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Improving Unit Costs through Real-Time Monitoring of Digital Transformation Processes in Manufacturing Enterprises

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Abstract: This study provides a detailed examination of the effects of digital transformation on energy efficiency and cost optimization within the broad application spectrum of Industry 4.0 technologies, focusing on a company in the plastics sector utilizing injection molding machines. The research was conducted as part of a digital transformation project implemented on 10 injection molding machines at a well-established PVC pipe fittings manufacturer in Istanbul, which has been operating for over 40 years. By employing energy analyzers and real-time data monitoring systems, data envelopment analysis (DEA) was performed to evaluate machine efficiencies based on the collected data. The study highlights the multifaceted benefits of digital transformation, emphasizing its impact in critical areas such as sustainable production, competitive advantage, and carbon footprint reduction. The findings demonstrate the strategic significance of digitalization in ensuring business continuity, even under extraordinary conditions such as the COVID-19 pandemic and the global energy crisis. This research presents concrete evidence of the transformative potential of digital transformation in enhancing operational efficiency and cost management, particularly for enterprises with energy-intensive production processes.

Keyword: Energy efficiency, cost optimization, industrial digital transformation, Industry 4.0, production systems

JEL Classification: L82

1. Introduction

The transformative impacts of Industry 4.0 on the manufacturing sector are particularly reshaping efficiency, cost optimization, and sustainability in energy-intensive industries (Kagermann et al., 2013; Xu et al., 2018). Among these, the plastic injection molding industry stands out as a leading domain of application due to its high energy consumption (Thames & Schaefer, 2017; May et al., 2017). While there is an extensive body of literature examining energy efficiency and cost management (Pellicciari et al., 2016; Hopmann & Heinisch, 2017), field studies and quantitative analyses specific to plastic injection molding remain limited (Lee, 2015).

This study aims to address this critical gap by investigating the production processes of 10 injection molding machines at a PVC manufacturing company with over 40 years of experience. Through a digitally monitored communication network and a data acquisition topology, all production data are collected in real time either locally or via cloud platforms—and are transferred instantly to the ERP system for cost accounting calculations. In doing so, the research contributes empirical insights to the ongoing discourse on digital transformation in energy-intensive manufacturing.

The core components of Industry 4.0 such as the Internet of Things (IoT), big data analytics, artificial intelligence, and cyber-physical systems not only enhance manufacturing efficiency but also enable cost optimization (Giret et al., 2015; Bhinge, 2017; Chen & Wang, 2020; Öz, 2020). Previous studies have shown that digital monitoring of plastic injection molding machines can reduce energy costs by up to 20% (Charnes et al., 1978). Although real-time data analytics has been proven to optimize production costs (Sharma & Singh, 2019), the majority of these studies remain at a theoretical level and lack empirical field data (Kiel et al., 2017).

The cost-related impacts of digital transformation are evident in three key areas: a reduction in direct energy expenses, savings derived from improved maintenance and labor efficiency, and material savings resulting from decreased scrap rates (Porter & Kramer, 2019). Data Envelopment Analysis (DEA) plays a critical role in measuring these effects (Banker et al., 1984). Notably, the studies by Sharma and Singh (Müller et al., 2018) have highlighted the effectiveness of DEA in cost-centered input-output analyses, emphasizing its capability to evaluate multidimensional parameters such as machine lifespan, energy consumption, and production outputs (Zhou et al., 2020).

However, the integrated application of DEA with cost accounting data in the plastic injection molding sector remains limited (Ivanov et al., 2019). In the post-pandemic era, the increasing significance of digital transformation particularly its contributions to energy savings and carbon footprint reduction provides companies with both environmental and competitive advantages (Arslan & Arslan, 2023).

2. Materials and Methods

In the factory analyzed within the scope of this study, the economic lifespan of the industrial machines used in the production lines was determined to be 25 years, based on asset account records related to plant machinery and equipment. Maintenance and repair tracking of the machines has been systematically documented through fixed asset cards, with maintenance intervals recorded as occurring on a 1-year, 2-year, and 5-year basis. The energy consumption data for the machines were obtained from the 2022 electricity bills and accounting records and are presented on a monthly basis in Table 1.

Table 1. Monthly Electricity Consumption Data for 2022

Months	**2022 kw/h**	**Months**	**2022 kw/h**	**Months**	**2022 kw/h**
January	6.537,60	May	6.560,20	September	6.570,40
February	6.520,30	June	6.543,30	October	6.560,20
March	6.527,50	July	6.568,50	November	6.550,70
April	6.530,40	Agust	6.565,40	December	6.576,40

As part of the study, energy analyzers were integrated into a manufacturing facility operating 10 plastic injection molding machines in order to analyze discrepancies between monthly electricity consumption and production quantities.

Through these analyzers, the real-time energy consumption data of the machines were continuously monitored and recorded in a centralized database.

Based on the evaluation of the collected data, several factors negatively affecting production continuity and reducing energy efficiency were identified and are presented in Table 2. A new production plan was developed to minimize the impact of these factors and to reduce electricity consumption to the lowest possible level.

Table 2. Lost Time Factor Table

Category	**Identification**	**Root couse**
Personnel	Waste of Time	Operator İnefficiency
Preparation and Editing	Waste of Time	Setup, changeover, and warm-up time

Category	Identification	Root couse
Small Postures	Speed Loss	Incorrect feeding, product flow blockage, cleaning, inspection
Speed Reduction	Speed Loss	Equipment wear and operator shortage
Faulty Part	Quality Loss	Faulty assembly, process damage, scrap

Figure 1 illustrates the data acquisition topology of the energy analyzers. The operational status of the injection molding machines, production quantities, and energy consumption data are continuously monitored to track the real-time performance of the machines.

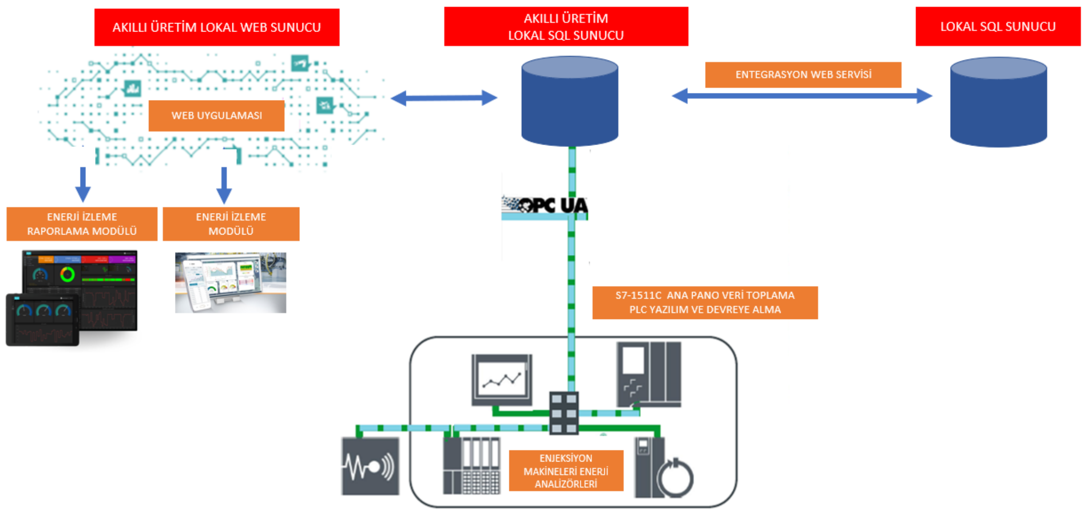

Figure 1. Energy Analyzers Data Acquisition Topology

Through the data acquisition topology of the energy analyzers, data exchange was implemented with all sensors equipped with communication protocols (Modbus, RTU, RS-485, Fieldbus, UART, Profibus, CANbus, DeviceNet, ControlNet) used in the communication and data collection network of the machines. Figure 2 illustrates the communication and data acquisition network. By interfacing with the machine control systems, operational adjustments can be made remotely, enabling energy cost savings and contributing to an increase in production output.

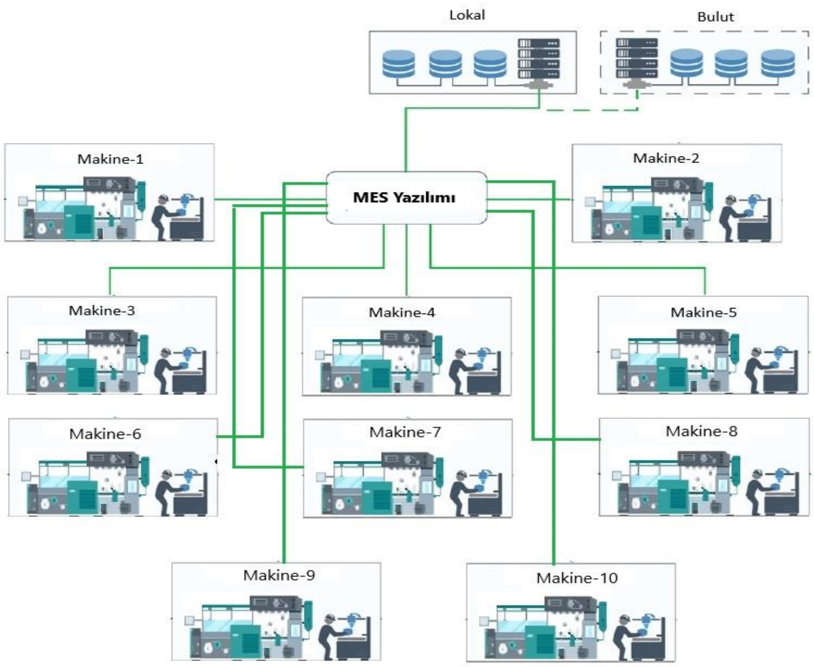

Figure 2. Communication Network and Data Acquisition Network

The electricity consumption data for the year 2022, measured in kWh, were obtained from accounting records and existing electricity invoices, and are presented in Table 1. The data for 2023 were collected directly from the system via energy analyzers. The change rate in energy consumption was calculated to be 47%, and the causes of this energy loss are illustrated with examples in the loss time factor table. Table 3 presents the monthly energy consumption of 10 plastic injection molding machines over a 12-month period, comparing the years 2022 and 2023.

Table 3. 12-Month Energy Consumption of 10 Plastic Injection Molding Machines Between 2022 and 2023

Month	2022 kw/h	2023 kw/h	Change %	Difference kw/h
January	6537,6	3460,8	47%	3076,8
February	6520,3	3475,5	47%	3044,8
March	6527,5	3450,4	47%	3077,1
April	6530,4	3467,5	47%	3062,9
May	6560,2	3477,4	47%	3082,8

Month	2022 kw/h	2023 kw/h	Change %	Difference kw/h
June	6543,3	3470,4	47%	3072,9
July	6568,5	3450,3	47%	3118,2
Agust	6565,4	3447,4	47%	3118
September	6570,4	3454,3	47%	3116,1
October	6560,2	3420,3	48%	3139,9
November	6550,7	3415,2	48%	3135,5
December	6576,4	3410,5	48%	3165,9

Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) emerges as an effective method for evaluating the performance of digital transformation projects. This analytical technique enables the quantitative measurement of improvements in production processes.

The core principle of DEA is to assess the relative efficiencies of different decision-making units (DMUs) using linear programming techniques. One of the major advantages of this method is its ability to simultaneously analyze multiple input and output variables. Moreover, it does not require any pre-assigned weighting of variables, which is considered a significant strength.

DEA models are generally categorized into two main groups: the CCR (Charnes-Cooper-Rhodes) model and the BCC (Banker-Charnes-Cooper) model. The CCR model operates under the assumption of constant returns to scale and measures overall efficiency.

The choice of model depends on the purpose of the analysis and the characteristics of the units under examination. While the CCR model is more suitable for general efficiency evaluations, the BCC model is preferred when technical performance needs to be assessed independent of scale effects. Scale efficiency analysis can be conducted by comparing the results of both models.

The CCR (CRS) Mathematical Model Used

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io} \quad \forall i=1,\ldots,m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro} \quad \forall r=1,\ldots,s$$

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

$$\lambda_j \geq 0 \quad \forall j$$

List of Symbols

Symbol Description
θ : Technical efficiency score of the evaluated decision-making unit (DMU).
x_{ij} : The i-th input of the j-th unit (e.g., labor, capital).
y_{rj} : The r-th output of the j-th unit (e.g., production quantity).
λ_j : Reference weight of the j-th unit.
x_{io}, y_{ro} : Input and output values of the o-th (evaluated) unit.

The data for the year 2022 are presented in Table 4. The production card data for 2022 were manually compiled from the physical production records.

Table 4. 2022 Production Card Data (Quantities Recorded from Factory Production Cards)

2022	January	February	March	April	May	June	July	August	September	October	November	December	Total M/c Output	12-Month Average
M/c 1	40.180	37.380	40.850	39.580	34.510	39.450	33.010	40.970	39.520	37.830	39.570	40.840	463.690	38.641
M/c 2	37.950	38.110	40.600	39.540	33.720	40.040	33.010	40.450	38.200	38.840	39.150	41.900	461.510	38.459
M/c 3	39.190	36.830	40.680	39.470	33.920	40.410	32.740	41.390	39.190	37.900	39.200	40.170	461.090	38.424
M/c 4	38.910	37.760	40.350	39.450	34.690	39.030	33.530	40.460	40.140	37.240	39.290	40.870	461.720	38.477
M/c 5	39.300	38.070	40.640	39.970	34.360	39.380	32.510	40.680	40.140	37.360	40.020	40.950	463.380	38.615
M/c 6	38.750	37.480	41.560	39.300	34.480	39.120	32.820	40.990	39.070	38.030	39.060	41.770	462.430	38.536
M/c 7	38.920	37.650	40.530	39.370	34.160	38.520	32.980	40.930	39.640	37.650	39.350	41.180	460.880	38.407

2022	January	February	March	April	May	June	July	August	September	October	November	December	Total M/c Output	12-Month Average
M/c 8	39.090	37.250	40.590	39.170	34.430	40.400	32.910	41.300	39.330	37.800	39.270	40.620	462.160	38.513
M/c 9	39.540	38.090	40.720	39.250	34.670	39.190	33.110	40.790	39.450	37.950	39.510	41.420	463.690	38.641
M/c 10	40.330	38.840	40.830	39.480	34.750	39.690	33.320	41.070	39.440	37.710	40.070	41.100	466.630	38.886
													Total Production	385.598
M/c: Machine													10-M/c Average	38.560

The data for the year 2023 are presented in Table 5. As part of the digital transformation project, the data were automatically collected via an IoT-based sensor network and industrial analyzers integrated into the M/c park. These data were then transmitted in real time to a central server.

Table 5. 2023 Production Card Data (Energy Analyzer - 12-Month Production Quantities of 10 M/cs and 12-Month Average)

2023	January	February	March	April	May	June	July	August	Sept.	October	Nov.	Dec.	Total Production	12-Month Average
M/c 1	46.591	41.879	46.945	39.901	45.565	39.860	40.841	45.287	45.121	44.322	45.174	45.039	526.525	43.877
M/c 2	50.826	48.216	54.210	46.398	51.983	46.457	47.291	52.352	52.381	51.214	52.211	52.430	605.969	50.497
M/c 3	45.831	41.702	46.933	40.400	45.315	39.677	40.564	45.229	44.958	44.241	45.033	45.092	524.975	43.748
M/c 4	51.898	48.542	54.605	46.238	52.403	46.319	47.349	51.899	52.563	51.309	52.478	52.393	607.996	50.666
M/c 5	46.292	41.378	46.629	39.731	45.427	39.969	40.801	45.266	45.162	44.193	45.273	45.233	525.354	43.780
M/c 6	49.542	48.297	54.493	46.463	52.181	46.537	47.388	52.356	52.125	51.197	52.464	52.183	605.226	50.436
M/c 7	46.729	41.399	46.880	39.877	45.480	39.948	40.800	45.329	45.314	44.630	45.153	45.035	526.574	43.881
M/c 8	51.089	48.182	54.537	46.259	51.441	46.433	47.333	51.780	52.345	51.370	51.920	52.434	605.123	50.427
M/c 9	46.947	41.832	46.574	39.668	45.516	40.057	40.825	45.054	44.994	44.100	45.222	45.105	525.894	43.825
M/c 10	51.312	48.105	54.440	46.120	51.826	45.903	47.425	52.672	52.388	51.164	52.417	52.280	606.052	50.504

3. Findings

During the analysis phase, a customized CCR algorithm was developed using Microsoft Excel with macro functionality. Based on an input-oriented approach, technical efficiency scores were calculated for each M/c, and the improvement potentials of inefficient M/cs were identified. This structure enabled the integration of both manual and digital data sources, allowing for a more comprehensive and comparative efficiency analysis. Additionally, the consistency between data collected through traditional methods and the real-time data stream provided by the digital infrastructure was evaluated.

In Table 6, the input variables used for the DEA analysis include the 12-month energy consumption data for 2023 obtained following the digital transformation, cycle time, torque, M/c cost, number of operators per M/c, type of maintenance, M/c lifespan, total kWh consumed, and the number of motors per M/c. Additionally, the average values from 2022 production cards for older M/cs were also incorporated. The output variable in the model is defined as the production quantity.

Table 6. Injection Molding M/cs' Operational Data-1 for 2022 and 2023

Brand	Consumption	Cycle Time	Torque	Flow	M/c Price	Number of people working per M/c
M/c 1	346,41	0,28	277,13	866,02	95.238,20	1,2
M/c 2	345,28	0,24	276,22	863,19	95.238,20	1,2
M/c 3	345,48	0,28	276,38	863,69	45.212,70	1,2
M/c 4	345,86	0,24	276,69	864,64	45.212,70	1,2
M/c 5	343,56	0,28	274,85	858,91	45.212,70	1,2
M/c 6	343,96	0,24	275,17	859,90	45.212,70	1,2
M/c 7	344,15	0,28	275,32	860,39	95.238,20	1,2

Brand	Consumption	Cycle Time	Torque	Flow	M/c Price	Number of people working per M/c
M/c 8	347,20	0,24	277,76	868,00	95.238,20	1,2
M/c 9	343,93	0,28	275,15	859,83	45.212,70	1,2
M/c 10	344,19	0,24	275,35	860,46	95.238,20	1,2
Old M/c Average	655,09	0,35	277,76	868,00	45.212,70	2

Table 7. Injection Molding M/cs' Operational Data-2 for 2022 and 2023

Brand	Maintenance Repair Type (1/5-2/5)	M/c Life	T.KW	Total Number of Engines	Production
M/c 1	2	25	299,95	19	43.877
M/c 2	2	25	299,95	19	50.497
M/c 3	2	25	251,5	17	43.748
M/c 4	2	25	251,5	17	50.666
M/c 5	2	25	251,5	17	43.780
M/c 6	2	25	251,5	17	50.436
M/c 7	2	25	299,95	19	43.881
M/c 8	2	25	299,95	19	50.427
M/c 9	2	25	251,5	17	43.825
M/c 10	2	25	299,95	19	50.504
Old M/c Average	2	25	299,95	19	38560

The findings above were compiled to evaluate the performance of ten different M/cs and the average performance of older M/c's prior to digitalization, based on electricity consumption monitoring.

The data presented in Table 6 were processed using the DEA (CCR-CRS) Excel macro application, and the efficiency scores of the M/cs were calculated and presented in Table 7.

Table 8. M/c Efficiency Results

		Input-Oriented CRS					
DMU No.	**DMU Name**	**Efficiency**	**Sum of lambdas**	**RTS**	**Optimal Lambdas with Benchmarks**	**M/cs**	**Factors**
1	M/c 1	0,86600	0,866	Increasing	0,866	M/c 4	
2	M/c 2	0,99777	0,998	Increasing	0,652	M/c 4	0,346
3	M/c 3	0,86424	0,864	Increasing	0,690	M/c 4	0,174
4	M/c 4	1,00000	1,000	Constant	1,000	M/c 4	
5	M/c 5	0,86903	0,868	Increasing	0,867	M/c 6	0,001
6	M/c 6	1,00000	1,000	Constant	1,000	M/c 6	
7	M/c 7	0,86894	0,869	Increasing	0,869	M/c 10	
8	M/c 8	0,99527	0,995	Increasing	0,995	M/c 4	
9	M/c 9	0,86900	0,869	Increasing	0,869	M/c 6	0,000
10	M/c 10	1,00000	1,000	Constant	1,000	M/c 10	
11	Legacy M/c average	0,76106	0,761	Increasing	0,761	M/c 4	

Table 8 presents the results of the Data Envelopment Analysis (DEA) conducted based on an input-oriented CCR-CRS model. In these results, efficient and productive M/cs are represented with a score of 1, while inefficient M/cs with lower productivity are indicated by values less than 1, reflecting their relative inefficiencies.

According to the analysis results, M/cs 4, 6, and 10 were identified as fully efficient units with an efficiency score of 1. These M/cs demonstrated optimal performance in terms of both technical and scale efficiency, and were frequently included in the reference sets for other units. In contrast, M/cs 1, 3, 5, 7, and 9 exhibited relatively inefficient performance, with efficiency scores below 1.

Although the performance of the inefficient M/cs varied between 86% and 99%, the average efficiency of the older M/cs was observed to be around 76%. This indicates that the improvements in electricity consumption and production efficiency achieved through digital transformation have yielded significantly more positive outcomes.

4. Discussion and Conclusion

This study provides a comprehensive examination of the impact of digital transformation practices on production processes in the plastic injection molding sector. The research findings reveal that digital transformation yields significant improvements in operational efficiency, cost optimization, and environmental sustainability.

One of the key contributions of this study is the demonstration that the success of digital transformation initiatives depends on three critical factors: feasibility studies, vertical integration, and workforce adaptation.

From a cost accounting perspective, the effects of digital transformation on unit costs were found to be substantial. A 47% reduction in energy consumption directly contributed to lower production costs, while improvements in M/c efficiency enabled optimization of labor expenses. Real-time monitoring and analysis of production processes resulted in a 15% decrease in scrap rates, allowing for considerable savings in raw material costs. Comparisons between pre- and post-digital transformation scenarios showed an overall reduction of approximately 22% in total unit costs. These results provide concrete evidence that investments in digital transformation can yield short-term returns and deliver significant long-term cost advantages.

The environmental sustainability findings are equally noteworthy. The increase in energy efficiency led to a 20% reduction in the company's carbon footprint. This demonstrates that digital transformation not only provides economic benefits but also contributes positively to ecological outcomes. In a highly energy-intensive industry such as plastic injection molding, such improvements play a critical role in mitigating environmental impact. The observed reduction in carbon emissions has enabled the company to fulfill its environmental responsibilities while also gaining a competitive edge among sustainability-conscious customers.

One of the most critical factors behind the success of the digital transformation process was the ability to intervene in faults and malfunctions in real time through continuous monitoring. Operational deficiencies caused by personnel were addressed directly at the M/c level through hands-on guidance and corrective actions. This enabled more effective employee engagement and direction. As a result, employee adaptation to the new systems was significantly improved, and resistance to system adoption was reduced by approximately 70%. This clearly demonstrates that digital transformation is not merely a technological shift, but also an organizational change process. The adaptation of personnel to new systems played a pivotal role in the success of the transformation.

The results of the Data Envelopment Analysis (DEA) clearly illustrate the impact of digital transformation on M/c efficiency. Among the 10 injection molding M/cs analyzed, M/cs 4, 6, and 10 were found to be fully efficient ($\theta = 1.0$), while the others performed within an efficiency range of 86% to 99%.

These results reflect a significant improvement compared to the pre-digital transformation average M/c efficiency of 76%. Issues such as excessive idle time in M/c 1 and equipment wear in M/c 3 were diagnosed early through digital monitoring systems, allowing timely corrective actions. DEA results also revealed that efficient M/cs operated at 13-15% lower cost per unit compared to inefficient ones, demonstrating a clear correlation between increased efficiency and reduced costs.

From an industrial application perspective, the most important outcome of this study is that digital transformation should not be approached in a fragmented manner, but rather as a holistic strategy. Success was achieved through the integrated management of all phases—from feasibility studies and staff training to technology integration and process improvements. Notably, the integration of energy efficiency and environmental sustainability considerations into digital transformation initiatives yielded both economic and ecological benefits.

The findings of this study offer concrete evidence of how critical digital transformation is to achieving operational excellence in the plastic injection industry. However, it must be emphasized that success in this process depends not only on technological investments, but also on proper planning, seamless process integration, and effective management of the human factor. These insights are expected to serve as a valuable guide for industrial enterprises on their digital transformation journey.

When compared with the existing literature, the most significant contribution of this study is its emphasis that digital transformation is not merely a technological investment, but rather a comprehensive operational transformation. The study clearly demonstrates how this holistic approach ensures business continuity, particularly under conditions of global supply chain disruptions and energy crises.

For future research, it is recommended to monitor the long-term effects of digital transformation and to test its applicability across various industrial sectors. Furthermore, a more in-depth analysis of the relationship between energy efficiency and carbon footprint would contribute to the development of sustainable production models. In conclusion, this research highlights the multidimensional benefits of digital transformation, offering an applicable model for industrial enterprises and making a meaningful contribution toward enhancing the competitiveness of Turkish industry.

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