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Partial productivity measurement: validation for a transdisciplinary model

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Abstract

Labor productivity refers to the efficiency with which resources are used to obtain goods or services. Its calculation involves methods that include precise variables representing the performance of productive units; however, it is necessary to understand the outcomes when integrating social and human variables into the measurement process. The objective of this study is to describe the relevance of a new transdisciplinary model based on the partial measurement of productivity in an industrial company, applying a traditional indicator model, the Data Envelopment Analysis (DEA) technique, and a categorical model. The research focused on the work centers involved in raw material transformation, and the workforce analyzed consisted of operators who remained constant during the eight months of the study. The results indicate significant differences among the methods, showing large fluctuations in productivity values across periods. The inclusion of transdisciplinary variables in a categorical model increases productivity values compared to the DEA model. The high contrast between traditional models is due to the partial use of information to measure the indicator. There is evidence to confirm the proposed objective and to support the continued development of a model for measuring productivity that integrates transdisciplinary variables.

Keywords: Operations research; production engineering; resources management; measuring methods; mathematical models.

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Medición de la productividad parcial: validación para un modelo transdisciplinar

Resumen

La productividad laboral hace referencia a la eficiencia con la cual se utilizan los recursos para obtener bienes o servicios, para calcularla se emplean métodos que incluyen variables exactas del desempeño de las unidades productivas; pero es necesario conocer los resultados al integrar variables sociales y humanas en el proceso de medición. El objetivo es describir la pertinencia de un nuevo modelo transdisciplinar a partir de la medición parcial de la productividad en una empresa industrial, aplicando un modelo tradicional de indicadores, la técnica Análisis Envolvente de Datos y un modelo categórico. La investigación incluyó los centros de trabajo de transformación de la materia prima, la fuerza laboral analizada son los operarios que permanecieron constantes durante los últimos ocho meses del estudio. Los resultados indican marcadas diferencias entre los métodos, se presentan altas fluctuaciones en los valores de la productividad entre periodos; la inclusión de variables transdisciplinares en un modelo categórico eleva los valores de la productividad con respecto al modelo Análisis Envolvente de Datos. El alto contraste entre los modelos tradicionales se debe al uso parcial de la información para medir el indicador; hay evidencia para confirmar el objetivo propuesto y continuar con el desarrollo de un modelo para la medición de la productividad integrado por variables transdisciplinares.

Palabras clave: Investigación de operaciones; Ingeniería de la producción; gestión de recursos; métodos de medición; modelos matemáticos.

1. Introduction

Productivity is one of the ways through which a company can demonstrate its level of performance and can be defined as a ratio. Kozai et al. (2022) define productivity as “a relationship between outcomes and the time it takes to achieve them, and a relationship between the quantity and quality of goods or services produced and the quantity and quality of resources used to produce them” (p. 3). However, measuring productivity in itself does not reflect the benefits of a high indicator result; it is the management of business productivity that addresses the needs of the current economic environment. According to Ramírez-Méndez et al. (2021, p. 190), “Globalization demands that organizations improve their production processes, increase quality, grow, and enhance competitiveness”—improvements that can be achieved, among other strategies, by increasing business productivity (Ulloa-Pimienta et al., 2023; Kaydos, 2020).

Measuring productivity involves selecting the variables that affect the performance of the productive units under study, executing measurements, analyzing results, and making decisions (Demuner-Flores et al., 2023; Barradas-Martínez et al., 2021). The measurement process may occur directly when one or more input variables lead to the production of one or more output variables (Muñoz-Choque, 2021). Various methods exist to measure productivity, most of which are formulated using quantitative variables (Yong-Chung et al., 2024). This is partly because methods for obtaining data are less complex than those involving variables from the social and human sciences (Modrak, 2018). Likewise, parametric and nonparametric statistical models, as well as econometric models, tend to align better with requirements for financial reporting and compliance with tax obligations (Vartia, 2008).

One of the techniques for measuring productivity is partial measurement, in which the total output of a system is calculated using only one resource: “it is the ratio between a measure of output quantity and the quantity of a single input used, such as labor or capital” (Moreno-Rodríguez, 2022, p. 12; Franco-López et al., 2021; Fernández, 2023). Productivity for different resources can also be measured independently; in this case, it is referred to as physical partial productivity, since the measurement is related to the amount of input resource used or the output resource obtained (Caro-Ballestas et al., 2017; Cequea et al., 2011).

The aim is to demonstrate that it is possible to develop a new productivity model integrating transdisciplinary variables, based on the results obtained from partial measurement using three conventional methods. The techniques evaluated include efficiency and quality indicators, the DEA technique, and a categorical analysis that incorporates several variables affecting labor productivity—all within the stages of developing the new model.

The measurement was conducted in a metal-mechanical company located in the Valle de Aburrá region (Antioquia, Colombia), engaged in the manufacture of plastic products. The company uses a methodology based on production level to measure efficiency, which in this paper is referred to as the traditional productivity measurement. This corresponds to a non-frontier technique that does not require comparison with other productive units, as it evaluates efficiency in absolute terms (Elia et al., 2017).

For the DEA simulation, the data were mixed in nature and related to the company’s production operations for the labor force, considering production levels per labor and per machinery. DEA is a useful technique for processing the productivity indicator (Riaño-Henao & Larrea-Serna, 2021). DEA is a nonparametric statistical tool that consists of a set of mathematical models based on linear programming, which allows for the analysis of the efficiency of a group of productive units that use the same resources to produce the same products (Kloke & McKean, 2024). To do this, it establishes an efficient frontier for the productive units under study (Fontalvo-Herrera & De la Hoz-Granadillo, 2020). DEA is particularly valuable for efficiency measurement; its main benefit lies in “a correct definition of the unit under evaluation -Decision-Making Unit (DMU) in the DEA context- and its inputs and outputs, so that, once applied, it is possible to establish classifications between efficient and inefficient units” (Buitrago-Suescún et al., 2017, p. 149), thus enabling improvement analysis for the least efficient units.

The Decision Making Unit (DMU) is the resource on which the efficiency assessment is carried out; DMUs must be homogeneous units in the sense that they use the same type of resources to obtain the same type of results, albeit in different quantities (Diabat et al., 2015). Typically, machinery, labor, and materials are the main DMUs employed as variables for measurement in DEA (Dror et al., 2028).The categorical analysis covers a broader scope and uses variables such as labor, production, quality, disposition/attitude, and absenteeism, which are evaluated by individuals in middle-management roles related to operations (Tang et al., 2023). In this model, variables are rated according to defined criteria and the evaluator's own judgment, inevitably introducing a degree of subjectivity into the model (Trizano-Hermosilla, 2017).

In a categorical analysis, the objective is to analyze "the results obtained with data of a binary nature, based on different alternatives using strategies for the analysis of dichotomous categorical data" (Filippini et al., 2018). Categorical data refer to a type of information that can be stored and identified based on names or labels. These are qualitative data that can be grouped into categories rather than measured numerically (Agresti & Kateri, 2025).

The baseline information for this research was provided by the production management department. The partial productivity measurement was applied to the 25 machines/work centers that were in operation and the 47 employees who remained constant during the period of analysis. This means that while these individuals may have been absent on some occasions, they worked consistently throughout the research period, thereby ensuring a higher level of reliability in the investigative process.

With the commitment of the company's management and its solid operations, both qualitative and quantitative information were collected regarding production level per worker and production level per machine. This information was used to calculate partial productivity through three approaches: the company's own efficiency and quality indicator method, Data Envelopment Analysis (DEA), and a categorical model. The results of the three partial productivity measurement methods were then compared in order to examine the suitability of a model that integrates transdisciplinary variables into productivity measurement.

2. Searching for a transdisciplinary method to measure productivity

The company uses a traditional methodology to estimate productivity based on the calculation of efficiency (E) and quality (Q) for the labor and machinery resources. For this purpose, it uses records corresponding to time worked (TL), downtime (TP), sum of conforming units produced (SUP), sum of nonconforming units (SUM), and the budgeted ideal number of units for the production area. Table 1 shows the results of the calculation of average partial productivity for labor over the eight-month period, according to the company's efficiency and quality indicator procedure.

Table 1
Average Efficiency and Quality – Production Level per Worker

# Worker	1	2	3	4	5	6	7	8	9	10	11	12
Average efficiency	0,85	0,87	0,85	0,79	0,85	0,86	0,85	0,85	0,89	0,88	0,83	0,86
Average quality	0,99	0,99	0,99	1,00	0,98	0,99	0,98	0,99	0,99	0,98	0,97	0,98
# Worker	13	14	15	16	17	18	19	20	21	22	23	24
Average efficiency	0,79	0,87	0,87	0,88	0,87	0,88	0,84	0,86	0,85	0,81	0,78	0,87
Average quality	0,99	0,99	0,99	1,00	0,98	0,98	0,99	0,98	1,00	0,98	0,97	0,98
# Worker	25	26	27	28	29	30	31	32	33	34	35	36
Average efficiency	0,22	0,87	0,85	0,88	0,85	0,85	0,8	0,88	0,85	0,87	0,89	0,75
Average quality	0,99	0,99	0,99	0,99	0,98	1,00	0,97	0,98	0,99	0,96	0,99	0,99
# Worker	37	38	39	40	41	42	43	44	45	46	47	
Average efficiency	0,88	0,88	0,85	0,86	0,15	0,88	0,72	0,87	0,85	0,85	0,85	
Average quality	0,98	0,99	0,99	0,99	0,98	0,99	0,99	1,00	0,98	0,98	0,99	

From Table 1, it can be concluded that operators have an average productivity level ranging from 15% (worker 41) to 89% (workers 9 and 35). This smooths out the individual results, where efficiency can reach levels as low as 2% (worker 41 in July) and as high as 105% (worker 29 in August). However, the average productivity shows that not only worker 41 has a low productivity level (15%), but also worker 25 (22%). The other workers have an average productivity level higher than 72%, according to the company's traditional productivity measurement method—this is higher than the 62% labor productivity reported for manufacturing industries in Colombia (DANE, 2025; Jaimes et al., 2018).

When productivity is analyzed from the perspective of effectiveness, as measured by the quality indicator, the average results are more favorable, reaching levels above 96% and, in many cases, 100%. This is explained by the high production volume and the low amount of nonconforming product.

Taking advantage of the availability of information and with the objective of deepening the analysis, Table 2 presents representative descriptive measures for the main measures of central tendency and dispersion.

Table 2
Measures of Central Tendency and Dispersion – Production Level per Worker

	Indicator	
Statistical	% Efficiency	% Quality
Average	0,82	0,99
Moda	0,58	1,00
Median	0,86	0,99
max	1,05	1,00
min	0,02	0,78

Cont... Table 2

Range	1,03	0,22
Standard deviation	0,18	0,023
Variance	0,03	0,001
Coefficient of variation	0,22	0,023

The sample statistics show that the data used in the research are consistent and stable; the central values are representative of the series. The data show less dispersion for the quality indicator, whose coefficient of variation (CV) is 2%, confirming this assertion. Regarding the efficiency indicator, the results are normally distributed; on average, the data deviate from the mean by 18%, with 82% of the data concentrated around the center—behavior attributable to a normal distribution. For both indicators, the mean is higher than 80%, which would place the data series in the third quartile (Q3) if a non-central position measure were applied.

Using the available information on production level per machine, Tables 3, 4, and 5 were constructed. Table 3 presents the available machine hours per month grouped by injection machine tonnage and by business days per month (TD). Table 4 records the calculations for machine-month available hours and machine-month operating time percentage, using the variables operating time (TO), downtime (TP), and conforming units produced (SUP). Table 5 shows the values for the quality indicator based on the total kilograms produced per month (machine hours).

Table 3
Available Time – Injection Molding Machines

Month		January	February	March	April	May	June	July	August
Day/month		25	24	25	24	26	23	25	25
Injection (Ton)	# Machine	TD	TD	TD	TD	TD	TD	TD	TD
100	2	1200	1152	1200	1152	1248	1104	1200	1200
200	3	1800	1728	1800	1728	1872	1656	1800	1800
300	5	3000	2880	3000	2880	3120	2760	3000	3000
500	4	2400	2304	2400	2304	2496	2208	2400	2400
800	4	2400	2304	2400	2304	2496	2208	2400	2400
1000	4	2400	2304	2400	2304	2496	2208	2400	2400
1200	3	1800	1728	1800	1728	1872	1656	1800	1800
Total	25	15000	14400	15000	14400	15600	13800	15000	15000

Table 4
Efficiency Indicator – Production Level per Machine

Month		January		February		March		April	
Injection (Ton)	# Machine	TO	% TO	TO	% TO	TO	% TO	TO	% TO
100	2	987,5	0,82	940,1	0,82	980,0	0,82	924,7	0,80
200	3	1542,5	0,86	1525,5	0,88	1523,5	0,85	1396,7	0,81

Cont... Table 3

300	5	2818,6	0,94	2932,5	1,02	2715,7	0,91	2270,7	0,79
500	4	2053,6	0,86	2317,2	1,01	2517,0	1,05	1945,4	0,84
800	4	1925,1	0,80	2329,3	1,01	2309,1	0,96	1980,5	0,86
1000	4	2233,0	0,93	2243,9	0,97	2395,3	1,00	1934,5	0,84
1200	3	1585,3	0,88	1437,1	0,83	1679,5	0,93	1251,8	0,72
Total	25	13145,7	0,87	13725,5	0,93	14120,1	0,93	11704,3	0,81
Month		May		June		July		August	
Injection (Ton)	# Maquine	TO	% TO	TO	% TO	TO	% TO	TO	% TO
100	2	920,2	0,74	608,1	0,55	469,4	0,4	871,6	0,7
200	3	1378,4	0,74	940,7	0,57	854,2	0,5	1380,0	0,8
300	5	2739,4	0,88	2310,9	0,84	2525,5	0,8	3012,5	1,0
500	4	2066,0	0,83	2206,1	1,00	2163,1	0,9	1894,0	0,8
800	4	1954,7	0,78	1799,3	0,81	1936,3	0,8	2235,0	0,9
1000	4	2085,3	0,84	1703,8	0,77	1864,5	0,8	2256,3	0,9
1200	3	1474,3	0,79	1170,8	0,71	1043,4	0,6	1236,6	0,7
Total	25	12618,2	0,80	10739,7	0,75	10856,2	0,7	12885,9	0,83

The set of injection molding machines shows an average utilization rate above 80%. According to the partial measurement carried out by the operations management department, efficiency or productivity levels range between 40% (100-ton injection machines in July) and 105% (500-ton injection machines in March), as shown in Table 4.

According to the results in Table 5, the manufacturing quality indicator is high, reaching Six Sigma (6ƛ) levels in accordance with the principles of statistical quality control theory (Ahmed et al., 2020). Note the minimum average quality percentage of 96.49% and a maximum of 99.98%, evidence of Lean Manufacturing behavior at the upper control limit (Palange & Dhatrak, 2021).

Table 5
Quality Indicator – Production Level per Machine

Month	January	February	March	April	May	June	July	August
Kg compliant	890333	1350369	921189	684726	759883	722456	708997	736057
Kg no compliant	201	164	656	9993	27621	18691	14756	18610
Kg total	890534	1350533	921845	694719	787505	741147	723753	754666
Quality indicator	0,9998	0,9999	0,9993	0,9856	0,9649	0,9748	0,9796	0,9753

Subsequently, a DEA model was chosen, as this technique has demonstrated robustness in analyzing labor and machinery resources. At this stage of the research, it was essential to obtain the efficiency of the resources competing against themselves and against each other within the simulated time horizon. The complete model includes eight windows—one for each month—named window1 through window8, in which the monthly productivity results are obtained while internally comparing the behavior of the input variables (TL, TP, and SUM) and the output variable (SUP); the DMUs are the 47 workers.

For example, window1 evaluates what happens month by month with each worker's productivity, comparing them across all eight months and against their peers. Window5 calculates worker productivity as a five-month moving average—January through May, February through June, March through July, and April through August—showing variability in the scale measurements. Window8 calculates productivity as the eight-month moving average. This publication does not include all DEA results, as the aim is to highlight the significant differences between the various measurement methods.

The synthesis of the DEA model simulation for labor is presented in Table 6, which shows the average productivity of the workers over time.

Table 6
Model DEA window I-V

# W	Simple-Average month to month	Moving-Average two months	Moving-Average three months	Moving-Average four months	Moving-Average five months	Moving-Average six months	Moving-Average seven months	Moving-Average eigth months
1	0,3717	0,1993	0,1599	0,1479	0,1335	0,1144	0,1189	0,1115
2	0,3581	0,1667	0,1379	0,1237	0,1105	0,0865	0,0860	0,0840
3	0,8010	0,8143	0,7870	0,7944	0,7722	0,7373	0,6835	0,6068
4	0,3332	0,2616	0,1824	0,1603	0,1412	0,1293	0,1453	0,1376
5	0,6675	0,4683	0,3613	0,3501	0,3328	0,3071	0,3180	0,2870
6	0,3908	0,1934	0,1542	0,1410	0,1268	0,1116	0,1132	0,1317
7	0,4764	0,3943	0,3563	0,3330	0,3225	0,3215	0,3139	0,2862
8	0,3184	0,1548	0,1298	0,1183	0,1042	0,0859	0,0826	0,0813
9	0,3299	0,1900	0,1370	0,1242	0,1090	0,0921	0,0954	0,0936
10	0,4632	0,3529	0,2916	0,2314	0,1823	0,1586	0,1594	0,1708
11	0,4693	0,3429	0,2977	0,2878	0,2778	0,2468	0,2635	0,2391
12	0,2485	0,1647	0,1320	0,1170	0,1019	0,0700	0,0736	0,0791
13	0,2712	0,1687	0,1337	0,1311	0,1191	0,0961	0,0924	0,0881
14	0,3523	0,2965	0,2376	0,2139	0,1948	0,1846	0,2151	0,1985
15	0,2482	0,1330	0,1128	0,0992	0,0820	0,0644	0,0634	0,0647
16	0,4161	0,3335	0,2861	0,2441	0,1954	0,1560	0,1559	0,1790
17	0,3970	0,2489	0,1758	0,1603	0,1480	0,1417	0,1563	0,1508
18	0,5682	0,4116	0,3405	0,3102	0,2646	0,2360	0,2215	0,2176

Cont... Table 6

19	0,5336	0,2805	0,1754	0,1574	0,1354	0,1109	0,1109	0,1195
20	0,6011	0,2974	0,2662	0,2326	0,2066	0,1965	0,1844	0,1783
21	0,5908	0,4520	0,3987	0,3993	0,3635	0,2810	0,2610	0,2489
22	0,6585	0,4942	0,4379	0,4042	0,3627	0,3240	0,3021	0,3106
23	0,4813	0,3510	0,3461	0,3119	0,2851	0,2753	0,2463	0,2260
24	0,5229	0,3677	0,2752	0,2345	0,1999	0,1838	0,2059	0,2198
25	0,4809	0,2745	0,2327	0,2152	0,1843	0,1592	0,1599	0,1522
26	0,2996	0,1822	0,1498	0,1343	0,1178	0,0912	0,0883	0,0881
27	0,2659	0,1615	0,1390	0,1262	0,1126	0,1010	0,1006	0,1020
28	0,4010	0,2210	0,1896	0,1657	0,1452	0,1367	0,1264	0,1165
29	0,3284	0,1769	0,1449	0,1317	0,1100	0,0874	0,0875	0,0986
30	0,3324	0,2284	0,1853	0,1777	0,1597	0,1327	0,1326	0,1250
31	0,4689	0,3549	0,3465	0,3307	0,3156	0,3069	0,2745	0,2536
32	0,5237	0,3878	0,2940	0,2471	0,2058	0,1826	0,2024	0,1946
33	0,4135	0,2045	0,1590	0,1487	0,1336	0,1092	0,1069	0,1041
34	0,3028	0,2247	0,1948	0,1791	0,1616	0,1450	0,1383	0,1393
35	0,2728	0,2002	0,1765	0,1496	0,1238	0,1046	0,0996	0,0948
36	0,3448	0,1870	0,1549	0,1463	0,1268	0,1048	0,1030	0,1033
37	0,4952	0,2977	0,2798	0,2901	0,2822	0,2341	0,2118	0,1971
38	0,3571	0,2402	0,1904	0,1683	0,1476	0,1304	0,1353	0,1285
39	0,4823	0,2992	0,2940	0,2675	0,2521	0,2486	0,2241	0,2060
40	0,3621	0,2520	0,1925	0,1770	0,1603	0,1441	0,1360	0,1312
41	0,2910	0,1693	0,1263	0,1106	0,0832	0,0690	0,0690	0,0767
42	0,3863	0,2145	0,1481	0,1302	0,1137	0,0994	0,1089	0,1348
43	0,5079	0,3339	0,2631	0,2406	0,2140	0,1864	0,1859	0,1982
44	0,5144	0,3943	0,3118	0,2570	0,2174	0,1799	0,1801	0,2144
45	0,5021	0,3868	0,3005	0,2422	0,1960	0,1669	0,1755	0,2239
46	0,3462	0,2677	0,2380	0,2022	0,1707	0,1432	0,1403	0,1378
47	0,4780	0,3651	0,2729	0,2220	0,1625	0,1260	0,1352	0,1320

The results indicate high variability in worker productivity based on production volume. In fact, average productivity decreases as DEA simulates cumulative periods. In this case, only workers 3, 5, 20, and 22 achieve productivity levels above 60%, but in DEA, a unit is considered efficient only when its score equals one (1); all other cases are considered inefficient. Therefore, under DEA, very few workers are efficient in specific time periods, and none achieve an average efficiency of 100% over the analyzed horizon.

Table 7 shows the statistical summary of the eight DEA windows for the three input variables and the output variable.

Table 7
DEA model = DEA-Solver-LV(V8)/ Window(Window-I-V)

Month	Statistics	TL	TP	SUM	SUP	Correlation	TL	TP	SUM	SUP
January	Max	14579	9308	29	113149	TL	1,00	0,06	0,36	0,42
	Min	278	60	0	485	TP	0,06	1,00	0,17	-0,04
	Average	8409	1377	5	14344	SUM	0,36	0,17	1,00	0,01
	SD	3794	1816	7	17730	SUP	0,42	-0,04	0,01	1,00
February	Max	14973	3692	51	644842	TL	1,00	0,11	0,03	-0,05
	Min	2066	0	0	1500	TP	0,11	1,00	-0,02	-0,04
	Average	8845	875	4	26376	SUM	0,03	-0,02	1,00	-0,05
	SD	3703	810	8	92546	SUP	-0,05	-0,04	-0,05	1,00
March	Max	19268	29302	60	35372	TL	1,00	0,19	0,37	0,68
	Min	1485	0	0	1635	TP	0,19	1,00	0,33	-0,04
	Average	9476	1942	9	12812	SUM	0,37	0,33	1,00	0,50
	SD	4744	4275	12	8529	SUP	0,68	-0,04	0,50	1,00
April	Max	78675	24614	563	3807091	TL	1,00	0,33	-0,04	0,95
	Min	1907	0	0	1002	TP	0,33	1,00	-0,05	0,31
	Average	9485	1812	136	92624	SUM	-0,04	-0,05	1,00	-0,15
	SD	10796	4000	131	547755	SUP	0,95	0,31	-0,15	1,00
May	Max	81092	15529	3294	4426510	TL	1,00	-0,06	-0,01	0,94
	Min	1698	0	0	1297	TP	-0,06	1,00	-0,05	-0,08
	Average	10464	1297	442	107503	SUM	-0,01	-0,05	1,00	-0,10
	SD	11072	2344	580	636935	SUP	0,94	-0,08	-0,10	1,00
June	Max	62559	5618	1303	3779165	TL	1,00	0,26	0,02	0,89
	Min	257	2	0	128	TP	0,26	1,00	0,29	0,00
	Average	8856	767	281	106166	SUM	0,02	0,29	1,00	-0,14
	SD	9646	1146	334	552937	SUP	0,89	0,00	-0,14	1,00
July	Max	86840	6672	1213	4494163	TL	1,00	0,71	0,09	0,95
	Min	679	15	0	1319	TP	0,71	1,00	0,06	0,68
	Average	9810	950	205	107560	SUM	0,09	0,06	1,00	-0,07
	SD	11997	1243	237	646845	SUP	0,95	0,68	-0,07	1,00
August	Max	30618	15854	1090	49616	TL	1,00	0,02	0,33	0,58
	Min	1372	30	0	1465	TP	0,02	1,00	-0,04	-0,01
	Average	9797	1389	260	15552	SUM	0,33	-0,04	1,00	0,56
	SD	5469	2879	258	11194	SUP	0,58	-0,01	0,56	1,00

The variability of the data leads to a high standard deviation for all variables, even for SUM, which reports few or no nonconforming units. As for the correlation between variables, the picture does not change significantly, except for the correlation between SUP and TL during the months of May, June, and July, which is directly proportional and greater than 0.89. Overall, it can be stated that DEA does not allow for a normal adjustment of the data, as it penalizes productivity due to the presence of TP and SUM variables. Even when these variables are removed from the model, productivity does not improve.

The data in Table 8 present the average efficiency measurement of the machines during the eight-month study period. The analysis performed is similar to that conducted for the workers' production level.

Table 8
DEA Model – Machinery Productivity (Average per Month)

Machine	C-Average	C-Average	C-Average	C-Average	C-Average	C-Average	C-Average	C-Average
INY 01	0,97	0,90	0,85	0,78	0,68	0,55	0,49	0,46
INY 02	0,93	0,85	0,81	0,78	0,67	0,50	0,41	0,39
INY 03	0,88	0,79	0,74	0,67	0,58	0,46	0,41	0,39
INY 04	0,97	0,88	0,82	0,75	0,66	0,54	0,48	0,46
INY 05	0,87	0,79	0,76	0,70	0,59	0,44	0,36	0,34
INY 06	0,96	0,90	0,82	0,76	0,67	0,56	0,44	0,43
INY 07	0,82	0,71	0,65	0,59	0,50	0,38	0,32	0,32
INY 08	0,79	0,68	0,62	0,56	0,47	0,35	0,30	0,30
INY 09	0,75	0,67	0,65	0,62	0,57	0,47	0,41	0,41
INY 10	0,81	0,67	0,64	0,59	0,54	0,43	0,38	0,36
INY 11	0,72	0,63	0,57	0,51	0,45	0,33	0,30	0,30
INY 12	0,75	0,65	0,60	0,53	0,46	0,34	0,31	0,30
INY 13	0,74	0,64	0,59	0,53	0,46	0,35	0,31	0,32
INY 14	0,77	0,67	0,62	0,55	0,47	0,36	0,33	0,37
INY 15	0,83	0,73	0,67	0,59	0,52	0,40	0,36	0,36
INY 16	0,79	0,68	0,63	0,58	0,51	0,41	0,39	0,42
INY 17	0,75	0,65	0,60	0,54	0,47	0,35	0,31	0,31
INY 18	0,79	0,69	0,64	0,57	0,50	0,39	0,33	0,32
INY 19	0,84	0,74	0,69	0,62	0,54	0,42	0,37	0,36
INY 20	0,80	0,71	0,65	0,58	0,50	0,39	0,34	0,34
INY 21	0,77	0,65	0,62	0,58	0,52	0,41	0,35	0,34
INY 22	0,86	0,76	0,71	0,64	0,57	0,48	0,45	0,47
INY 23	0,80	0,71	0,66	0,61	0,54	0,44	0,41	0,43
INY 24	0,89	0,75	0,68	0,62	0,55	0,46	0,45	0,41
INY 25	0,92	0,86	0,80	0,74	0,63	0,50	0,40	0,39

The results are higher than those obtained in the labor force analysis in Table 6. In this case, more than half of the machines show individual productivity above 80%, which is overshadowed in the monthly average by the lower-performing measurements. Likewise, a decline in monthly averages is observed, demonstrating that DEA is an effective model for comparing the productivity of a resource against itself but not for comparing it with other units of the same resource over a defined time interval. Consequently, DEA is not appropriate for drawing conclusions about the overall productivity of the organization.

Finally, as a pilot test of the proposed transdisciplinary productivity model, a categorical model was developed in which the variables involved are social and human in nature. The measurement was applied to the same 47 employees assessed under the traditional model and DEA model. The foundation for this model is an instrument called comprehensive evaluation, where each employee is rated by several evaluators, and an overall score is calculated.

The three production supervisors (S) provide three separate ratings for work quality, disposition/attitude, and absenteeism, which are averaged into a single score weighted at 50%. Absenteeism is measured by the number of times the employee is absent due to illness, the total days lost, and the consolidated monthly absenteeism record, including descriptions and supporting evidence of the causes. The injection mechanics (M), which interact directly with the operating staff, provide feedback about the employees. During each shift, a lead mechanic is responsible for machine setup and troubleshooting; they are aware of which operators open machine doors, run out of material, move panels, or cause downtime, as well as who produces nonconforming products to gain an advantage. Like the supervisors, their scores are averaged and weighted at 20%.

The Quality (Q), Data Entry (D), and Assembly (E) teams also provide assessments. In Quality, three inspectors evaluate employees, and their scores are averaged with a weight of 10%. The variables considered include quality rejections, returns, and the employee's attitude and willingness to accept feedback or corrective actions. The Data Entry team similarly provides input on which employees miscalculate, fail to fill out, or incorrectly complete control forms, and this score is weighted at 10%. The Assembly staff provide an assessment based on teamwork since they support production operators by performing material feeding relief shifts, assisting with products that require two operators, or working on line packaging as needed. Their evaluation, focused on teamwork and collaboration, is weighted at 5%. Finally, the Occupational Health and Safety (SO) department provides a score weighted at 5%, based on absenteeism data and supporting evidence.

The Operations Director reviews the results of employees whose overall score is below three. For these employees, their personnel file and 17 additional criteria are reviewed, which include disciplinary records such as tardiness, verbal and written warnings, formal disciplinary hearings, delays in returning from breaks, use of jewelry or prohibited accessories, improper use of personal protective equipment (PPE), mask compliance, use of cell phones or headphones, and commitment to the organization as measured by the number of public holidays worked and overtime contributed. Based on this analysis, employees are granted a 15- to 30-day period to improve their performance or face termination. The combined assessment of social, human, and quantitative variables within a single categorical model is presented in Table 9.

Table 9
Categorical Model – Productivity Measurement

# Worker	1	2	3	4	5	6	7	8	9	10	11	12
Total	4,18	4,57	4,25	3,5	4,57	4,8	4,11	4,47	3,88	4,67	4,25	2,97
# Worker	13	14	15	16	17	18	19	20	21	22	23	24
Total	2,43	3,90	3,47	4,37	3,90	4,28	4,87	3,20	4,07	4,50	2,76	2,58
# Worker	25	26	27	28	29	30	31	32	33	34	35	36
Total	3,77	3,20	2,97	4,80	4,09	3,14	3,85	4,17	4,00	2,98	2,95	3,93
# Worker	37	38	39	40	41	42	43	44	45	46	47	
Total	4,40	4,02	4,28	3,14	2,76	3,88	4,40	4,35	4,67	4,83	5,00	

The results show that worker productivity ranges from 2.43 points (48.6% – Worker 13) to 5 points (100% – Worker 47), with an amplitude of 2.57 points (51.4%), an average score of 3.92 points (78.4%), a standard deviation of 0.685, and a coefficient of variation of 17.5%, confirming data consistency. Additionally, thirty-nine employees achieve productivity scores above 70%, figures comparable to Colombia's national labor productivity indicator for 2024, which was estimated at 0.62 (62%) or 3.1 according to the categorical model scale.

It appears that with the categorical model, a qualitative smoothing of the data is applied when several stakeholders within the company are responsible for evaluating a cluster of transdisciplinary variables related to the employees, taking into account predefined criteria. However, the evaluators act with an inherent degree of human subjectivity, which is nearly impossible to eliminate through soft or even complex methods.

3. Conclusions

The operations management department maintains a broad perspective on employee performance within the plant by measuring efficiency and quality indicators, identifying which workers fall below the 60% threshold—considered by management as the lower limit for reevaluation, retraining, or dismissal. It is confirmed that, from a technical standpoint, machinery is a critical resource for the company's operations, as the transformation activities largely depend on the functioning of the injection molding machines.

According to the information provided, the quantitative data that the organization records regarding exact variables for calculating efficiency and effectiveness indicators are not considered when making decisions about employee retention, revealing a limited use of available information. Furthermore, the company measures overall corporate productivity through the calculation of Overall Equipment Efficiency (OEE), which includes partial measurement indicators such as quality, performance, and availability as components of efficiency.

The results from applying the DEA model indicate that the productivity of operational staff fluctuates significantly throughout the analyzed period, with ups and downs every two months. The variability in workforce volume prevents obtaining a comprehensive measurement of productivity. Moreover, productivity measurements decrease when absenteeism and total production variables are measured jointly, making the model sensitive and unstable. This destabilization of the DEA model is due to the forced inclusion of a soft variable into a model designed for strictly quantitative data, which causes it to react negatively. Therefore, DEA is limited to the use of strictly quantitative variables.

The categorical model, on the other hand, produces comparatively higher productivity measurements than DEA, seemingly as a result of integrating transdisciplinary variables—primarily social and human—into the model. However, subjectivity remains the main limitation of this model because, despite the variables being clearly defined and rating levels being established, human bias can influence the results for various reasons. The outcome of the categorical model cannot be directly compared with production level measurements per operator/machine or with other resources available to operations management, suggesting, as with the traditional measurement, a possible omission of critical information when making decisions that directly affect a worker's immediate future.

Although there are several techniques to measure productivity, the business reality reveals the interdisciplinary presence of factors that affect processes but are not considered. One potential solution to this gap is the incorporation of transdisciplinary variables into a new model that leverages knowledge of traditional models and the multidimensionality of the disciplines converging within complex systems.

A dialogue among disciplines is essential for productivity measurement. It is necessary to move beyond a reductionist stance and include all available process-related information to obtain metrics aligned with reality, thereby enabling effective decision-making. Strategies of flexibility and growth should be developed to complement efficiency and quality as productivity output indicators, integrating them within a network of interrelated variables.

It is indeed possible to bring transdisciplinary variables together within a single model. To achieve this, it is necessary to clear the mindset, shift away from reductionist paradigms, and commit the required willingness, knowledge, and effort to properly collect the necessary information, ensuring appropriate associations between variables at the time of measurement.

The development path for the transdisciplinary productivity measurement model has been extensive. The theoretical formulation of the model has been completed, including the identification of endogenous variables and the formation of clusters of associated latent variables. With the convergence of the model, it has been explained using the Structural Equation Modeling (SEM) technique, and the predictive model has been executed through inferential statistics of the explanatory model—all activities preceding the development of the software.

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