62% of the subsectors in Group 1 and 23.81% in Group 2 exhibited high overall efficiency, while 100% of both groups demonstrated high pure efficiency and increasing returns to scale, which confirms—only for pure efficiency—the fourth hypothesis proposed; that is, at least 50% of the manufacturing subsectors have a high overall and pure efficiency.

Having the information that each subsector exhibits increasing returns to scale presents an opportunity for companies in all subsectors. This is because it allows for the potential to save resources allocated to human capital while maintaining the same sales volume or, alternatively, to provide a more detailed focus on the process carried out by human capital. In this scenario, sales should ideally be higher.

## 6. Conclusions

In Mexico, the manufacturing industry serves as the primary driver of economic growth and plays a crucial role in innovation, technology diffusion, and PIB contribution. Recognizing whether the management of productive factors—human capital—has been efficient, along with identifying areas of opportunity within each economic activity subsector, enables a country to adapt, modify, or continue its growth trajectory both economically and socially.

Human capital is the most critical resource within an organization, exerting a profound influence on the quality and quantity of production and, consequently, inherently impacting its productivity and sales. Thus, recognizing that training investment for each subsector of the manufacturing economic activity has a significant effect on sales is of the utmost importance. This realization—whether directly or indirectly—motivates business owners to invest in their personnel, shifting the perspective from viewing training as an expense to considering it as an investment that yields substantial returns.

Through DEA models, the overall and pure efficiency were identified in each economic activity subsector of the Mexican manufacturing industries. Notably, 100% of the SMEs exhibited high pure efficiency ($\geq$75%), with 90.47% of them demonstrating increasing returns. This condition is of the utmost significance, as the manufacturing sector is highly dynamic due to the existence of these returns. The opportunity to enhance productivity and sales can have far-reaching impacts on costs, prices, profits, production, employment, and investment, subsequently influencing economic fluctuations, inflation, company survival, and growth of companies and therefore the country.

The findings confirm the crucial role that investment in training, wages, and days worked plays in enhancing the efficiency and overall performance of small- and medium-sized enterprises (SMEs) across various subsectors. The results emphasize the importance of recognizing human capital as a pivotal resource in driving productivity and economic growth. The identification of high efficiency and the understanding of the factors contributing to it provide valuable guidelines for businesses seeking to optimize their operations and performance.

The current study is pioneering in the application of DEA models to calculate the efficiency of each economic activity subsector based on human capital. Furthermore, it stands out as one of the few studies that proposes the generation of employee number subgroups within SMEs, with the intention of providing results that are much closer to reality.

While the results of the current research contribute to advancing the understanding of the benefits generated by investment in human capital and provide a general overview of the efficiency within each Mexican manufacturing subsector, there is still much to do in a country like Mexico, where economic growth and social progress are intricately tied to efficient resource utilization.

In essence, this research contributes to the academic understanding of the relationship between human capital and business outcomes, and it also provides valuable insights for (1) entrepreneurs, (2) organizations seeking to improve their efficiency and contribute to the economic and social advancement of the country, and (3) the promotion of public policies related to businesses, such as regulations, laws, and policies that incentivize the creation, development, and growth of enterprises.

Future research:

- Perform annual comparisons for each of the subsectors within the manufacturing industry, incorporating weighting factors.
- Analyze the efficiency within each subsector rather than between subsectors.
- Employ output-oriented DEA models to analyze efficiency.

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