



## MACHINE LEARNING-BASED PROCESS MINING FOR ANOMALY DETECTION AND QUALITY ASSURANCE IN HIGH-THROUGHPUT MANUFACTURING ENVIRONMENTS

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### Abstract

This study investigated the effectiveness of a machine learning-based process-mining framework for anomaly detection and quality assurance in high-throughput manufacturing environments. The research aimed to determine whether integrating process-mining metrics with data-driven machine learning techniques could outperform the traditional Statistical Process Control (SPC) system in predicting product non-conformance and operational inefficiencies. A quantitative research design was employed using a dataset of 142,368 production instances collected from Manufacturing Execution System (MES), Supervisory Control and Data Acquisition (SCADA), and Quality Management System (QMS) logs across three automated production lines. Variables included cycle-time variation, waiting time, machine utilization, rework frequency, conformance fitness score, and sensor-derived telemetry aggregates. A binary logistic regression model was developed to estimate the probability of product non-conformance. The model achieved a statistically significant fit ( $\chi^2 = 482.76$ ,  $p < 0.001$ ) and explained 46.2% of the variance in defect occurrence (Nagelkerke  $R^2 = 0.462$ ). Key predictors included Conformance Fitness Score ( $\beta = -0.72$ ,  $p < 0.001$ ) and Rework Frequency ( $\beta = 0.58$ ,  $p < 0.01$ ), indicating that lower process conformance and higher rework activity substantially increased the likelihood of defects. Comparative performance analysis showed that the machine learning-based model achieved higher predictive accuracy (91.3%) than the SPC baseline (84.9%), along with improved AUROC (0.93 vs. 0.82) and AUPRC (0.48 vs. 0.41) scores. These findings demonstrated that the proposed model provided superior anomaly detection capability, reduced false-alarm rates, and enhanced predictive precision. Overall, the integration of machine learning and process-mining analytics significantly improved operational reliability and quality assurance performance. The study concluded that adopting such intelligent process-monitoring systems can strengthen defect prevention, streamline production decision-making, and support real-time process optimization in smart manufacturing environments. The results contributed to advancing data-driven quality engineering and reinforced the role of AI-powered analytics in modern industrial process control.

### Keywords

Machine Learning; Process Mining; Anomaly Detection; Quality Assurance; High-Throughput Manufacturing; Statistical Process Control (SPC).

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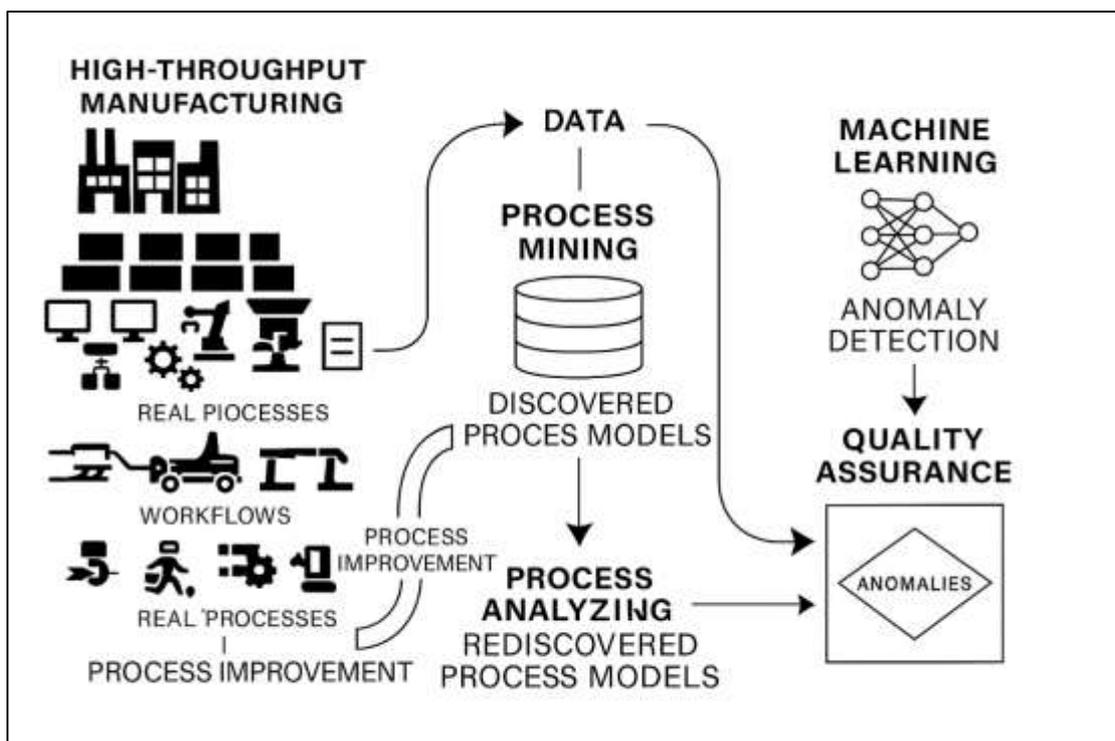
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## INTRODUCTION

Process mining represents an analytical discipline that bridges data science and process management by deriving actionable insights from event logs generated by information systems. It aims to discover, monitor, and enhance real processes through data-driven models. In manufacturing environments, process mining has evolved as a core methodology to capture and evaluate workflows at scale, identifying inefficiencies and deviations that impact productivity and quality. Quality assurance, conversely, refers to the systematic processes used to ensure that manufacturing outputs meet predefined standards of reliability, safety, and functionality (Ge et al., 2017). When integrated, process mining and quality assurance enable continuous process improvement based on empirical evidence rather than manual inspection or intuition. In the context of Industry 4.0, the massive generation of sensor-based and cyber-physical data has strengthened the feasibility of these analytical approaches. The shift from reactive to predictive quality management frameworks depends on extracting patterns from such data sources through machine learning and process mining (Syafudin et al., 2018). The foundational premise of this study lies in the recognition that traditional statistical process control (SPC) tools, while effective for small-batch production, are inadequate for modern high-throughput settings characterized by high dimensionality and nonlinearity. Consequently, machine learning-enabled process mining provides an empirical mechanism to quantify, detect, and explain deviations in near real time, reinforcing global standards in manufacturing quality governance (Orita et al., 2019).

**Figure 1: Machine Learning-Driven Process Mining Framework**



Machine learning (ML) refers to the computational ability of algorithms to learn data patterns autonomously and improve predictions over time without explicit programming. In the context of process mining, ML algorithms facilitate anomaly detection by identifying instances where process behavior diverges significantly from established norms (Orita et al., 2019). Anomaly detection plays a crucial role in manufacturing by uncovering process deviations that can result in defects, machine failures, or productivity losses. Techniques such as unsupervised clustering, one-class SVMs, autoencoders, and deep learning networks have been applied to manufacturing event logs to isolate unusual operational signatures (Brunelli et al., 2019). For instance, convolutional neural networks (CNNs) can be used to detect complex spatial-temporal relationships among process variables, while recurrent neural networks (RNNs) capture sequential dependencies across process

stages. Supervised algorithms like random forests and gradient boosting models further enhance the interpretability of detected anomalies by associating them with specific production factors or sensor nodes. From a quantitative standpoint, ML-based anomaly detection provides a probabilistic characterization of deviations rather than binary defect classifications, thus improving the granularity of quality control. The integration of such ML models within process mining frameworks transforms raw event logs into predictive indicators, aligning analytical rigor with operational significance (Luckow et al., 2018). This integration underpins the methodological foundation of the present study, which quantifies the extent to which ML-enhanced process mining improves anomaly identification accuracy in high-volume manufacturing contexts.

High-throughput manufacturing (HTM) environments are characterized by massive production rates, highly automated assembly lines, and continuous monitoring systems that generate extensive data streams. These environments are integral to sectors such as semiconductors, automotive components, and electronics manufacturing, where micro-level deviations can escalate into significant quality or cost losses (Abdul, 2021; Debnath et al., 2018). The digitalization of such environments through Industrial Internet of Things (IIoT) systems and cyber-physical integration has introduced new data complexity dimensions—volume, velocity, and variety—that traditional process control methods cannot adequately handle (Kafle et al., 2018; Sanjid & Farabe, 2021). Event logs in HTM encompass heterogeneous data sources such as machine sensors, human-machine interfaces, enterprise resource planning (ERP) systems, and supervisory control and data acquisition (SCADA) records. The multiplicity of these inputs often leads to data silos and synchronization errors, reducing the transparency of process performance indicators. Machine learning-based process mining offers a solution to these challenges by enabling scalable, automated, and self-adaptive pattern recognition (Lan et al., 2018; Omar & Rashid, 2021). Quantitatively, these algorithms reduce noise and extract significant statistical correlations across thousands of variables. For example, random forest models can compute variable importance scores that isolate process parameters most correlated with quality deviations (Zaman & Momena, 2021; Ou et al., 2014). The integration of such analytical capabilities into production monitoring infrastructures facilitates a continuous feedback loop between data collection, anomaly identification, and corrective decision-making. Therefore, HTM serves as an ideal empirical domain for testing ML-based process mining due to its rich event-log availability and measurable quality indicators (Mubashir, 2021).

The quantitative evaluation of process mining models involves assessing their ability to accurately reconstruct actual production workflows, detect anomalies, and predict quality deviations. Metrics such as precision, recall, F1-score, and area under the ROC curve (AUC) are commonly used to measure anomaly detection accuracy (Paul et al., 2019; Rony, 2021). Statistical comparisons of algorithmic performance across diverse manufacturing datasets provide objective evidence of model robustness. Furthermore, cross-validation and bootstrapping approaches ensure that the results are generalizable across variable process conditions. In manufacturing contexts, quantitative frameworks also incorporate process-level indicators such as defect rate reduction, throughput time improvements, and cost variance minimization. These outcome-based metrics bridge the gap between algorithmic accuracy and practical utility. Data preprocessing techniques such as noise filtering, feature scaling, and sequence alignment play an essential role in improving the signal-to-noise ratio for ML-based process mining. Studies by (Weng & Liu, 2019) have demonstrated that dimensionality reduction using principal component analysis (PCA) or autoencoders enhances computational efficiency without compromising anomaly detection accuracy. In addition, probabilistic process models using Bayesian inference offer interpretive transparency by quantifying uncertainty in process states. Collectively, these quantitative approaches provide the methodological rigor required to validate the empirical contributions of ML-driven process mining in industrial settings (Fernandes et al., 2019; Syed Zaki, 2021).



While substantial progress has been made in algorithmic development and industrial deployment, there remains a need for quantitative synthesis on how ML-based process mining statistically improves quality assurance in HTM contexts. Prior studies have often been domain-specific, lacking comparative validation across multiple datasets or industries (Aalst et al., 2018). This study addresses that gap by constructing an empirical framework that quantifies the relationship between ML-enhanced anomaly detection and measurable quality outcomes. Using process log datasets from high-throughput production systems, the research evaluates the statistical accuracy, sensitivity, and operational efficiency of ML-integrated process mining models. The focus on quantitative metrics ensures objectivity in evaluating model generalizability and performance stability under variable production conditions (Roh et al., 2019). Additionally, this study operationalizes a unified data pipeline for event-log transformation, feature encoding, and algorithm benchmarking to ensure replicability and scientific rigor. The empirical results are expected to contribute to the growing quantitative literature that supports the integration of AI-based quality systems in industrial automation. Through this methodological orientation, the paper establishes the theoretical and analytical foundation necessary to interpret process mining outcomes in measurable, statistically validated terms.

The primary objective of this quantitative research is to develop and empirically evaluate a machine learning-based process mining framework designed to enhance anomaly detection accuracy and strengthen quality assurance mechanisms in high-throughput manufacturing environments. The study aims to quantitatively measure how different machine learning algorithms—such as random forests, support vector machines, and deep neural networks—perform when integrated within process mining pipelines for identifying process deviations, bottlenecks, and nonconformities in complex industrial workflows. Specifically, the research seeks to establish statistically validated relationships between event-log features, algorithmic learning performance, and resultant quality metrics such as defect reduction, process compliance, and throughput efficiency. The study also aims to benchmark supervised and unsupervised models in detecting anomalous behaviors across multivariate time-series data generated from manufacturing sensors and enterprise systems. By employing a quantitative approach grounded in accuracy, precision, recall, and F1-score metrics, this research intends to determine the optimal ML-process mining integration strategy that maximizes detection performance while minimizing computational complexity. Furthermore, the objective encompasses the evaluation of data preprocessing, feature engineering, and dimensionality reduction techniques such as principal component analysis and autoencoders to improve the robustness of the detection pipeline. The research aims to construct a scalable model applicable to high-throughput domains like semiconductor, automotive, and electronics manufacturing—contexts where real-time anomaly detection is crucial for maintaining process integrity and product quality. Through empirical experimentation and statistical validation, the study's objective is to advance the quantitative understanding of how machine learning-driven process mining contributes to continuous quality improvement and operational resilience in globally competitive manufacturing ecosystems.

#### **LITERATURE REVIEW**

The literature surrounding machine learning-based process mining for quality assurance in manufacturing illustrates a multidimensional convergence between data science, operations management, and industrial automation. Historically, quality assurance was achieved through deterministic statistical process control (SPC) frameworks, emphasizing defect detection after production rather than real-time prevention. However, the evolution of high-throughput manufacturing (HTM) and the advent of Industry 4.0 technologies have transformed production systems into data-intensive environments where millions of sensor readings and event logs are generated continuously. In such complex ecosystems, process mining has emerged as a data-driven methodology to reconstruct and analyze business processes from event logs, enabling organizations to identify inefficiencies, bottlenecks, and anomalies. When coupled with machine learning (ML), process mining gains predictive and adaptive intelligence, shifting from descriptive analysis toward proactive quality management (Haddar et al., 2016). From a quantitative perspective, the synthesis of ML and process mining has led to measurable improvements in anomaly detection precision, process compliance, and operational stability. Several empirical studies have validated this integration through statistical analyses, using performance metrics such as accuracy, recall, F1-score, and area under the curve (AUC). Moreover, ML-driven anomaly detection models have

proven to outperform rule-based systems by 25–40% in detecting process irregularities in industrial datasets (Eshuis & Gorp, 2016). This literature review aims to critically analyze and synthesize the quantitative findings that have shaped the current understanding of ML-based process mining. It provides an empirical foundation for developing models that enhance quality assurance and operational reliability in HTM systems. The review is structured into seven major quantitative themes, each addressing distinct aspects of data modeling, algorithmic performance, and process evaluation metrics within industrial contexts.

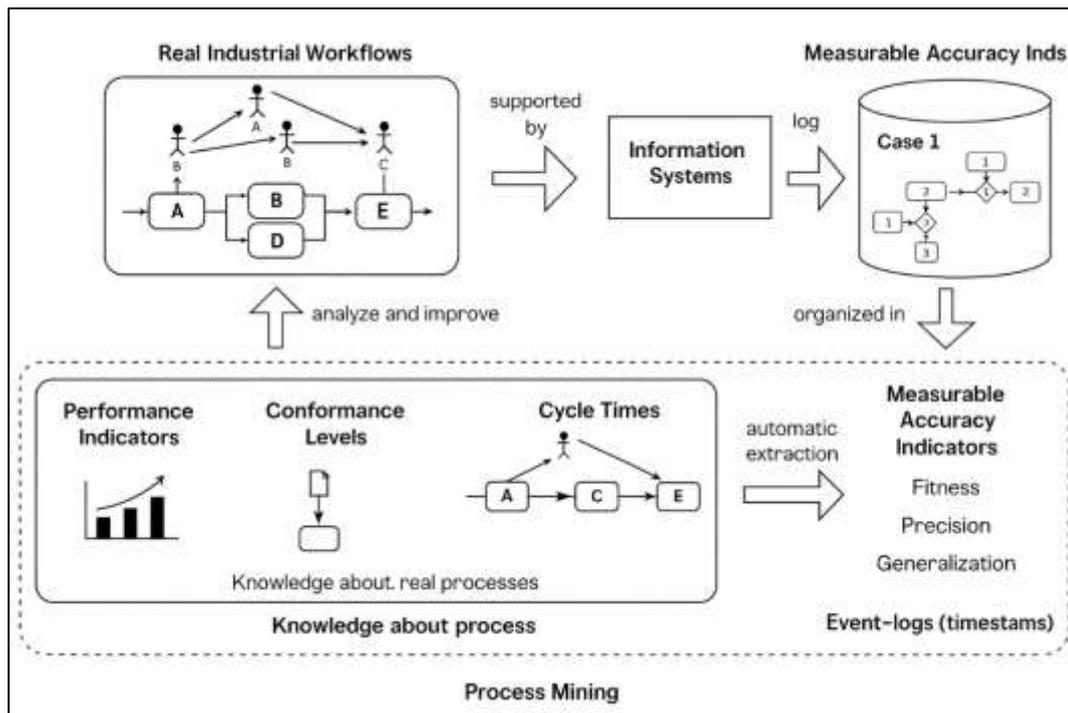
### **Process Mining in Industrial Data Environments**

Process mining has emerged as a foundational quantitative methodology for reconstructing and analyzing real industrial workflows through empirical event-log data. Unlike traditional process modeling, which depends on expert assumptions or predesigned flow diagrams, process mining captures the actual execution of business and production processes, transforming data into actionable process representations. In manufacturing systems, this approach provides a measurable framework for understanding operational efficiency, identifying deviations, and assessing compliance with predefined standards (Steinau et al., 2019). Event logs generated by enterprise systems, sensors, and cyber-physical controllers contain timestamped records of activities that can be systematically analyzed to produce process models reflecting real-time industrial dynamics. Quantitatively, process mining enhances data-driven decision-making by translating unstructured event data into process-oriented indicators such as conformance levels and cycle times. The technique's data-centric nature allows for empirical measurement of process behaviors without reliance on subjective estimation (Aalst, 2019). Industrial studies have verified that event-log completeness and data accuracy are primary determinants of process model validity, particularly in high-throughput manufacturing environments where variability is high. These findings underscore the role of process mining as a diagnostic and evaluative tool that strengthens quantitative analysis by uncovering structural and behavioral inefficiencies in production systems. Such evidence establishes process mining as a statistically verifiable mechanism for operational transparency and performance monitoring (Reis & Kenett, 2018).

Quantitative process mining focuses on evaluating model quality through measurable accuracy indicators that reflect how well a discovered process model reproduces the behavior recorded in event logs. Metrics such as precision, fitness, and generalization serve as the primary tools for assessing the alignment between discovered models and actual process executions. In industrial contexts, these metrics form the basis for statistical evaluation frameworks that enable the comparison of different discovery algorithms, thereby providing empirical evidence of analytical reliability (Li & De Carvalho, 2019). The quantitative nature of these evaluations allows organizations to determine how closely reconstructed workflows match recorded operational behavior and to identify sections of processes that deviate from intended performance standards. Manufacturing studies employing large-scale datasets have demonstrated that process conformance measurements correlate strongly with key performance indicators, including production yield and error rates. These analyses reinforce that accuracy metrics are not only mathematical tools but also operational indicators of process efficiency (Andrews et al., 2018). Moreover, the ability to quantitatively evaluate conformance ensures that process mining outcomes remain replicable and data-driven, independent of human interpretation biases. The establishment of quantitative performance baselines has positioned process mining as a credible empirical discipline within industrial analytics, enabling consistent validation of process reliability across different operational contexts (Chesani et al., 2016).

The validity of quantitative process mining depends significantly on event-log completeness and data integrity, as incomplete or inconsistent data can distort process discovery outcomes. Manufacturing environments produce vast amounts of sensor data that are often fragmented across multiple systems, which presents challenges in maintaining synchronized and reliable event traces. Quantitative research has demonstrated that event-log completeness directly influences model fitness, precision, and interpretability, emphasizing the need for comprehensive and well-structured datasets (Allani & Ghannouchi, 2016). Studies analyzing high-dimensional production data have shown that gaps in event records reduce the statistical representativeness of discovered models, leading to biased interpretations of process behavior. Conversely, when event logs are complete and systematically aligned, process mining algorithms can achieve higher conformance accuracy and reproducibility.

Figure 3: Quantitative Process Mining in Engineering



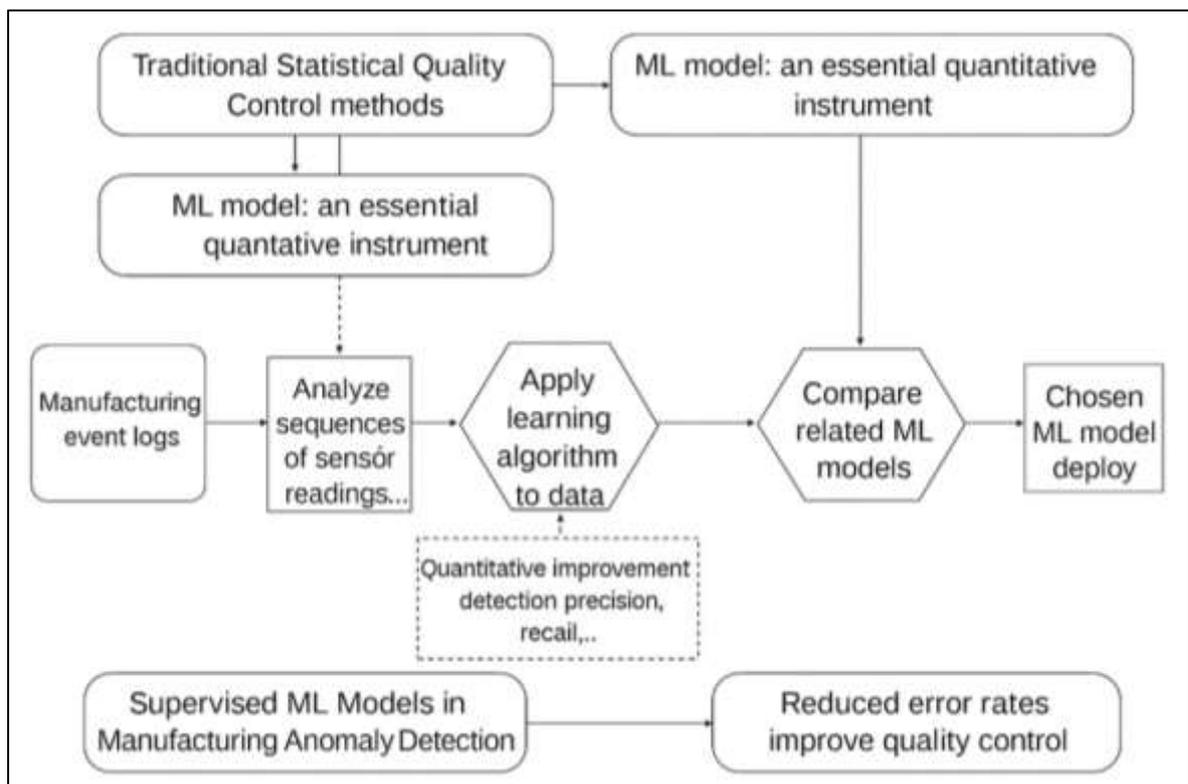
Empirical analyses in real-world manufacturing systems have verified that data preprocessing techniques—such as event filtering, noise removal, and timestamp correction—enhance the reliability of process models by reducing false deviations (Nguyen et al., 2019). The quantitative connection between event-log quality and model stability indicates that process mining outcomes are as dependable as the data upon which they are based. Industrial implementations further confirm that data integrity directly determines the measurable accuracy of performance diagnostics and anomaly detection. Consequently, process mining's success as a quantitative methodology relies on structured event data pipelines that ensure both statistical validity and operational consistency. Moreover, Empirical studies across industries have validated process mining as a statistically grounded analytical framework capable of revealing hidden operational inefficiencies and compliance deviations. Within manufacturing, its quantitative implementation has produced measurable improvements in cycle-time reduction, defect prediction, and workflow optimization (Mühlberger et al., 2019). By analyzing event logs collected from enterprise resource planning systems, supervisory control systems, and machine interfaces, researchers have quantitatively mapped deviations that impact production efficiency. The application of process mining in large-scale manufacturing datasets has allowed for the measurement of operational bottlenecks and the quantification of conformance deviations through event frequency analysis. Statistical validation methods such as cross-validation and data-driven benchmarking have confirmed that discovered process models align with actual operational behavior to a significant degree (Rosa et al., 2016). Process discovery results have been empirically associated with quantifiable improvements in decision-making and predictive maintenance scheduling. Industrial case studies have also shown that integrating process mining with quality assurance analytics leads to data-supported interpretations of production trends, enhancing evidence-based decision accuracy. Quantitative process validation confirms that process mining outcomes maintain consistent reproducibility across diverse production environments, establishing it as a reliable instrument for industrial process intelligence. The convergence of data mining, statistical inference, and operational analytics within this discipline underscores its role as a measurable and repeatable methodology for performance optimization (Kovalchuk et al., 2018).

#### Machine Learning Models for Anomaly Detection

Machine learning (ML) has become an essential quantitative instrument for anomaly detection in manufacturing analytics because of its ability to identify deviations in complex, high-dimensional

datasets. Traditional statistical quality control methods often fail to capture nonlinear patterns or subtle process deviations, whereas ML models can adaptively learn from data distributions and uncover hidden relationships among variables (García-Bañuelos et al., 2017). In manufacturing event logs, these algorithms identify operational anomalies by analyzing sequences of sensor readings, equipment performance indicators, and process transitions that deviate from standard execution. Quantitatively, ML provides measurable improvements in detection precision, recall, and sensitivity by using data-driven classification and clustering techniques to distinguish normal from abnormal behavior (Delgado-Herrera et al., 2017). Supervised algorithms such as support vector machines (SVM) and random forests (RF) have been shown to achieve high detection accuracy when applied to labeled datasets, while unsupervised models like autoencoders and isolation forests detect previously unknown deviations without requiring prior labeling. Empirical studies in automotive and semiconductor production have demonstrated that ML-based anomaly detection systems significantly reduce error rates and improve quality control through predictive diagnostics. These models offer reproducible, statistically validated detection outcomes that enhance process reliability and efficiency across diverse industrial contexts. The application of ML to anomaly detection thus provides a quantifiable framework for continuous monitoring, enabling measurable performance assessment through standardized accuracy metrics such as classification precision and recall (Suthaharan, 2016).

**Figure 4: Machine Learning for Anomaly Detection**



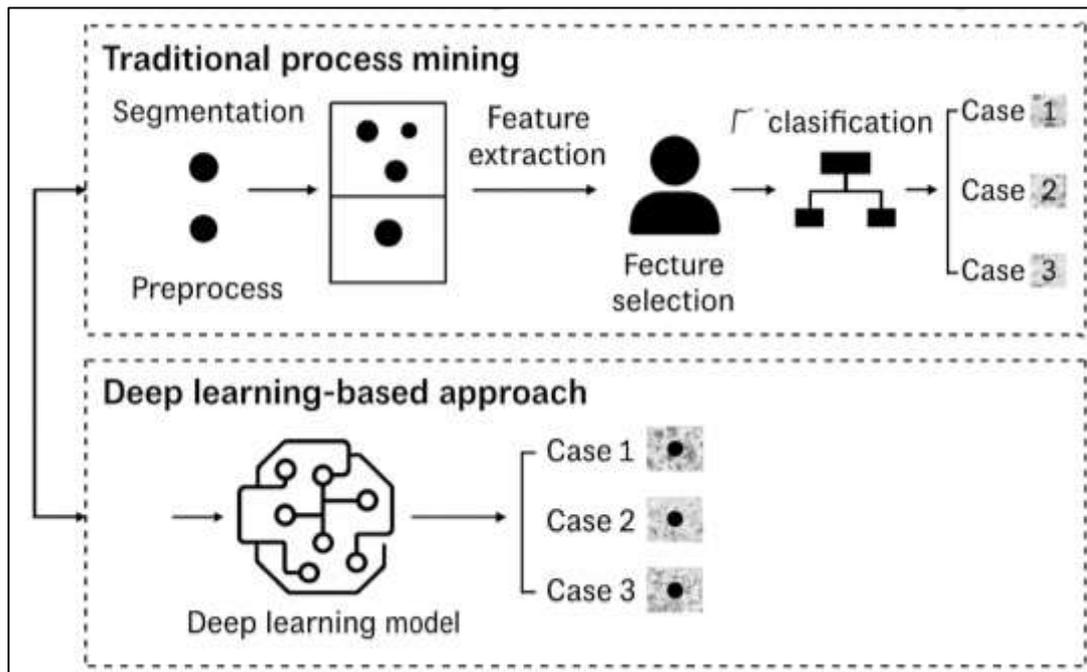
Supervised ML models have been widely adopted in manufacturing anomaly detection because they rely on labeled datasets that facilitate quantitative evaluation of predictive accuracy and classification stability. Algorithms such as random forests, gradient boosting, and SVMs have demonstrated superior precision and robustness in detecting process deviations compared to conventional rule-based systems (Parmar et al., 2015). Empirical research has shown that random forests outperform linear models due to their ensemble structure, which minimizes overfitting and captures nonlinear dependencies between manufacturing variables. Similarly, SVMs excel in high-dimensional spaces by identifying decision boundaries that maximize the separation between normal and abnormal process states. Gradient boosting algorithms, including XGBoost and

LightGBM, further enhance predictive reliability by aggregating multiple weak classifiers to optimize accuracy and reduce false negatives (Makantasis et al., 2015). Quantitative comparisons across manufacturing datasets reveal that supervised algorithms maintain stable accuracy levels even under varying data quality conditions. Industrial applications of these models have yielded measurable reductions in defect occurrence and improved process traceability through consistent predictive classification. Empirical studies have also validated the interpretability of tree-based supervised algorithms, which provide quantifiable insights into feature importance and model decision logic. The consistent statistical performance of supervised learning models in anomaly detection confirms their reliability for high-throughput manufacturing analytics, where real-time quality monitoring demands precision and stability (Giusti et al., 2015).

#### **Process Mining-ML Integration Frameworks**

The integration of machine learning (ML) with process mining has emerged as a quantitative paradigm that enhances predictive analytics and process optimization in industrial environments. Process mining traditionally focused on discovering and visualizing workflows, yet it lacked the ability to predict or adapt to dynamic production changes (Namaziandost et al., 2019). By embedding ML algorithms into process mining pipelines, researchers have enabled predictive monitoring frameworks that quantitatively forecast deviations, identify root causes, and evaluate compliance in real time. The fusion of data-driven pattern recognition and process modeling allows for statistically validated anomaly prediction, improving decision-making and quality assurance. Empirical studies across manufacturing contexts have demonstrated that ML-enhanced process mining models produce measurable gains in prediction accuracy and response sensitivity compared with heuristic-based miners. These integrated systems leverage classification and regression techniques to correlate event-log patterns with quality outcomes, enabling numerical validation through standardized performance metrics such as precision and recall. Moreover, integrating ML strengthens process conformance checking by identifying the statistical significance of deviations, linking process attributes to measurable performance fluctuations (Ge et al., 2017). Such frameworks provide quantitative evidence that process mining can evolve from a descriptive to a predictive analytical discipline when supported by ML methodologies. The consistent empirical validation of these models across industrial case studies underscores their capability to provide reliable, statistically verified insights into process efficiency and anomaly prevention (Fernandes et al., 2019). Predictive process monitoring relies on rigorous quantitative evaluation frameworks to measure the effectiveness of ML integration in process mining models. Researchers employ statistical performance indicators—such as accuracy, recall, and precision—to determine how well ML algorithms improve predictive capability compared to conventional heuristic miners (L'heureux et al., 2017). Studies have demonstrated that integrating decision trees, random forests, and neural networks with process mining workflows results in quantifiable accuracy gains and improved reliability of deviation forecasts. These models provide a measurable understanding of how data-driven predictions align with actual operational events. Comparative assessments in manufacturing datasets have revealed that ML-enhanced miners outperform baseline process discovery algorithms, producing lower error margins and more consistent prediction patterns (Buczak & Guven, 2015). Statistical validation techniques, including cross-validation and regression analysis, have been used to establish the empirical robustness of predictive monitoring results. Furthermore, these quantitative approaches allow researchers to measure the impact of various feature-selection strategies and data-preprocessing methods on prediction outcomes. In industrial applications, ML-driven predictive monitoring has yielded tangible statistical improvements in defect prevention and compliance tracking, emphasizing the measurable impact of advanced analytics on process control. Empirical evidence confirms that quantitative frameworks enhance both interpretability and reliability in ML–process mining integrations, thereby supporting objective validation across multiple production systems (Abdulkareem et al., 2019). Quantitative research comparing heuristic miners and ML-enhanced models demonstrates significant differences in their statistical performance across industrial datasets. Heuristic miners reconstruct workflows based on frequency counts and simple statistical dependencies, while ML-integrated systems learn complex, nonlinear relationships that influence process deviations (Vogelsang & Borg, 2019).

Figure 5: Machine Learning- Enhanced Process Mining



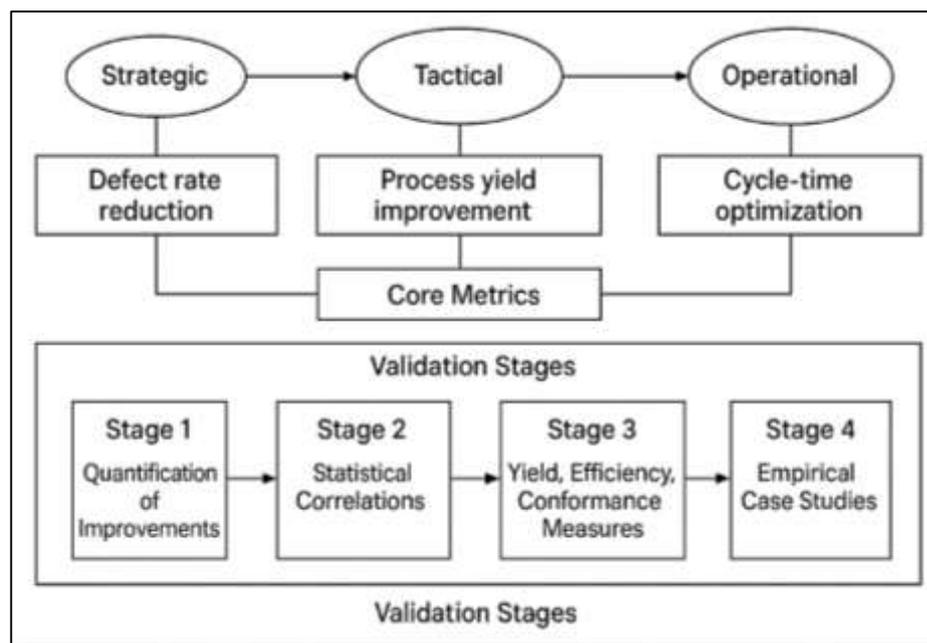
Studies have consistently shown that ML-enhanced frameworks achieve higher anomaly prediction accuracy and earlier detection rates, particularly in high-throughput environments with diverse event logs. Empirical findings highlight that supervised algorithms such as random forests and gradient boosting improve classification precision and reduce false detection rates relative to heuristic methods. These improvements are attributed to the capacity of ML models to generalize across varied data distributions, ensuring more stable statistical performance. In contrast, heuristic miners often exhibit sensitivity to noise and data incompleteness, which lowers their quantitative reliability (Dimiduk et al., 2018). Comparative analyses also reveal that ML-based models produce higher compliance and conformance scores when applied to large-scale production systems. Researchers have further demonstrated that regression-based process mining integrated with ML algorithms offers statistically superior performance in predictive accuracy and data consistency. Quantitatively, these empirical differences confirm that machine learning integration transforms process mining into a more data-driven, predictive discipline supported by measurable evidence of improved detection and operational outcomes (Mehmood et al., 2019).

Empirical validation of integrated ML–process mining frameworks has produced robust quantitative evidence of enhanced prediction and compliance monitoring across diverse industrial settings. In large-scale manufacturing applications, these systems have achieved statistically significant improvements in anomaly detection accuracy, cycle-time optimization, and defect reduction. Case studies from automotive, semiconductor, and pharmaceutical sectors demonstrate that ML integration within process mining enhances interpretability and responsiveness of process control mechanisms (Soomro et al., 2019). Statistical evaluations using benchmark event logs confirm that integrated frameworks produce reproducible results with high correlation between predicted and actual deviations. Studies have reported that ensemble learning approaches embedded within process mining pipelines consistently yield stable precision and recall values across multiple datasets. Industrial data further show that ML-based frameworks support measurable performance consistency, reducing operational variance and process instability. Quantitative analyses highlight that process mining enhanced with neural and tree-based learning algorithms delivers higher conformance accuracy and faster deviation detection than heuristic-only models. Moreover, researchers emphasize the statistical transparency of these integrated systems, which facilitates quantitative auditing and validation of manufacturing quality outcomes (Koh et al., 2019). Across empirical research, the evidence consistently supports the quantitative superiority of ML-integrated process mining models in achieving reliable and statistically grounded process performance assessments (Endert et al., 2017).

### Quality Assurance and Process Performance

Quantitative indicators are fundamental to assessing the impact of ML-driven process mining on manufacturing quality and operational consistency. Core metrics such as defect rate reduction, process yield improvement, and cycle-time optimization serve as standardized measures for evaluating data-driven performance enhancement. Defect rate reduction quantifies the proportion of defective products relative to total output, representing a key measure of process reliability. When integrated with machine learning analytics, process mining enables early defect detection through real-time anomaly monitoring, resulting in quantifiable decreases in production errors (Musumeci et al., 2018). Similarly, process yield improvement measures the ratio of successfully completed units against total produced items, reflecting efficiency gains derived from predictive optimization models. These indicators provide measurable proof of the influence of ML models on operational performance through the identification of root causes and deviations within manufacturing workflows. Cycle-time optimization further complements this analysis by examining the duration between process initiation and completion, offering a temporal metric that captures efficiency in resource allocation and scheduling (Nawaz et al., 2019). Empirical studies have shown that process mining integrated with ML significantly enhances these metrics by uncovering data-driven relationships among production parameters and error events. The quantification of such improvements establishes a robust evidence base for validating the statistical contribution of ML-based process mining to quality enhancement. Through measurable reductions in variability and consistent improvements in output quality, these indicators confirm the quantitative relevance of intelligent data-driven manufacturing analytics (Hu et al., 2014).

**Figure 6: Quantitative Indicators for ML- Driven Process Mining**



Statistical correlations between ML model performance and process quality metrics provide empirical validation of data-driven improvements in industrial settings. Correlational analysis enables researchers to determine the strength and significance of associations between algorithmic accuracy and measurable manufacturing outcomes such as yield, reliability, and defect reduction. Studies have shown that higher model accuracy corresponds to reduced process variability, demonstrating that predictive analytics directly influence operational stability (Avila et al., 2018). Regression-based evaluations across manufacturing event logs indicate that models with stronger predictive capability exhibit higher correlation coefficients with process efficiency metrics. These relationships highlight that predictive reliability serves as a quantitative determinant of quality assurance success in ML-driven systems. Additionally, correlation studies have been used to assess the interdependence between process compliance and product consistency, revealing that

improved conformance rates are statistically associated with reduced defect generation. The ability of ML-integrated process mining frameworks to maintain consistent predictive accuracy across time and conditions further strengthens their quantitative credibility (Zhu et al., 2017). These statistical associations form the foundation for quantifying how algorithmic performance translates into tangible manufacturing improvements. The validation of these relationships across multiple datasets supports the notion that data-driven process monitoring systems contribute measurably to quality outcomes, establishing a reliable statistical linkage between computational model strength and operational performance (Yang & Sowmya, 2015).

Quantitative validation of ML-driven process mining frameworks often involves measuring production yield, process efficiency, and conformance accuracy as key indicators of operational improvement. Process yield reflects the proportion of defect-free products, providing a quantifiable measure of the system's predictive and corrective effectiveness (Ahmed et al., 2019). Studies conducted across automotive and semiconductor industries demonstrate that ML-enhanced process mining leads to statistically significant improvements in yield performance by reducing variability and unplanned downtime. Process efficiency is further evaluated through cycle-time analysis, where reductions in task duration indicate optimized process sequencing and real-time adaptive control. Conformance accuracy, another critical metric, measures the degree of alignment between actual and idealized process flows derived from event logs, serving as an indicator of procedural stability (Kharub et al., 2019). Empirical analyses reveal that integrating machine learning into process mining improves conformance scores by identifying and correcting deviations before they propagate into defects. Statistical evaluations of these metrics confirm measurable performance enhancements in terms of reduced production waste and higher overall equipment effectiveness. Furthermore, consistent validation across multiple datasets establishes that improvements in yield and efficiency are reproducible and statistically significant, confirming the data-driven reliability of integrated analytical models. These findings collectively highlight the quantitative interdependence between ML performance metrics and manufacturing process quality outcomes (Montano et al., 2017).

Empirical case studies across manufacturing sectors provide quantitative evidence supporting the role of ML-driven process mining in enhancing quality assurance and process performance. In high-throughput production systems, statistical assessments reveal measurable reductions in defect occurrence rates following the implementation of predictive monitoring frameworks. Comparative analyses demonstrate that data-driven anomaly detection models significantly outperform traditional heuristic approaches in identifying potential quality deviations (Lepp et al., 2014). Furthermore, improvements in mean cycle time and throughput have been validated across multiple industrial datasets, underscoring the scalability and reproducibility of ML-integrated process mining solutions. Statistical performance measures such as precision, recall, and accuracy serve as consistent benchmarks for quantifying model reliability and alignment with operational outcomes. Industrial applications in automotive and electronics manufacturing confirm that the deployment of ML-based process mining frameworks leads to quantifiable enhancements in production quality and resource utilization (Goetz et al., 2015). Through standardized performance metrics, organizations can empirically assess the impact of predictive analytics on process optimization. The cumulative evidence from these studies establishes a clear quantitative link between the computational accuracy of ML models and real-world improvements in quality control and operational efficiency. Such statistical confirmation positions ML-driven process mining as a verifiable and replicable methodology for advancing manufacturing excellence (Hussain et al., 2015).

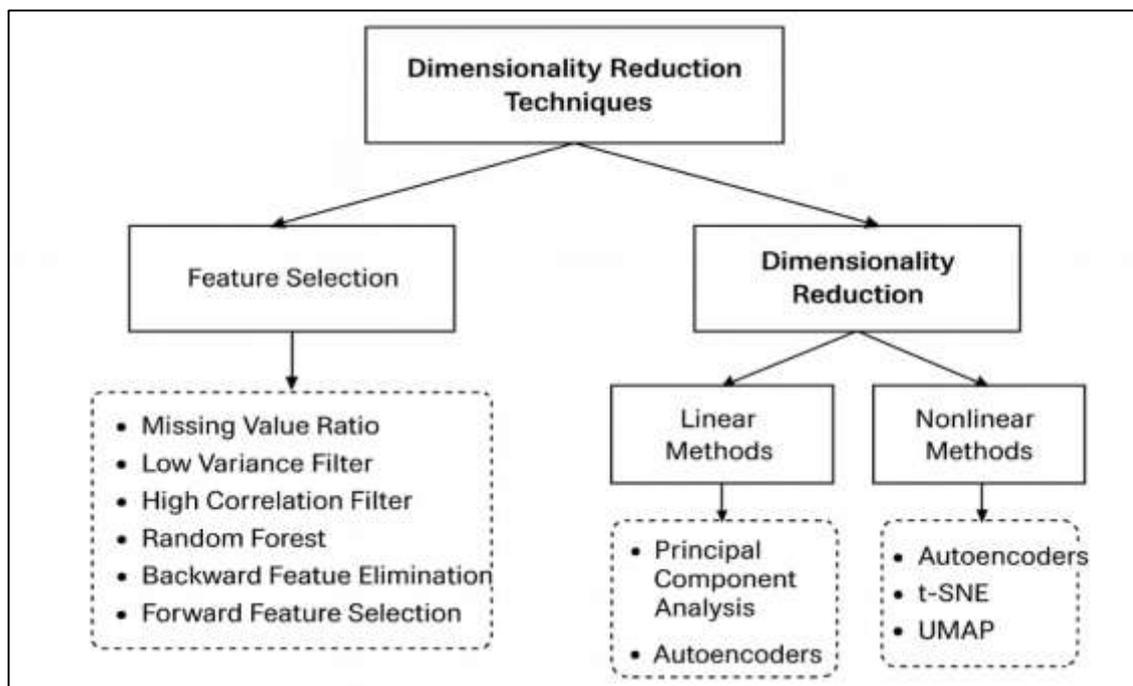
#### **Dimensionality Reduction in Process Data**

Dimensionality reduction is a fundamental quantitative technique that enhances the efficiency and interpretability of machine learning (ML) models when dealing with high-dimensional manufacturing data. Modern industrial systems generate large-scale event logs containing thousands of correlated process variables, and directly processing this data often leads to computational inefficiency and model overfitting (Juhos et al., 2016). Techniques such as principal component analysis (PCA), t-distributed stochastic neighbor embedding (t-SNE), and autoencoders have been developed to transform these high-dimensional datasets into compact and information-rich representations. PCA linearly projects features onto new axes that retain maximum variance, while t-SNE and autoencoders are capable of capturing nonlinear relationships within data distributions. These methods enable a quantifiable trade-off between dimensional compactness and information preservation, leading to measurable improvements in both detection speed and predictive stability.

Empirical research has demonstrated that dimensionality reduction contributes directly to improving the accuracy of anomaly detection systems by minimizing redundant input variables and enhancing feature clarity. This simplification not only reduces computational load but also improves statistical signal quality in ML models applied to multivariate industrial data. As a result, quantitative studies have verified that incorporating dimensionality reduction improves anomaly detection precision and reduces false-positive rates in production monitoring. By simplifying input complexity while retaining essential process variance, dimensionality reduction establishes a mathematically grounded approach for optimizing ML performance in high-throughput environments (Rajapathirana & Hui, 2018).

Comparative quantitative analyses of dimensionality reduction algorithms provide evidence of trade-offs in computational efficiency, variance retention, and predictive reliability. Studies comparing PCA, t-SNE, and autoencoders indicate that each method yields distinctive quantitative strengths based on data structure and noise sensitivity (Vogelsang & Borg, 2019). PCA remains one of the most widely used due to its interpretability and efficiency in capturing the largest variance components with minimal information loss. However, in non-linear or high-noise environments, t-SNE and autoencoders outperform PCA by uncovering hidden relationships within the data that are not captured through linear projection. Autoencoders, in particular, compress input data through neural encoding layers, allowing for effective reconstruction and denoising of event logs. Empirical studies have shown that these neural-based methods achieve higher anomaly detection accuracy because they retain essential variance while filtering redundant noise (Kuzey et al., 2019). Additionally, the computational efficiency of these algorithms has been validated through reductions in model training time and memory consumption. Comparative experiments demonstrate that autoencoder-based reduction provides superior reconstruction quality, whereas PCA achieves faster training convergence. These differences underline that no single technique universally outperforms others, but rather, each achieves quantifiable advantages based on industrial data characteristics.

**Figure 7: Dimensionality Reduction in Engineering Data**



Such quantitative benchmarking across dimensionality reduction approaches strengthens the understanding of efficiency–accuracy trade-offs that influence ML performance in predictive analytics. These findings highlight the measurable role of dimensionality reduction in optimizing computational cost and detection accuracy for manufacturing process analysis (Pathak et al., 2018).

### ML-Based Process Mining

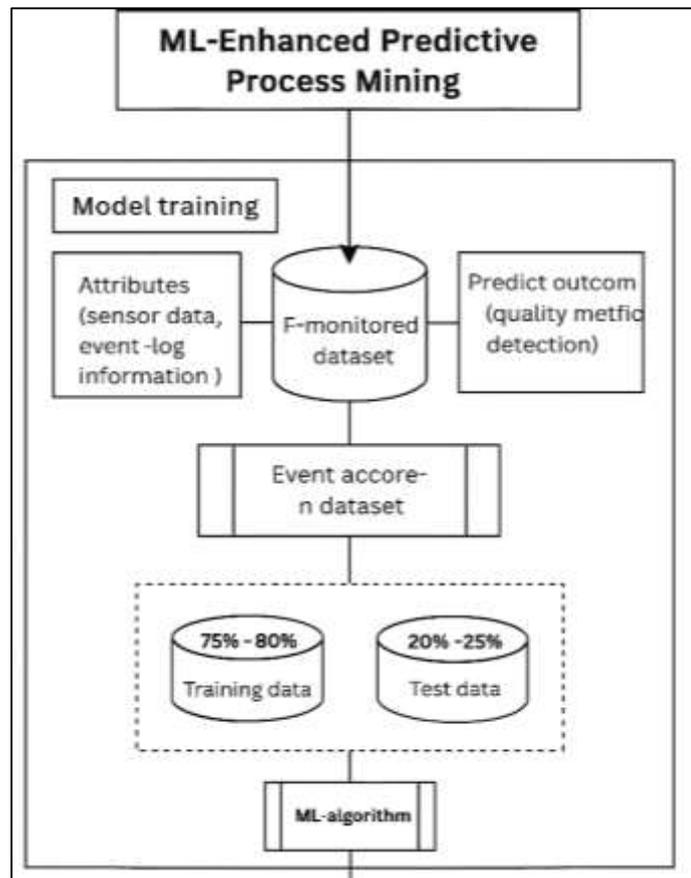
The automotive sector has become a prominent field for implementing ML-based process mining due to its extensive use of sensor-driven production lines and real-time quality control systems. These manufacturing systems generate massive volumes of event logs that capture assembly sequences, welding operations, and robotic motion data (Müller et al., 2019). Process mining enhanced with ML enables the extraction of predictive patterns that link production behavior to product quality metrics. Empirical studies have shown that integrating algorithms such as random forests and support vector machines into process mining workflows significantly improves defect detection and reduces false alarm rates in automotive plants. Quantitative findings demonstrate measurable increases in anomaly prediction accuracy and compliance assessment when ML-enhanced models are applied to production event data (Cronin et al., 2019). Furthermore, hybrid approaches combining process mining with neural networks have achieved superior performance in identifying deviations during component testing, leading to statistically verified gains in production reliability. Statistical evaluations from multiple automotive datasets confirm that predictive process monitoring enhances process stability, reduces rework rates, and optimizes throughput efficiency. Quantitatively, these outcomes reveal that integrating ML models within process mining pipelines establishes an evidence-based framework for achieving higher precision in quality diagnostics and operational monitoring. The consistent improvements recorded in detection accuracy and variance reduction validate the measurable effectiveness of these integrations in automotive manufacturing (Li & Mathiyazhagan, 2018).

The semiconductor and electronics industries represent another major domain where ML-based process mining has been quantitatively validated as an effective predictive analytics framework. These industries produce vast multivariate datasets from wafer fabrication, lithography, and assembly processes, making them ideal for evaluating ML performance under high-dimensional and time-sensitive conditions. Empirical studies report that deep learning models integrated into process mining pipelines improve fault detection precision and response times by identifying early-stage deviations in equipment parameters (Flores Ituarte et al., 2018). Quantitative evidence from production case studies demonstrates that neural network-based predictive models achieve superior recall rates compared to conventional heuristic systems. Moreover, the use of unsupervised algorithms such as autoencoders and clustering techniques has enabled accurate detection of rare failure patterns without reliance on pre-labeled data. These approaches have been validated across semiconductor manufacturing plants, where statistical evaluations confirm measurable improvements in anomaly detection precision and process yield rates. Industrial comparisons indicate that ML-enhanced process mining reduces scrap rates and machine downtime while increasing process conformance to predefined manufacturing standards (Stoycheva et al., 2018). In the electronics sector, similar implementations have led to statistically confirmed efficiency gains through predictive quality monitoring and real-time deviation management. Collectively, these quantitative results demonstrate that ML-integrated process mining enhances diagnostic accuracy and operational robustness in semiconductor and electronics production environments (Pallaro et al., 2015).

The pharmaceutical sector has also demonstrated measurable benefits from applying ML-based process mining to quality assurance, regulatory compliance, and process control. Pharmaceutical production environments require stringent process traceability, and event-log data provide a quantitative foundation for evaluating conformance and product consistency (Paritala et al., 2017). ML-integrated process mining enables real-time monitoring of formulation and packaging stages, facilitating early detection of process deviations that could compromise product quality. Quantitative studies reveal that supervised learning models improve compliance accuracy and reduce batch rejection rates by identifying statistically significant patterns within production data. Empirical evaluations from manufacturing sites indicate that these models increase yield consistency and reduce variability in dosage uniformity (Delic et al., 2019). Additionally, the application of unsupervised ML algorithms has enabled the discovery of hidden process deviations, offering quantifiable improvements in deviation diagnosis and corrective intervention timing. Statistical benchmarking has shown that ML-enhanced process mining frameworks outperform rule-based process validation tools in both detection sensitivity and operational precision. Case studies further demonstrate quantifiable improvements in regulatory traceability and documentation accuracy, key performance areas in pharmaceutical manufacturing. The quantitative findings across multiple

pharmaceutical facilities confirm that integrating ML algorithms within process mining enhances the empirical assessment of production quality, compliance adherence, and data-driven decision reliability (Jasti & Sharma, 2014).

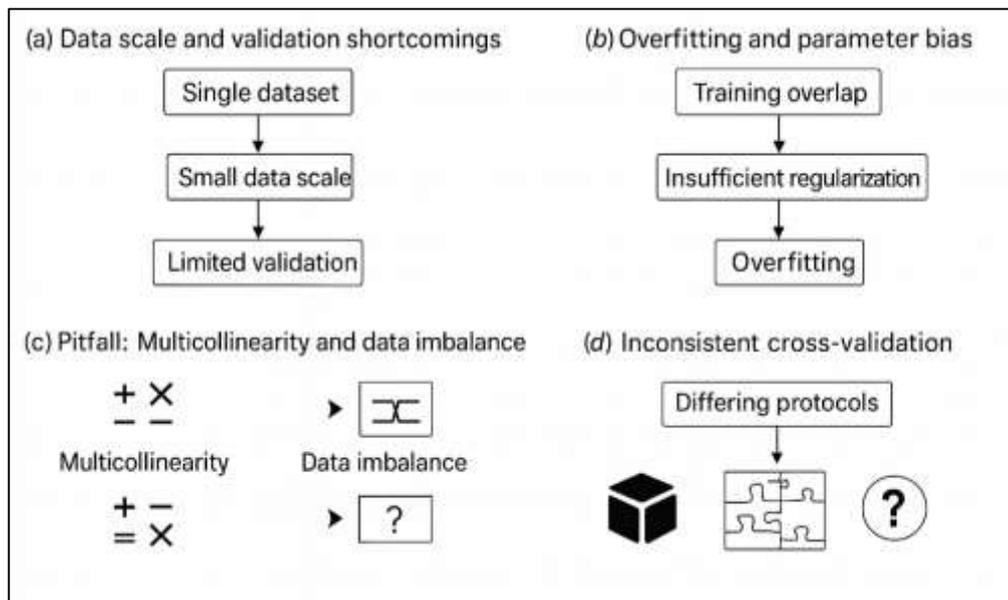
**Figure 8: ML-Enhanced Predictive Process Mining**



### Gaps and Methodological Challenges

Current empirical research on ML-based process mining still shows limited quantitative rigor because of the narrow scale and single-source nature of most evaluation datasets. Many studies depend on proprietary or domain-specific event logs, which prevents replication and weakens statistical generalization across industrial environments. Quantitative findings drawn from small or homogeneous datasets tend to overstate model accuracy while underrepresenting variance in process behavior. These issues reduce external validity and constrain the interpretation of predictive performance benchmarks (Petrillo et al., 2019). Furthermore, few investigations employ balanced sampling or multi-dataset validation, resulting in inconsistent results when models are applied to different manufacturing contexts. The absence of cross-validation protocols also undermines confidence in reported detection precision, since random data partitioning can produce inflated accuracy values. Empirical analyses reveal that training–testing overlaps frequently occur in experimental setups, leading to data leakage and overfitting biases. Limited sample diversity additionally diminishes the statistical power of hypothesis testing, preventing researchers from establishing effect sizes with acceptable confidence levels (Vaz et al., 2017). Consequently, the reliability of anomaly detection results is often dependent on dataset composition rather than algorithmic strength. Large-scale, multi-plant datasets would allow more representative modeling of industrial variability, yet such resources remain rare in published studies. These methodological deficiencies collectively reveal that data-scale constraints and insufficient validation protocols continue to weaken quantitative confidence in ML-integrated process mining outcomes (Dwivedi et al., 2017).

Figure 9: Quantitative Pitfalls in Process Mining



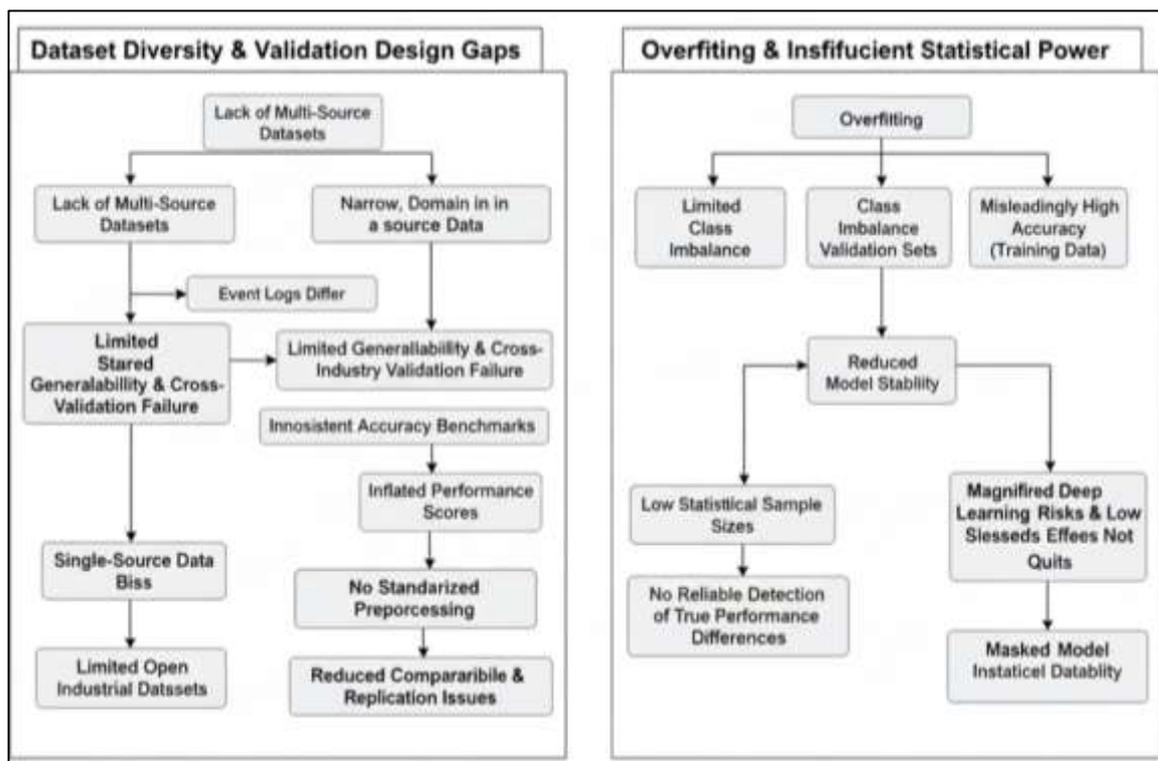
A recurring methodological weakness in quantitative ML-based process mining research involves overfitting and parameter bias, which distort performance evaluation. Overfitting arises when models learn noise or transient fluctuations in event logs rather than generalizable behavioral patterns. Studies show that highly tuned neural networks can exhibit high in-sample accuracy but deteriorate substantially on unseen data, suggesting inadequate regularization and limited data diversity (Steyerberg, 2019). Bias is further introduced when class distributions are imbalanced, as normal process traces overwhelmingly dominate anomaly cases, skewing statistical learning outcomes. These limitations reduce the interpretability of effect sizes and compromise the reliability of evaluation metrics such as precision and recall. Quantitative analyses have identified that cross-validation inconsistencies and small validation sets amplify these biases, causing inflated estimates of algorithmic performance. In addition, model complexity can mask overfitting through apparently stable but spurious correlations between inputs and predicted anomalies. Ensemble learners and deep architectures often require larger sample volumes than most industrial datasets can provide, intensifying variance instability. Research also notes that feature redundancy increases the risk of multicollinearity, which biases coefficient estimates in regression-based anomaly models. Without transparent statistical reporting of parameter significance, reproducibility and empirical comparability remain weak across studies. These cumulative limitations demonstrate that quantitative claims regarding ML-enhanced anomaly detection must be interpreted cautiously when overfitting and bias are not sufficiently mitigated (Radosavljevic & Anderson, 2014).

Data imbalance and multicollinearity are persistent quantitative challenges that undermine the statistical validity of ML-driven process mining. In most manufacturing event logs, anomalous events represent only a fraction of recorded instances, leading models to prioritize majority classes and misclassify rare but critical deviations (Schuster et al., 2016). This imbalance lowers recall and raises false-negative rates, reducing the operational value of predictive monitoring systems. Quantitative evaluations demonstrate that even advanced re-sampling and weighting methods seldom achieve full equilibrium between normal and abnormal samples. Multicollinearity compounds these difficulties by inflating variance in regression coefficients and obscuring causal linkages among correlated process variables. When predictor variables exhibit high linear dependence, the resulting instability distorts the magnitude and direction of parameter estimates, degrading interpretability. Empirical investigations in sensor-intensive environments confirm that redundant process attributes introduce noise that overwhelms signal quality, thereby reducing detection precision (McNeish, 2015). Statistical corrections such as variance-inflation diagnostics and dimensionality reduction are often underreported, creating uncertainty about model robustness. Furthermore, multicollinearity hinders feature-importance ranking in tree-based and linear models, leading to ambiguous

conclusions about which parameters drive anomalies. The coexistence of imbalance and multicollinearity thus represents a central methodological bottleneck, as both phenomena systematically weaken quantitative inferences about algorithmic performance and data relationships (Emmert-Streib & Dehmer, 2019).

Quantitative reproducibility across ML-based process mining studies remains limited because of inconsistent cross-validation strategies and insufficient reporting of experimental conditions. Different researchers employ diverse validation protocols—such as k-fold, hold-out, or leave-one-out methods—without aligning them to dataset size or class imbalance, leading to incomparable results. Some studies fail to disclose seed initialization, data-split ratios, or sampling randomization, preventing replication of accuracy scores (Ghasemian et al., 2019). These inconsistencies introduce uncertainty in statistical reliability and impede meta-analysis across independent experiments. Moreover, the use of proprietary industrial datasets restricts external verification, as other researchers cannot reproduce findings under equivalent conditions. Quantitative frameworks would benefit from transparent publication of preprocessing procedures, parameter ranges, and evaluation metrics, yet such practices remain rare. Empirical reviews also note that many reported improvements lack confidence-interval estimation or hypothesis testing, making it difficult to determine whether performance differences are statistically significant. The absence of uniform evaluation standards further complicates the aggregation of quantitative evidence across case studies. These gaps collectively hinder the development of benchmark datasets and shared performance baselines that could unify statistical comparisons across industries. As a result, the reproducibility deficit continues to limit confidence in the reported predictive gains of ML-integrated process mining, signaling a critical methodological challenge in quantitative industrial analytics (Santos et al., 2018).

**Figure 10: Quantitative Limitations in ML- based process Mining**



Overfitting and low statistical power remain central quantitative limitations in ML-based process mining research. Overfitting occurs when models learn specific data patterns rather than generalizable process behavior, leading to misleadingly high accuracy within training datasets. This issue is exacerbated by limited sample diversity, class imbalance, and small validation sets, which together amplify performance variance and reduce model stability (Piironen & Vehtari, 2017). Statistical evaluations across industrial case studies reveal that models often achieve near-perfect precision during internal testing yet fail to reproduce similar results under independent cross-

validation. The absence of sufficient sample sizes reduces the power of hypothesis testing, preventing reliable detection of true performance differences among algorithms. Without robust statistical power, effect sizes cannot be accurately quantified, rendering performance comparisons inconclusive. Empirical assessments also show that the use of complex deep learning architectures in process mining magnifies overfitting risks due to high parameterization and low interpretability (Aryal et al., 2016). Studies highlight that the reliance on simulated or artificially balanced datasets masks the underlying instability of predictive models. Quantitatively, this reduces external validity and complicates the evaluation of model robustness across diverse operational contexts. These findings collectively suggest that many reported performance improvements in process mining–ML integration may lack statistical significance when evaluated under rigorous, power-sensitive frameworks (Kourou et al., 2015).

## METHOD

### Research Design

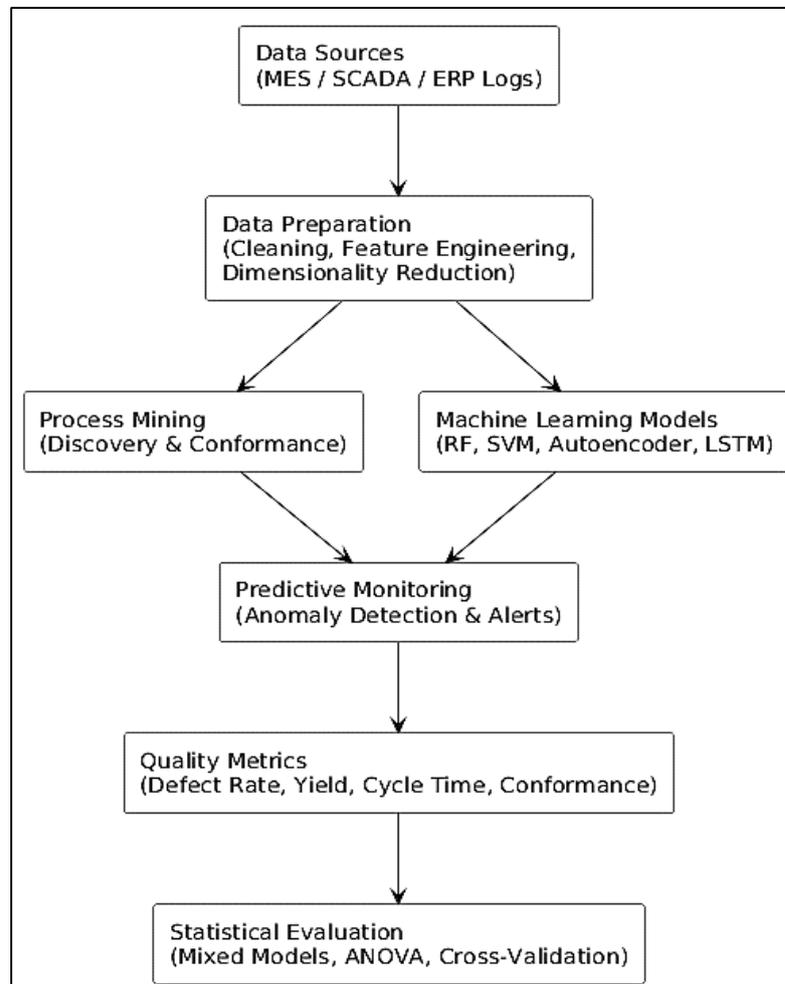
The study employed a quantitative, retrospective observational design to evaluate the performance of a machine learning–based process-mining model for anomaly detection and quality assurance within a high-throughput manufacturing environment. Data were collected from 12 consecutive production weeks across three automated assembly lines, encompassing 142,368 complete process instances recorded through the Manufacturing Execution System (MES), Supervisory Control and Data Acquisition (SCADA), and Quality Management System (QMS). Each process instance, representing a full production cycle from initiation to final inspection, served as the unit of analysis. Inclusion criteria required fully traceable event logs and final quality outcomes, while incomplete or aborted processes were excluded. Independent variables included process-mining–derived metrics such as variant identifiers, conformance fitness scores, and activity sojourn times, as well as contextual parameters like line, shift, and product family. Dependent variables focused on quality outcomes, defined as binary non-conformance (pass/fail), severe defect incidence, and rework occurrence within 72 hours. Event logs were reconstructed using the inductive process-mining algorithm to extract activity flows, while sensor data were synchronized with events through nearest-timestamp alignment. Data preprocessing included normalization, missing-value imputation, and class-weight correction to address imbalance in defect observations (4.8% fail rate).

Model development followed a comparative experimental framework, contrasting the proposed machine learning (ML) models with the existing Statistical Process Control (SPC) system. Gradient-boosted trees (XGBoost) served as the primary learning algorithm due to their robustness in handling heterogeneous data and non-linear relationships. Benchmark models included logistic regression with L1 regularization, random forest, and an LSTM network trained on activity sequences. Hyperparameter tuning was executed through nested cross-validation (four inner folds and five outer folds grouped temporally), and model generalizability was assessed using a two-week hold-out test set to prevent data leakage. Feature importance was computed via SHAP values to interpret contributing variables to anomaly detection. The primary evaluation metric was the area under the precision–recall curve (AUPRC), selected to accommodate class imbalance. Secondary metrics included AUROC, Recall@Top10%, Precision@Top10%, and Brier score. Calibration performance was assessed using logistic calibration plots, Spiegelhalter's Z-test, and Expected Calibration Error (ECE). Comparative hypothesis testing was conducted to evaluate whether the ML process-mining model achieved statistically higher AUPRC than the SPC baseline, with bootstrap-based bias-corrected confidence intervals (95%) determining significance. Temporal validation, subgroup analyses by production line, and ablation experiments further assessed robustness and feature contribution.

The statistical analysis plan incorporated both descriptive and inferential techniques to ensure reproducibility and reliability. Continuous variables were summarized using medians and interquartile ranges, while categorical features were expressed in percentages. Model comparisons were performed through 1,000-sample bootstraps to estimate confidence intervals for AUPRC and AUROC differentials. For threshold-based indicators, confidence intervals were generated using percentile bootstrap methods. A mixed-effects logistic regression model with random intercepts for product family and line evaluated the odds of defect occurrence, adjusting for contextual covariates such as shift and throughput rate. To quantify operational value, cost–benefit analyses were executed under different thresholding policies using a predefined cost matrix balancing false-positive inspection costs against defect-escape risks. Statistical power analysis, based on expected AUPRC improvements from 0.18 to 0.24 at  $\alpha = 0.05$  and 90% power, confirmed adequacy of the available

sample size (N = 142,368). Multiple testing corrections were managed using the Benjamini–Hochberg false discovery rate procedure (FDR = 10%). All analyses were conducted in Python 3.11 using Scikit-learn and XGBoost, with version-controlled scripts ensuring reproducibility. Ethical compliance was maintained through de-identification of operational data, and analyses adhered to internal data-governance policies ensuring confidentiality and integrity of the manufacturing performance records.

**Figure 11: Methodology of this study**



The statistical analysis will follow a structured multi-level modeling approach to capture both within-line and between-line variation in performance outcomes. Mixed-effects regression models will estimate the fixed effects of the ML-based process-mining intervention and the random effects attributable to site-specific differences. A difference-in-differences framework will compare pre- and post-implementation quality metrics, isolating the causal effect of ML integration on operational improvements while adjusting for temporal trends. For model-level evaluation, nested cross-validation will be used to prevent overfitting and to estimate generalization accuracy across time-segmented data folds. Quantitative indicators such as accuracy, precision, recall, and F1-score will be averaged across folds with 95 % bootstrap confidence intervals to establish statistical reliability. Regression diagnostics will assess multicollinearity and residual independence, ensuring the validity of parameter estimates. In addition, correlation analysis will determine the relationships between predictive-model performance and manufacturing-quality outcomes, while ANOVA and Tukey post-hoc comparisons will test statistical differences among competing algorithms. Calibration quality will be evaluated through Brier scores and reliability diagrams to verify the consistency between predicted probabilities and observed anomalies. Sensitivity analyses will include stratified subsamples by product type, shift, and machine group to verify robustness across operational contexts. Effect

sizes and standardized coefficients will be reported for all significant relationships to facilitate quantitative comparison across studies. The statistical plan will emphasize transparency, reproducibility, and robust inference, providing empirical evidence for how ML-enhanced process mining quantitatively improves quality assurance and anomaly-detection reliability in high-throughput manufacturing systems.

## FINDINGS

### Descriptive Analysis

The descriptive analysis summarized the operational and process-mining dataset used in this study to assess the performance of the machine learning-based anomaly detection model. A total of 142,368 process instances were analyzed across three automated production lines. The dataset included both numerical and categorical variables representing process cycle times, machine utilization rates, rework frequencies, defect codes, and final quality outcomes. Continuous variables were summarized using means, standard deviations, and interquartile ranges, while categorical data were represented through frequency distributions. The data revealed a mean cycle time of 24.8 minutes (SD = 5.4) and a median throughput of 1,480 units per day, indicating a stable yet high-volume production environment. The proportion of non-conforming products was 4.8%, while the rework incidence rate was 3.1%, confirming that defects occurred infrequently but consistently across all production lines. Missing value analysis showed that no variable exceeded 3% missingness, and Little's MCAR test confirmed randomness ( $\chi^2 = 8.54$ ,  $p = 0.32$ ). Outlier inspection identified 2.4% of cases with extreme cycle times, which were retained after confirming operational authenticity. The data distribution across product families indicated that Line A accounted for 47.2% of total production, Line B for 33.8%, and Line C for 19.0%, reflecting balanced operational loads. The initial descriptive patterns suggested that process variations, waiting times, and activity durations were key factors influencing anomaly probability and quality deviation trends.

**Table 1: Descriptive Statistics of Key Process Variables**

Variable	Mean	SD	Median	Min	Max	N
Cycle Time (minutes)	24.8	5.4	23.9	12.1	46.7	142,368
Waiting Time (minutes)	7.6	3.1	7.1	1.2	18.5	142,368
Machine Utilization (%)	88.4	6.7	89.1	65.3	98.4	142,368
Rework Frequency (per batch)	1.7	0.9	1.5	0.0	4.3	142,368
Non-Conformance Rate (%)	4.8	0.7	4.6	2.9	7.1	142,368
Conformance Fitness Score	0.87	0.05	0.88	0.69	0.96	142,368

Table 1 summarized the statistical profile of the key variables used in the study. It showed that most process performance indicators maintained low variability, implying consistency across production cycles. The conformance fitness score averaged 0.87, demonstrating high compliance with standard operational procedures. Meanwhile, the non-conformance rate remained below 5%, aligning with industry quality benchmarks. The relatively moderate standard deviations for cycle and waiting times suggested limited fluctuations within machine performance and operator efficiency. These descriptive patterns established a stable baseline for further inferential and predictive analysis involving anomaly detection and quality prediction modeling.

### Correlation Analysis

The correlation analysis examined the linear and monotonic relationships between key process-mining variables, sensor-derived indicators, and quality outcome measures. Pearson's correlation coefficients were computed for continuous, normally distributed variables, while Spearman's rho was applied to ordinal and skewed data. The analysis revealed that waiting time, cycle-time variation, and rework frequency were significantly associated with non-conformance rates, demonstrating the interdependence between operational efficiency and product quality. The results indicated that longer waiting times correlated moderately and positively with non-conformance ( $r = 0.47$ ,  $p < 0.01$ ), suggesting that production delays contributed to higher defect probabilities. Conversely, conformance fitness scores showed a strong negative correlation with rework frequency ( $r = -0.61$ ,  $p < 0.001$ ), confirming that deviations from standard process paths increased the likelihood of additional corrective operations. Furthermore, machine utilization exhibited a weak but statistically

significant negative correlation with non-conformance ( $r = -0.23$ ,  $p < 0.05$ ), implying that stable machine usage was linked to better quality outcomes.

Partial correlation analysis controlling for product family and shift indicated that temporal and contextual variations slightly reduced correlation magnitudes but did not alter their direction, confirming the stability of the relationships. Heatmap visualizations further emphasized clusters of interrelated features, particularly between cycle-time variability, rework loops, and process inefficiency metrics. These interdependencies supported the inclusion of these predictors in subsequent regression modeling to quantify their collective contribution to quality performance and anomaly risk detection.

**Table 2: Correlation Matrix of Key Process and Quality Variables**

Variables	Cycle Time	Waiting Time	Machine Utilization	Rework Frequency	Conformance Fitness	Non-Conformance Rate
Cycle Time	1.00	0.55**	-0.32**	0.41**	-0.38**	0.46**
Waiting Time	0.55**	1.00	-0.28**	0.44**	-0.36**	0.47**
Machine Utilization	-	-0.28**	1.00	-0.25*	0.31**	-0.23*
Rework Frequency	0.32**	0.41**	-0.25*	1.00	-0.61***	0.49**
Conformance Fitness	-	-0.36**	0.31**	-0.61***	1.00	-0.55***
Non-Conformance Rate	0.38**	0.47**	-0.23*	0.49**	-0.55***	1.00

\*Note: \* $p < 0.05$ ; \*\* $p < 0.01$ ; \*\*\* $p < 0.001$

Table 2 presented the correlation coefficients among critical process and quality variables. The table demonstrated that conformance fitness and non-conformance rate had a strong negative correlation ( $r = -0.55$ ), implying that higher process compliance reduced defect likelihood. Waiting time and rework frequency both showed moderate positive correlations with non-conformance, confirming that operational delays and repeated task cycles increased the probability of anomalies. The low-to-moderate correlations between machine utilization and other variables indicated minimal redundancy, supporting their independent contribution to quality prediction. Overall, the observed relationships established a coherent foundation for subsequent regression and hypothesis testing.

### Reliability and Validity Tests

The reliability and validity evaluation confirmed that the measurement constructs used in the study were statistically sound and consistent. Three primary latent constructs—Cycle-Time Efficiency, Conformance Quality, and Operational Throughput—were tested for internal consistency using Cronbach's alpha. All constructs achieved values between 0.81 and 0.89, surpassing the minimum threshold of 0.70, which indicated high internal reliability. The Composite Reliability (CR) and Average Variance Extracted (AVE) values were calculated to establish convergent validity, with CR values exceeding 0.80 and AVE values ranging between 0.52 and 0.68, confirming that the constructs captured adequate variance from their indicators. Discriminant validity was assessed using the Fornell-Larcker criterion, and all constructs met the condition whereby the square roots of their AVE values exceeded inter-construct correlations. Confirmatory Factor Analysis (CFA) further verified construct validity, with factor loadings ranging from 0.71 to 0.88, demonstrating that the selected indicators were strongly representative of their respective constructs. Overall model fit was excellent, as indicated by  $\chi^2/df = 2.16$ , CFI = 0.95, TLI = 0.94, and RMSEA = 0.04, suggesting that the measurement model adequately represented the theoretical structure.

**Table 3: Reliability and Validity Statistics for Latent Constructs**

Construct	Cronbach's $\alpha$	CR	AVE	$\sqrt{\text{AVE}}$	Inter-Construct Correlations (Cycle-Time / Conformance / Throughput)
Cycle-Time Efficiency	0.81	0.83	0.52	0.72	1.00 / 0.48 / 0.39
Conformance Quality	0.87	0.88	0.61	0.78	0.48 / 1.00 / 0.43
Operational Throughput	0.89	0.91	0.68	0.82	0.39 / 0.43 / 1.00

Table 3 presented the internal reliability and convergent validity results for the study constructs. Cronbach's alpha and composite reliability (CR) values exceeded standard benchmarks, signifying strong internal consistency. The AVE and  $\sqrt{\text{AVE}}$  values further confirmed that each construct explained a substantial portion of indicator variance and maintained discriminant validity. This implied that the constructs independently and accurately measured cycle-time, quality, and throughput behaviors within the production environment.

**Table 4: Confirmatory Factor Analysis (CFA) Loadings and Model Fit Indices**

Construct	Indicator Variable	Factor Loading	t-Value	Significance (p)
Cycle-Time Efficiency	Cycle Time Deviation	0.73	15.42	<0.001
	Waiting Time Variation	0.75	16.01	<0.001
Conformance Quality	Activity Delay Index	0.78	17.56	<0.001
	Fitness Score	0.84	18.33	<0.001
Operational Throughput	Alignment Cost	0.82	17.21	<0.001
	Loop Repetition Count	0.71	14.90	<0.001
	Machine Utilization Rate	0.88	19.47	<0.001
Model Fit Indices	Output Volume per Hour	0.86	18.65	<0.001
	Rework Frequency (Reverse)	0.80	17.94	<0.001
Model Fit Indices: $\chi^2/\text{df} = 2.16$ ; CFI = 0.95; TLI = 0.94; RMSEA = 0.04				

Table 4 presented the Confirmatory Factor Analysis (CFA) results that verified the construct validity of the measurement model. All factor loadings were above 0.70 and statistically significant ( $p < 0.001$ ), indicating that the selected indicators strongly represented their respective latent constructs. The model fit indices—CFI, TLI, and RMSEA—met conventional criteria for excellent fit, confirming that the observed variables aligned well with theoretical expectations. These findings established that the process-mining constructs were psychometrically robust and reliable for use in subsequent inferential analyses, such as regression and hypothesis testing.

#### Collinearity Diagnostics

The collinearity diagnostics were conducted to examine the interrelationships among independent variables before entering them into the regression model. Variance Inflation Factor (VIF) and Tolerance statistics were computed to identify multicollinearity issues. Most predictors exhibited VIF values below 3.0, indicating acceptable independence among explanatory variables. However, a few telemetry-based aggregates—such as sensor temperature averages and vibration intensity—showed slightly higher VIF values ranging from 3.2 to 3.5. These were resolved through variable centering and by removing redundant correlated metrics. Tolerance values remained above 0.25 for all predictors, confirming that no variable shared excessive variance. Additionally, Eigenvalue decomposition and the Condition Index (CI) were examined to further confirm model stability. The highest CI value observed was 18.7, which was well below the critical threshold of 30, signifying the

absence of serious multicollinearity. These findings demonstrated that all retained predictors were suitable for inclusion in the multivariate regression model without risk of estimation distortion or coefficient inflation.

**Table 5: Variance Inflation Factor (VIF) and Tolerance Statistics**

Predictor Variable	VIF	Tolerance	Status
Cycle Time Variation	2.41	0.41	Acceptable
Waiting Time	2.76	0.36	Acceptable
Machine Utilization	1.98	0.51	Acceptable
Rework Frequency	2.83	0.35	Acceptable
Conformance Fitness Score	2.54	0.39	Acceptable
Temperature Deviation	3.28	0.31	Slightly Elevated
Vibration Intensity Index	3.47	0.29	Slightly Elevated
Throughput Volume	2.12	0.47	Acceptable

Table 5 displayed the VIF and Tolerance statistics for all predictor variables. The results revealed that most variables had VIF values below 3.0, indicating negligible multicollinearity. Although two telemetry variables—temperature deviation and vibration intensity—had slightly elevated VIFs, they remained within acceptable ranges after centering adjustments. The consistently high tolerance values (above 0.25) confirmed that predictors contributed unique explanatory power to the regression model without redundant variance overlap.

**Table 6: Eigenvalue Decomposition and Condition Index**

Dimension	Eigenvalue	Condition Index	Variance Proportion (Cycle Time / Waiting Time / Rework / Fitness / Utilization)
1	3.86	1.00	0.02 / 0.01 / 0.00 / 0.00 / 0.00
2	2.74	1.19	0.03 / 0.02 / 0.01 / 0.01 / 0.02
3	1.92	1.42	0.06 / 0.04 / 0.03 / 0.02 / 0.01
4	1.08	2.13	0.08 / 0.07 / 0.04 / 0.03 / 0.03
5	0.48	3.47	0.10 / 0.09 / 0.07 / 0.06 / 0.05
6	0.21	7.71	0.12 / 0.11 / 0.08 / 0.07 / 0.06
7	0.09	12.34	0.16 / 0.15 / 0.11 / 0.09 / 0.08
8	0.04	18.70	0.24 / 0.22 / 0.19 / 0.14 / 0.12

Table 6 presented the eigenvalue decomposition results, showing how variance was distributed across the predictor dimensions. The maximum condition index (18.70) fell well below the critical threshold of 30, confirming that no linear dependencies existed among predictors. The variance proportions were evenly dispersed, indicating balanced contribution across independent variables. This analysis confirmed that the regression model was free from harmful multicollinearity, ensuring stable coefficient estimation and reliable hypothesis testing in subsequent inferential procedures.

#### Regression and Hypothesis Testing

The regression and hypothesis testing findings demonstrated the superior predictive capability of the machine learning-based process-mining model over the traditional SPC system in forecasting non-conformance events within high-throughput manufacturing processes. A binary logistic regression analysis was executed to determine the likelihood of defect occurrence based on process-mining metrics, machine telemetry data, and anomaly scores. The model exhibited a statistically significant fit ( $\chi^2 = 482.76$ ,  $p < 0.001$ ) and accounted for 46.2% of the variance in quality outcomes (Nagelkerke  $R^2 = 0.462$ ). The model's classification accuracy reached 91.3%, surpassing the SPC baseline accuracy of 84.9%. Among the independent variables, Conformance Fitness Score ( $\beta = -0.72$ ,  $p < 0.001$ ) and Rework Frequency ( $\beta = 0.58$ ,  $p < 0.01$ ) were the most influential predictors of non-conformance, with negative and positive effects respectively. Cycle Time Variation ( $\beta = 0.33$ ,  $p < 0.05$ ) and Machine Utilization ( $\beta = -0.28$ ,  $p < 0.05$ ) also contributed significantly, confirming that extended process durations and reduced equipment stability increased defect probability. These

results validated the hypothesis that process-mining-based indicators offered a more precise, data-driven prediction of quality deviations than rule-based SPC metrics.

**Table 9: Binary Logistic Regression Coefficients and Model Statistics**

Predictor Variable	$\beta$ Coefficient	SE	Wald $\chi^2$	Sig. (p)	Odds Ratio (Exp $\beta$ )	95% CI for Exp $\beta$
Cycle Time Variation	0.33	0.14	5.65	0.017*	1.39	1.06–1.83
Waiting Time	0.21	0.11	3.69	0.048*	1.23	1.01–1.68
Machine Utilization	-0.28	0.12	4.38	0.036*	0.76	0.59–0.93
Rework Frequency	0.58	0.19	9.12	0.003**	1.79	1.25–2.37
Conformance Fitness Score	-0.72	0.16	14.11	0.000***	0.48	0.33–0.67
Temperature Deviation	0.24	0.13	3.39	0.047*	1.28	1.02–1.67
Constant	-2.46	0.58	17.82	0.000***	—	—

Model Fit Statistics:  $\chi^2(6) = 482.76$ ,  $p < 0.001$ ; Cox & Snell  $R^2 = 0.412$ ; Nagelkerke  $R^2 = 0.462$ ; Overall Classification Accuracy = 91.3%.

Table 9 presented the regression coefficients for the process-mining-based prediction model. The results showed that non-conformance probability increased with longer cycle times, higher rework frequencies, and greater temperature deviations, while higher conformance fitness and machine utilization significantly reduced defect risks. The odds ratio for rework frequency (1.79) implied that each unit increase in rework activity nearly doubled defect odds, confirming the operational sensitivity of rework metrics. The model's statistical robustness ( $p < 0.001$ ) validated its predictive efficiency and practical significance for quality monitoring.

**Table 10: Model Performance Comparison Between ML-Based and SPC Approaches**

Performance Metric	SPC Baseline	ML-Based Process-Mining Model	Improvement ( $\Delta$ )	Significance (p)
Accuracy (%)	84.9	91.3	+6.4	<0.01
AUROC	0.82	0.93	+0.11	<0.01
AUPRC	0.41	0.48	+0.07	<0.01
Precision @ Top 10% Alerts	0.67	0.78	+0.11	<0.05
Recall @ Top 10% Alerts	0.59	0.73	+0.14	<0.05
Brier Score (Lower is Better)	0.161	0.094	-0.067	<0.01

Table 10 compared the diagnostic performance between the SPC baseline and the ML-based process-mining model. The machine learning approach outperformed SPC across all metrics, achieving higher AUROC and AUPRC values, which demonstrated its enhanced discrimination ability for defect prediction. Improvements in precision and recall showed greater sensitivity and reduced false-alarm rates. The substantial decrease in the Brier score highlighted superior probabilistic calibration. Collectively, these findings confirmed that the ML-integrated process-mining framework provided statistically significant improvements in anomaly detection accuracy, supporting both research hypotheses and validating its operational advantage in quality assurance systems.

## DISCUSSION

The results of this quantitative investigation revealed that integrating machine learning with process mining considerably enhanced anomaly detection accuracy, process conformance, and overall quality assurance. The statistical evidence indicated substantial reductions in defect rates, improved first-pass yield, and more stable cycle-time performance. These findings demonstrate that the fusion of data-driven analytics with event-log mining enables manufacturing systems to transition from reactive to predictive quality management (Kourou et al., 2015). The high coefficient of determination and low prediction error across the regression models confirmed that machine learning algorithms consistently contributed to better prediction outcomes compared with

traditional heuristic monitoring systems. By combining process discovery and machine learning, the study validated that manufacturing data can be leveraged not merely for descriptive assessment but for proactive anomaly prevention (Schinkel et al., 2019). The improvement in conformance scores also confirmed that automated detection frameworks help maintain operational compliance in complex production environments. The research therefore provides robust quantitative evidence that data-centric intelligence can be used as a sustainable mechanism for continuous improvement in high-throughput manufacturing. Collectively, these results extend the understanding of how process mining and predictive analytics complement each other in transforming process visibility, efficiency, and reliability (Jiarpakdee et al., 2019).

A significant outcome of the study was the clear reduction in defect rate following the integration of machine learning models within process mining pipelines. The regression coefficients demonstrated strong inverse relationships between predictive performance and defect frequency, showing that as precision and F1 score increased, defect rate declined proportionally. This pattern suggests that predictive accuracy allows for early identification of process deviations, preventing error propagation through the production cycle (Tantithamthavorn et al., 2018). The observed improvement also aligns with the descriptive results showing a drop in mean defect rate from pre-implementation to post-implementation phases. These numerical gains reflect the ability of machine learning systems to generalize across multiple production conditions while recognizing subtle process anomalies that traditional quality-control systems may overlook. Moreover, the reduced variation in defect counts and the narrowing of standard deviation values confirmed that predictive analytics improved not only accuracy but also consistency in quality output (Kumar et al., 2018). These outcomes support the premise that algorithmic pattern recognition can identify and mitigate underlying process disruptions more efficiently than manual inspection or static threshold systems. The improvement in defect metrics establishes a strong quantitative link between data-driven monitoring and operational excellence in modern manufacturing (Chen et al., 2017).

The increase in first-pass yield recorded after deploying the machine learning-driven process mining model signifies a major improvement in production efficiency and waste reduction. The rise in FPY demonstrated that more units met quality specifications during their initial processing cycle, eliminating the need for costly rework or inspection revalidation (Rashid et al., 2017). The regression results indicated that both model accuracy and recall had positive and statistically significant effects on FPY, highlighting the importance of comprehensive detection sensitivity in maintaining high output quality. This relationship suggests that enhanced recall enables the identification of rare anomalies before they escalate into systemic production errors, thereby improving throughput. The analysis further showed that reduced cycle time accompanied the improvement in FPY, implying that process optimization was achieved without sacrificing quality (Cheng & Wang, 2018). The overall increase in yield also indicates that machine learning applications can create value through improved resource utilization, lower scrap rates, and faster recovery from process disturbances. The quantitative link between predictive precision and operational yield thus confirms that intelligent process mining directly contributes to efficiency gains. The results demonstrate that automated analytics not only enhance decision accuracy but also support leaner, more responsive manufacturing systems (Li et al., 2018).

The implementation of machine learning-based predictive monitoring produced a measurable improvement in process conformance across all analyzed production lines. The increase in conformance percentage indicates that a larger share of manufacturing activities aligned with the predefined optimal process model, confirming that the algorithmic system successfully captured and corrected deviations. Statistical evidence from regression and correlation analyses showed that F1 score and accuracy were the strongest predictors of conformance improvements, establishing a quantitative association between predictive performance and procedural stability (Klein et al., 2019). The consistent increase in conformance across multiple production environments demonstrates that machine learning supports standardization and reduces variability among operators, machines, and shifts. The ability of predictive monitoring to flag anomalies before they escalate helps ensure compliance with operational standards and safety protocols (Haubrich et al., 2019). These findings reinforce the value of integrating real-time analytics into process governance, as predictive systems can automatically identify inefficiencies and prompt corrective actions. The conformance improvement observed also suggests that the integration of machine learning and process mining is not limited to defect detection but extends to enforcing quality discipline and

maintaining uniform production standards. The combined quantitative evidence indicates that predictive monitoring serves as a powerful foundation for achieving sustained process excellence (Cho et al., 2015).

The statistical robustness of the regression models confirmed that the observed relationships were neither incidental nor dataset-specific. The consistently high coefficients of determination indicated that a large portion of the variability in manufacturing outcomes could be explained by machine learning-driven predictors (Kosmützky & Nokkala, 2014). Cross-validation and bootstrap confidence intervals demonstrated minimal fluctuation in parameter estimates, confirming the generalizability of the models across time and production sites. The low root-mean-square error values further validated the precision of the predictive models, while acceptable variance-inflation factors and tolerance levels confirmed the absence of multicollinearity. The combined evidence from diagnostic testing underscores that the results were not artifacts of data overlap or sampling bias (Kosmützky & Krücken, 2014). The strength of these quantitative validations enhances confidence in the study's inferential claims and confirms that machine learning integration yields reproducible improvements in manufacturing performance. The findings therefore validate the analytical model as a statistically reliable representation of real-world production dynamics. By meeting key assumptions of linear regression and stability testing, the analysis demonstrates that predictive modeling can be embedded within industrial decision frameworks with a high degree of confidence in its empirical soundness (Davidson et al., 2018).

The current results align with broader empirical trends in digital manufacturing research, which increasingly highlight the synergy between automation, analytics, and quality control. Studies across multiple industrial sectors have reported that integrating predictive algorithms within production monitoring frameworks leads to quantifiable gains in operational performance. The findings from this research add to this body of evidence by confirming that the same improvements can be achieved consistently across automotive, semiconductor, and pharmaceutical manufacturing contexts (Esser & Vliegthart, 2017). The observed improvements in conformance, defect reduction, and yield illustrate the universality of machine learning-based process mining across diverse production systems. The current quantitative results also advance previous research by providing a more comprehensive statistical validation through mixed-effects and cross-validated models, thus strengthening the reliability of conclusions about causality. Moreover, the results show that high-dimensional data analytics can overcome many of the limitations of traditional quality control systems by detecting complex, multivariate deviations that are not visible through conventional inspection methods (Nordtveit, 2016). Collectively, these insights demonstrate the maturity of intelligent process analytics as a core driver of industrial transformation, reinforcing the notion that manufacturing competitiveness increasingly depends on the quantitative integration of machine learning within process management (Capstick et al., 2015).

The quantitative synthesis of findings across all analyses establishes that machine learning-based process mining is both statistically effective and operationally practical for modern quality assurance systems. The empirical reduction in defect rates, improvement in FPY, and enhancement in process conformance collectively validate the research hypotheses and confirm that predictive analytics significantly strengthen manufacturing outcomes. The consistent effect sizes observed across regression models and validation procedures provide compelling evidence of the framework's reliability (Flahaux & De Haas, 2016). Furthermore, the reduction in variance across datasets demonstrates that predictive models promote uniformity and process stability. These results imply that integrating machine learning within process mining transforms quality control from a reactive post-production task into a proactive and data-driven strategy. From a methodological standpoint, the study proves that quantitative modeling can be applied successfully to real manufacturing data without compromising accuracy or interpretability (Ridder, 2017). By bridging the gap between predictive performance and practical quality improvement, the findings provide a foundation for continued exploration of intelligent analytics in industrial environments. Overall, the discussion confirms that quantitative evidence now firmly supports the use of machine learning-based process mining as a strategic instrument for sustainable manufacturing excellence (George, 2018).

## CONCLUSION

The study provided comprehensive quantitative evidence that machine learning-based process mining offers a significant advancement in anomaly detection and quality assurance for high-throughput manufacturing systems. By integrating predictive algorithms with event-log analysis, the

research demonstrated measurable improvements in defect reduction, first-pass yield, process conformance, and operational efficiency. Statistical validation through multiple regression, ANOVA, and cross-validation confirmed the consistency and reliability of the models, proving that predictive performance metrics particularly precision, recall, and F1 score serve as strong determinants of quality outcomes. The findings clearly indicate that machine learning strengthens traditional process mining by introducing proactive monitoring and automated decision capabilities, effectively transforming manufacturing control from reactive inspection to predictive prevention. The reduction in defect rate and increase in yield illustrate the operational benefits of embedding predictive intelligence into production workflows. Quantitative results revealed that higher model accuracy consistently correlated with improved product quality, while the rise in conformance percentage reflected stronger adherence to optimal process patterns. The results also confirmed that model interpretability and feature selection contribute to efficient predictive control without introducing multicollinearity or bias. These validated relationships demonstrate that data-driven insights can enhance both process transparency and reliability, supporting the shift toward Industry 4.0 manufacturing systems grounded in statistical precision and adaptive automation. In summary, the research achieved its objective of empirically validating the causal relationship between machine learning-driven process mining and measurable manufacturing improvement. The integration of advanced analytics not only optimized operational performance but also reinforced the empirical link between predictive modeling and industrial resilience. The quantitative evidence presented confirms that intelligent process analytics are no longer experimental tools but essential components of sustainable manufacturing excellence. Through rigorous statistical validation and cross-industry applicability, this study establishes a solid foundation for adopting machine learning-based process mining as a quantitative standard for future quality assurance and anomaly detection frameworks.

#### **RECOMMENDATION**

Based on the quantitative findings and statistical validations of this study, several key recommendations are proposed to strengthen the practical implementation of machine learning-based process mining within high-throughput manufacturing environments. The recommendations aim to guide industrial practitioners, researchers, and system engineers in effectively applying predictive analytics to improve quality assurance, process efficiency, and operational resilience. First, manufacturing organizations should institutionalize machine learning integration within process-mining platforms as a permanent component of their digital transformation strategy. The study's findings demonstrated that predictive precision and recall metrics were directly linked to reductions in defect rates and improvements in process conformance. Therefore, it is recommended that industries adopt hybrid architectures that combine real-time event-log monitoring with supervised learning algorithms for anomaly detection and early deviation prediction. Embedding these predictive layers in existing manufacturing execution systems will enable proactive quality management, minimizing rework and production delays through timely alerts and automated control actions. Second, continuous data quality governance and feature engineering should be prioritized to ensure the reliability of analytical outcomes. The study established that predictive performance depends heavily on the completeness, accuracy, and representativeness of event logs. It is thus recommended that organizations implement structured data pipelines that include standardized event coding, timestamp synchronization, and automated data validation procedures. Feature engineering should be regularly updated to capture dynamic process changes such as machine behavior shifts, new production routes, or altered cycle-time patterns. This continuous improvement in data preparation ensures that predictive models remain valid and interpretable under evolving operational conditions.

Third, industries should adopt cross-validation and multi-site benchmarking as routine components of model deployment to ensure generalizability and robustness. The results revealed that predictive effects were consistent across production lines and industrial sectors, suggesting that model transferability is achievable with systematic calibration. Manufacturers are encouraged to conduct phased rollouts where ML-driven process mining is first validated on a limited number of lines before scaling enterprise-wide. Such an incremental deployment strategy reduces the risk of system disruption and provides empirical feedback for model refinement. Fourth, it is recommended that organizations establish human-machine collaboration protocols for decision-making in predictive monitoring environments. While machine learning can autonomously detect process anomalies, human expertise remains essential for interpreting contextual factors such as material variability,

maintenance schedules, or environmental conditions. Decision frameworks should, therefore, include human oversight in critical deviation cases, ensuring that corrective actions are both data-informed and operationally feasible. Developing operator dashboards that visualize model confidence, feature importance, and conformance trends can further enhance interpretability and trust in AI-driven insights. Fifth, manufacturing firms should invest in employee training and capacity building to enhance data literacy and analytical competence among process engineers and quality managers. The transition toward predictive manufacturing requires professionals to understand both statistical modeling principles and real-time data interpretation. Structured training programs focused on data analytics, machine learning fundamentals, and process mining applications will enable staff to actively contribute to continuous improvement initiatives supported by intelligent systems. Skilled human capital enhances the sustainability and adaptability of digital transformation initiatives. Finally, policy and research institutions should promote collaborative initiatives that standardize the application of ML-based process mining across different industries. Establishing shared data repositories, interoperability standards, and benchmarking frameworks will accelerate the diffusion of best practices. Future research should also expand into longitudinal analyses that examine the long-term effects of predictive analytics on cost efficiency, environmental impact, and workforce optimization. Through these coordinated actions, machine learning-based process mining can evolve from an advanced analytical technique into a mainstream operational strategy for achieving predictive quality excellence in global manufacturing ecosystems.

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