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Measuring the Performance Impact of Industry 4.0 in Manufacturing SMEs: An Integrated MPI–Explainable Machine Learning Framework

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Abstract

This study investigates the performance implications of Industry 4.0 (I4.0) adoption in manufacturing small and medium-sized enterprises (SMEs) through an integrated analytical framework combining transformation modeling, composite performance measurement, and explainable machine learning. A structured dataset of 120 SMEs across five industrial sectors was analyzed to quantify changes in operational, economic, and sustainability-related performance before and after digital transformation. A novel Manufacturing Performance Index (MPI) was developed to capture multidimensional performance outcomes. The results reveal statistically significant improvements across all performance dimensions following I4.0 adoption ($p < 0.001$). Notable gains include increases in production output, overall equipment effectiveness, and labor productivity, accompanied by reductions in defect rates, machine downtime, production costs, and energy consumption. The MPI increased from 43.86 to 53.22, indicating a substantial overall performance enhancement. High pre–post correlations ($r > 0.80$) suggest that digital transformation reinforces existing operational capabilities rather than fundamentally altering firm structures. Explainable machine learning analysis identify overall equipment effectiveness, defect rate, production cost, and machine downtime as the most influential drivers of performance. SHAP-based results further reveal nonlinear and heterogeneous effects, indicating that performance gains vary depending on firm-specific conditions and implementation strategies. Additional analyses demonstrate the presence of distinct SME archetypes and confirm that I4.0 acts as a performance amplifier, with benefits distributed unevenly across firms. The proposed framework contributes to the literature by providing a transparent, data-driven approach for quantifying and interpreting digital transformation outcomes. It also provides practical decision support for SMEs seeking to prioritize investments and benchmark performance improvements within Industry 4.0 environments.



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1. Introduction

The Fourth Industrial Revolution (Industry 4.0, I4.0) represents a major transformation of manufacturing systems through the integration of advanced digital technologies into

interconnected production environments, fundamentally reshaping production processes and value creation [1–3]. Introduced at the Hannover Fair in 2011 as part of the German Industrie 4.0 initiative, the concept aims to enhance industrial competitiveness by promoting intelligent, digitally connected manufacturing systems driven by technological innovation [4–6].

Industry 4.0 is characterized by extensive digitization, real-time data exchange, and intelligent system integration, enabling the development of highly connected and adaptive manufacturing environments [7–9]. Its core objective is to establish smart factories in which Cyber-Physical Systems (CPS), the Internet of Things (IoT), and the Internet of Systems seamlessly integrate physical and digital processes to support autonomous, responsive, and data-driven production [10,11].

Industry 4.0 adoption is enabled by a broad set of digital technologies, often characterized as a technology-driven transformation of manufacturing systems [12]. Key enabling technologies include the Internet of Things (IoT), Big Data and Analytics (BDA), cloud computing, Artificial Intelligence (AI), Machine Learning (ML), Digital Twins (DT), robotics, simulation, and additive manufacturing (AM) [13–15]. Together, these technologies enable real-time connectivity, intelligent decision-making, and integrated production processes, thereby enhancing productivity, operational efficiency, and resource utilization across the manufacturing value chain [16–18].

Industry 4.0 adoption is particularly important for small and medium-sized enterprises (SMEs), which constitute the backbone of many economies and make substantial contributions to employment and value creation [19,20]. Despite their economic significance, SMEs generally lag behind larger organizations in adopting Industry 4.0 technologies because of structural constraints, including limited financial resources, insufficient technological capabilities, and inadequate strategic planning for digital transformation [21–26].

SMEs also encounter substantial barriers to Industry 4.0 adoption, including financial constraints, limited technical expertise, workforce skill shortages, and the complexity of implementing advanced digital technologies [27–32]. Consequently, many SMEs remain in the early stages of digital transformation or experience slow implementation progress [33]. When adoption does occur, it typically begins with relatively accessible technologies, such as cloud computing and IoT, before expanding to more advanced solutions, including Big Data Analytics and Cyber-Physical Systems (CPS) [34–39].

The primary objective of Industry 4.0 adoption in SMEs is to transform conventional manufacturing systems into smart factories that enhance operational efficiency, flexibility, and competitiveness [40]. This transformation is enabled by real-time data exchange, system integration, and data-driven decision-making supported by interconnected digital technologies, particularly IoT and Big Data Analytics [41–44].

Industry 4.0 improves manufacturing performance by enhancing operational efficiency and system integration. Vertical integration strengthens coordination among internal functions, improving quality while reducing waste and operating costs, whereas horizontal integration enhances collaboration with suppliers and customers, leading to better demand forecasting, inventory management, and logistics performance [45–48].

From a performance perspective, Industry 4.0 technologies improve operational reliability, flexibility, and cost efficiency [49,50]. Advanced robotics, Cyber-Physical Systems (CPS), and predictive maintenance enhance production accuracy, reduce equipment downtime, and extend machine lifespan, thereby improving overall manufacturing performance [51–54].

Strategically, Industry 4.0 enables mass customization by allowing manufacturers to deliver individualized products while retaining the efficiency advantages of large-scale production [55]. Technologies such as additive manufacturing and advanced robotics

enhance production flexibility and customization capabilities, creating important growth opportunities for SMEs operating in increasingly competitive markets [56,57].

Although the potential of Industry 4.0 to enhance manufacturing performance is widely recognized, empirical evidence of its impacts on SMEs—particularly those operating in resource-constrained and developing-economy contexts—remains limited. Most existing studies focus on large enterprises or technologically mature environments, leaving important questions regarding how resource-constrained SMEs can successfully implement and benefit from digital transformation. Furthermore, manufacturing performance is often evaluated using isolated indicators, limiting the assessment of its multidimensional nature and the complex interactions among operational, economic, and sustainability-related dimensions.

To address these limitations, this study proposes an integrated analytical framework that combines transformation modeling, a composite Manufacturing Performance Index (MPI), and explainable machine learning to evaluate the multidimensional effects of Industry 4.0 adoption in manufacturing SMEs. The proposed MPI provides a unified measure of operational, economic, and sustainability-related performance, while explainable artificial intelligence (XAI), heterogeneity analysis, and unsupervised learning are employed to identify key performance drivers, structural patterns, and firm-specific differences. By integrating these complementary analytical techniques, the proposed framework not only quantifies digital transformation outcomes but also provides transparent insights into their underlying mechanisms and practical implications. Consequently, this study contributes to the literature by offering a reproducible methodological framework and a practical decision-support tool for benchmarking and prioritizing Industry 4.0 investments in manufacturing SMEs.

2. Related Work

I4.0 is characterized by the intelligent networking of machines and processes through advanced information and communication technologies, enabling the seamless integration of physical and digital environments via Cyber-Physical Systems (CPS) [58]. This wave of digitalization, driven by emerging technologies, introduces substantial innovations in three key domains: intelligent data-driven operational systems, flexible production paradigms such as mass customization, and human-centric collaboration models that enhance sustainability and resilience.

The primary novelty of I4.0 lies in its foundational technologies, which enable unprecedented levels of automation, system integration, and real-time data exchange. Core enabling technologies include the Internet of Things (IoT), Big Data, cloud computing, and Digital Twins (DT). The convergence of these technologies generates vast volumes of dynamic data, which function as the “lifeblood” of modern production systems, significantly enhancing manufacturing efficiency, flexibility, and agility. At the same time, these capabilities support the management of increasing product complexity and customization requirements. In particular, key characteristics such as transparency, interoperability, and virtualization play a fundamental role in enabling scalable mass personalization and transforming customer engagement into co-creation processes [58].

Artificial intelligence (AI) represents a critical component of this transformation, enabling machines to perform autonomous functions such as monitoring, interpretation, diagnostics, and decision-making. Machine learning (ML) and deep learning (DL) techniques are increasingly employed to support predictive maintenance and minimize equipment downtime, thereby enhancing operational reliability [59]. In parallel, the concept of the Digital Twin has emerged as a major innovation, providing real-time virtual representations of physical systems. These models enable predictive analytics, performance forecasting,

and simulation-based optimization, allowing manufacturers to improve decision-making, product quality, and operational efficiency while reducing waste and preventing system failures [60].

Additive manufacturing (AM), often referred to as 3D printing, represents another cornerstone technology of I4.0. By shifting from subtractive to additive production processes, AM significantly reduces material waste and post-processing requirements while enabling the efficient production of complex geometries. Furthermore, AM shortens product development cycles and promotes decentralized production systems, thereby supporting flexible and distributed manufacturing networks [61,62]. In this context, advanced manufacturing technologies, including robotics and AM, contribute directly to higher levels of supply chain integration and coordination [62].

I4.0 technologies also enable decentralized and autonomous system behaviors such as self-organization and self-control in manufacturing and logistics environments. As a result, production systems become more adaptive, data-driven, and capable of responding dynamically to uncertainties. However, the transition toward I4.0 is particularly challenging for small- and medium-sized enterprises (SMEs), which face specific structural limitations compared to large multinational enterprises (MNEs) [63].

Although SMEs constitute the backbone of industrial economies and play a crucial role in employment and economic growth, they often struggle to adopt I4.0 concepts and technologies effectively [64,65]. Successful digital transformation requires overcoming multiple internal and external barriers while leveraging organizational capabilities and external support mechanisms. In particular, resistance to change and short-term operational focus frequently hinder the transition toward digitalization. Nevertheless, certain organizational competencies and environmental factors can substantially accelerate adoption processes [66].

SMEs operate in highly competitive environments characterized by increasing product complexity, shorter product life cycles, and growing demand for customized solutions. To remain competitive, they must enhance their ability to produce a diverse range of products in small batches without compromising cost efficiency or quality [67]. The adoption of smart manufacturing and smart factory principles is therefore considered essential for achieving agile and highly responsive production systems [68]. Consequently, I4.0 adoption has become a critical factor for ensuring long-term growth and competitiveness in SMEs [69,70].

Financial constraints remain one of the most significant barriers to implementation [71,72]. The adoption of I4.0 technologies often requires substantial investments in equipment, infrastructure, and workforce training, which are frequently perceived as high-risk due to uncertain returns on investment (ROI) [73]. These challenges are particularly pronounced in developing economies. In addition, SMEs commonly face deficiencies in technical expertise and digital competencies, limiting their capacity to implement and maintain advanced technological systems [74,75]. Organizational inertia, driven by conservative managerial mindsets and short-term decision-making, further impedes digital transformation efforts [76].

Conversely, managerial support and organizational commitment play a decisive role in facilitating successful adoption [77]. Strong leadership enables the development of strategic visions, allocation of resources, and mitigation of internal resistance, while fostering a culture that is open to innovation and digitalization [75,76]. Furthermore, collaboration—both internal and external—acts as a key enabler. Partnerships with technology providers, consultants, and competence centers support knowledge acquisition and capability development [78]. External networks, including suppliers and customers, also play a crucial role

in driving adoption, while governmental support mechanisms such as subsidies and policy incentives can significantly reduce financial barriers and stimulate investment [79].

Rather than pursuing radical transformation, SMEs typically adopt I4.0 technologies through incremental and phased approaches. Initial implementation focuses on foundational technologies that deliver immediate operational benefits with relatively low risk and cost [80]. Early adoption often includes IoT-based monitoring systems and cloud computing solutions, which enhance data accessibility and system integration without requiring fundamental structural changes [80,81]. Advanced technologies, including big data analytics and AI, are usually adopted at later stages, once sufficient data infrastructure and internal capabilities have been established [82].

The primary motivation for I4.0 adoption is the improvement of operational performance and overall organizational efficiency [83,84]. Empirical evidence indicates that firms with higher readiness levels achieve significant improvements in productivity, efficiency, and process optimization. In particular, leading SMEs adopt digital technologies to enhance production efficiency and maintain global competitiveness [85,86]. These investments facilitate faster and data-driven decision-making processes, contributing to increased operational agility [87]. Additionally, quality management is strengthened through real-time monitoring and predictive maintenance capabilities, reducing defects and improving system reliability [88].

Despite these operational benefits, the short-term impact on financial performance may remain limited due to high implementation costs and long payback periods [70]. However, I4.0 adoption fosters important organizational capabilities, particularly ambidexterity, which enables firms to balance efficiency-oriented exploitation with innovation-driven exploration [89]. Moreover, the workforce structure is transformed, with increasing demand for higher-level cognitive, analytical, and collaborative skills. This shift highlights the importance of integrating technical and soft skills in modern production environments and redefines the role of operators as autonomous and decision-oriented actors [90].

Despite the growing body of research on Industry 4.0 adoption in SMEs, several important limitations remain. First, a large proportion of existing studies rely on qualitative assessments or focus on a limited set of performance indicators, providing only a partial view of the multidimensional nature of manufacturing performance. As a result, integrated evaluation frameworks that simultaneously capture operational, economic, and sustainability dimensions are still relatively scarce. Second, although prior empirical research generally reports positive associations between I4.0 adoption and firm performance, there is a lack of structured and reproducible methodological approaches that systematically quantify performance changes between pre- and post-adoption stages. In particular, mathematically grounded transformation models that enable consistent comparison across firms are still underdeveloped. Third, while the role of digital capabilities has been widely acknowledged, limited attention has been given to the variability of performance outcomes across firms. Existing studies rarely examine how performance improvements are distributed, whether they follow heterogeneous patterns, or how underlying structural differences shape these outcomes.

Finally, although recent advances in data-driven analytics have introduced machine learning techniques into manufacturing research, the integration of predictive modeling with explainable artificial intelligence and unsupervised learning remains fragmented. As a consequence, the joint analysis of performance drivers, causal relationships, and firm-level archetypes is still insufficiently explored.

Addressing these gaps requires a unified analytical framework that combines transformation modeling, composite performance measurement, and advanced data-driven methods. In this context, the present study develops an integrated approach that not only

quantifies the magnitude of performance improvements associated with I4.0 adoption but also reveals their structural characteristics and firm-specific variability.

Unlike previous studies that primarily focus on individual aspects of Industry 4.0 implementation, such as maturity assessment, manufacturing performance measurement, or explainable machine learning, the proposed framework integrates these perspectives within a unified analytical approach. Specifically, this study combines a multidimensional Manufacturing Performance Index (MPI), statistical inference, explainable machine learning, and unsupervised clustering to evaluate Industry 4.0 adoption using empirical data collected from manufacturing SMEs. This integrated methodology enables both comprehensive performance assessment and transparent interpretation of the factors driving digital transformation outcomes, thereby extending existing research on Industry 4.0 performance evaluation.

3. Methodology

3.1. Digital-Transformation-Based Performance Estimation Framework

The empirical analysis is based on a structured dataset consisting of 120 manufacturing SMEs across five industrial sectors, including food ($n = 29$), textile ($n = 22$), machinery ($n = 24$), chemical ($n = 26$), and energy ($n = 19$). Data were collected between March and September 2023, yielding a response rate of 75.0%.

Data were collected using a structured survey instrument together with operational performance records provided by the participating SMEs. Organizational characteristics and Industry 4.0 readiness indicators were obtained through the survey, while manufacturing performance indicators were compiled from company operational records and verified with the participating firms wherever possible to ensure consistency and completeness.

The pre-I4.0 performance indicators represent manufacturing performance prior to the implementation of Industry 4.0 technologies, whereas the post-I4.0 indicators correspond to performance after implementation. The interval between the two measurement periods was approximately 12 months, allowing sufficient time for the operational effects of Industry 4.0 adoption to become observable.

Participating firms were selected using predefined inclusion criteria to ensure that they represented manufacturing SMEs that had implemented Industry 4.0 technologies and were able to provide both organizational and operational performance information. The study included SMEs from five manufacturing sectors to capture a broad range of production environments while maintaining sectoral diversity. The selected sectors represent important manufacturing activities within the study region and were chosen to improve the applicability of the proposed analytical framework across different industrial contexts.

Prior to model development, all variables were organized into two main groups to reflect firm characteristics and digital readiness conditions. The first group, Organizational Characteristics, includes sectoral activity area (SAA), number of employees (NoE), and company type (CT). The second group, Industry 4.0 Readiness Indicators, consists of conceptual understanding, perceived cost, awareness, and need for transition, each measured using validated five-point Likert scales. These indicators are used to capture SMEs' strategic orientation and cognitive preparedness for adopting Industry 4.0 (I4.0) technologies.

The empirical analyses presented in this study were conducted exclusively using the observed pre- and post-I4.0 performance data collected from the participating SMEs. To support interpretation of the observed relationships, a mathematical performance framework was subsequently developed. The framework is conceptual in nature and is intended to describe the expected effects of Industry 4.0 adoption on manufacturing performance. It was not used to generate, estimate, or modify the empirical observations analyzed in this study.

At the core of this framework lies a composite Digital Transformation Effect Factor for each SME i , which represents its expected improvement potential from I4.0 adoption. This factor integrates three key dimensions widely emphasized in digital transformation research: automation readiness, system integration capability, and workforce digital maturity [91]. After normalization to the range [0, 1], the factor is defined as:

$$DTEF_i = \frac{A_i + S_i + D_i}{3} \quad (1)$$

where A_i denotes automation adoption, S_i represents system integration, and D_i captures digital-skill readiness.

To conceptually represent the variability in Industry 4.0 implementation outcomes across manufacturing SMEs, the framework incorporates an uncertainty term that reflects the influence of unobserved organizational, technological, and operational factors. This term provides a theoretical representation of implementation uncertainty commonly reported in the digital manufacturing literature [91] and is included solely to enhance the conceptual completeness of the framework. It was not used to generate, modify, or estimate the empirical observations analyzed in this study.

$$\varepsilon_i = 1 + N(0, 0.02) \quad (2)$$

The uncertainty term represents the variability that may arise from differences in organizational characteristics, implementation strategies, workforce capabilities, and other factors that cannot be explicitly represented in a simplified conceptual framework. Its inclusion is intended solely to illustrate the potential heterogeneity of Industry 4.0 implementation effects and does not affect the empirical analyses reported in this study.

The relationships between the observed pre- and post-adoption performance indicators are conceptually represented through the following multiplicative framework:

$$X_i^{(post)} = X_i^{(pre)} \times (1 + \alpha_x DTEF_i) \cdot \varepsilon_i \quad (3)$$

where X denotes a manufacturing performance indicator, α_x represents an indicator-specific improvement coefficient, $DTEF_i$ is the Digital Transformation Effect Factor of SME i , and ε_i represents a conceptual uncertainty term reflecting potential variation in implementation outcomes.

The α coefficients were selected from ranges reported in previous Industry 4.0 and digital manufacturing studies to provide a theoretical representation of expected performance improvements. In the present study, these coefficients support the conceptual interpretation of the framework and were not used to generate, estimate, or modify the empirical observations analyzed in this study. The coefficients αX were conceptually calibrated according to empirically reported I4.0 impacts, incorporating ranges such as productivity gains of 10–30%, defect reductions of 20–40%, and OEE increases of 5–15% [92,93].

Equation (3) provides a generalized representation applicable to different dimensions of manufacturing performance, including productivity, quality, operational efficiency, cost, energy consumption, workforce productivity, supply chain performance, and profitability. Positive values of α_x conceptually represent indicators expected to improve following Industry 4.0 adoption, whereas negative values represent indicators expected to decrease, such as defect rates, resource consumption, downtime, or operational costs.

The framework is intended solely to illustrate the theoretical direction and relative magnitude of expected performance changes associated with Industry 4.0 implementation. All statistical analyses, machine learning models, clustering analyses, and interpretability

assessments presented in this study were conducted using the observed empirical data collected from the participating manufacturing SMEs.

3.2. Development of the Manufacturing Performance Index (MPI)

To capture the multidimensional impact of I4.0 adoption, a composite Manufacturing Performance Index (MPI) was constructed. The index integrates 17 performance indicators spanning production output, quality, cost efficiency, energy consumption, delivery performance, and workforce productivity, consistent with multidimensional performance measurement frameworks in digital manufacturing research [94].

For each $SME_i = 1, \dots, 120$, both pre- and post-I4.0 values were obtained for all indicators. To ensure comparability across different measurement scales, a combined Min–Max normalization was applied:

$$N_{ij}^{(k)} = \frac{X_{ij}^{(k)} - \min(X_j)}{\max(X_j) - \min(X_j)}, k \in \{pre, post\} \quad (4)$$

Beneficial indicators (e.g., productivity, output, OEE) were used directly:

$$P_{ij}^{(k)} = N_{ij}^{(k)} \quad (5)$$

Non-beneficial indicators (e.g., cycle time, defect rate, cost, energy consumption) were inverted to ensure consistent interpretation:

$$P_{ij}^{(k)} = 1 - N_{ij}^{(k)} \quad (6)$$

The MPI was then calculated as the unweighted mean of the transformed indicators:

$$MPI_i^{(k)} = \frac{1}{17} \sum_{j=1}^{17} P_{ij}^{(k)} \quad (7)$$

The net impact of digital transformation is expressed as:

$$\Delta MPI_i = MPI_i^{post} - MPI_i^{pre} \quad (8)$$

Positive values indicate performance improvement, whereas negative values reflect deterioration.

The equal-weighting approach was adopted to ensure methodological transparency, reproducibility, and ease of interpretation. Given the absence of a universally accepted weighting framework for multidimensional manufacturing performance assessment in Industry 4.0-enabled SMEs, equal weighting avoids introducing subjective preferences among the selected indicators. Although alternative weighting methods, such as expert-based weighting, entropy weighting, AHP, or PCA, may be employed in future studies, the present approach provides a balanced representation of the operational, economic, quality, sustainability, and productivity dimensions included in the Manufacturing Performance Index (MPI).

The proposed MPI is intended as a transparent composite performance measure rather than a definitive weighting framework. Future studies should evaluate the robustness of the index using alternative weighting strategies, such as AHP, entropy weighting, PCA, or other multi-criteria decision-making approaches.

3.3. Descriptive and Inferential Statistics

Descriptive and inferential statistical techniques were employed to quantify and validate the performance changes associated with I4.0 adoption. Descriptive statistics—including mean, standard deviation, and standard error—were used to summarize the central tendency, dispersion, and variability of all performance indicators.

To evaluate temporal changes between pre- and post-adoption states, paired-sample correlation analysis and paired-sample *t*-tests were performed. Correlation analysis was used to assess the degree of linear association between pre- and post-I4.0 values, while paired-sample *t*-tests were conducted to determine whether observed differences are statistically significant.

This combination of descriptive and inferential methods provides a rigorous statistical foundation for the subsequent analysis stages, including predictive modeling, interpretability assessment, heterogeneity analysis, and structural evaluation.

Beyond mean-based comparisons, the analytical framework was extended to capture variation, structural patterns, and distributional characteristics in performance outcomes. These extensions, detailed in Section 4, allow for a more comprehensive understanding of how digital transformation effects differ across firms, enabling the identification of heterogeneous responses, latent performance dimensions, and firm-level archetypes.

3.4. Feature Selection and Preprocessing

Prior to model development, all input variables were systematically examined to ensure data quality, numerical stability, and analytical reliability. Missing values were assessed across all indicators, and no substantial gaps requiring imputation were identified. In addition, multicollinearity diagnostics were conducted using Pearson correlation coefficients and variance inflation factors (VIF), allowing the detection of redundant or highly correlated features that could adversely affect model performance.

All variables were subsequently transformed into a standardized scale using Min–Max normalization, ensuring comparability across heterogeneous measurement units. To maintain consistency in interpretation, non-beneficial indicators—such as defect rate, cycle time, downtime, cost, and energy consumption—were inversely scaled so that higher transformed values uniformly represent improved performance outcomes.

Feature selection was performed through a hybrid approach combining model-based importance measures and SHAP-based sensitivity analysis. This approach allows the identification of features that contribute most significantly to predictive performance while retaining indicators with theoretical relevance. As a result, the final feature set reflects both empirical significance and conceptual completeness, ensuring that the modeling framework captures the multidimensional nature of manufacturing performance.

3.5. Machine Learning Models and Training Strategy

To model the complex and nonlinear relationships between performance indicators, six ensemble learning algorithms were employed: Random Forest (RF), Gradient Boosting (GB), Bagging Regressor, AdaBoost, LightGBM (LGBM), and Extra Gradient Boosting (XGB-E). These models were selected due to their ability to capture nonlinear interactions, reduce overfitting, and deliver robust predictions in heterogeneous industrial datasets.

The dataset was partitioned into training (80%) and testing (20%) subsets using stratified sampling to preserve distributional characteristics across observations. Hyperparameter tuning was conducted using grid search combined with 10-fold cross-validation within the training dataset, ensuring optimal model configuration while reducing the risk of overfitting. The final models were subsequently evaluated on an independent test set using R^2 , RMSE, and MAE to assess predictive performance and generalization capability.

All models were trained using standardized, directionally consistent input features derived from the preprocessing stage. This alignment ensures that the learning algorithms operate on comparable feature contributions and enhances model interpretability. The theoretical foundations and formulations of the employed machine learning algorithms are summarized in Table 1.

Table 1. Summary of ML Models Used in the Study.

Model	Description	Theoretical Basis	Mathematical Formulation	Key References
Random Forest (RF)	An ensemble of decorrelated decision trees constructed using bootstrap samples of the dataset. Each tree is trained independently on a random subset of features, and predictions are aggregated through averaging (for regression) or majority voting (for classification). RF handles nonlinearities, high-dimensional data, and feature interactions robustly.	Bagging (Bootstrap Aggregating) with random feature subspace selection.	$h(x) = \frac{1}{B} \left(\sum_{b=1}^B h_b(x) \right)$ where $h_b(x)$ is the prediction of the b -th tree and B is the total number of trees.	[95–98]
Gradient Boosting (GB)	Sequential ensemble of weak learners (typically decision trees), where each successive tree focuses on minimizing the residual errors of the previous ensemble. It is effective in capturing complex nonlinear relationships and improving predictive accuracy.	Additive boosting minimizing a differentiable loss function.	$r_i^{(m)} = \left[\frac{\partial L(y_i, F_{m-1}(x_i))}{\partial F_{m-1}(x_i)} \right]$ where L is the loss function, F_{m-1} is the previous model, and $r_i^{(m)}$ is the pseudo-residual for the i -th observation.	[98,99]
Bagging Regressor	Combines multiple base regressors trained on bootstrap samples in parallel. The final prediction is obtained by averaging the outputs of all base regressors. Bagging reduces variance and improves model stability without increasing bias.	Bootstrap aggregation (bagging).	$\hat{f}(x) = \frac{1}{B} \sum_{b=1}^B f^b(x)$ where $f^{(b)}(x)$ is the b -th base model.	[100,101]
LightGBM (LGBM)	Gradient boosting framework optimized for speed and efficiency, using histogram-based binning and leaf-wise tree growth. Capable of handling large datasets with high-dimensional features while maintaining accuracy.	Gradient-based One-Side Sampling (GOSS) with leaf-wise tree growth.	$Split\ gain = \frac{1}{2} \left(\frac{G_L^2}{H_{L+\lambda}} + \frac{G_R^2}{H_{R+\lambda}} - \frac{(G_L+G_R)^2}{H_L+H_R-\lambda} \right)$ where G and H are the first- and second-order gradient statistics.	[102,103]
AdaBoost	Adaptive boosting method that sequentially trains weak learners, reweighting misclassified or poorly predicted instances in each iteration. Focuses on difficult observations to improve overall accuracy.	Adaptive boosting by adjusting sample weights to minimize classification or regression error.	$F_m(x) = F_{m-1}(x) + \alpha_m h_m(x)$ where $h_m(x)$ is the weak learner and α_m is its corresponding weight.	[104–107]
Extra Gradient Boosting (XGB-E)	Gradient boosting variant using second-order derivatives for improved optimization and regularization. Includes L1/L2 penalties and shrinkage to prevent overfitting. Suitable for heterogeneous data and complex feature interactions.	Regularized boosted tree optimization using both first- and second-order derivatives.	$w_j = - \frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} (h_i + \lambda)}$ Where g_i and h_i are the first- and second-order gradients for the i -th instance in leaf j .	[108–110]

In addition, the standardized feature space used for model training was retained for subsequent analytical stages, including clustering and structural analysis, thereby ensuring methodological consistency across predictive and unsupervised learning components.

3.6. Model Evaluation Metrics

The performance of the machine learning models was evaluated using a comprehensive set of complementary metrics to capture both explanatory power and predictive accuracy. These metrics include the coefficient of determination (R^2), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Nash–Sutcliffe Efficiency (NSE).

R^2 and NSE were used to assess the proportion of variance explained by the models, providing an overall measure of goodness-of-fit. MAE and RMSE quantify prediction errors in absolute terms, while MAPE captures relative error magnitude, enabling comparison across different scales.

Model evaluation was carried out independently for both training and testing datasets in order to assess generalization capability and detect potential overfitting. This dual evaluation framework ensures that models not only achieve high accuracy on training data but also maintain predictive reliability when applied to unseen observations.

The selection of multiple, complementary performance metrics allows for a robust and balanced assessment of model performance, ensuring that conclusions are not dependent on a single evaluation criterion.

3.7. Model Interpretability via SHAP

To enhance the transparency of model predictions and address the interpretability challenges commonly associated with ensemble learning methods, SHAP (SHapley Additive exPlanations) was employed as the primary interpretability framework.

SHAP quantifies the contribution of each feature to the predicted outcome based on cooperative game theory principles. This approach provides both global and local interpretability. At the global level, SHAP values summarize the overall importance of features across all observations, enabling the identification of the key drivers of manufacturing performance. At the local level, they capture the contribution of each feature to individual predictions, allowing detailed examination of firm-specific performance patterns.

By decomposing predictions into additive feature contributions, SHAP enables a consistent interpretation of nonlinear and interaction effects captured by ensemble models. This is particularly important in the context of Industry 4.0, where performance outcomes emerge from complex interactions among operational, technological, and organizational variables.

Furthermore, the interpretability insights derived from SHAP are used as a reference point for subsequent heterogeneity and structural analyses, facilitating the integration of machine learning outputs with distributional and clustering-based perspectives. This integration strengthens the analytical coherence of the study and enhances its applicability for decision-making.

4. Results

4.1. Overall Comparative Analysis of Pre- and Post-I4.0 Performance Indicators

A comprehensive statistical assessment was conducted to evaluate the changes in operational performance of 120 manufacturing SMEs before and after the adoption of Industry 4.0 (I4.0) technologies. This evaluation integrates descriptive statistics, paired-sample correlation analysis, and paired-sample *t*-tests, providing a multi-layered examination of

performance variation across operational, economic, quality, productivity, and sustainability dimensions. The results are summarized in Tables 2–4.

Descriptive statistics presented in Table 2 indicate clear directional shifts in key performance indicators following I4.0 adoption. Resource consumption metrics such as electricity (EECB → EECA), natural gas (NGB → NGA), and water usage (WTB → WTA) exhibit noticeable reductions, suggesting improved operational efficiency. In contrast, productivity-related indicators—including production quantity (PQB → PQA), production rate (PRB → PRA), and labor productivity (LPB → LPA)—show substantial increases, signaling enhanced output capacity.

Table 2. Paired-Sample Descriptive Statistics for Pre- and Post-I4.0 Performance Variables.

Pair	Variable	Mean	N	Std. Deviation	Std. Error Mean
1	EECB	129.6427	120	64.9433	5.9285
	EECA	116.8958	120	58.2139	5.3142
2	NGB	12,570.5748	120	6364.0379	580.9545
	NGA	11,599.6912	120	5842.7552	533.3681
3	WTB	1269.2715	120	626.9697	57.2342
	WTA	1195.2348	120	587.8979	53.6675
4	PQB	32,098.6434	120	22,762.4035	2077.9136
	PQA	41,982.7650	120	31,419.7656	2868.2191
5	PRB	44.7170	120	33.4564	3.0541
	PRA	56.6166	120	44.3540	4.0489
6	PCTB	2.0117	120	1.2410	0.1133
	PCTA	1.6071	120	1.0046	0.0917
7	DRB	4.6924	120	1.2447	0.1136
	DRA	3.5681	120	1.1933	0.1089
8	OEEB	88.3031	120	2.7645	0.2524
	OEEA	91.6748	120	3.6445	0.3327
9	MDTB	43.0652	120	9.2623	0.8455
	MDTA	32.6237	120	9.1712	0.8372
10	ECB	485,236.8403	120	243,028.5301	22,185.3680
	ECA	438,310.7398	120	218,244.6747	19,922.9219
11	PPEB	1227.7573	120	1177.2987	107.4722
	PPEA	1625.3230	120	1577.6976	144.0234
12	LPB	1.7196	120	1.6779	0.1532
	LPA	2.2105	120	2.1890	0.1998
13	NCB	18,185.8797	120	4242.1660	387.2550
	NCA	15,532.5458	120	3884.4756	354.6025
14	DPB	84.7500	120	4.7443	0.4331
	DPA	87.5405	120	5.2561	0.4798
15	ITRB	4.7363	120	0.6871	0.0627
	ITRA	5.9677	120	1.1025	0.1007
16	PCB	53.4271	120	31.6400	2.8883
	PCA	43.6462	120	25.8283	2.3578
17	PFRB	16.2493	120	8.5579	0.7812
	PFRA	20.9358	120	11.1007	1.0134
18	MPIB	43.8573	120	5.1728	0.4722
	MPIA	53.2154	120	6.9442	0.6339

Table 3. Paired-Sample Correlation Between Pre- and Post-I4.0 Variable.

Pair	Variables	N	Correlation (r)	Sig. (2-Tailed)
1	EECB & EECA	120	0.991	<0.001
2	NGB & NGA	120	0.994	<0.001
3	WTB & WTA	120	0.995	<0.001
4	PQB & PQA	120	0.983	<0.001
5	PRB & PRA	120	0.988	<0.001
6	PCTB & PCTA	120	0.967	<0.001
7	DRB & DRA	120	0.864	<0.001
8	OEEB & OECA	120	0.866	<0.001
9	MDTB & MDTA	120	0.805	<0.001
10	ECB & ECA	120	0.992	<0.001
11	PPEB & PPEA	120	0.981	<0.001
12	LPB & LPA	120	0.985	<0.001
13	NCB & NCA	120	0.932	<0.001
14	DPB & DPA	120	0.951	<0.001
15	ITRB & ITRA	120	0.867	<0.001
16	PCB & PCA	120	0.982	<0.001
17	PFRB & PFRA	120	0.976	<0.001
18	MPIB & MPIA	120	0.759	<0.001

Note: All pre–post pairs exhibit strong correlations (most > 0.85), indicating high internal consistency across measurement periods.

Table 4. Paired-Sample *t*-Test Results for Pre- and Post-I4.0 Variables.

Pair	Variable Comparison	Mean Diff.	Std. Dev.	Std. Error Mean	95% CI (Lower–Upper)	t	df	Sig. (2-Tailed)
1	EECB–EECA	12.7469	10.5100	0.9594	10.8471/14.6467	13.286	119	<0.001
2	NGB–NGA	970.8836	861.6482	78.6574	815.1342/1126.6330	12.343	119	<0.001
3	WTB–WTA	74.0367	71.6625	6.5419	61.0831/86.9902	11.317	119	<0.001
4	PQB–PQA	−9884.1216	9938.7563	907.2802	−11,680.6269/−8087.6162	−10.894	119	<0.001
5	PRB–PRA	−11.8996	12.4603	1.1375	−14.1519/−9.6473	−10.462	119	<0.001
6	PCTB–PCTA	0.4047	0.3717	0.0339	0.3375/0.4719	11.927	119	<0.001
7	DRB–DRA	1.1243	0.6376	0.0582	1.0091/1.2396	19.316	119	<0.001
8	OEEB–OECA	−3.3718	1.8635	0.1701	−3.7086/−3.0349	−19.821	119	<0.001
9	MDTB–MDTA	10.4415	5.7598	0.5258	9.4004/11.4826	19.859	119	<0.001
10	ECB–ECA	46,926.1005	38,826.1561	3544.3269	39,907.9792/53,944.2218	13.240	119	<0.001
11	PPEB–PPEA	−397.5656	481.9705	43.9977	−484.6854/−310.4458	−9.036	119	<0.001
12	LPB–LPA	−0.4909	0.6104	0.0557	−0.6013/−0.3806	−8.810	119	<0.001
13	NCB–NCA	2653.3339	1537.7060	140.3727	2375.3819/2931.2859	18.902	119	<0.001
14	DPB–DPA	−2.7905	1.6438	0.1501	−3.0876/−2.4934	−18.596	119	<0.001
15	ITRB–ITRA	−1.2315	0.6114	0.0558	−1.3420/−1.1210	−22.065	119	<0.001
16	PCB–PCA	9.7809	7.9397	0.7248	8.3458/11.2161	13.495	119	<0.001
17	PFRB–PFRA	−4.6866	3.3282	0.3038	−5.2882/−4.0850	−15.425	119	<0.001
18	MPIB–MPIA	−9.3581	4.5222	0.4128	−10.1755/−8.5407	−22.669	119	<0.001

Note: All pre–post differences are statistically significant ($p < 0.001$), indicating substantial performance changes following I4.0 transition.

Quality and stability indicators also display marked improvements. Defect rates (DRB → DRA) and production cycle times (PCTB → PCTA) decrease, while overall equipment effectiveness (OEEB → OECA) increases. Machine downtime (MDTB → MDTA) is significantly reduced, reflecting the positive impact of predictive maintenance and data-driven process control mechanisms.

The correlation analysis in Table 3 reveals strong and statistically significant relationships between pre- and post-I4.0 values for all performance indicators ($r > 0.80$, $p < 0.001$ in most cases). These high correlations suggest that the relative operational performance of the participating SMEs remained broadly consistent between the pre- and post-adoption periods. In other words, firms that performed relatively well before Industry 4.0 adoption generally continued to perform relatively well after adoption, while exhibiting statistically significant improvements in the analyzed performance indicators.

The paired-sample *t*-test results reported in Table 4 confirm that all observed performance differences are statistically significant ($p < 0.001$). The magnitude and direction of these differences provide strong empirical evidence of the effectiveness of I4.0 implementation.

Production-related indicators demonstrate substantial positive change, with increases in output (PQA) and production rate (PRA), accompanied by reductions in cycle time (PCTA). Similarly, equipment-level improvements are evident through increased OEEA and reduced downtime. Workforce productivity improves significantly, as reflected in higher production per employee and labor productivity values.

Cost-related indicators—including energy cost (ECB $\rightarrow$ ECA), production cost (PCB $\rightarrow$ PCA), and maintenance cost (NCB $\rightarrow$ NCA)—decline notably following digital transformation. These reductions are consistent with efficiency gains resulting from automation, real-time monitoring, and process optimization. In parallel, sustainability-related metrics show measurable improvements, with reductions in energy and resource consumption across all examined dimensions.

A key aggregate outcome is the increase in the Manufacturing Performance Index (MPI), which rises from 43.86 (pre-I4.0) to 53.22 (post-I4.0). This substantial improvement reflects simultaneous gains across multiple operational dimensions.

The combined evidence from descriptive, correlational, and inferential analyses demonstrates that I4.0 adoption leads to consistent, statistically significant, and multi-dimensional performance improvements in SMEs. Rather than causing isolated changes, digital transformation appears to generate broad-based enhancements across efficiency, productivity, cost management, and sustainability, reinforcing its role as a transformative driver of manufacturing competitiveness.

4.2. Correlation Structure Among Post-I4.0 Performance Indicators

To further understand the internal structure of post-adoption performance, the relationships among the 18 post-I4.0 indicators were examined through correlation analysis. The resulting correlation matrix is illustrated in Figure 1, which highlights the underlying structure and interdependencies among performance dimensions.

The results reveal distinct clusters of strongly correlated variables, indicating that performance improvements following I4.0 adoption are not uniformly distributed but instead emerge in structured groups.

A particularly strong cluster is observed among resource consumption variables—electricity consumption (EECA), natural gas usage (NGA), water consumption (WTA), and energy cost (ECA)—with very high correlation levels ($R^2 \approx 0.90$ – 1.00). This suggests that resource efficiency improvements occur in an integrated manner, reflecting the interconnected nature of industrial energy systems. Facilities that achieve reductions in one resource dimension tend to exhibit parallel improvements in others.

A second cluster involves production and productivity-related indicators, including production quantity (PQA), production rate (PRA), and labor productivity (LPA). These variables display moderate-to-strong correlations ($R^2 \approx 0.48$ – 0.99), indicating that operational throughput improvements are closely associated with enhanced workforce efficiency. This relationship aligns with the synergistic effects of I4.0 technologies such as automation, real-time data analytics, and intelligent scheduling systems.

In contrast, quality and process stability indicators, such as defect rate (DRA) and production cycle time (PCTA), show weak correlations with energy and throughput metrics ($R^2 < 0.10$). This suggests that quality-related improvements are governed by relatively independent mechanisms, likely driven by specialized digital tools such as machine vision systems and statistical process control.

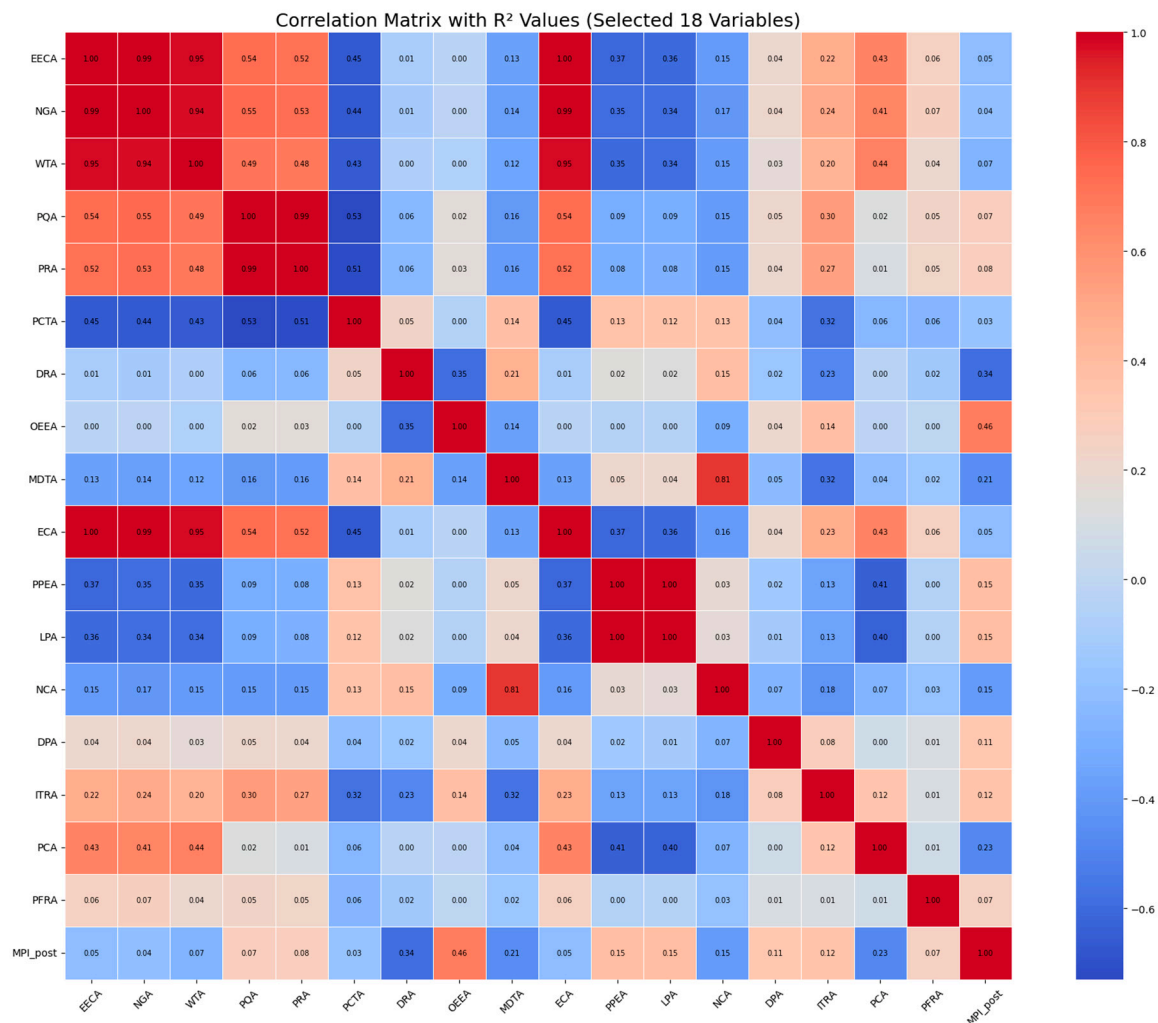


Figure 1. Correlation Matrix of Post-I4.0 Performance Indicators (R² Values).

Machine downtime (MDTA) exhibits moderate correlations with both operational and productivity variables ($R^2 \approx 0.12\text{--}0.36$), indicating that while reductions in downtime contribute to performance improvements, they do not translate directly into proportional increases in production output due to the influence of additional operational constraints.

The post-I4.0 MPI exhibits modest correlations with individual indicators ($R^2 \approx 0.05\text{--}0.46$), reflecting its role as a composite index integrating multiple performance dimensions. Rather than being dominated by a single variable group, MPI captures a balanced representation of efficiency, cost, quality, and sustainability.

Collectively, these results demonstrate that I4.0 implementation produces a structured and multidimensional impact on manufacturing performance. Rather than influencing all metrics in a uniform manner, digital transformation strengthens specific performance domains—particularly resource efficiency and production throughput—while preserving the relative independence of quality-related processes. This multidimensional structure underscores the importance of composite performance measures such as MPI for capturing the full scope of digital transformation effects.

4.3. Feature Importance and SHAP-Based Explainability Analysis

A model-driven interpretability analysis was conducted to identify the post-I4.0 performance indicators that most strongly influence the Manufacturing Performance Index (MPI). The SHAP analysis was performed using the observed post-I4.0 performance data

collected from the participating SMEs and was employed to explain the predictions of the machine learning models. It was not intended to evaluate or validate the mathematical framework presented in Section 3.1. Ensemble learning outputs were complemented with SHAP to quantify both the relative importance of each feature and its directional impact on predicted performance outcomes. The results are illustrated in Figures 2 and 3.

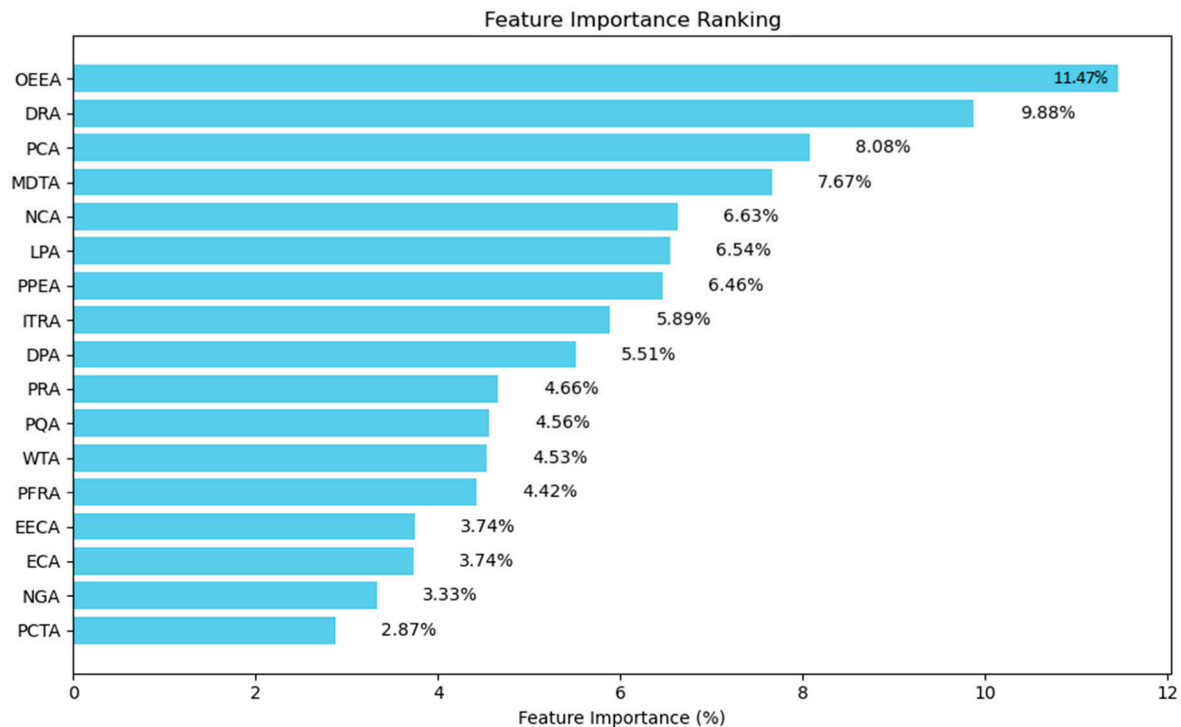


Figure 2. Feature Importance Ranking for Post-I4.0 MPI Prediction.

The feature importance ranking presented in Figure 2 reveals that Overall Equipment Effectiveness after I4.0 (OEEA) is the most influential predictor, accounting for approximately 11.47% of total model importance. This is followed by Defect Rate after I4.0 (DRA), Production Cost after I4.0 (PCA), and Machine Downtime after I4.0 (MDTA). The dominance of these variables highlights the central role of operational efficiency, quality control, and cost structure in determining manufacturing performance within digitally transformed SMEs.

These findings indicate that performance improvements are not evenly driven across all indicators. Instead, a relatively small subset of efficiency- and stability-related variables explains a substantial portion of overall performance variation. Variables such as production cycle time (PCTA) and energy cost (ECA), while relevant, exhibit comparatively lower importance, suggesting a secondary contribution to overall performance outcomes.

The SHAP analysis presented in Figure 3 provides a more granular interpretation of feature effects by illustrating both their magnitude and direction. High values of OEEA consistently generate positive SHAP contributions, reflecting strong positive effects on MPI. Conversely, higher values of defect rate (DRA) produce negative contributions, confirming the inverse relationship between quality losses and overall manufacturing performance.

The beeswarm plot further reveals that these relationships are not strictly linear but vary across observations. For instance, the impact of variables such as production rate (PRA), maintenance cost (NCA), and delivery performance (DPA) differs depending on the operational characteristics of individual firms. This variability suggests the presence of context-dependent effects, where similar levels of a given indicator may produce different outcomes depending on the broader system configuration.

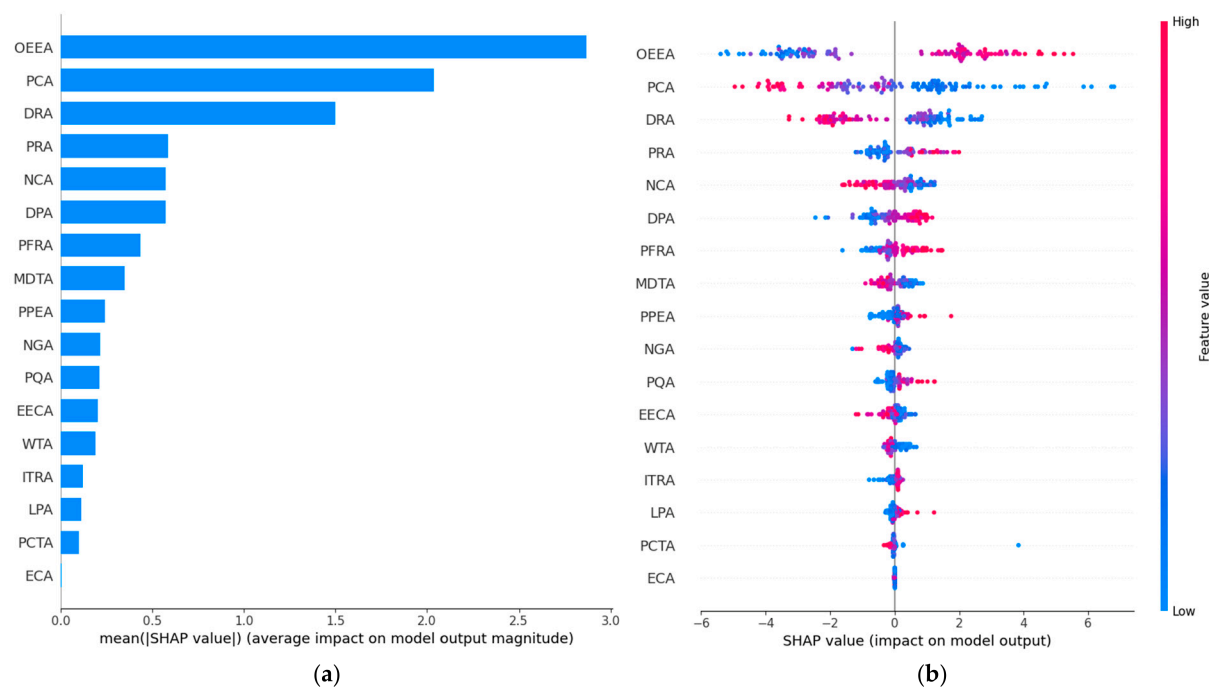


Figure 3. SHAP Summary Plots for Post-I4.0 MPI Prediction (a) Mean absolute SHAP values indicating feature contribution magnitude; (b) Beeswarm plot showing direction and distribution of feature impacts.

In addition, several features display asymmetric influence patterns, where improvements in certain performance ranges yield disproportionately higher gains. This indicates that the marginal benefit of digital transformation is not constant and may depend on initial performance conditions and operational thresholds.

Taken together, the feature importance and SHAP analyses demonstrate that post-I4.0 performance improvements are primarily driven by efficiency optimization, cost reduction, and quality stabilization mechanisms. The results also reveal that these effects operate in a nonlinear and context-sensitive manner, emphasizing the importance of firm-specific implementation strategies rather than uniform digital transformation approaches.

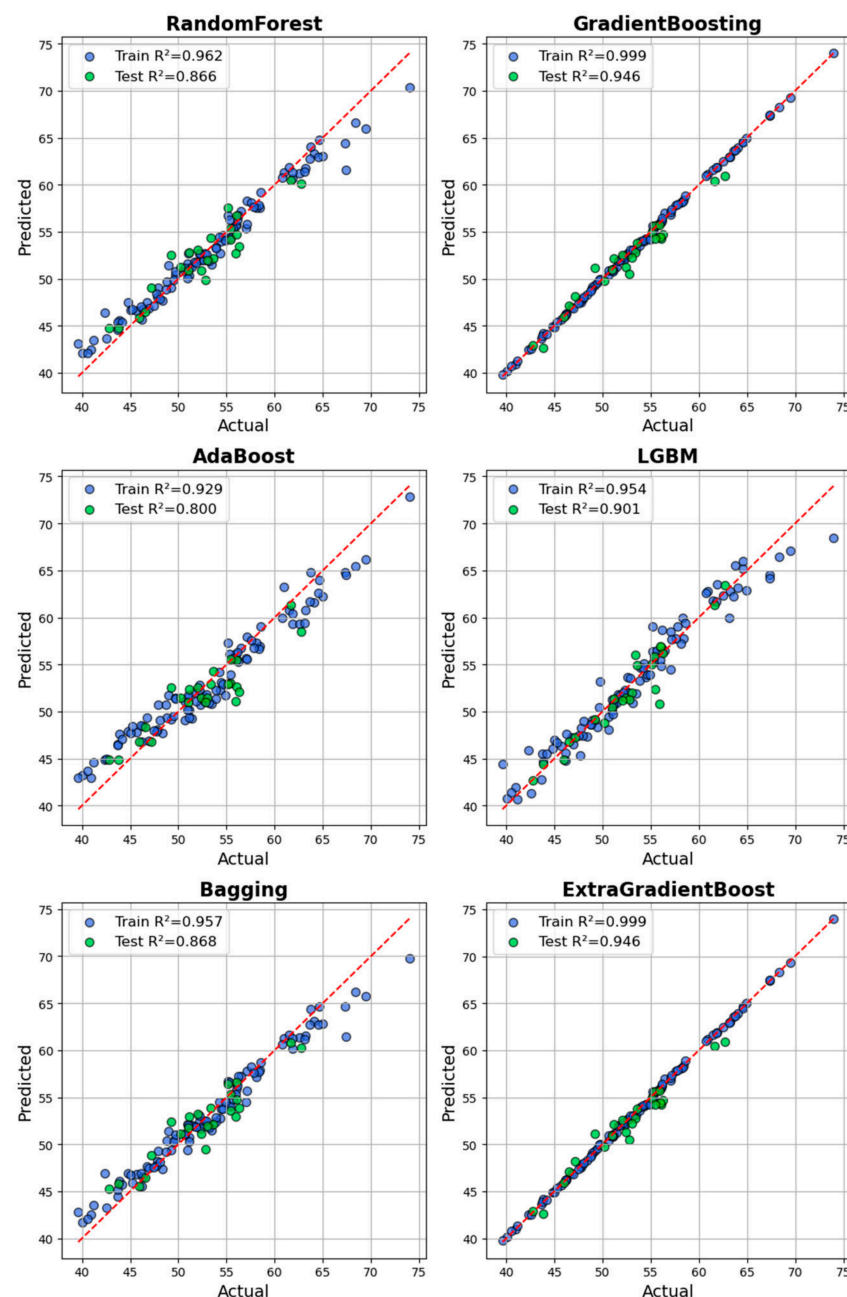
4.4. Model Performance Evaluation

The predictive capability of the proposed framework was evaluated using six ensemble learning models: Random Forest, Gradient Boosting, AdaBoost, LightGBM, Bagging, and Extra Gradient Boosting. Model performance was assessed based on both explanatory power and prediction error, using R^2 , MAE, RMSE, MAPE, and Nash–Sutcliffe Efficiency (NSE). The comparative results are presented in Table 5 and Figure 4.

The results shown in Figure 4 indicate that all models achieve strong predictive performance, with test-set R^2 values exceeding 0.79. Among the evaluated models, Gradient Boosting and Extra Gradient Boosting exhibit the highest accuracy, both achieving R^2_{test} values of approximately 0.946. LightGBM follows with a slightly lower but still strong performance ($R^2_{\text{test}} = 0.901$), while Random Forest and Bagging deliver moderate but stable results ($R^2_{\text{test}} \approx 0.866$ – 0.868). In contrast, AdaBoost demonstrates comparatively weaker performance ($R^2_{\text{test}} = 0.799$), indicating limitations in capturing complex nonlinear relationships within the dataset.

Table 5. Model Performance Metrics for Post-I4.0 MPI Prediction.

Model	MAE-Train	MAE-Test	RMSE-Train	RMSE-Test	MAPE-Train	MAPE-Test	NSE-Train	NSE-Test
Random Forest	1.0369	1.4890	1.4322	1.7734	1.9817	2.8225	0.9618	0.8658
Gradient Boosting	0.1413	0.9101	0.1858	1.1222	0.2683	1.7088	0.9994	0.9463
AdaBoost	1.6451	1.6803	1.9507	2.1656	3.1880	3.1633	0.9292	0.7999
LightGBM (LGBM)	1.1775	1.0028	1.5755	1.5215	2.2121	1.8755	0.9538	0.9012
Bagging	1.1441	1.4986	1.5260	1.7618	2.1688	2.8803	0.9567	0.8675
Extra Gradient Boost	0.1413	0.9101	0.1858	1.1222	0.2683	1.7088	0.9994	0.9463

**Figure 4.** R^2 Performance Comparison of Ensemble Models.

Error-based metrics reported in Table 5 support these findings. Gradient Boosting and Extra Gradient Boosting achieve the lowest prediction errors (MAE = 0.910; RMSE = 1.122; MAPE = 1.709), confirming their superior generalization capability. LightGBM also performs well, though with slightly higher error levels. AdaBoost records the highest error values, suggesting limited suitability for high-dimensional, heterogeneous performance data.

The Nash–Sutcliffe Efficiency values further confirm model consistency. The top-performing models (Gradient Boosting and Extra Gradient Boosting) achieve NSE_test values close to 0.95, indicating a strong ability to reproduce observed variability. Other models deliver acceptable but comparatively lower performance levels.

The consistency between high predictive accuracy and stable generalization performance reinforces the reliability of the modeling framework. Moreover, the alignment between model outputs and SHAP-based interpretations suggests that the learned relationships are not spurious but reflect meaningful structural patterns within the data. These results demonstrate that ensemble learning models are highly effective tools for capturing the complex, multidimensional relationships that characterize post-I4.0 manufacturing performance in SMEs.

4.5. Advanced Structural and Heterogeneity Analysis

Advanced statistical and unsupervised learning approaches were employed to extend the empirical findings beyond aggregate effects, enabling the examination of heterogeneity, causal mechanisms, and structural differentiation across SMEs.

These methods, including variance-based analysis, distributional modeling, mediation analysis, dimensionality reduction, and clustering, provide a comprehensive and structured perspective on the variability and underlying patterns of digital transformation outcomes across firms and contexts.

4.5.1. Heterogeneity and Distributional Effects

The heterogeneity of performance improvements was first examined using ANOVA and quantile-based methods. The ANOVA results reported in Table 6 indicate that differences in Δ MPI across firm size (EMP) and sector (IND) are not statistically significant at conventional levels. However, a clear directional pattern is observed in group means, with larger firms and certain sectors exhibiting higher average performance gains. This suggests that although variability is not strong enough to yield statistical significance, structural tendencies favor specific firm and sectoral profiles.

The distributional analysis, summarized in Table 7, reveals substantial variation in performance outcomes across firms. The mean Δ MPI increases from 3.21 in the lowest quantile (Q1) to 15.84 in the highest quantile (Q5), resulting in a large spread of 12.62 units. This wide dispersion demonstrates that the benefits of I4.0 adoption are not evenly distributed, but instead vary significantly across firms.

Further disaggregation by firm size and sector, presented in Table 8, confirms this pattern. Firms in higher quantiles consistently achieve larger improvements regardless of size, while sectoral differences become more pronounced at upper performance levels. In particular, firms in sectors IND = 3–5 dominate the upper quantiles, indicating that sector-specific characteristics influence the magnitude of performance gains.

Quantile regression results reinforce these findings by showing that the influence of sectoral factors becomes stronger at higher performance levels. The statistically significant positive coefficient for IND = 3 at the upper quantile ($q = 0.75$) suggests that sectoral advantages are particularly relevant among high-performing firms. In contrast, firm size does not exhibit consistent effects across quantiles, indicating that scale alone is not a decisive factor once firms reach higher levels of performance.

These results collectively indicate that I4.0 acts as a performance amplifier, where firms with more favorable initial conditions or structural advantages experience disproportionately higher gains.

Table 6. ANOVA Results and Group Means for Δ MPI.

(a) ANOVA Results					
Source	SS	df	MS	F	p-Value
C (EMP)	121.054	3	40.351	2.024	0.114
Residual	2312.486	116	19.935	—	—
C (IND)	160.257	4	40.064	2.027	0.095
Residual	2273.283	115	19.768	—	—
(b) Group Means					
Category	Level		Mean Δ MPI		
EMP	1		9.03		
EMP	2		8.48		
EMP	3		10.76		
EMP	4		11.08		
IND	1		8.25		
IND	2		8.64		
IND	3		10.94		
IND	4		10.66		
IND	5		10.57		

Table 7. Quantile Distribution of Δ MPI.

Quantile	Mean	Std	Range	N
Q1_Low	3.215	1.833	−0.47–5.41	24
Q2	6.704	0.810	5.45–7.90	24
Q3	9.323	0.713	8.02–10.44	24
Q4	11.711	0.862	10.47–13.18	24
Q5_High	15.837	2.057	13.22–22.82	24

Table 8. Quantile Cross-Analysis of Δ MPI by Firm Size (EMP) and Industry (IND).

Quantile	EMP1	EMP2	EMP3	EMP4	IND1	IND2	IND3	IND4	IND5
Q1_Low	2.03	4.08	2.47	—	3.08	2.42	3.84	3.34	4.20
Q2	6.38	6.71	7.02	7.03	6.96	6.29	6.29	7.18	6.89
Q3	9.57	9.17	9.35	—	9.49	8.90	10.41	8.88	9.64
Q4	11.88	11.72	11.55	11.81	11.55	11.62	12.34	11.87	11.71
Q5_High	15.38	15.94	16.31	13.67	14.92	13.96	16.91	16.03	16.05

4.5.2. Mediation Analysis of Performance Mechanisms

The causal relationship between firm size, digital capability, and performance improvement was further investigated using a mediation framework. The results, summarized in Table 9, provide insight into whether Industry 4.0 capability (I4C) serves as an intermediary mechanism linking firm size to performance outcomes.

The findings indicate that the relationship between firm size and I4C (path a) is positive but not statistically significant, suggesting that larger firms do not systematically exhibit higher digital capability levels. In contrast, the relationship between I4C and Δ MPI (path b) is strongly significant, highlighting the critical role of technological capability in driving performance improvements.

The total effect of firm size on Δ MPI is only weakly significant, and the direct effect becomes statistically insignificant when I4C is included in the model. The indirect effect remains statistically insignificant and is not supported by bootstrap confidence intervals, indicating that I4C does not function as a robust mediator in this relationship.

Table 9. Mediation Analysis Results (EMP → I4C → ΔMPI).

Path	Coefficient	Std. Error	p-Value	Boot CI (2.5%)	Boot CI (97.5%)
a (EMP → I4C)	0.111	0.148	0.457	–	–
b (I4C → ΔMPI)	1.633	0.271	<0.001	–	–
c (Total Effect)	0.888	–	0.077	–	–
c' (Direct Effect)	0.706	–	0.109	–	–
a × b (Indirect Effect)	0.181	0.244	0.458	−0.361	0.703

The mediation analysis did not identify a statistically significant indirect effect of Industry 4.0 capability (I4C) on the relationship between firm size and manufacturing performance. Therefore, the proposed mediation mechanism was not supported in the present sample. Although the observed coefficients may provide useful insights for future investigation, they should not be interpreted as evidence of an indirect effect.

These findings imply that digital transformation outcomes are not primarily determined by firm size, but rather by how effectively firms develop and utilize technological capabilities. Performance gains depend more on implementation quality and operational integration than on scale alone.

4.5.3. Dimensional Structure of Performance Indicators

To investigate the structural organization of performance indicators, Principal Component Analysis (PCA) was conducted. The eigenvalue distribution in Figure 5 suggests that approximately eight components should be retained under the Kaiser criterion, while the cumulative variance in Figure 6 indicates that a relatively small number of components captures the majority of total variance.

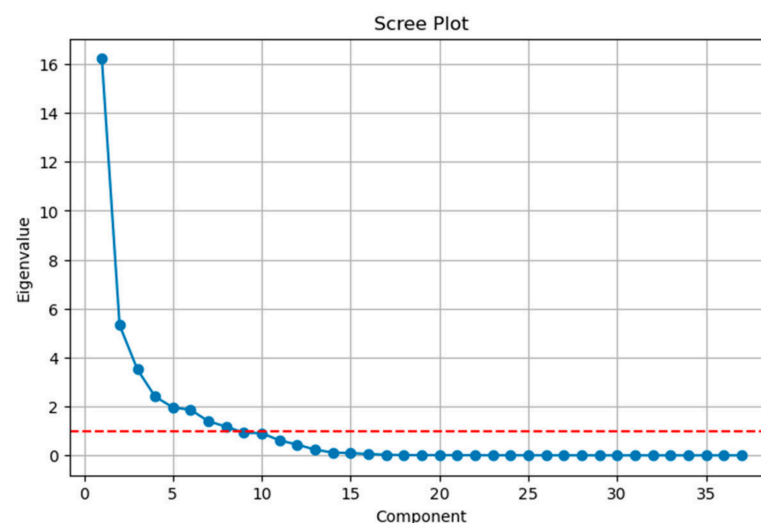


Figure 5. Scree Plot of PCA Components (Eigenvalues vs. Component Number). The red dashed line indicates the Kaiser criterion (eigenvalue = 1), and the blue dots represent the eigenvalues of the principal components.

The factor loading structure, illustrated in Figure 7, reveals the presence of distinct latent dimensions underlying post-I4.0 performance.

Resource and energy-related variables cluster strongly within the first principal component, forming a unified efficiency dimension. Production and operational variables are distributed across secondary components, while maintenance and cost-related indicators form another cohesive grouping. Quality-related variables exhibit distinct loading patterns, reinforcing their relative independence from productivity and resource consumption dimensions.

Workforce productivity indicators and delivery-related metrics also emerge as separate factors, indicating that human performance and supply-chain responsiveness represent distinct domains of performance.

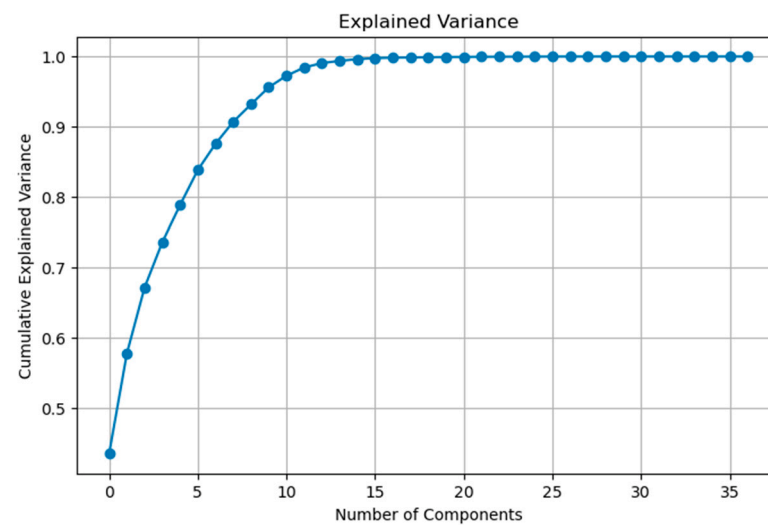


Figure 6. Cumulative Explained Variance of PCA Components. The blue dots and line represent the cumulative explained variance as successive principal components are included.

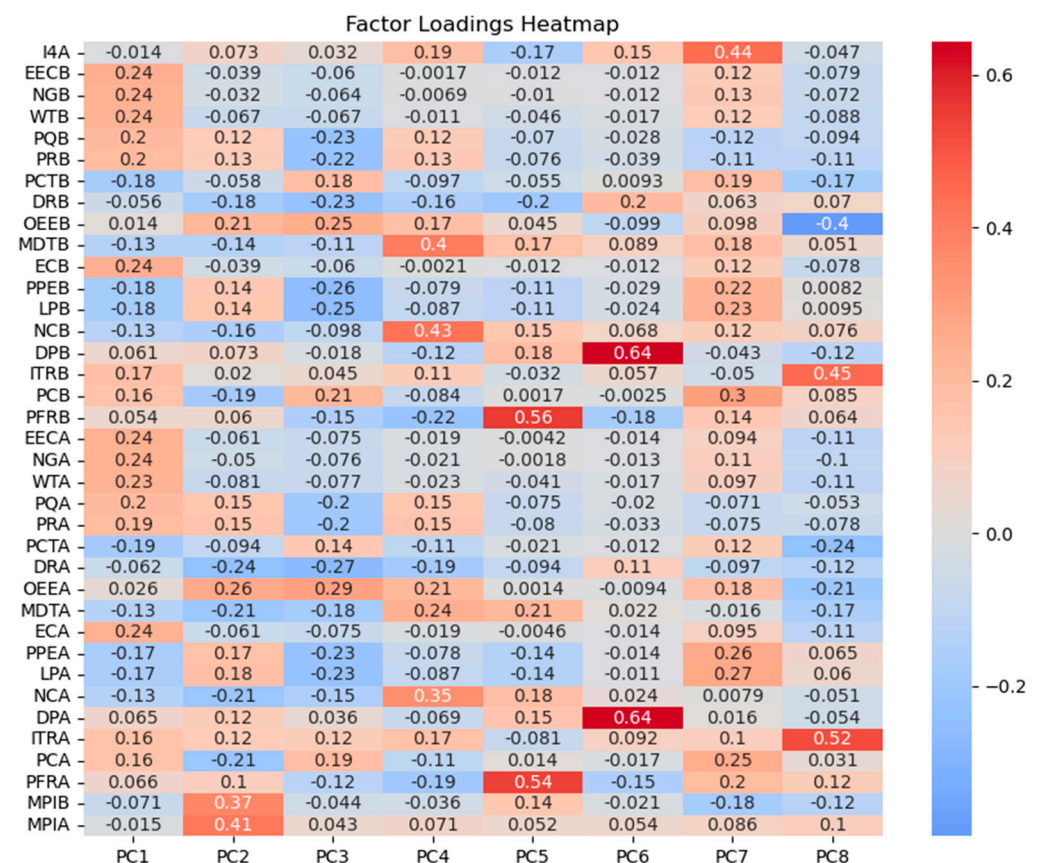


Figure 7. Factor Loadings Heatmap for PCA Components. Negative values denote negative factor loadings (−, U+2212).

The MPI components form an independent latent dimension, confirming that the composite index captures a unique combination of performance signals rather than simply reflecting a single dominant factor.

These results provide strong evidence that post-I4.0 performance is inherently multidimensional, with multiple independent but interrelated dimensions contributing to overall outcomes.

4.5.4. SME Archetypes and Sectoral Distribution Patterns

Building on the structural insights from PCA, clustering analysis was conducted to identify distinct SME archetypes. A three-cluster solution was selected based on optimization criteria, and the resulting structure is visualized in Figure 8, where clusters are clearly separated in the reduced PCA space.

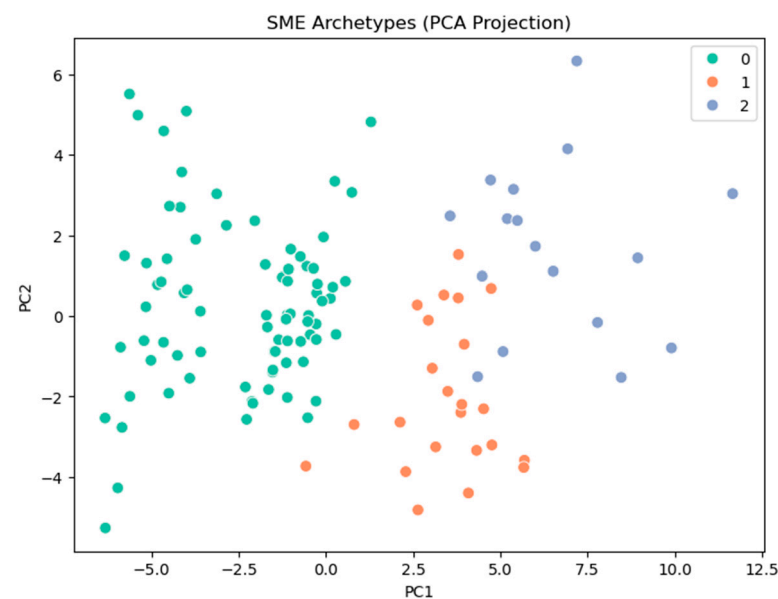


Figure 8. SME Archetypes Based on PCA Projection (PC1–PC2).

The clustering results reveal three distinct firm profiles: (1) low-performance or traditional SMEs, (2) transitioning SMEs, and (3) advanced I4.0-driven SMEs. The identified clusters were derived from the observed post-I4.0 performance data collected from the participating SMEs and therefore represent empirical performance patterns within the study sample rather than predefined or theoretically imposed categories.

The sectoral distribution of these clusters, presented in Figure 9, shows a strong concentration of low-performance firms across all industries, while advanced SMEs are more selectively distributed and particularly concentrated in specific sectors. This pattern is further reinforced by the archetype distribution heatmap in Figure 10, which shows that high-performance firms remain relatively scarce and unevenly distributed.

The cluster profiles summarized in Table 10 highlight clear differences in Δ MPI and overall performance characteristics across archetypes. Advanced SMEs consistently achieve the highest performance gains, while traditional SMEs exhibit relatively modest improvements.

These findings indicate that digital transformation operates as a stratifying mechanism, creating differentiated performance groups rather than producing uniform improvements across firms. Sectoral characteristics and firm capabilities jointly shape the likelihood of belonging to higher-performance clusters.

The integration of heterogeneity analysis, mediation modeling, PCA, and clustering provides a coherent understanding of post-I4.0 performance dynamics. Variation across firms is substantial, causal pathways are capability-driven rather than scale-driven, performance dimensions are structurally diverse, and firm outcomes are segmented into distinct archetypes. This multi-layered evidence reinforces the interpretation that Industry 4.0

does not produce homogeneous performance improvements but instead amplifies existing differences while restructuring performance along multiple independent dimensions.

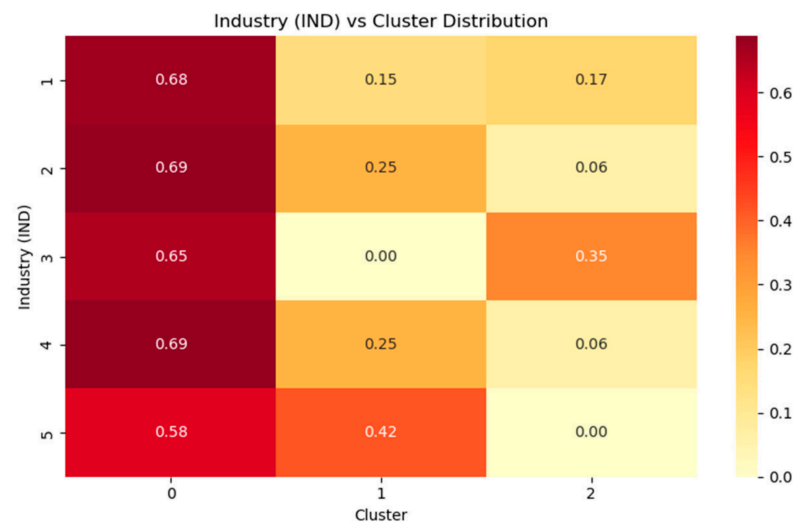


Figure 9. Heatmap of Industry (IND) vs. Cluster Distribution.

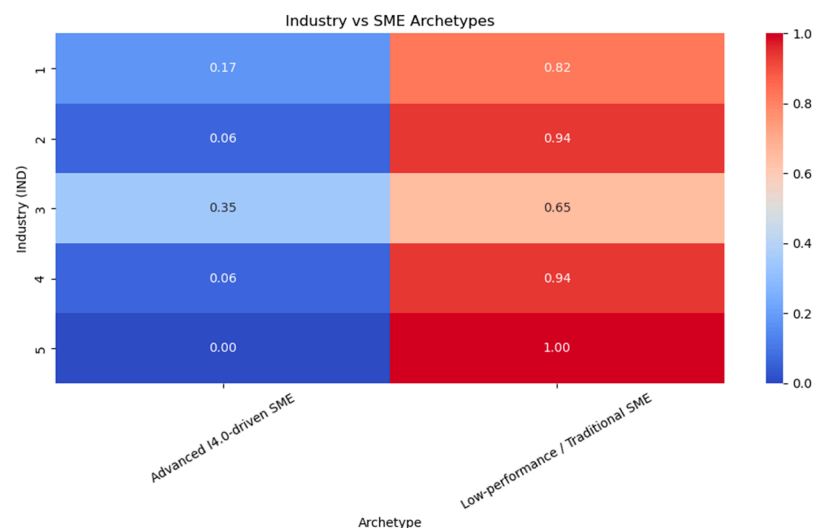


Figure 10. Industry (IND) vs. SME Archetype Distribution.

Table 10. Cluster-Based SME Archetype Profiles (Mean Values).

Cluster	Archetype	Avg. Δ MPI	General Profile
0	Low-performance/Traditional SME	Low (~5–8)	Lower productivity, higher costs, limited I4.0 impact
1	Transitioning SME	Medium (~8–12)	Moderate improvement, partial digital transformation
2	Advanced I4.0-driven SME	High (~12–18)	High efficiency, strong digital integration

5. Discussion

The present study provides robust empirical evidence demonstrating that the adoption of Industry 4.0 (I4.0) technologies leads to substantial and multidimensional performance improvements in manufacturing SMEs. By integrating classical statistical methods with explainable artificial intelligence techniques, the findings extend beyond theoretical expectations.

tations and offer a comprehensive, empirically grounded understanding of performance outcomes that are measurable, interpretable, and context-sensitive.

One of the central insights emerging from the results is that I4.0 functions primarily as a performance amplifier rather than a uniform equalizer across firms. The strong correlations observed between pre- and post-adoption indicators suggest that digital transformation tends to reinforce and enhance existing operational structures rather than fundamentally altering them. This interpretation is consistent with prior empirical research indicating that I4.0-related gains are context-dependent and influenced by firm-specific capabilities, sectoral characteristics, and technological maturity [13,84].

Within the SME context, this amplification effect aligns closely with studies emphasizing that digital transformation outcomes are contingent on organizational readiness, absorptive capacity, and managerial commitment [77,85]. The findings reinforce the view that performance improvements associated with I4.0 are cumulative and capability-driven rather than immediate or uniformly distributed. In this respect, the integration of explainable machine learning provides additional insight by identifying key performance drivers. Indicators such as overall equipment effectiveness, machine downtime, defect rates, and production costs emerge as dominant contributors to the Manufacturing Performance Index (MPI), highlighting the critical role of operational efficiency and process stability.

These findings provide strong empirical support for the importance of predictive maintenance and smart operations within I4.0 environments. Data-driven maintenance approaches, supported by IoT-enabled monitoring and diagnostic systems, have been widely recognized as essential for reducing downtime, extending equipment lifecycles, and stabilizing production processes [2]. The observed inverse relationship between downtime-related variables and overall performance further confirms the effectiveness of cyber-physical systems and real-time monitoring infrastructures in enabling autonomous and adaptive manufacturing systems [9,111].

At the same time, the results reveal that the effects of I4.0 technologies are neither linear nor uniform across different performance dimensions. The heterogeneous and nonlinear relationships identified through SHAP analysis indicate that digital transformation outcomes vary considerably depending on the operational context and initial performance conditions of firms. This observation is consistent with previous research suggesting that the benefits of specific technologies—such as Big Data Analytics or advanced robotics—depend on firm-level capabilities, resource availability, and strategic alignment [50].

The evidence further supports the notion that SMEs typically adopt I4.0 technologies in an incremental and capability-driven manner, prioritizing solutions that enhance operational visibility, flexibility, and efficiency [26,65]. In this regard, the findings challenge deterministic interpretations of digital transformation and instead support contingency-based perspectives, where adoption pathways and outcomes are shaped by firm-specific constraints and opportunities.

An important contribution of the study lies in demonstrating that improvements in sustainability-related indicators are not isolated outcomes but are structurally embedded within digital transformation processes. The statistically significant reductions in energy and resource consumption suggest that efficiency gains achieved through I4.0 adoption inherently contribute to more sustainable production systems. This finding is consistent with recent literature emphasizing the role of digital technologies in enabling resource optimization, waste reduction, and process transparency [83,112].

Moreover, the strong interrelationships observed among energy and cost variables support theoretical frameworks associated with the circular economy, which highlight the role of digitalization in facilitating closed-loop systems, improved resource coordination, and enhanced resilience [113]. From this perspective, I4.0 can be considered not only as

a productivity-enhancing paradigm but also as a key enabler of sustainable and resilient manufacturing systems.

Beyond operational and environmental outcomes, the findings also point to broader organizational implications. The observed stabilization and improvement of performance indicators suggest that I4.0 adoption contributes to increased organizational resilience and adaptability. This is consistent with empirical evidence indicating that digital technologies enhance both operational performance and long-term survival capabilities by enabling more flexible and responsive production systems [11].

In parallel, the results indirectly highlight the growing importance of human-centric and organizational factors in digital transformation processes. Previous studies have emphasized the increasing demand for new skill sets, including cognitive, collaborative, and analytical capabilities, as well as the evolving role of human operators in digitally integrated environments [75,114]. These observations are further aligned with emerging Industry 5.0 perspectives, which advocate for the integration of human intelligence with advanced technologies to enhance both resilience and sustainability [1].

From a methodological standpoint, this study contributes to the literature by combining predictive analytics with explainable artificial intelligence to interpret complex performance relationships. While machine learning methods are increasingly used in manufacturing contexts, their practical adoption is often constrained by limited transparency and interpretability [14,17]. By employing SHAP-based explanations, this study addresses this limitation and responds to recent calls for more interpretable and responsible AI applications in industrial decision-making. The results demonstrate that explainable models not only improve predictive accuracy but also enhance managerial understanding and decision support [115].

These findings are broadly consistent with previous empirical studies reporting that improvements in equipment effectiveness, quality performance, predictive maintenance, and operational efficiency are among the principal benefits associated with Industry 4.0 adoption in manufacturing SMEs. The present results extend these studies by integrating multidimensional performance assessment with explainable machine learning, thereby providing a transparent interpretation of the relative contribution of individual performance indicators to overall manufacturing performance.

The managerial implications of these findings are substantial. Rather than pursuing broad and technology-intensive transformation strategies, SMEs should prioritize targeted investments that directly improve equipment effectiveness, maintenance capabilities, and process stability. The use of integrated performance measurement frameworks—such as the MPI—can facilitate more informed decision-making by linking digital investments to tangible outcomes across cost, quality, flexibility, and sustainability dimensions [116,117].

From a policy perspective, the observed heterogeneity in performance outcomes highlights the need for tailored support mechanisms. Financial incentives, skill development programs, and access to technological expertise are particularly critical in addressing the structural barriers faced by SMEs, especially in developing economies [118–120]. Such targeted interventions can help reduce adoption risks and enable more inclusive digital transformation processes.

Taken together, the findings confirm that I4.0 adoption enhances SME performance through a synergistic interplay of operational efficiency, predictive maintenance, sustainability improvements, and organizational resilience. Importantly, the study demonstrates how these dimensions interact in practice and highlights the value of explainable machine learning in bridging the gap between analytical rigor and managerial relevance. In doing so, it advances the growing body of literature at the intersection of Industry 4.0, sustainability, and human-centric manufacturing systems [5,121].

6. Conclusions

This study provides a comprehensive empirical assessment of the performance implications of Industry 4.0 (I4.0) adoption in manufacturing SMEs by integrating classical statistical approaches with explainable machine learning techniques. Through the development of a composite Manufacturing Performance Index (MPI), the analysis captures multiple dimensions of firm performance, including operational efficiency, quality, cost, energy consumption, delivery, and workforce productivity. The findings demonstrate statistically significant improvements across all examined indicators following I4.0 adoption, with simultaneous reductions in defect rates, machine downtime, production costs, and resource consumption, alongside increases in production output, equipment effectiveness, and labor productivity. The strong correlation structure between pre- and post-adoption indicators further indicates that digital transformation tends to reinforce existing firm-level capabilities, supporting the interpretation of I4.0 as a performance amplifier rather than a uniform equalizer across SMEs.

The explainable machine learning analyses provide additional insights into the mechanisms underlying these performance gains. Key drivers of post-I4.0 performance include overall equipment effectiveness, defect rate, production cost, and machine downtime, underscoring the central role of predictive maintenance, process stabilization, and data-driven quality control.

The conclusions presented in this study are supported by empirical data collected from 120 manufacturing SMEs and interpreted using an integrated analytical framework combining multidimensional performance measurement and explainable machine learning. The proposed framework provides both practical decision support for manufacturing SMEs and a reproducible methodological contribution to Industry 4.0 performance assessment.

Moreover, SHAP-based analysis reveals that these relationships are inherently nonlinear and context-dependent, indicating that the magnitude of performance improvements varies across firms depending on their operational configurations and implementation strategies. The consistency observed between statistical significance, predictive accuracy, and model interpretability strengthens the robustness of the proposed analytical framework and highlights its suitability as a reliable tool for performance assessment in digitally transforming manufacturing environments.

From a practical perspective, the findings offer important implications for both managers and policymakers. For SME managers, the results emphasize the need to prioritize targeted digital investments that directly enhance operational efficiency, maintenance intelligence, and process reliability, rather than pursuing broad and resource-intensive automation strategies. For policymakers, the observed heterogeneity in outcomes highlights the importance of tailored support mechanisms, including financial incentives, capability-building programs, and access to technological expertise, particularly in resource-constrained environments. The study contributes to the literature by proposing an interpretable, data-driven, and multidimensional framework that enables the systematic measurement and benchmarking of digital transformation performance in SMEs.

Despite these contributions, several limitations should be acknowledged. The empirical analysis is based on a structured SME dataset within a specific industrial and regional context, which may limit the generalizability of the findings to other sectors or large-scale enterprises. In addition, the pre-post analytical design does not fully capture long-term dynamic effects, such as technological maturation and lagged performance impacts. The MPI, while comprehensive, does not explicitly include certain organizational and human-centric dimensions, such as digital culture, workforce skills, and governance capabilities. Furthermore, the aggregated representation of I4.0 technologies does not differentiate between specific technological configurations or adoption pathways. Future research should

address these limitations by employing longitudinal and cross-country datasets, incorporating broader performance dimensions aligned with Industry 5.0 perspectives, and exploring technology-specific and configurational approaches. Such efforts would further enhance the understanding of how digital transformation evolves over time and how firms can optimize their adoption strategies to achieve sustainable and resilient performance improvements.

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